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Equilibrium selection in infinitely repeated games with communication*

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ABSTRACT

The present paper proposes a novel approach for equilibrium selection in the infinitely repeated prisoner's dilemma where players can communicate before choosing their strategies. This approach yields a critical discount factor that makes different predictions for cooperation than the usually considered sub-game perfect or risk dominance critical discount factors. In laboratory experiments, we find that our factor is useful for predicting cooperation. For payoff changes where the usually considered factors and our factor make different predictions, the observed cooperation is consistent with the predictions based on our factor.

Keywords: cooperation, communication, infinitely repeated game, machine learning
JEL Codes: C73, C92, D83

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1 Introduction

How can we predict cooperation in infinitely repeated games where players can communicate before choosing their strategies? Answering this question is of central importance for the application of infinitely repeated games to study social dilemmas. For example, when firms repeat an oligopoly infinitely often, both collusion and non-collusion are equilibria. To predict whether firms will collude, economists have build either on the sub-game perfect or the risk dominant critical discount factor. However, it is unclear to what extent the factors are useful for predicting collusion when firms can explicitly agree on collusion before choosing their strategies. Such explicit collusion is often seen as an important means for coordination among firms and, hence, key for antitrust policy (see, e.g., Awaya and Krishna, 2016; Fonseca and Normann, 2012). Thus, answering the question of how we can predict cooperation in infinitely repeated games where players can explicitly agree on cooperation is of central importance to antitrust policy, among others.

To answer this question theoretically, Section 2 presents an infinitely repeated prisoner's dilemma between two players. Each player is uncertain whether the other player will cooperate, but less so if they can agree to cooperate before choosing either to cooperate or to defect.

In this game, cooperation follows the sub-game perfect critical discount factor if and only if communication entirely eliminates the players' uncertainty. However, if communication reduces but does *not* entirely eliminate the players' uncertainty, cooperation follows a novel critical discount factor. For games where players can *not* communicate, cooperation follows the risk dominance critical discount factor.

Thus, from a game theoretical perspective, we propose to use either the sub-game perfect or our novel critical discount factor for predicting cooperation in games where players can communicate. This proposition has the following two implications.

First, the sub-game perfect and our novel critical discount factor make different predictions for games with communication that change the payoff from cooperating when the other defects. This is because the sub-game perfect critical discount factor assumes players are certain that the other player will cooperate and, hence, ignore the payoff from cooperating when the other defects. Our novel critical discount factor, however, is based on the idea that players are more, but *not entirely*, certain that the other player will cooperate and, hence, account for the payoff from cooperating when the other defects.

Second, for this game, communication helps cooperation. This holds when using either the sub-game perfect or our novel critical discount factor for predicting cooperation in games where players can communicate and the risk dominance critical discount factor in games where they can *not*. This is because, in contrast to risk dominance, both the sub-game perfect and our novel discount factor assume that players are more certain that the other player will cooperate and, hence, less tempted to defect. Thus, cooperation is more likely in games where players can agree on cooperation than in games where they can *not*.

To test whether the sub-game perfect, the risk dominance or our novel critical discount factor fare better in predicting cooperation in games where players can communicate, we run laboratory experiments. In the laboratory experiments, subjects play the infinitely repeated prisoner's dilemma. Between the laboratory experiments, we vary the payoff from cooperating when the other defects and whether players can communicate. We present the laboratory experiments in Section 3 in more detail. Section 4 derives predictions for cooperation between the laboratory experiments based on our novel critical discount factor.

The results in Section 5 show that our critical discount factor is a useful tool for predicting cooperation in games with communication. First, in line with the first implication of the theory, we find that changes in the payoff from cooperating when the other defects affect cooperation in both games with and without communication. Second, in line with the second implication of the theory, we find that the overall cooperation rate is higher in games with communication than in ones without communication.

Several papers study communication (see, among others, Andres et al., 2023; Bigoni et al., 2012; Cooper and Kühn, 2014; Fonseca and Normann, 2012) and equilibrium selection (see Dal Bó and Fréchette, 2018) in infinitely repeated games. However, they abstract from how communication can moderate equilibrium selection. This moderation has only been discussed by parallel work of Boczoń et al. (2023). The authors indicate that the current approach is inappropriate for predicting cooperation in games where players can communicate.[1]

By proposing an appropriate critical discount factor for predicting cooperation in infinitely repeated games where players can communicate before choosing their strategies, this paper makes at least two important contributions to the economics literature. The two important contributions to the literature are as follows.

