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Research paper

Cooperation in multiplayer dilemmas[☆]Ismael Martínez-Martínez^a, Hans-Theo Normann^{b,*}^a Compass Lexecon, Paseo de la Castellana 7, 28046 Madrid, Spain^b Düsseldorf Institute for Competition Economics (DICE), Heinrich-Heine-Universität Düsseldorf, Universitätsstraße 1, 40225 Düsseldorf, Germany

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ABSTRACT

We analyze infinitely repeated multiplayer prisoner's dilemmas in continuous-time experiments. As the number of players changes, our design keeps the payoffs of the all-defection, all-cooperation, and unilateral defection and cooperation outcomes constant, thus controlling for the minimum discount factor required for cooperation to be an equilibrium. For all group sizes, we study three different variants of the prisoner's dilemma. In further treatments, we allow actions to be chosen from a continuous set. We find that cooperation rates decrease with the number of players, a result that we can attribute to the increased strategic uncertainty in larger groups. The different payoff matrices also affect cooperation. For the payoff matrices with lower levels of cooperation, the group-size effect is weaker. The availability of a continuous action set strongly reduces cooperation rates.

1. Introduction

Seventy-five years after its introduction, there is a striking surge of research on the prisoner's dilemma. One part of this current stream of research looks at the determinants of cooperation in the infinitely repeated game where meta data from supergames yield new insights (Dal Bó and Fréchet, 2018),¹ and a key factor can be related to concepts of strategic uncertainty (Blonski et al., 2011; Blonski and Spagnolo, 2015; Dal Bó and Fréchet, 2011). In terms of experimental methodology, the continuous-time experiments are an important leap forward, allowing immediate and asynchronous action adjustments (Friedman and Oprea, 2012; Oprea et al., 2014; Bigoni et al., 2015). These and other² lines of new research suggest that the prisoner's dilemma continues to inspire exciting and innovative research.

Our paper extends these approaches and new methodological advances to multiplayer prisoner's dilemmas. Whereas the above research exclusively uses the standard two-player environment, we study the prisoner's dilemma in groups of different sizes, with up to nine players. Group sizes larger than two are rather frequent and relevant when it comes to issues such as team collaboration,

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¹ See Embrey et al. (2018) and Mengel (2018) for meta-studies of finitely repeated prisoners' dilemmas and one-shot games (Mengel, 2018).

² Several papers address the question of the strategies players adopt in repeated prisoner's dilemmas (Dal Bó and Fréchet, 2011; Fudenberg et al., 2012; Friedman and Oprea, 2012; Bigoni et al., 2015; Dal Bó and Fréchet, 2019). Furthermore, there are novel analyses of memory-one (or Markov) strategies; Belief-free equilibria (Ely and Välimäki, 2002; Ely et al., 2005; Breitmoser, 2015) and zero-determinant strategies (Press and Dyson, 2012; Hilbe et al., 2014, 2015).

joint effort to provide collective goods, or common pool extraction. So it seems important to go beyond the classic two-player setup. While a number of experiments have examined the effects of group size on cooperation, most of these study finitely repeated games, and many of them are oligopoly studies. An exception is the closely related study by Boczoń et al. (2025), which was conducted independently of our paper. See our literature survey in Section 2.

A key feature of our experiment and our main contribution is that we control for the minimum discount factor required for cooperation to be an equilibrium in the infinitely repeated game: For any number of players, we keep constant the payoffs in the all-defect, all-cooperate, unilateral-defection, and unilateral-cooperation outcomes. This implies that the repeated-game incentive constraint, as reflected in the minimum discount factor, for cooperation is identical for all group sizes.³ Because of this design feature, we can make a clean comparison of the cooperation rates across different group sizes. This important difference distinguishes our study from previous N -player studies.⁴

Whereas the repeated-game constraint in our experiments is the same for all group sizes, we expect the number of players to have an effect due to strategic uncertainty. Blonski et al. (2011), Blonski and Spagnolo (2015), and Dal Bó and Fréchette (2011) propose this concept for two-player infinitely repeated dilemma games. Our theory part extends the concepts of strategic uncertainty to more than two players. The traditional repeated-game approach as reflected in the incentive constraint compares the gain from a unilateral defection vs. the loss from a punishment path in a given equilibrium. Strategic uncertainty, by contrast, captures the uncertainty (or riskiness) when choosing a cooperative or defective repeated-game strategy. Put differently, strategic uncertainty is about equilibrium selection. Our design can disentangle the two possible mechanisms by which an increase in the number of players may affect cooperation: One, by making cooperative outcomes more difficult to be supported in equilibrium, and, two, by making cooperative equilibria less likely to be selected. As we control for the first mechanism, increased riskiness remains as an explanation for group-size effects. We show how strategic uncertainty changes theoretically in the number of players and we compare these predictions with experimental data.

Our research also contributes to the discussion about the determinants of cooperation. In their meta study, Dal Bó and Fréchette (2018) show how payoffs (gain from unilateral defection, loss from unilateral cooperation) affect cooperation. We study three different prisoner's dilemma payoff matrices to show how payoff differences affect cooperation in multiplayer games, that is, how they interact with the number of players.

The paper's third contribution is its study of the effect of continuous time (Friedman and Oprea, 2012; Bigoni et al., 2015) on larger groups. While a couple of papers with continuous-time experiments depart from the two-player setup (Oprea et al., 2014; Benndorf et al., 2021), these experiments are difficult to compare because the action spaces and incentives differ. Our research connects these isolated islands by analyzing a comprehensive set of group sizes for comparable prisoner's dilemmas, in continuous time.

In addition to the classic “cooperate or defect” pure-strategy setup of the prisoner's dilemma, we study an experimental treatment in which participants have access to a continuous action set. One motivation for these experiments is that in larger groups, subjects face intermediate levels of cooperation, which can complicate the comparison of two- and multiplayer experiments. Beyond simply changing the action space, the continuous action set variants may have some merit per se. There is considerable research interest in notions of gradualism (Kartal et al., 2021, for example, for the trust game): players can gradually increase the level of cooperation, thereby reducing the potential loss from unilateral cooperation.

To summarize, our experiments study groups with two, three, four, six, and nine players, and we keep constant the minimum discount factor required for cooperation. Subjects play 21 supergames with three different multiplayer prisoner's dilemma payoff matrices in continuous time and with a stochastic horizon. In addition to a standard two-action version, we analyze games with a continuous action set.

Our results are as follows. First, cooperation rates decrease with the number of players, conditional on having cooperation being equally difficult to be supported in equilibrium for all group sizes, and consistent with strategic uncertainty. Second, our variations of the payoff matrices, which make cooperative outcomes more difficult to be supported in equilibrium, also play a role. For these payoff matrices, the effect of larger groups is reduced. Third, allowing a continuous action set strongly reduces cooperation rates, suggesting that the availability of intermediate levels of cooperation leads to an escalation of conflict rather than gradual cooperation.

Section 2 is the literature review. Section 3 introduces our experimental design and the theory. Section 4 presents our results. Section 5 discusses the results, and Section 6 concludes.

2. Literature

A number of laboratory experiments analyze the effect of the player numbers. For oligopoly, early contributions are the Cournot and Bertrand experiments of Fouraker and Siegel (1963) and Dolbear et al. (1968) comparing two vs. three and two vs. four players,

³ It may seem that larger groups “naturally” require a higher minimum discount factor for cooperation, suggesting that our goal of controlling for this is somewhat artificial. However, a larger number of players does not always imply a higher minimum discount factor. Fonseca and Normann (2008) and Kühn (2012) present standard oligopoly models where larger groups require a *lower* minimum discount factor. Thus, the theory does not suggest a general relationship between group size and the minimum discount factor.

⁴ This is also true in linear public good games that adjust the marginal per capita rate of contributions for N : Since the payoff from unilateral defection increases in N , the minimum discount factor is larger for larger groups.

respectively.⁵ A first comprehensive set of group sizes (two to five player Cournot games) is analyzed in [Huck et al. \(2004\)](#). [Potters and Suetens \(2013\)](#) survey the oligopoly literature, and further oligopoly data and metadata on group sizes can be found in [Engel \(2015\)](#) and [Horstmann et al. \(2018\)](#). Numbers effects have also been investigated in repeated public goods experiments, again mostly finitely repeated. [Isaac et al. \(1994\)](#) have groups of four, ten, 40 and 100, and [Weimann et al. \(2019\)](#) have voluntary contribution mechanisms (VCMs) with groups of size eight, 60 and 100. [Diederich et al. \(2016\)](#) conduct a VCM experiment with 1110 subjects divided into groups of 10, 40, and 100. They find a positive and significant group size effect. [Nosenzo et al. \(2015\)](#) study four- and eight-player VCMs with a high and low marginal per capita return (MPCR). They observe a positive effect of group size in the low MPCR condition but a negative effect of group size in the high MPCR condition. The evidence is more limited for infinitely repeated games. [Lugovsky et al. \(2017\)](#) is an exception as they compare finitely vs. infinitely repeated for two- and four-player VCMs.

Closely related to this study are the recent N -player dilemma experiments by [Boczoń et al. \(2025\)](#). They run infinitely repeated games with two, four and ten players. Like our us, they study infinitely repeated N -player prisoner's dilemma experiments in conjunction with variations of the payoff parameters and make predictions based on strategic uncertainty, as suggested by [Blonski et al. \(2011\)](#), [Blonski and Spagnolo \(2015\)](#) and [Dal Bó and Fréchet \(2011\)](#).⁶ However, [Boczoń et al. \(2025\)](#) are more directly concerned with the assessment of strategic uncertainty. They use a N -player dilemma model with both perfectly correlated and independent beliefs (player's expectations over the opponents' cooperativeness) as a tool. They also analyze how explicit communication affects strategic uncertainty. The focus of our paper is an evaluation of the comparative statics of N for a larger set of group sizes in the N -player game to see how these differ from those in the two-player case. The two papers also differ in other more technical dimensions.⁷

As for dilemma experiments in continuous time, the seminal contribution is [Friedman and Oprea \(2012\)](#). They find very high cooperation rates, higher than in comparable discrete-time variants. [Bigoni et al. \(2015\)](#) run two-player prisoner's dilemmas in continuous time and show that a deterministic horizon leads to more cooperation than an indefinite horizon. [Friedman et al. \(2015\)](#) run Cournot two- and three-player games over 1200 periods and find some cooperation after an initial competitive phase. For medium-sized groups, [Oprea et al. \(2014\)](#) find some cooperation in four-player public goods experiments. However, this depends on whether time is continuous or discrete and on the availability of communication. At the lower end of the spectrum, [Benndorf et al. \(2021\)](#) find near-zero cooperation in groups of 12.⁸ Our experiment is the first to use a continuous action space for the prisoner's dilemma with $N \geq 2$, and the first to use continuous time to test a wide range of group sizes.