First, we show how we can predict explicit collusion vs. how we can predict tacit collusion. This ties our paper to the industrial organization literature (see, e.g., Awaya and Krishna, 2016; Cooper and Kühn, 2014; Fonseca and Normann, 2012). In this literature, there is a gap between economic theory and antitrust policy. The latter distinguishes between explicit and tacit collusion, while the former does not (see Harrington, 2008, and the literature therein). The present paper contributes a novel approach for equilib-

[1]Using a variation to the discount rate, the authors make cooperation a *"knife-edge"*, whether both cooperation and defection can arise in equilibrium or only defection, and find the positive effects of communication on cooperation dissipate once only defection is an equilibrium in laboratory experiments. This finding supports our novel approach for equilibrium selection.

rium selection to economic theory that can help to distinguish between explicit and tacit collusion.

Second, we add experimental evidence to the economics literature on infinitely repeated games in line with our game theoretical model. In this model, we suggest that communication fosters cooperation by reducing, but *not* entirely eliminating, subjects' uncertainty. This suggestion is in line with the experimental evidence in several ways. First, in this paper, we show that communication reduces, but *not* entirely eliminates, subjects' uncertainty.[2] Second, we present evidence indicating that communication fosters cooperation. Finally, Andres et al. (2023) establish the positive effect of uncertainty reduction on cooperation in the infinitely repeated prisoner's dilemma. Thus, we find ample experimental evidence for our suggestion. This links the paper at hand to the experimental economics literature on infinitely repeated games (see, e.g., Aoyagi et al., 2021; Boczoń et al., 2023; Bruttel and Kamecke, 2012; Dal Bó, 2005; Kartal and Müller, 2022). In this literature, we see that the risk dominance critical discount factor predicts cooperation much better than the sub-game perfect critical discount factor in games where players can *not* communicate (see Blonski et al., 2011; Breitmoser, 2015; Martínez-Martínez and Normann, 2022). The present paper adds to this literature experimental evidence indicating that our novel critical discount factor is a useful tool for predicting cooperation in games where players can communicate before choosing their strategies.

2 Theory

This section presents our novel approach for equilibrium selection in games with communication. Before turning to the approach, we formalize the stage game and the repetition procedure.

Stage Game In a symmetric prisoner's dilemma Γ, two players $i \in \{X, Y\}$ simultaneously face a choice a between cooperation (C) and defection (D), $A_i \in \{C, D\}$. Let $A = A_X \times A_Y$ be the set of action profiles with a generic element a. If both players co-

[2] This evidence is based on three results. First, we show that subjects beliefs about the probability that the other will cooperate are higher in games with communication than in games without communication. Second, we find that subjects worry about the payoff from cooperating when the other defects and, hence, are uncertain about the cooperation of the other player in games with communication. Third, using word embedding and unsupervised machine learning to evaluate the communication content, we provide further evidence that subjects are uncertain about the others cooperation. It is worth mentioning that we find qualitatively similar results between human hand-coding and our machine learning approach, suggesting this approach fares well in capturing the communication content. Thus, our results support the intuition that communication reduces, but *not* entirely eliminates, subjects' uncertainty. While the former two results link the paper at hand to the emerging experimental economics literature which looks at beliefs in infinitely repeated games (see, e.g., Aoyagi et al., 2021; Gill and Rosokha, 2023), the latter result links the present paper to an emerging literature using this computational method to evaluate text corpora in economics (see, e.g., Ash and Hansen, 2023).

operate, each player earns a reward payoff $g_i(a_i = C, a_j = C) = R$. If both players defect, each player earns a punishment payoff $g_i(a_i = D, a_j = D) = P$. If one player defects while the other one cooperates, the defector earns a temptation payoff $g_i(a_i = D, a_j = C) = T$ and the cooperator a sucker's payoff $g_i(a_i = C, a_j = D) = S$. The stage game payoffs in the prisoner's dilemma Γ are shown in Table 1.