There are few prisoner's dilemma experiments in which the action set differs from the standard two pure actions. See [Gangadharan and Nikiforakis \(2009\)](#), [Lugovsky et al. \(2017\)](#), and [Heuer and Orland \(2019\)](#). We discuss these in Section 5.

3. The experiment

3.1. Design

We implement a series of experimental prisoner's dilemma supergames in a multiplayer environment. The main treatment variable is the group size, with five realizations, $N \in \{2, 3, 4, 6, 9\}$.

In the $N = 2$ version of a prisoner's dilemma game, players simultaneously choose whether to cooperate (C) or defect (D) and receive payoffs according to a matrix of the form

$$\begin{pmatrix} R & S \\ T & P \end{pmatrix}.$$

The four entries are: the reward for joint cooperation, R , the temptation payoff resulting from unilateral defection when the other player cooperates, T , the sucker payoff resulting from cooperation when the other player defects, S , and the punishment payoff from mutual defection, P . The constraint $T > R > P > S$ makes D the dominant strategy. It is useful to normalize the payoffs to facilitate comparisons between different experimental designs. By scaling R to 1 and P to 0, the two normalized off-diagonal entries are as in the left matrix of [Table 1](#), with $g = (T - P)/(R - P) - 1 > 0$ and $l = (P - S)/(R - P) > 0$. With this normalization, g is the gain from unilateral defection whereas $-l$ is the loss from unilateral cooperation.

The following prisoner's dilemma game for $N \geq 2$ players ensures that the payoffs in the key outcomes (all cooperate, all defect, and unilateral cooperation and defection) remain constant as we vary the group size. For a player i in a group of size N , $\bar{c}_{-i} = m/(N - 1)$ denotes the fraction of cooperators among the $N - 1$ other players ($m \leq N - 1$). The normalized payoffs of player

⁵ [Dolbear et al. \(1968\)](#) present a finitely repeated oligopoly experiment with differentiated price competition, where a firm's sales and profits depend only on the average price of its competitors, regardless of their number. Their results are difficult to compare because their experiments have an uncertain duration, sometimes incomplete payoff information, and a continuous action set which allows for below-Nash pricing.

⁶ Strategic uncertainty has recently found other interesting and important applications. [Ghidoni and Suetens \(2022\)](#) and [Kartal and Müller \(2021\)](#) show theoretically how strategic uncertainty in the prisoner's dilemma is affected when moves are sequential rather than simultaneous, and they provide experimental evidence confirming these effects.

⁷ The two experiments have a different payoff structure when $N > 2$: In the design of [Boczoń et al. \(2025\)](#), rival cooperation is only successful when all of the other $N - 1$ players cooperate, resembling Bertrand competition. In contrast, we pay a payoff weighted by the number of cooperating/defecting rival players. [Boczoń et al. \(2025\)](#) assume that the unilateral gain from defection equals the unilateral loss from cooperation.

⁸ [Benndorf et al. \(2021\)](#) analyze a large number of different 2×2 games in continuous-time experiments. Here, we refer to the prisoner's dilemma games played in the single-population setup. In this setting, players earn the expected payoff as if they were playing against the aggregate strategy of their population. Since the population size is 12, it is essentially like playing in a group of 12.

Table 1
Stage-game matrices of the prisoner's dilemma.

	Normalized		Neutral		Defensive		Offensive	
	Cooperate	Defect	Cooperate	Defect	Cooperate	Defect	Cooperate	Defect
Cooperate	1, 1	$-l, 1 + g$	14, 14	6, 18	14, 14	2, 18	14, 14	6, 22
Defect	$1 + g, -l$	0, 0	18, 6	10, 10	18, 2	10, 10	22, 6	10, 10

i from choosing C and D are then $\pi_i(C_i, \bar{c}_{-i}) = \bar{c}_{-i} - (1 - \bar{c}_{-i})l$ and $\pi_i(D_i, \bar{c}_{-i}) = \bar{c}_{-i}(1 + g)$. The reward from full cooperation is $\pi_i(C_i, 1) = 1$, the payoff from all defect is $\pi_i(D_i, 0) = 0$, the temptation to defect unilaterally is $\pi(D_i, 1) = 1 + g$, and the payoff to a unilateral cooperator is $\pi_i(C_i, 0) = -l$. Thus, these payoffs are the same as for $N = 2$, regardless of the group size.

The second treatment variable concerns the stage-game payoffs. Participants in the experiment play the three different payoff matrices shown in Table 1, to the right of the normalized game. We refer to them as *neutral*, *defensive*, and *offensive*, following Dixit (2003) and Heller and Mohlin (2018). The payoffs from joint cooperation and complete defection are 14 and 10, respectively, in all games. This yields an efficiency gain from cooperation of 40%, common across treatments. The neutral matrix serves as the base case with $l = g = 1$. The defensive and offensive matrices are derived from the neutral one by increasing either l or g by one. In the defensive prisoner's dilemma, the incentive to defect is greater against a defector than against a cooperator ($l = 2 > g = 1$). The opposite is true in the offensive case ($l = 1 < g = 2$).⁹

Supergames are implemented in continuous time, as infinitely repeated games with an expected duration of 60 s. The experiments were run with ConG (Pettit et al., 2014), a software package for continuous-time experiments.¹⁰ In each supergame, subjects had 30 s to make their initial choice before continuous play began. The stopping time, T , of each supergame was determined by one random draw from the exponential distribution with an inverse scale of $1/60$ s. The expected length of the games did not vary and subjects had no prior information on the actual duration. The underlying stochastic termination rule was explained in the instructions (see the Supplementary Material) in two complementary ways: by showing a mock sample of lengths (including unusually short and long supergames) and by providing a discrete-time analog of a high continuation probability (0.9983), as done in Bigoni et al. (2015).¹¹ We committed to a seeded sequence of random realizations to allow for replications and extensions of the study. The realized durations in the experiments (126 observations) show that the experimental sample of game durations and the exponential distribution are not significantly different (Anderson–Darling test, $p = 0.779$).

Fig. 1 illustrates our experimental design. In each session, there are 24 subjects who were divided into groups with 2, 3, 4, 6, and 9 players in each supergame. Subjects played 21 supergames in all sessions. Each supergame was randomly assigned one of the three prisoner's dilemma matrices in Table 1 as the base game. The only restriction was that each payoff matrix should be used seven times per session. In other words, while the payoff matrix was random in every supergame, the draw was without replacement at the session level. Our design implies that five groups of different sizes played parallel games with one specific combination of payoff matrix and supergame duration in each of the 21 supergames. Fig. 1 provides an example. The comparisons of the group size and game matrix is within subjects accordingly.¹² The player partitions were randomized and reshuffled prior to the start of each supergame.¹³ Subjects were informed that no distinct group composition would be repeated more than once per session. (Group composition would be reshuffled until this constraint was met). To reiterate: The group size was not random. The payoff matrix was random without replacement. The length of a supergame was random. Player partitions were random, subject to the aforementioned constraint.

The decision screen (see screenshot in the instructions in the Supplementary Material) continuously informed subjects about their own action, the proportion of cooperators ("A" players) in their group, and their current and cumulative payoffs in this supergame. In $N > 2$ groups, subjects can infer how many cooperators are in the group, but they do not know who defected.

Finally, we run the N -player supergames in two basic variants that differ in the set of available actions, and we will refer to the two variants as Pure and Cont. In the Pure experiment, subjects had to select a pure action, either to cooperate (C) or to defect (D).

⁹ With respect to other prisoner's dilemma experiments in continuous time, Bigoni et al. (2015) implement a matrix with $l = 2$ and $g = 1$, as in our defensive case. Friedman and Oprea (2012) use four prisoner's dilemma matrices, allowing for changes in the diagonal entries. Their Easy and Hard games are neutral, with $l = g = 2/3$ and $l = g = 4$, respectively. Their Mix-a and Mix-b variants are offensive ($l = 2/3$, $g = 4/3$) and defensive ($l = 4$, $g = 2$), respectively, both with a 1 : 2 ratio, similar to our design.

¹⁰ All relevant information about the state of the system (choices, payoffs, history timelines, etc.) was recorded at very rapid intervals of 0.1 s. To put this scale into perspective, the only other quasi-continuous time experiment with an stochastic termination rule (that we are aware of) is Bigoni et al. (2015), who define intervals of 0.16 s in z-Tree. Other ConG experiments with deterministic duration use similar scales (Friedman and Oprea, 2012; Benndorf et al., 2021).

¹¹ The following calculation illustrates this. Consider the stopping time in a discrete time infinitely repeated game, $T_{\Delta t}$. This is a geometric random variable with parameter $1 - \delta_{\Delta t} = \lambda \Delta t$, where λ is a fixed positive parameter and Δt is the length of each time step in the stochastic game. When Δt is sufficiently small, the distribution of the geometric random variable $T_{\Delta t}$ tends to an exponential random variable with λ as the inverse of the expected duration: $\lambda = 1/\langle T \rangle$. For the particular case of our experiment, we get $\delta_{\Delta t} = 1 - \Delta t/\langle T \rangle = 1 - 0.1 \text{ s}/60 \text{ s} = 0.9983$.

¹² One rationale for using a within-subjects design is cost effectiveness as this design requires fewer participants than a between-subjects design. A second motive is that we expected subjects to learn whether or not to cooperate when they experience different group sizes. See footnote 24 with evidence on this. A downside of a within-subjects design is that carryover or order effects can occur. We addressed this issue in the econometric analysis by including dummy variables that capture the properties of the previously played game. The results in Table 2 suggest that order effects were probably not overly strong.

¹³ The median subject in the Pure experiment participated two times in a group of size $N = 2$, three times with $N = 3$, three times with $N = 4$, five times with $N = 6$, and eight times with $N = 9$.

	PD	T	$N = 2$	$N = 3$	$N = 4$	$N = 6$	$N = 9$
1) Neutral	36.6 s						
2) Offensive	244.8 s						
⋮	⋮		⋮	⋮	⋮	⋮	⋮
21) Neutral	231.6 s						

Fig. 1. Experimental design. Example of one session: Subject 18 played the Neutral game in a group of 4 in supergame 1, the Offensive game in a group of 6 in supergame 2, and the Neutral game again in a group of 2 in supergame 21. Column T shows the random duration of the supergames.