	C	D
C	R, R	S, T
D	T, S	P, P

Table 1: Stage game payoffs in the symmetric prisoner's dilemma $\Gamma(T, R, P, S)$.

Following Rapoport et al. (1965), a prisoner's dilemma Γ features the conditions $T > R > P > S$ and $2 \cdot R > T + S$. The condition $T > R > P > S$ ensures that agents earn more from mutual cooperation than from mutual defection ($R > P$). It also guarantees that cooperation entails a risk to earn less ($P > S$) as each player has an incentive to defect if the other player chooses to cooperate ($T > R$). The condition $2 \cdot R > T + S$ ensures that mutual cooperation is more efficient than the asymmetric outcome.

Repetition The horizon H of the repeated prisoner's dilemma is infinite. Following Aoyagi et al. (2021), h^t is a sequence of action profiles from round one to t. Each player chooses a strategy σ_i from the set of strategies Σ at the beginning of the game. The strategy σ_i maps from the set of all possible histories to actions $\sigma_i = (\sigma_i^1, \sigma_i^2, ...)$. Let $\sigma_i^t(h^{t-1})(a_i) \in [0, 1]$ be the probability of action a_i in round t given history h^{t-1}. The players have the discount factor δ, where $1 > \delta > 0$. Their utility equals the discounted sum of stage game payoffs shown in Equation 1.

$$u_i(\sigma) = (1 - \delta) \cdot \sum_{t=1}^{\infty} \delta^{t-1} \cdot E_\sigma[g_i(a^t)] \quad (1)$$

Multiplicity of Equilibria For any infinitely repeated prisoner's dilemma we can calculate the minimum critical discount factor required to support cooperation in a sub-game perfect equilibrium, in addition to defection, by focusing on the finite subset of strategies $Z \in \Sigma$ (see Dal Bó and Fréchette, 2018). This finite subset Z consists of two strategies: Grim trigger and always defect. Always defect is a strategy σ_i that chooses defection D for every history h^t. Grim trigger is a strategy σ_i that starts cooperating $\sigma_i^1(C) = 1$ and then chooses cooperation $\sigma_i^t(h^{t-1})(C) = 1$ if $h^{t-1} = (C, C), ..., (C, C)$ and $\sigma_i^t(h^{t-1})(C) = 0$ otherwise. There is ample experimental evidence that a substantial fraction of subjects focus on grim trigger and always defect (see, e.g., Dal Bó and Fréchette, 2019).[3] Given

[3]The experimental evidence shows that the majority of subjects choose three pure-strategies: grim trigger, always defect, and tit-for-tat. In games equal to and lower than $\delta = 0.75$, a majority of subjects

that the other player follows grim trigger, a player would obtain a payoff of $R \cdot \sum_{t=1}^{\infty} \delta^{t-1}$ by also following grim trigger, while she or he would obtain a payoff of $T + P \cdot \sum_{t=2}^{\infty} \delta^{t-1}$ by choosing always defect. Thus, if the other player is following grim trigger, a player has an incentive to choose grim trigger if and only if

$$R \cdot \sum_{t=1}^{\infty} \delta^{t-1} \geq T + P \cdot \sum_{t=2}^{\infty} \delta^{t-1} \tag{2}$$

This condition holds if δ is larger than or equal to the critical discount factor δ^{spe}:

$$\delta \geq \frac{T - R}{T - P} \equiv \delta^{spe}(T, R, P) \tag{3}$$

Hence, given that $\delta \geq \delta^{spe}$, there is a multiplicity of equilbria (see Blonski et al., 2011, and the literature therein for a proof). This fact raises the question of when players do play grim trigger.

Equilibrium Selection To answer this question, we derive a tool for equilibrium selection in games with communication. This tool is based on the idea of the size of the basin of attraction of always defect against grim trigger. It is derived as follows.

First, we postulate that each player i is endowed with a belief about the probability that the other player is following grim trigger, p_i, from the finite subset of strategies Z, where $1 \geq p_i \geq 0$. Thus, $1 - p_i$ is player i's belief about the probability that the other player is following always defect.