In the Cont experiment, subjects could also choose intermediate levels of cooperation by fixing any action between zero and one with a slider.¹⁴ Let $\sigma_i \in (0, 1)$ denote player i 's action, meaning that she cooperates with weight σ_i and defects with $1 - \sigma_i$. Then, her realized payoff in the Cont treatment reads:

$$\sigma_i \frac{\sum_{j \neq i} \sigma_j - (1 - \sigma_j)l}{N - 1} + (1 - \sigma_i) \frac{\sum_{j \neq i} \sigma_j (1 + g)}{N - 1}. \quad (1)$$

That is, subjects choose and realize intermediate levels of cooperation, they do not randomize between the two pure strategies. The computer interface is implemented with a customized extension of ConG (Pettit et al., 2014). Screenshots are available as part of the instructions in the Supplementary Material.

3.2. Theoretical background

Consider the normalized game in Table 1, repeated infinitely many times. Future payoffs are discounted with a factor δ . Appendix A contains detailed derivations and refers to the general payoffs (R, T, S, P) .

We begin with the Pure experiment. A first benchmark for cooperation is the default minimum discount factor when players follow a grim-trigger strategy (start by cooperating, and defect forever if a player defected in a previous round). Cooperating yields $1/(1 - \delta)$, while defecting yields $1 + g$. The grim trigger is thus a subgame-perfect Nash equilibrium if the following holds for the actual discount factor:

$$\delta > \frac{g}{1 + g} \equiv \underline{\delta}. \quad (2)$$

The discount factor implemented in the experiments ($\delta = 0.998\bar{3}$) exceeds this threshold, relevant to all treatments.

Whereas our design ensures that the various payoffs do not depend on N ($\underline{\delta}$ is the same for all group sizes), the minimum discount factor does differ for the different payoff matrices. The g payoff in Neutral and Defensive (both $g = 1$) is different from the one in Offensive ($g = 2$), so we obtain $\underline{\delta}_{\text{Neutral}} = \underline{\delta}_{\text{Defensive}} = 1/2$ and $\underline{\delta}_{\text{Offensive}} = 2/3$. Defensive differs from Neutral and Offensive with respect to the l payoff, but the standard minimum discount factor does not take into account the loss from unilateral cooperation as it merely reflects incentives to defect from a given equilibrium.

We now assume that players face strategic uncertainty (Blonski et al., 2011; Blonski and Spagnolo, 2015; Dal Bó and Fréchette, 2011). Players choose between two repeated-game strategies, grim trigger (GT) and always defect (AD), but they are uncertain of the strategy their opponents will play. Let p be the (identical) probability that any of i 's opponents play GT, and $1 - p$ is the probability that any player $\neq i$ plays AD. We generalize existing two-player analyses to the N -player case.

We calculate the expected payoffs from GT and AD. First, suppose that player i plays GT. After the initial period (that is, in $t = 1$), there are only two contingencies. With probability p^{N-1} , all players cooperate in $t = 0$ and, accordingly, earn $R = 1$ throughout the supergame, yielding an expected payoff of $p^{N-1}\delta/(1 - \delta)$. With the counter probability, at least one rival player fails to cooperate in $t = 0$ and therefore everyone defects afterwards such that payoffs are $P = 0$. Period $t = 0$ is a bit more complicated, since the expected payoff is given by the different combinations with which i faces m cooperators, $0 \leq m \leq N - 1$. In Appendix A, we show that the expected payoff from playing GT in $t = 0$ boils down to $p - (1 - p)l$. Altogether, $p - (1 - p)l + p^{N-1}\delta/(1 - \delta)$ is player i 's discounted payoff from GT. Now assume player i chooses AD. Regardless of the choices of the other players, the initial defect action triggers defection by all players in periods $t = 1, \dots, \infty$ and payoffs are zero. In $t = 0$, the expected payoff from choosing AD is

¹⁴ The multiplayer extension of the prisoner's dilemma, explained above for Pure strategies, also holds in Cont, interpreting $\bar{\epsilon}_i$ as the average level of cooperation among the $N - 1$ co-players (continuous between 0 and 1).

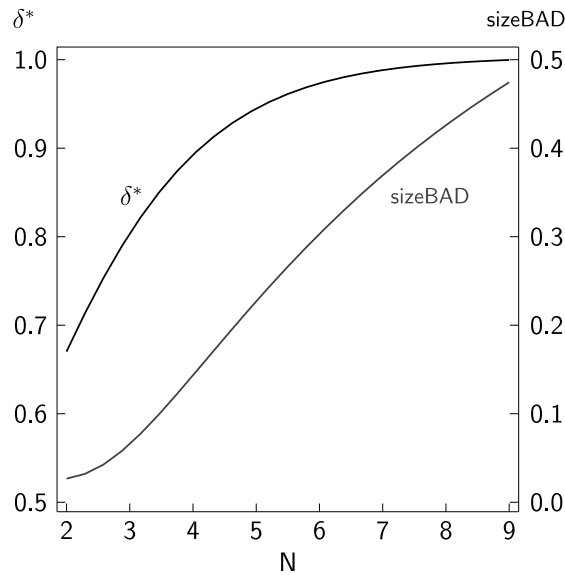


Fig. 2. Alternative minimum discount factor δ^* as in (5), and sizeBAD as in (6) as functions of N and for the Neutral game.

$p \cdot (1 + g) + (1 - p) \cdot 0$ (see Appendix A). Accordingly, $p(1 + g)$ is the discounted payoff from playing AD. Comparing expected payoffs from GT versus AD, we find that $p - (1 - p)l + p^{N-1}\delta/(1 - \delta) \geq p(1 + g)$ if and only if

$$\frac{\delta}{1 - \delta} \geq \frac{l}{p^{N-1}} + \frac{g - l}{p^{N-2}}. \quad (3)$$

This is a N -player condition for the emergence of cooperation (playing GT).

From (3), N -player versions of measures of strategic uncertainty can be obtained, and further results in the literature can be recovered. Blonski et al. (2011) and Blonski and Spagnolo (2015) propose an alternative minimum discount factor, δ^* . If this benchmark is exceeded, GT is the risk dominant strategy. So, the larger δ^* , the less likely a player is to cooperate. We solve (3) for δ and obtain:

$$\delta \geq \frac{gp + l(1 - p)}{gp + l(1 - p) + p^{N-1}}. \quad (4)$$

Intuitively, if $p = 1$ in (4), the standard minimum discount factor, $g/(1 + g)$ as in (2), results, and if $p = 0$, (4) becomes $\delta \geq 1$. For equilibrium selection according to risk dominance, a common assumption is $p = 1/2$, in which case (4) yields:

$$\delta \geq \frac{g + l}{g + l + \left(\frac{1}{2}\right)^{N-2}} \equiv \delta^*. \quad (5)$$

For $N = 2$, we obtain $\delta^* = (g + l)/(g + l + 1)$, the result of Blonski et al. (2011) and Blonski and Spagnolo (2015).

Dal Bó and Fréchet (2011, 2018) suggest the size of the basin of attraction of AD (sizeBAD). This is the belief of GT that would leave a player indifferent between the two strategies, given the actual discount factor used in the experiment. The larger sizeBAD, the less likely a player will cooperate. The N -player sizeBAD is only implicitly defined by (3), but an explicit solution can be obtained for the Neutral matrix ($g = l$)

$$p = \left(l \frac{1 - \delta}{\delta}\right)^{\frac{1}{N-1}}. \quad (6)$$

This is exactly the result of Boczoń et al. (2025) who generally impose $g = l$. For $N = 2$, (3) implies the finding of Ghidoni and Suetens (2022) which, for the normalized payoffs, reads $p \geq l/(l - g + \delta/(1 - \delta))$.

What predictions does this analysis suggest for group size, N ?¹⁵ Fig. 2 shows for the Neutral game matrix δ^* as in (5) and sizeBAD as in (6). Both metrics increase monotonically in N . This is true in general, not just for the Neutral matrix, as follows from (3) and (4). See Table 3 in the Supplemental Material which lists the numerical realizations of the sizeBAD (3) and δ^* (5) measures for the experimental group sizes and payoff matrices. We conclude:

Prediction 1 (Pure). Group size has a negative effect on cooperation rates.

¹⁵ Because $\delta = 0.9983 > \delta^*$ throughout, cooperating is the risk-dominant equilibrium. Since all experiments were run with the same δ , using the difference $\delta - \delta^*$ instead of δ^* does not yield any additional insights.

We turn to the effects of the payoff matrices. Compared to Neutral, the Defensive and Offensive matrices are generally an obstacle to cooperation. Defensive and Offensive increase either l or g compared to Neutral, so the right-hand side in (3) and the expressions in (4) and (5) increase.

Prediction 2 (Pure). Cooperation rates are lower in Defensive and Offensive, compared to Neutral.

Although Predictions 1 and 2 can in principle both be supported by the data, they are potentially conflicting. We expect the impact of group size on cooperation to be smaller with the Defensive and Offensive payoff matrices than with the Neutral one due to a ceiling effect. Cooperation should indeed be more difficult to achieve and maintain, even when subjects interact in pairs.¹⁶ Put differently, the group size should only have a smaller impact in Defensive and Offensive:

Prediction 3 (Pure). Group size has a smaller impact on cooperation in Defensive and Offensive, compared to Neutral.

Comparing Defensive and Offensive turns out to be ambiguous. To begin with, Offensive and Defensive share the same δ^* : In (5), only the sum $g + l$ matters for δ^* , and $g + l$ is the same for Offensive and Defensive. However, the more general benchmark (4) is the same for Offensive and Defensive if and only if $p = 1/2$, and it is greater for Defensive [greater for Offensive] if and only if $p < [>] 1/2$.¹⁷ This is intuitive: When players believe that rival cooperation is likely, the defection payoff, d , is important, while the loss from cooperation, l , is not. And vice versa when beliefs are low. As for sizeBAD, given the δ and N used in the experiment, the minimum belief required to play GT is larger in the Defensive treatment compared to Offensive, see Table 3 in the Supplemental Material. This is consistent with (4) in that sizeBAD is less than one half for the experimental parameters (see Fig. 2). If participants have different beliefs, or if they perceive the discount factor to be lower than implemented, the reverse sizeBAD prediction holds. We therefore refrain from making a prediction regarding Offensive vs. Defensive.

We now turn to the Cont treatment. Given player i 's action $\sigma_i \in (0, 1)$ and her rivals' actions $\sigma_{j \neq i}$, Eq. (1) states the realized payoffs. The continuous action set allows for lower cooperation levels $\sigma_i \in (0, 1)$, that is, players cooperate less than 100% and defect with a positive weight. Such limited defection is part of the cooperative strategy and is observable for all players. It can thus be distinguished from full defection which is still the myopic best reply and, in fact, the dominant action.

We focus on symmetric cooperative equilibria where $\sigma_1 = \sigma_2 = \dots = \sigma_N = \sigma \in (0, 1]$. Using (1), the R payoff when all players cooperate with σ and defect with $1 - \sigma$ simplifies to $R = \sigma(1 + (g - l)(1 - \sigma))$. The payoff from unilateral defection (that is, $\sigma_i = 0$ and $\sigma_{j \neq i} = \sigma$) reads $T = \sigma(1 + g)$ whereas unilateral cooperation ($\sigma_i = \sigma$ and $\sigma_{j \neq i} = 0$) yields $S = -\sigma l$. The all-defect payoff remains $P = 0$. Substituting $\sigma = 1$ in these formulas yields the corresponding payoffs in the Pure setting whereas employing $\sigma = 0$ (all defect) implies zero payoffs in all cases.

Next, we derive the minimum discount factor required for a GT strategy to be a subgame-perfect equilibrium. Using the above payoffs for R , D and T , one obtains

$$\underline{\delta} = \frac{l + \sigma(g - l)}{1 + g}$$

for the continuous-action-set case, where $\sigma = 1$ implies $\underline{\delta} = g/(1 + g)$ as in (2).

The question is whether a lower cooperation level in Cont, $\sigma \in (0, 1)$, can reduce the minimum discount factor compared to the one under full cooperation, $\sigma = 1$ (as in Pure). The sign of $\partial \underline{\delta} / \partial \sigma$ depends on the sign of $g - l$: For our Neutral ($g = l$) setup, we obtain $\underline{\delta} = 1/2$ for all σ , unchanged to the Pure case. For the Defensive ($g = 1 < l = 2$) treatment, we obtain $\underline{\delta} = 1 - \sigma/2$, so cooperating with $\sigma \in (0, 1)$ increases the minimum discount factor required compared to full cooperation. This suggests that, as with the Pure action set, cooperation will be more difficult than with Neutral. In Offensive ($g = 2 > l = 1$), we get $\underline{\delta} = (1 + \sigma)/3$, so cooperating with $\sigma \in (0, 1)$ requires a lower minimum discount factor than cooperating with $\sigma = 1$. We conclude that lower cooperation levels $\sigma \in (0, 1)$ can be more plausible in Offensive than in Defensive or Neutral. For low levels of cooperation ($\sigma \leq 1/2$), we obtain for Offensive that $\underline{\delta} = (1 + \sigma)/3 \leq 1/2$. Hence, there exist levels of δ such that cooperation with $\sigma \in (0, 1/2)$ can be an equilibrium in Cont but not in Pure (where $\sigma = 1$). We dismiss this case because the actual discount factor implemented in the experiment is much larger than $1/2$, and, even of this was not the case, the cooperation level would need to be substantially lower, such that cooperation can hardly be claimed to improve.¹⁸ In Appendix A, we extend our N -player condition for the emergence of cooperation (3) for a continuous action set. As with pure strategies, the analysis for the continuous action set suggest that larger group sizes will be an impediment to cooperation.

Prediction 4 (Cont). Group size has a negative impact on cooperation rates.

Prediction 5 (Cont). Cooperation rates are lower in Defensive and Offensive compared to Neutral.

Prediction 6 (Cont). Group size has less impact in Defensive and Offensive, compared to Neutral.

¹⁶ See also Table 3 in the Supplementary Material. The δ^* entries are smaller for Neutral than for Defensive/Offensive throughout, but this difference is smaller for larger N .

¹⁷ See Andres et al. (2023) for a detailed analysis of how δ^* is affected by beliefs.

¹⁸ Similar partially cooperative equilibria may also exist in the Pure setting. When risk-neutral players randomize and their mixed strategies are observable, the equilibria resemble the low-cooperation level equilibria in the Cont variant.

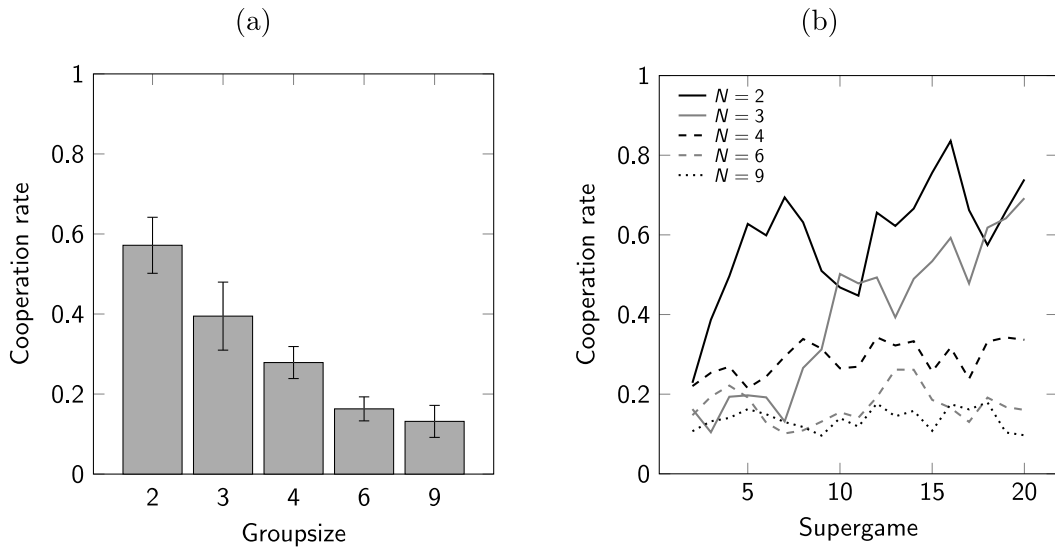


Fig. 3. (a) Mean cooperation in Pure by group size N , 95% confidence intervals based on bootstrapped standard errors clustered at the session level. (b) Evolution of average group cooperation over supergames in Pure. For both panels, the unit of observation is defined as in footnote 20.

3.3. Procedures

We conducted six sessions, three for Pure and three for Cont. No subject participated in more than one session and all sessions included 24 subjects, except for one session with 22 subjects.¹⁹ This makes a total of 142 participants. Appendix B contains power calculations for this sample size and the type of empirical analysis.

Subjects' earnings in the experiment were determined by the combination of their own and their rivals' choices, summed over the duration of each supergame, and scaled with respect to the expected length. While playing a supergame s , each individual i accumulated earnings $\Pi_{i,s} \equiv \frac{1}{60} \int_0^{T_s} \pi_i(\sigma_{i,s,t}, \tilde{c}_{-i,s,t}) dt$. The final payout to each subject was the average of the 21 supergames. Participants earned between €10 and €18.

Further details of the experimental procedures were as follows. The experiments took place at the DICElab of the University of Duesseldorf. We conducted the experiments between May 6 and May 20 2019, beginning with the three Pure sessions. No pilot sessions were conducted. Subjects were recruited from the lab subject pool using ORSEE (Greiner, 2015). Upon arrival at the lab, participants were randomly assigned a cubicle number. Printed instructions were distributed and summarized verbally. Participants were also given ample opportunity to ask questions individually and privately. The expected duration of the supergames is invariant (60 s), but the realized durations naturally differ. After the 21 supergames were completed, we collected additional data on demographics and individual preferences. Subjects completed a questionnaire based on Falk et al. (2016, 2018)—details are available in Table 4 in the Supplementary Material. The average duration of the sessions including the time for reading the instructions, the questionnaires, and payout was around one hour. The experiments themselves took about half an hour. We maintained anonymity throughout.

4. Results

We begin with an analysis of the Pure experiment in Section 4.1. Section 4.2 analyzes the Cont data. For the regression results, we report non-parametric bootstrapped standard errors, repeatedly resampling the observed data with replacement and recalculating the standard errors that are clustered at the session level. The results are robust when using regular (non-bootstrapped) standard errors either clustered at the session or subject level, or with subject fixed effects.

4.1. The Pure experiment

The effect of the number of players

Fig. 3(a) shows the average cooperation rates for the different group sizes. Consistent with Prediction 1, cooperation rates decrease monotonically with group size. The treatment variable N seems to produce a smooth pattern, a decrease of cooperation

¹⁹ In that session, we had two groups of four players and none with six players.

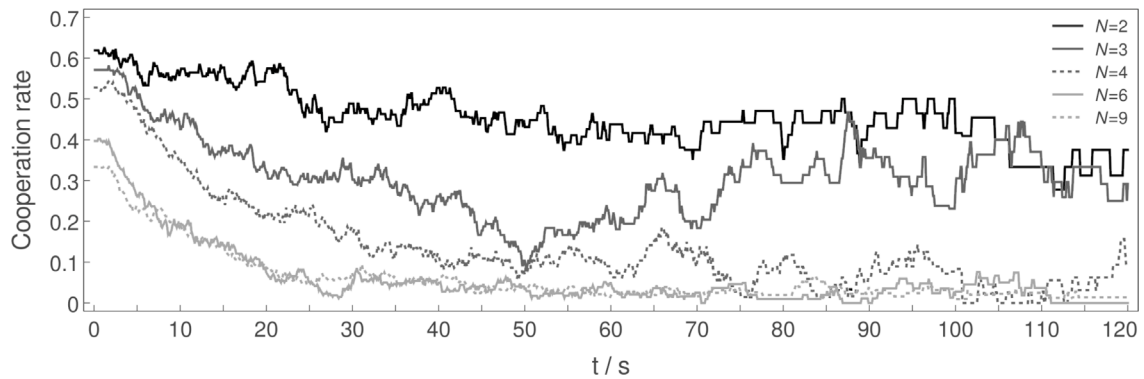


Fig. 4. Evolution of cooperation over time, by group size N . Pure data, group averages are conditional on a group being active: Out of the initial 63 groups, 43 were active after 30 s, 24 after 60 s, 15 after 90 s, and 8 after 120 s (for all N).