Second, we calculate the condition for when grim trigger will be chosen. Following grim trigger yields a value of $R \cdot \sum_{t=1}^{\infty} \delta^{t-1}$ if the other player is following grim trigger as well, and a value of $S + P \cdot \sum_{t=2}^{\infty} \delta^{t-1}$ if the other player is following always defect. Whereas following always defect yields a value of $T + P \cdot \sum_{t=2}^{\infty} \delta^{t-1}$ if the other player is following grim trigger, and a value of $P \cdot \sum_{t=1}^{\infty} \delta^{t-1}$ if the other player is following always defect as well. Hence, following grim trigger yields a value of $p \cdot (R \cdot \sum_{t=1}^{\infty} \delta^{t-1}) + (1 - p) \cdot (S + P \cdot \sum_{t=2}^{\infty} \delta^{t-1})$ and following always defect yields a value of $p \cdot (T + P \cdot \sum_{t=2}^{\infty} \delta^{t-1}) + (1 - p) \cdot (P \cdot \sum_{t=1}^{\infty} \delta^{t-1})$. Accordingly, the condition for when grim trigger will be chosen is calculated as follows.

$$p \cdot (R \cdot \sum_{t=1}^{\infty} \delta^{t-1}) + (1 - p) \cdot (S + P \cdot \sum_{t=2}^{\infty} \delta^{t-1}) \geq p \cdot (T + P \cdot \sum_{t=2}^{\infty} \delta^{t-1}) + (1 - p) \cdot (P \cdot \sum_{t=1}^{\infty} \delta^{t-1}) \tag{4}$$

This condition holds if δ is larger than or equal to the critical discount factor δ^*:

$$\delta \geq \frac{p \cdot (T - R - P + S) + P - S}{p \cdot (T - 2 \cdot P + S) + P - S} \equiv \delta^*(T, R, P, S, p) \tag{5}$$

choose grim trigger and always defect (see, e.g., Dal Bó and Fréchette, 2019). As we employ a continuation probability of $\delta = 0.75$ in the laboratory experiments, focusing on grim trigger and always defect seems to be plausible.

See Appendix A.1 for a proof.

Equation 5 shows the critical discount factor based on the idea of the size of the basin of attraction of always defect against grim trigger discussed in Dal Bó and Fréchette (2018) and the literature therein. In this literature, a common interpretation of the basin of attraction is that cooperation is less robust to strategic uncertainty when the value falls, and more robust when it goes up. In line with this literature, we propose cooperation to be more likely when δ^* falls and less likely when it goes up.

Third, following Catonini (2021), we postulate each player is uncertain on whether others will cooperate, but less so if they can agree to cooperate before choosing their strategies. There is experimental evidence indicating that communication reduces strategic uncertainty (see Bruttel and Petrishcheva, 2024; Dvorak and Fehrler, 2023; Kartal and Müller, 2022).

Considering this line of thinking, we find the following.

The sub-game perfect critical discount factor δ^{spe} predicts cooperation well if communication entirely eliminates strategic uncertainty: $p = 1$. Recall that δ^{spe} is based on the idea that the other player will play grim trigger and, hence, $p = 1$ captures this case. Thus, we can derive δ^{spe} from Equation (5) by plugging $p = 1$ into this equation.

However, a novel critical discount factor δ^+ predicts cooperation much better if communication reduces, but *not* entirely eliminates, strategic uncertainty: $1 > p^+ > 0.5$. By incorporating p^+ into Equation (5) we arrive at Equation (6).

$$\delta \geq \frac{p^+ \cdot (T - R - P + S) + P - S}{p^+ \cdot (T - 2 \cdot P + S) + P - S} \equiv \delta^+(T, R, P, S, p^+). \tag{6}$$

Equation (6) requires a focal belief, such as 0.9, in order for δ^+ to take a specific value. This focal belief, as we will see, corresponds to the experimental data and predicts cooperation fairly well.

For games where players can *not* agree on cooperation, the risk dominance selection criterion δ^{rd} predicts cooperation well because players remain maximally uncertain: $p = 0.5$. We can derive the risk dominant critical discount factor δ^{rd} from Equation (5) by plugging $p = 0.5$ into this equation. There is ample experimental evidence that assuming players are maximally uncertain about whether the other player will play grim trigger ($p = 0.5$) fares well in predicting cooperation in games without communication (see Breitmoser, 2015, and the literature therein). Grim trigger is risk dominant if δ is larger than or equal to the critical discount factor δ^{rd}:

$$\delta \geq \frac{T - R + P - S}{T - S} \equiv \delta^{rd}(T, R, P, S, p = 0.5) \tag{7}$$

From a comparison of Equation (3), Equation (6), and Equation (7), it is apparent that changes in the payoff from cooperating when the other player defects, S, affect risk dominance δ^{rd} and our novel critical discount factor δ^{+}, but do not affect the sub-game perfect critical discount factor δ^{spe}.

$$(8) \quad \frac{\partial \delta^{*}\big(T,R,P,S,p\big)}{\partial S} < 0 \quad \text{as long as } 1 > p > 0 \quad \text{and} \quad \frac{\partial \delta^{*}\big(T,R,P,S,p\big)}{\partial S} = 0 \quad \text{otherwise}$$

See Appendix A.2 for a proof. If $\overline{S} > \underline{S}$, then δ^{spe} in game $\Gamma(T,R,P,\underline{S})$ is equal to δ^{spe} in game $\Gamma(T,R,P,\overline{S})$. δ^{rd} in game $\Gamma(T,R,P,\underline{S})$ is higher than δ^{rd} in game $\Gamma(T,R,P,\overline{S})$. Similarly, δ^{+} in game $\Gamma(T,R,P,\underline{S})$ is higher than δ^{+} in game $\Gamma(T,R,P,\overline{S})$. There is an intuitive explanation for this. If players are uncertain $(1 > p)$ that the other player is following grim trigger, as implied by both δ^{+} and δ^{rd}, she or he must worry about the payoff from cooperating when the other agent defects: S. If, however, the player is certain $(p = 1)$ about the grim trigger of the other player, as implied by δ^{spe}, she or he will ignore the sucker's payoff S (see Equation (3)). More generally, the effect size of changes in the sucker's payoff S on δ^{+} decreases in p, see Andres et al. (2023) for a proof. Thus, Equation (3), Equation (6), and Equation (7) show that a variation of S should only affect risk dominance, δ^{rd}, and our novel critical discount factor δ^{+}, but not the sub-game perfect critical discount factor δ^{spe}.

From this comparison, we can also see that the increase in beliefs by communication decreases the critical discount factor:

$$(9) \qquad \frac{\partial \delta^{*}\big(T,R,P,S,p\big)}{\partial p} < 0$$

See Appendix A.3 for a proof. The critical discount factor in games without communication δ^{rd} is higher than the one in games with communication—irrespective of whether communication reduces uncertainty, δ^{+}, or eliminates uncertainty entirely, δ^{spe}. This is because the increase in beliefs causes the value from following grim to be higher than the value from following always defect. This implies that players are less tempted to defect and, hence, that the critical discount factor in games with communication is lower than in games without communication.

Overall, according to our game theoretical model, the sub-game perfect critical discount factor δ^{spe} predicts cooperation well if and only if communication entirely eliminates the players' uncertainty. However, if communication reduces but does *not* entirely eliminate the players' uncertainty, our novel critical discount factor δ^{+} predicts cooperation much better. For games where players can *not* agree on cooperation, the risk dominance critical discount factor δ^{rd} predicts cooperation well.

To clarify which critical discount factor, δ^{spe} or δ^{+}, predicts cooperation best in games where players can agree before choosing their strategies, we run laboratory experiments. The next section describes the experimental design.

3 Experimental Design

In the laboratory experiments, we vary the sucker's payoff S and whether subjects can communicate in a between-subject design. Across the treatments, subjects participate in a number of infinitely repeated prisoner's dilemma games. Subjects interact in a number of supergames to grasp the payoff structure. In each supergame, two subjects interact continuously (partner matching protocol). Between each supergame, subjects are rematched using a perfect stranger matching protocol. The perfect stranger matching protocol eliminates the chance that a subject is recognizing another subject, which he or she has met before, based on his or her style to communicate. Recognizing others may set up a chance of reputation building and, hence, may affect the choice to cooperate. The stage game and continuation probability is similar to Blonski et al. (2011), who report stable results in their third supergame.[4] Accordingly, there should be at least three supergames per treatment. We employ five supergames per treatment. Ergo, a perfect (stranger) matching graph involves six subjects (see Both et al., 2016, and the literature therein).