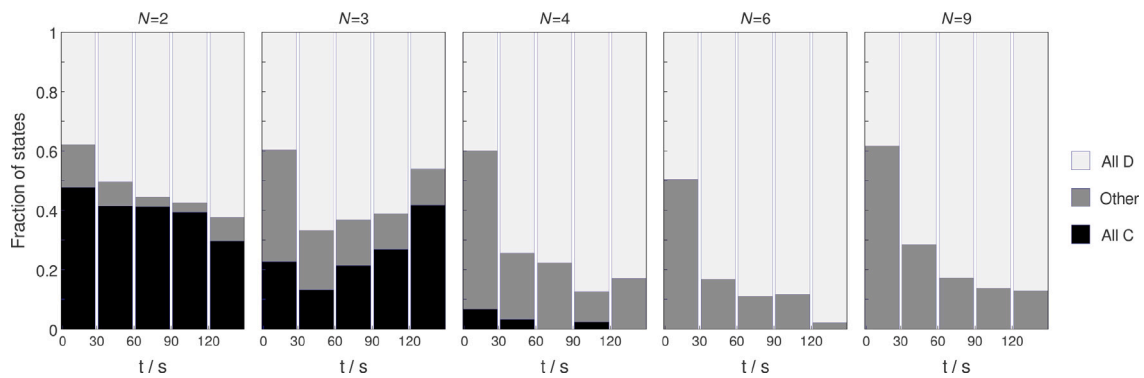


Fig. 5. Fraction of time spent in the different outcomes, Pure data.

in N . The highest cooperation rates are obtained for the smallest groups, with a mean of $\langle \bar{c} \rangle = 0.572$ for $N = 2$, and the lowest rates are observed for $N = 9$, with a mean of $\langle \bar{c} \rangle = 0.132$.²⁰ In Table 2, we report regression analyses that confirm the statistical significance of these findings.

How does average play develop over the course of the 21 supergames? Fig. 3(b) shows the moving mean of group cooperation rates for all N , with a span of three supergames to reduce noise. Cooperation in small groups increase over supergames. In the last seven supergames, the cooperation rates are 29.3 (45.3) percentage points for $N = 2$ ($N = 3$) higher than in the first seven supergames. That is, subjects learn to cooperate with supergame repetition. This is not the case for the larger groups with $N \geq 4$.

Not only do subjects gain experience in how to play across supergames, but cooperation also shows pronounced time trends within supergames. Fig. 4 shows five timelines, one for each N . Cooperation decreases with time, especially in the first 30 to 50 s. Cooperation rates for $N = 2$ suffer the least from this decrease over time. Groups of three players start with a decrease, but manage to increase again, seem to stabilize towards the end of the interval, and later reach the level of the $N = 2$ groups.²¹ The negative effect of duration on cooperation is stronger for $N \geq 4$. They lose almost all of their cooperative choices within the first minute of play.

The time trends in the data raise the question of miscoordination. To what extent do players coordinate on outcomes where all players cooperate or defect? Fig. 5 shows coordination rates over time in five panels, one corresponding to each group size. The

²⁰ Averaging the data at the group-supergame level, the experiment contains 315 data points, namely five group sizes in 21 supergames, times three sessions. Let $c_{i,t}$ be the cooperation level of player i at time t in a supergame, and $\bar{c}_t = \frac{1}{N} \sum_i c_{i,t}$ be the mean cooperation level among the N players that form a group. Then group cooperation rates are defined as time-averages, $\langle \bar{c} \rangle = \frac{1}{T} \int_0^T \bar{c}_t dt$, where $\langle \rangle$ indicate that the average is taken at the group level, and T is the realized length of the supergame. Figure 10 in the Supplementary Material provides additional details by session.

²¹ The increase in the average cooperation of the $N = 3$ groups at about 50 s in Fig. 4 seems to be the result of several groups being able to coordinate on cooperative outcomes again, after the marked initial drop that is also seen for $N > 3$. Consistent with this, Fig. 5 shows an increase in the proportion of “all cooperate” states beginning after the 30 s bin. Conspicuously, the reverse trend for the $N = 3$ groups in Fig. 4 occurs when cooperation rates were rather low (below 10%), and the reverse differs from the trend of the $N = 2$ groups which (at least on average) did not experience such low cooperation rates.

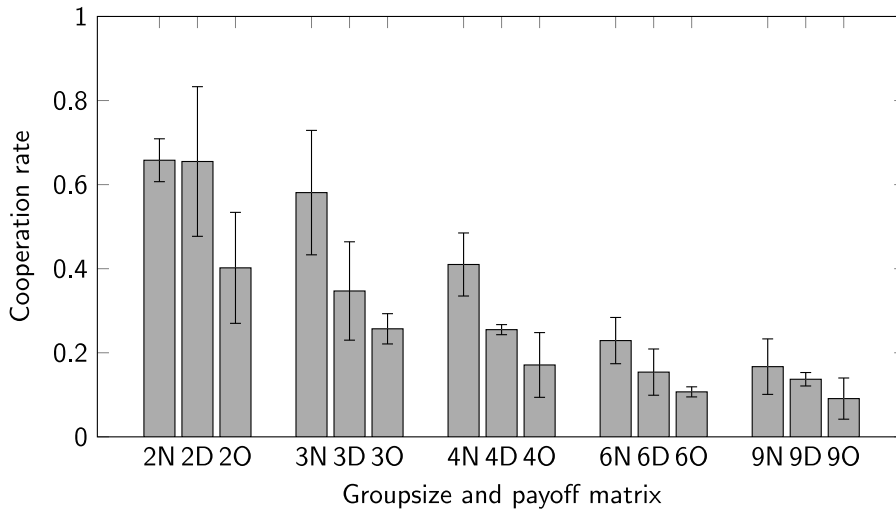


Fig. 6. Average group cooperation conditional on payoff matrix, N, D, and O refer to the Neutral, Defensive, and Offensive payoff matrix, respectively, 2–9 refer to the group size, 95% confidence intervals based on estimations with bootstrapped standard errors clustered at the session level, Pure data.

data are summarized in bins of 30 s, with the last bin containing all $t > 120$ s. We highlight the outcomes $\langle \bar{c} \rangle = 0$ (all defect) in gray, $\langle \bar{c} \rangle = 1$ (all cooperate) in black and pool in gray all other outcomes involving some degree of coordination failure. For the groups with $N \leq 3$, there is a substantial share of full cooperation outcomes right at the beginning of the supergame. For $N = 2$, this share declines moderately over time. The $N = 3$ groups manage to increase the proportion of $\langle \bar{c} \rangle = 1$ states and reduce the share of miscoordination after the first bin. For groups with $N \geq 4$, there are few or no full cooperation outcomes. The outcome where all players defect already accounts for roughly 40% of the outcomes in the first bin and, over the course of the play, the proportion of coordination failures (shown as “Other”) decreases and is replaced by complete defections.

Whereas the average cooperation rates in Fig. 3(a) decrease gradually and smoothly in N , Fig. 5 rather suggests an abrupt collapse of “all C” for groups of four or more players. This is not contradictory: The pronounced decline in cooperation during the first minute, as shown in Fig. 4, is reflected by the high degree of coordination failure in the first bins of Fig. 5. The decrease also implies that the average cooperation differs in a less pronounced manner than the rate of coordination on “all C”.

The impact of the payoff matrices

We will now address the question of how significant the various payoff matrices are. Fig. 6 shows the cooperation rates per matrix conditional on group size. For a given N , there is more cooperation with the Neutral payoff matrix than with Defensive payoffs, and more with Defensive payoffs than with the Offensive matrix throughout. This is consistent with Prediction 2. (As noted in the theory section, we do not make a prediction regarding Offensive vs. Defensive.) For all three matrices, cooperation decreases monotonically in N .

Regression analysis

The linear probability models in Table 2 provide a thorough econometric analysis and formal testing of our predictions. The dependent variable in all regressions is the time-averaged cooperation rate of subject i in supergame s .²² Our main independent variables are the continuous variable Group Size, $N_{i,s}$ and the dummy variables for the Defensive (d.) and Offensive (d.) payoff matrices. To address the issue of experience, we add the continuous variable Supergame to the regression, and we also include the length of the supergame (Length T_s), also continuous. We interact the main variables with the dummy variable for the Cont (d.) treatment (discussed below), so that the effects of the independent variables can be obtained from the table for both the Pure and Cont treatments. Regression (1) includes the main variables and their interactions with the Cont (d.). Regression (2) adds the interactions with group size. Regression (3) additionally includes three sets of control variables.

In regression (1), the non-interacted coefficients (the first set of regressors) apply to the Pure data. We find that the coefficient of Group size, $N_{i,s}$ is negative and significant, consistent with Prediction 1. We also see that Offensive and Defensive have a negative and significant effect on cooperation, consistent with Prediction 2. Supergame is positive and (weakly) significant, confirming the descriptive evidence in Fig. 3(b). Length, $T_s / 60$ s is negative and significant, as is evident from the negative time trends in Fig. 4.

²² With 142 subjects and 21 supergames, there are 2982 observations. The specification in the last column includes variables referring to the previous supergame, resulting in the removal of 142 observations. An additional 240 observations were dropped due to 12 subjects for whom the questionnaire measures were unavailable.

Table 2
Regression analyses of cooperation choices.

	Cooperation, $c_{i,s}$					
	(1)		(2)		(3)	
Group size, $N_{i,s}$	−0.047***	(0.006)	−0.034***	(0.008)	−0.037***	(0.005)
Defensive (d.)	−0.091***	(0.025)	−0.192***	(0.030)	−0.191***	(0.021)
Offensive (d.)	−0.123***	(0.020)	−0.278***	(0.045)	−0.247***	(0.049)
Supergame	0.004*	(0.002)	0.021**	(0.008)	0.019***	(0.007)
Length, $T_s/60$ s	−0.075***	(0.020)	−0.095**	(0.039)	−0.088*	(0.053)
Cont (d.)	−0.289***	(0.036)	−0.283***	(0.083)	−0.249**	(0.129)
Group size, $N_{i,s} \times$ Cont (d.)	0.036***	(0.007)	0.035***	(0.011)	0.036***	(0.012)
Defensive (d.) $\times$ Cont (d.)	0.089***	(0.028)	0.209***	(0.044)	0.193***	(0.051)
Offensive (d.) $\times$ Cont (d.)	0.073*	(0.041)	0.144**	(0.065)	0.085	(0.058)
Supergame $\times$ Cont (d.)	−0.005**	(0.002)	−0.015*	(0.009)	−0.013	(0.009)
Length, $T_s/60$ s $\times$ Cont (d.)	0.026	(0.032)	0.070	(0.067)	0.060	(0.071)
Defensive (d.) $\times$ Group size, $N_{i,s}$			0.017**	(0.007)	0.017***	(0.005)
Offensive (d.) $\times$ Group size, $N_{i,s}$			0.025***	(0.004)	0.023***	(0.004)
Supergame $\times$ Group size, $N_{i,s}$			−0.003***	(0.001)	−0.002***	(0.001)
Length, $T_s/60$ s $\times$ Group size, $N_{i,s}$			0.003	(0.004)	0.002	(0.006)
Defensive (d.) $\times$ Group size, $N_{i,s} \times$ Cont (d.)			−0.020**	(0.008)	−0.018**	(0.007)
Offensive (d.) $\times$ Group size, $N_{i,s} \times$ Cont (d.)			−0.011*	(0.007)	−0.004	(0.006)
Supergame $\times$ Group size, $N_{i,s} \times$ Cont (d.)			0.002	(0.001)	0.001	(0.001)
Length, $T_s/60$ s $\times$ Group size, $N_{i,s} \times$ Cont (d.)			−0.007	(0.007)	−0.006	(0.008)
<i>Previous supergame:</i>						
Group smaller previous game					0.006	(0.010)
Defensive previous game					−0.002	(0.024)
Offensive previous game					0.002	(0.024)
Length, $T_s/60$ s previous game					0.029**	(0.013)
<i>Demographics:</i>						
Age					−0.002*	(0.001)
Female (d.)					−0.054***	(0.012)
Lab experience (cat.)					−0.008	(0.014)
Bachelor (d.)					−0.089	(0.069)
Master (d.)					−0.126**	(0.056)
Economics & Business (d.)					−0.028	(0.048)
Science & Medicine (d.)					−0.044	(0.059)
Arts, Humanities & Law (d.)					−0.072*	(0.038)
<i>Preference survey:</i>						
Risk taking					−0.031**	(0.013)
Time discounting					0.007	(0.015)
Trust					0.030**	(0.012)
Altruism					0.028	(0.019)
Positive reciprocity					−0.009	(0.023)
Negative reciprocity					−0.000	(0.011)
Constant	0.621***	(0.021)	0.546***	(0.056)	0.748***	(0.082)
Observations	2982		2982		2600	
Adjusted R^2	0.171		0.192		0.236	

¹ Linear regressions, bootstrapped standard errors, clustered at the session level.

² One unit of observation is the cooperation rate (time-average) of subject i in supergame s .

* Significance level: indicate p -values lower than 0.10.

** Significance level: indicate p -values lower than 0.05.

*** Significance level: indicate p -values lower than 0.01.

When we add the interactions with Group size, $N_{i,s}$ in regressions (2) and (3),²³ we expect from [Prediction 3](#) a diminished effect of the group size with the Defensive and Offensive payoff matrix. The regressions confirm this: Defensive (d.) $\times$ Group size, $N_{i,s}$ and Offensive (d.) $\times$ Group size, $N_{i,s}$ are both positive and significant. They further suggests that the effect of Supergame is weaker in larger groups, as the interaction Supergame $\times$ Group size, $N_{i,s}$ is in regression (2) negative and significant. Length, $T_s/60$ s $\times$ Group size, $N_{i,s}$ is insignificant.

[Prediction 3](#) leaves open the question of whether the group size has a significant overall impact for these payoff matrices. To answer this question, we tested the conditional effect of group size for the Defensive payoff matrix, which is the sum of the coefficients Group size, $N_{i,s}$ and Defensive (d.) $\times$ Group size, $N_{i,s}$. This conditional effect was negative and significant in post-hoc

²³ While the (non-interacted) main variables discussed above are still statistically significant and have the same sign also in regressions (2) and (3), their interpretation changes: Group size, $N_{i,s}$ only applies to the Neutral matrix and the coefficients of the other main variables correspond to a hypothetical group size of zero.

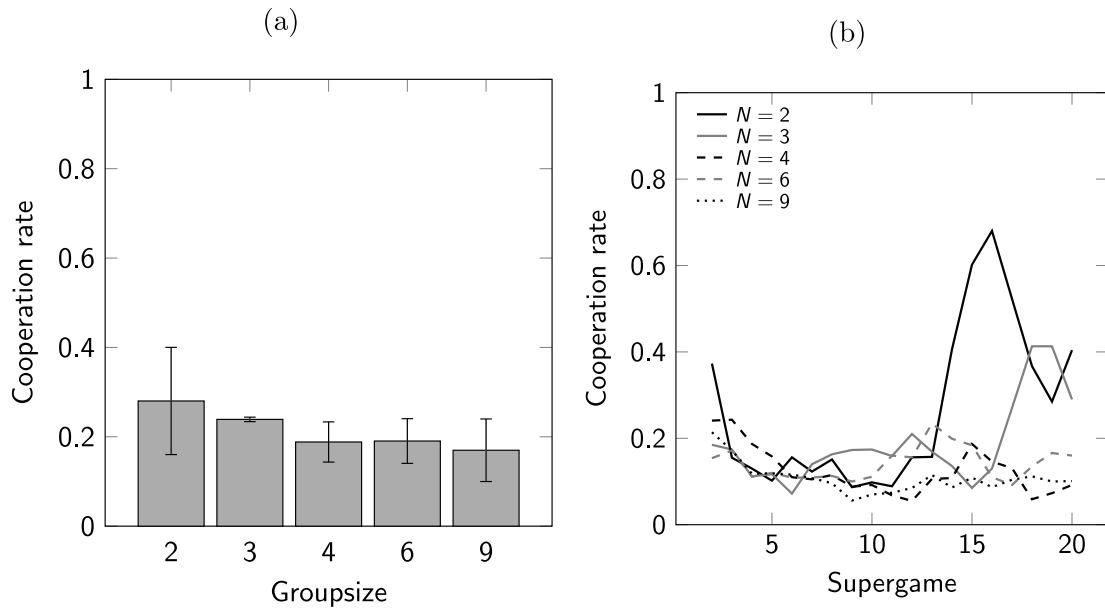


Fig. 7. (a) Mean cooperation in the Cont experiment, by group size N , unit of observation defined as in footnote 20, 95% confidence intervals based on bootstrapped standard errors clustered at the session level, (b) Evolution of average group cooperation over supergames in Cont, unit of observation defined as in footnote 20.

Wald tests of regression (2) ($p = 0.026$), meaning that group size has a negative effect in Defensive. However, the same is not true for Offensive where the sum of Group size, $N_{i,s}$ and Offensive (d.) $\times$ Group size, $N_{i,s}$ is not significantly different from zero ($p = 0.468$). The same holds in regression (3), with $p < 0.001$ for Defensive (d.) and $p = 0.117$ for Offensive (d.) Since Group size, $N_{i,s}$ alone is negative and significant in regressions (2) and (3), we conclude that it negatively affects cooperation separately with the Neutral and Defensive payoff matrix, but not with the Offensive one.

Regression (3) of Table 2 differs from regression (2) in that we add the three sets of control variables: The properties of the previous supergame, demographic characteristics, and the results of a preference survey. These controls are specific to individual subjects.

Regarding the properties of the previous supergame in regression (3), we included a dummy variable to indicate whether the subject was in a smaller group previously, as well as two dummy variables to indicate whether the subject's previous game matrix was Defensive or Offensive. We find that the "Group smaller previous game" dummy variable and the payoff matrices of the previous supergame have no significant impact. This is important because a correlation could have indicated that order effects may be present due to the within-subjects design.²⁴ We also analyze the length of the previous supergame. The variable does have a positive and significant effect on cooperation, confirming the evidence from the large meta data set in Mengel et al. (2022).

As for the vector of demographic characteristics and the results of the preference survey (Falk et al., 2016, 2018) in (3), it turns out that some of the demographic characteristics are statistically significant: Age (weakly significant), female, graduate student status ("Master"), and major (Arts, Humanities, and Law, weakly significant). All of these have a negative sign. Among the individual's preference items, we observe that the risk measure is negative and significant, while the trust measure is positive and significant. A main takeaway from adding the demographics and the preference survey in (3) is that this does not change our main results.²⁵

Consistent with Predictions 1–3, we summarize:

Result 1. Conditional on cooperation being equally difficult to be supported in equilibrium for all group sizes, we find that: (i) The average level of cooperation decreases with the number of players, N . (ii) The Defensive and Offensive payoff matrices negatively impact cooperation. (iii) Group size has a smaller impact on cooperation with the Defensive and Offensive payoff matrices than with the Neutral matrix.

The meta study of Dal Bó and Fréchette (2018) finds that the overall cooperation in $N = 2$ supergames depends on and is largely similar to the initial choices. We therefore implement the regressions in Table 2 also for the initial actions, omitting supergame

²⁴ The same conclusion is supported by the results of Boczoń et al. (2025) who supplement their between-subjects analysis with a within-subjects robustness check, but find no effect. Their within-subjects data shows an even stronger effect when N changes from two to four than their between-subjects data does.

²⁵ Three interactions are significant in regression (2) but not in regression (3). We discuss in Section 4.2 that, whether these interpretations are significant, is immaterial to their interpretation.

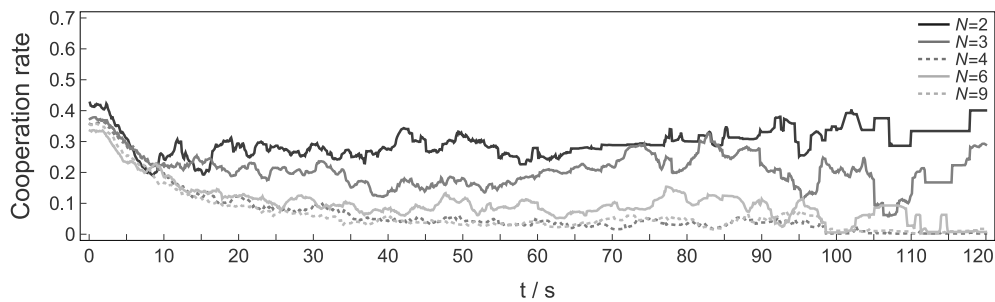


Fig. 8. Evolution of cooperation over time, by group size N (Cont data), group averages are conditional on a group being active: Out of the initial 63 groups, 34 were active after 30 s, 23 after 60 s, 13 after 90 s, and 5 after 120 s (for all N).

length (which was unknown when the initial action was chosen). As the patterns of the initial choices are essentially the same as for the overall rate of cooperation in Table 2 (including demographics and preferences), and as the coefficients have similar magnitudes, we skip the details here and refer the reader to Table 5 in the Supplementary Material.