Communication In each supergame, before subjects set their action a_i in round one, a free-form chat window opens for 60 seconds. A pre-play free-form chat window enables subjects to negotiate their strategy choice and, then, to choose a strategy for a supergame.[5]

Stage Game After the free-form chat window closes, both subjects choose their action a_i simultaneously in the infinitely repeated prisoner's dilemma $\Gamma(T = 100, R = 90, P = 80, S)$.[6] To provide a neutral frame, $A_i = \{C, D\}$ is renamed into $A_i = \{A, B\}$. Following each round, subjects receive feedback about their own action, the action of the other agent and their own payoff in that round and the supergame so far.

[4] To adopt the stage game and continuation probability of Blonski et al. (2011), has the distinct advantage that we know how many supergames are needed for subject's to grasp the payoff structure and, hence, allows us to choose the number of supergames accordingly.

[5] Communication in every round, for example, would enable agents to say sorry for unilateral defection and, hence, enable them to re-negotiate their strategy. To hinder them to re-negotiate, we choose pre-play communication (see Farrell and Maskin, 1989; Harstad, 2012).

[6] Subjects choosing actions and not strategies has the distinct advantage that we can compare our results to those of Blonski et al. (2011) and other studies. In the literature, it is common that subjects choose actions and not strategies. According to Dal Bó and Fréchette (2011) and Dal Bó and Fréchette (2018), subjects focus on grim and always defect in those studies.

Repetition After every round $t \geq 2$ the game continues with a probability δ and ends with a probability $1-\delta$. A probability δ' is drawn from a uniform distribution over $[0,1]$. If and only if $\delta' \leq \delta$ another round starts for all pairs. The continuation probability is $\delta = 0.75$.

Treatments We employ a between-subject design varying the sucker's payoff S and whether subjects can communicate.[7] Thus, we consider four treatments: NoComm70, NoComm0, Comm70 and Comm0. In NoComm70 no free-form chat window opens and the sucker's payoff equals 70 and in NoComm0, no free-form chat window opens and the sucker's payoff equals 0. In Comm70 a free-form chat window opens and the sucker's payoff equals 70 while in Comm0 a free-form chat window opens too, but the sucker's payoff equals 0.

Probability Each subject i is asked immediately after having chosen their action and before they receive feedback to state their probability $\tilde{p}_i$ that the other agent will cooperate, on an intuitive slider without a default. A subject's belief about the others action in round one is a proxy for her or his assessment about the others strategy choice.[8] For the following reasons, we do not incentives the belief elicitation procedure. First, due to the evidence that incentivized belief elicitation affects subsequent actions choices and the chance of this influencing the subsequent action choices differently for a change in the sucker's payoff S and a communication possibility, respectively (see Gächter and Renner, 2010). Second, due to the ample experimental evidence that communication can increase a players belief about the cooperation of the other player (see Ellingsen et al., 2018, and the literature therein). Third, to opt for simplicity whenever possible (see Aoyagi et al., 2021). Following Gill and Rosokha (2023), to make the belief elicitation procedure as minimally invasive as possible, we only elicit beliefs in the first round of the first and the last supergame. This procedure aims to prevent any contamination on subsequent action choices by the probability elicitation stage.

Procedure Assignment to different treatments is random in the sense that subjects signing up for a session do not know which treatment is run. Before the experiment starts, subjects are seated randomly at computer terminals. Instructions are given in written form. The instructions are presented in Appendix B. After the instructions are

[7] To eliminate the chances of an experimenter demand effect, a between-subject design and not a within-subject design (as in Blonski et al., 2011) is employed. Here, a within-subject design may result in a non-constant experimenter demand effect between treatments where people can and can *not* communicate. The reason is that communication can be used to discuss what the experimenter wants and, hence, it may be more salient in treatments where people can communicate than in treatments where they can not.