4.2. The Cont experiment

The effect of the number of players

Fig. 7(a) shows the cooperation rates for the different group sizes in the Cont experiment.²⁶ A decrease of cooperation in the group size, N , is noticeable, but it is not as pronounced as in the Pure data. Fig. 7(b) shows the moving mean of group cooperation rates for all N , with a span of three supergames to reduce noise. Apart from short-lived surges towards the final supergames in the $N = 2$ and $N = 3$ groups, cooperation rates decline rather than increase. Overall, the impression from Figs. 7(a) and 7(b) is that cooperation rates in Cont are low, and they are substantially lower compared to Pure. While we do not have a prediction regarding the comparison of Cont vs. Pure, the regression analysis in Table 2 (discussed under “regression analysis”) confirms that the difference is significant.

Fig. 8 shows that cooperation rates either decline pronouncedly ($N > 3$) or stay roughly constant ($N \leq 3$). But even for groups of two and three, the levels achieved are markedly lower than in Fig. 4 (Pure data). An analysis of the outcomes in Cont (as in Fig. 5 for the Pure data) is not informative and hence omitted: The fraction of groups where players manage to (virtually) all cooperate is restricted to very few $N = 2$ groups.

The effect of the payoff matrices

Fig. 9 shows how cooperation in Cont depends on the payoff matrix for a given N . Contrary to Prediction 5 and the Pure treatment, the cooperation rates are not always higher with the Neutral matrix. Neither does the Offensive matrix always have the lowest cooperation rates as in Fig. 6. While for the Neutral and the Defensive matrix, cooperation rates decline in N (weak monotonicity), this is not the case for the Offensive matrix. Furthermore, the large confidence intervals indicate that any existing differences must be interpreted cautiously.

Regression analysis

Table 2 contains the linear probability models also for the Cont treatment. As expected from the descriptive results, cooperation rates are significantly lower in the Cont experiment. With the coefficient of Cont being -0.289 in regression (1), the difference is substantial. We discuss this disruptive result in Section 5. Turning to the interactions of the main regressors with the Cont treatment (variable $\times$ Cont (d.)) in regression (1), we note that Group size, $N_{i,s}$, Defensive (d.), Offensive (d.), Supergame, and Length, $T_s/60$ s when interacted with Cont (d.) all have the opposite sign as the non-interacted variables. This means that their effect is weaker in Cont compared to the Pure treatment, which is intuitive because of the generally lower cooperation level in the Cont treatment. In regression (1), the interaction is significant for Group size, $N_{i,s}$, Defensive (d.) and Supergame, weakly significant for Offensive (d.), and insignificant for Length, $T_s/60$ s.

We now analyze Predictions 4 and 5 with the help of regression (1). To see whether the main variables Group size, $N_{i,s}$, Defensive (d.), and Offensive (d.) have impact in Cont, we test their conditional effect for the Cont data by adding the corresponding coefficient and its interaction. In post-hoc Wald tests, the sum of Group size, $N_{i,s}$ and Group size, $N_{i,s} \times$ Cont (d.) is significantly different from zero ($p = 0.007$), as also evident in Fig. 7(a). As for the influence of the payoff matrices in Cont, the sum of the coefficients Defensive (d.) and Defensive (d.) $\times$ Cont (d.) is not significantly different from zero ($p = 0.847$), and neither is the sum of the coefficients Offensive (d.) and Offensive (d.) $\times$ Cont (d.) ($p = 0.143$). We conclude that there is support for Prediction 4 but not for Prediction 5.

A further set of regressors in regressions (2) and (3) includes the two-way interactions of the main variables with the Cont treatment and group size (variable $\times$ Group size, $N_{i,s} \times$ Cont (d.)) which allows a test of Prediction 6. However, the coefficients have

²⁶ Figure 11 in the Supplementary Material provides additional details by session.

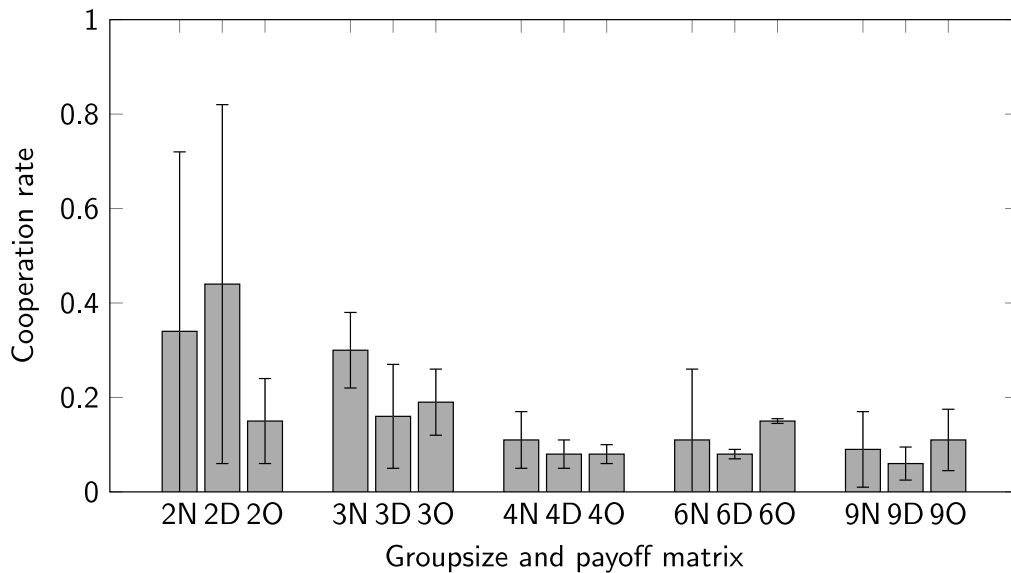


Fig. 9. Average group cooperation conditional on payoff matrix, N, D, and O refer to the Neutral, Defensive, and Offensive payoff matrix, respectively, 2–9 refer to the group size, 95% confidence intervals based on estimations with bootstrapped standard errors clustered at the session level, Cont data.

the opposite sign that we expected. Defensive (d.) $\times$ Group size, $N_{i,s} \times \text{Cont (d.)}$ is negative and significant (in both regression (2) and (3)), and Offensive (d.) $\times$ Group size, $N_{i,s} \times \text{Cont (d.)}$ is negative and either weakly significant (regression (2)) or not significant (in (3)). This means that the Defensive and the Offensive payoff matrices are (significantly or not) more strongly correlated with the group size than the Neutral matrix.

As above with the Pure data, we check whether there is a correlation of cooperation and group size when we look at the payoff matrices separately. For the Neutral matrix, we test whether Group size, $N_{i,s}$ plus Group size, $N_{i,s} \times \text{Cont (d.)}$ differs from zero. This is not the case ($p = 0.877$ in (2) and $p = 0.953$ in (3)). Whether the group size has an effect for Defensive depends on whether the sum of Group size, $N_{i,s}$, Group size, $N_{i,s} \times \text{Cont (d.)}$ and Defensive (d.) $\times$ Group size, $N_{i,s} \times \text{Cont (d.)}$ is negative and different from zero. This is the case in both in regression (2) ($p = 0.042$) and regression (3) ($p = 0.011$). For Offensive, the sum is not significantly different from zero ($p = 0.212$ in (2) and $p = 0.605$ in (3)).²⁷

Consistent with Prediction 4 but contradictory to Predictions 5 and 6, we conclude as follows:

Result 2. Conditional on cooperation being equally difficult to be supported in equilibrium for all group sizes, we find that: (i) Cooperation rates in Cont are significantly lower than in Pure. (ii) The average level of cooperation decreases with the number of players, N . (iii) The Offensive and Defensive payoff matrix have no significant impact on cooperation. (iv) Group size has a greater impact on cooperation with the Defensive matrix than with the Neutral matrix.

5. Discussion

A first main result is that, in the Pure treatment, group size has a negative effect on cooperation rates. The result is significant because, in a methodological innovation, our setup makes cooperation equally difficult to be supported in equilibrium for all group sizes. In contrast, in previous experimental studies, increasing the number of players can reduce cooperation, either because the larger groups make cooperative outcomes harder to be supported in equilibrium, or because larger groups make cooperative equilibria less likely to be selected. With our setup, we show that increased strategic uncertainty matters in larger groups even though we control for the minimum discount factor required for cooperation. This is consistent with the theory of strategic risk in repeated games (Blonski et al., 2011; Blonski and Spagnolo, 2015; Dal Bó and Fréchette, 2011), which we extend from the two- to the multi-player case: Larger groups make cooperation more difficult by increasing the risk that one or more players choose a defective strategy. Boczoń et al. (2025) find similar effects regarding the impact of strategic uncertainty in N -player games. By allowing for communication between players, they demonstrate how strategic uncertainty can be overcome and coordination can be improved. This finding is related to Oprea et al. (2014) who find a strong impact of communication in a four-player public good game when choices are in continuous time.

²⁷ A regression analysis of initial actions in the Cont treatment can be found in Supplementary Material, Table 5.

Coordination on the fully cooperative outcome is limited to two-player and three-player groups, as noted for example in [Huck et al. \(2004\)](#), who succinctly put this result as “two are few and four are many”, [Fonseca and Normann \(2012\)](#), or [Horstmann et al. \(2018\)](#). The fact that our experiments are in continuous time does not seem to change this finding. Consistent with this, multi-period experiments show some cooperation for two and three players ([Oprea et al., 2014](#)), but not for four players ([Oechssler et al., 2016](#)).

[Friedman and Oprea \(2012\)](#) and [Bigoni et al. \(2015\)](#) also conduct prisoner’s dilemma experiments in continuous time. [Friedman and Oprea \(2012\)](#) have games with a finite duration of one minute (corresponding to the expected duration of our games). The median cooperation rate in their Easy treatment (which is Neutral in our terminology, see footnote 9) reads 0.931. With a median of 0.784 (all supergames, $N = 2$), our rate for neutral games is similar, although not excessively proximate. [Bigoni et al. \(2015\)](#) have “long stochastic” games with an expected duration of 60 s, as in our experiments, and the payoffs correspond exactly to our Defensive setup (see footnote 9). [Bigoni et al. \(2015\)](#) find a cooperation rate of 0.669 (median 0.848). [Fig. 6](#) shows for $N = 2$ a mean cooperation rate of 0.655 in Defensive, and we find a median of 0.933. The similarity of the cooperation rates in our data may seem surprising, since in our experiment each individual experiences more defections and lower cooperation rates in the larger groups. However, this does not seem to strongly affect cooperation in small groups.

The most disruptive and perhaps surprising result we find is the low level of cooperation in the Cont treatment. Related findings, although not that pronounced, have been reported in finitely repeated settings. [Gangadharan and Nikiforakis \(2009\)](#) analyze a linear public good game with two and ten actions. Consistent with our results, they observe that the smaller action set somewhat improves the frequency of cooperative actions in the initial periods with four players. Different from our data, they find no effect in later periods and no change at all when there are two players. [Lugovsky et al. \(2017\)](#) provide evidence on differences in cooperation between comparable prisoner’s dilemma and public-good games. Their results suggest that, framing the game as a (two-action) VCM game as opposed to the common prisoner’s dilemma, may lead subjects to be more cooperative. They also find that a binary-action VCM tends to cooperate better than the usual ten-action variant (both finitely repeated). Finally, [Heuer and Orland \(2019\)](#) analyze a two-player one-shot prisoner’s dilemma where subjects either choose one pure action (cooperate or defect) or they can “mix” by deciding with how many out of ten rival players in the session they (purely) cooperate or defect, respectively. With “mixing”, lower cooperation rates result.

Given the low cooperation rates in Cont, we conclude that gradualism does not occur in our data. Gradualism has been investigated, foremost theoretically, in different contexts by, for example, [Sobel \(1985\)](#), [Kranton \(1996\)](#) or [Watson \(2002\)](#). For our prisoner’s dilemma, the notion of gradualism suggests that players initially and cautiously choose low levels of cooperation. If matched by the other players, they then slowly increase the cooperation. However, it is precisely this increase of cooperation that does not occur because too few players are willing to make the sacrifice, that is, raise their action and make others follow. A related experimental finding was recently reported by [Kartal et al. \(2021\)](#) for two- vs. three-action trust games. [Kartal et al. \(2021\)](#) find some evidence of gradualist strategies. They delineate circumstances under which gradualism is clearly beneficial and when its effect is minor compared to “all-or-nothing” setups which can lead to drastically improved trust levels.

6. Conclusion

We study cooperation in a social dilemma played by larger groups. We address the research questions raised by the recent and growing literature on the two-player prisoner’s dilemma: What are the determinants of cooperation? Does strategic uncertainty matter? Given the importance of these questions, it is somewhat unfortunate that the results have been obtained exclusively in two-player environments, limiting the applicability of this research. We modify the two-action prisoner’s dilemma to allow for arbitrary group sizes. Our innovative experiment controls for strategic incentives (same minimum discount factor for all group sizes). This novel design allows us to study larger group sizes using the same groundbreaking methods proposed for the two-player game.

We find both intuitive comparative statics effects as well as counterintuitive results: In addition to demonstrating the negative effect of group size on cooperation, we confirm in a clean setting that cooperation is limited to relatively small groups of two and three. Defect rates increase with group size. These results are consistent with notions of strategic uncertainty. Some of the determinants of cooperation found to be relevant in two-player games are quite similar and significant even in larger groups. These results suggest a potential for cooperation in larger groups if strategic uncertainty can be overcome. Finally, the availability of a continuous action set, which emerges as a natural extension of the multiplayer setting, leads to a drastic reduction in cooperative choices. While group size continues to influence cooperation, other determinants do not have explanatory power here.

In terms of future research, it seems promising to relate some of our key findings (conditional cooperation in large groups, but almost no cooperation with continuous action sets) to the literature on conditional cooperation in public goods experiments. The latter typically involve more than two players and more than two actions, but they still differ from our setup. Analyzing both in a unified framework may tell us more about the interaction of action space, group size and (conditional) cooperation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Mathematical derivations

We begin with the non-normalized prisoner's dilemma payoffs $\begin{pmatrix} R & S \\ T & P \end{pmatrix}$. Excluding player i , there are $N - 1$ players and, among those, m cooperate. Accordingly, player i 's stage-game payoff from cooperating is

$$\pi(C, m; N - 1) = \frac{m}{N - 1} R + \frac{N - m - 1}{N - 1} S$$

and the payoff when defecting reads

$$\pi(D, m; N - 1) = \frac{m}{N - 1} T + \frac{N - m - 1}{N - 1} P.$$

Players face strategic uncertainty. Let p be the (identical) probability that any of i 's opponents play a grim trigger (GT) strategy, and $(1 - p)$ is the probability that a player $\neq i$ plays always defect (AD).

First, suppose that player i plays GT. After the initial period (that is, in $t = 1$), there are only two contingencies. With probability p^{N-1} , all players cooperated in $t = 0$ and thus maintain cooperation throughout the supgame, yielding an expected payoff of

$$p^{N-1} \sum_{t=1}^{\infty} \delta^t R = p^{N-1} \frac{\delta}{1 - \delta} R.$$

With the counter probability, at least one rival player failed to cooperate in $t = 0$ and therefore everyone defects afterwards:

$$(1 - p^{N-1}) \sum_{t=1}^{\infty} \delta^t P = (1 - p^{N-1}) \frac{\delta}{1 - \delta} P.$$

In period $t = 0$, the expected payoff from choosing GT is given by the different factorial combinations with which i faces m cooperators (where $0 \leq m \leq N - 1$):

$$\sum_{m=0}^{N-1} \binom{N-1}{m} p^m (1-p)^{N-m-1} \left(\frac{m}{N-1} R + \frac{N-m-1}{N-1} S \right)$$

This can be rewritten as

$$\underbrace{\frac{R}{N-1} \sum_{m=0}^{N-1} \binom{N-1}{m} p^m (1-p)^{N-m-1} m}_{=(N-1)p \rightarrow \text{the binomial mean}} + \underbrace{\frac{N-1}{N-1} S \sum_{m=0}^{N-1} \binom{N-1}{m} p^m (1-p)^{N-m-1}}_{=1 \rightarrow \text{the total mass}} - \underbrace{\frac{S}{N-1} \sum_{m=0}^{N-1} \binom{N-1}{m} p^m (1-p)^{N-m-1} m}_{=(N-1)p}$$

Hence, the expected payoff from playing GT in $t = 0$ is $pR + (1 - p)S$. Summing up, the discounted payoff from GT is

$$pR + (1 - p)S + \frac{\delta}{1 - \delta} p^{N-1} R + \frac{\delta}{1 - \delta} (1 - p^{N-1}) P$$

Second, assume player i chooses AD. Regardless of the choices of the other players, the initial defect action triggers full defection by all players in periods $t = 1, \dots, \infty$. Thus,

$$\sum_{t=1}^{\infty} \delta^t P = \frac{\delta}{1 - \delta} P.$$

In $t = 0$, the expected payoff from AD is given by

$$\sum_{m=0}^{N-1} \binom{N-1}{m} p^m (1-p)^{N-m-1} \left(\frac{m}{N-1} T + \frac{N-m-1}{N-1} P \right)$$

We can rewrite this (as above for GT) and obtain an expected payoff of $pT + (1 - p)P$. Altogether, the discounted payoff from AD is

$$pT + (1 - p)P + \frac{\delta}{1 - \delta} P.$$

Comparing expected payoffs from GT versus AD, we obtain

$$pR + (1 - p)S + \frac{\delta}{1 - \delta} p^{N-1} R + \frac{\delta}{1 - \delta} (1 - p^{N-1}) P \geq pT + (1 - p)P + \frac{\delta}{1 - \delta} P$$

or

$$\frac{\delta}{1 - \delta} p^{N-1} (R - P) \geq p(T + S - R - P) + (P - S). \quad (7)$$

Employing the normalization $R = 1$, $P = 0$, $T = 1 + g$ and $S = -l$, Eq. (7) reads

$$\frac{\delta}{1 - \delta} p^{N-1} \geq p(g - l) + l.$$

Dividing by p^{N-1} , we obtain (3) in the main text.

This approach readily extends when the continuous action set is available. Plugging $R = \sigma(1 + (g-l)(1-\sigma))$, $T = \sigma(1+g)$, $S = -\sigma l$ and $P = 0$ (see main text) into (7), we obtain

$$\frac{\delta}{1-\delta} p^{N-1} \geq \frac{l + p\sigma(g-l)}{1 + (1-\sigma)(g-l)}. \quad (8)$$

One can verify that the partial derivative of the right-hand side with respect to σ depends on the sign of $g-l$ as claimed in the main text. As in the Pure case, this equation can be solved explicitly for sizeBAD when $g = l$, in which case σ has no effect. We finally derive the continuous-action-set version of δ^* . Substituting $p = 1/2$ in (8) and rearranging yields

$$\delta \geq \frac{2l + \sigma(g-l)}{2l + \sigma(g-l) + \left(\frac{1}{2}\right)^{N-2} (1 + (g-l)(1-\sigma))}.$$

Once again, plugging in $\sigma = 1$ yields the result of the pure-strategy setup.

Appendix B. Power calculations

Our power calculations regarding N were based on the oligopoly experiments meta data by Engel (2015). Using the normalized averages and standard deviations from data reported in the working paper version of the paper (Engel, 2006, Table 10), we simulated three times 21 random observations in three clusters for 2, 3, 4, 6, and 8 firms (nine were unavailable, and there was only one observation for ten firms). We then regressed the cooperation variable on the number of players, clustering at the session level. In 1000 runs, the probability of detecting a significant effect of group size was greater than 96.9%, assuming a p -value of 0.05.

For the power calculations of the effect of the Defensive and Offensive payoff matrices, we used the $N = 2$ prisoner's dilemma meta dataset in Dal Bó and Fréchette (2018). Our Neutral and Defensive/Offensive games have $\delta^* = 0.667$ and $\delta^* = 0.75$, respectively (see Eq. (5)); or $\delta - \delta^* = 0.248$ and $\delta - \delta^* = 0.332$. To estimate the expected effect size, we referred to Dal Bó and Fréchette (2018)'s data, identifying 13 supergames where $\delta - \delta^* = 0.233$ and 34 supergames where $\delta - \delta^* = 0.355$, which closely correspond to our game parameters. In these subsets of their data, the average cooperation rate was 76.75 (SD 11.03) for Neutral and 54.24 (SD 16.57) for Offensive/Defensive. This observed difference of 22.51 units served as the target effect size for our power simulation. Running 1000 linear regressions with 7 randomly generated observations times three clusters each, the probability of correctly detecting a significant effect of a dummy variable for Defensive/Offensive matrix on cooperation, clustered at the session level and given $p = 0.05$ was 75.2%.

Appendix C. Supplementary material

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jebo.2025.107262>.

Data availability

Data will be made available on request.

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