[8] For example, if a subject is certain that the other subject cooperates in the first round, he or she is certain that the other subject is following a cooperative strategy such as grim.

read, subjects are asked comprehension questions on the screen to ensure and to make it common knowledge they all understand the important parts of the experiment. The comprehension questions are presented in Appendix C. Only after all subjects passed the comprehension questions, the experiment starts. The experiment was conducted in May 2022 at the University of Potsdam and a total of 132 students participated. The subject's final earnings are the sum of their payoffs in points, plus a show-up fee. They earned (participated), on average, 14.83 euro (36 minutes) with a minimum of 9.80 euro (29 minutes) and a maximum of 22.00 euro (45 minutes). Across the subjects, 30 participated in NoComm70, Comm70 and Comm0, respectively, and 42 in NoComm0. Similar to Blonski et al. (2011), in total, we observe 1.401 stage game interactions.

4 Hypotheses

In the following, we set up hypotheses to state the effect of changes in the sucker's payoff S and the effect of communication on the rate of cooperation, respectively. Before turning to these hypotheses, we introduce a set of hypotheses on the effect of communication on beliefs. In our model, we argue that communication fosters certainty: the belief in games with communication (p^+) is higher than in games without communication ($p = 0.5$). Thus, we expect that beliefs in treatments with communication are, on average, higher than in ones without communication.

Hypothesis 1a. *The mean belief in* Comm70 *is higher than in* NoComm70.[9]

Hypothesis 1b. *The mean belief in* Comm0 *is higher than in* NoComm0.[9]

Next, this section introduces the hypotheses on the effect of changes in the sucker's payoff S on the rate of cooperation. It is apparent from Table 2 that changes in the sucker's payoff S, do not affect the sub-game perfect critical discount factor δ^{spe}. While changes in the sucker's payoff S do affect the novel critical discount factor δ^+ due to $1 > p^+$ and in games without communication (δ^{rd}). Thus, according to our novel critical discount factor δ^+, we expect the rate of cooperation in treatments with a sucker's payoff equal to 70 to be higher than in treatments with a sucker's payoff equal to 0 in games with communication and in ones without communication (δ^{rd}), respectively.

Hypothesis 2a. *The rate of cooperation in* Comm70 *is higher than in* Comm0.

Hypothesis 2b. *The rate of cooperation in* NoComm70 *is higher than in* NoComm0.

Finally, this section turns to the hypotheses on the effect of communication on the rate of cooperation. Table 2 shows that the sub-game perfect critical discount factor δ^{spe} in

[9]This hypothesis was not preregistered.

games with communication is equal to the one in games without communication. According to our game theoretical model, however, the critical discount factor in games without communication is higher than in ones with communication ($\delta^{rd} > \delta^{+}$) in $\Gamma(T, R, P, \underline{S})$ and $\Gamma(T, R, P, \overline{S})$, respectively, for $\overline{S} > \underline{S}$. This aspect of the model indicates that the rate of cooperation in treatments with communication is higher than in ones without communication.

Hypothesis 3a. *The rate of cooperation in* COMM70 *is higher than in* NOCOMM70.[9]

Hypothesis 3b. *The rate of cooperation in* COMM0 *is higher than in* NOCOMM0.[9]

Following Cooper and Kagel (2023) and Kartal and Müller (2022), we analyze the communication content to better understand why subjects made certain choices. This analyzes may provide suggestive evidence on whether subjects are indeed uncertain about the cooperation of the other subject.

5 Results

In this section, we first study the effect of communication on beliefs. Second, we study the effect of changes in the sucker's payoff S on cooperation in games with and without communication, respectively. We then continue to investigate the effect of communication on cooperation. Finally, this section turns to the estimation of strategies used and to the analyses of the communication content.

Beliefs Table 2 presents the mean belief in the first and final supergame split up by treatments. It is apparent from this figure that the mean belief in treatments with communication is substantially higher than in ones without communication. A one-sided Wilcoxon-Mann-Whitney test with continuity correction[10] shows that the mean belief in the first supergame in COMM70 (COMM0) is significantly higher than in NOCOMM70 (NOCOMM0): $p < 0.01$ ($p < 0.01$). The result is very similar if we instead consider the final supergame: $p = 0.01$ ($p < 0.01$). Thus, our data clearly supports Hypothesis 1a and Hypothesis 1b that the mean belief in treatments with communication is higher than in ones without communication.

Cooperation Table 2 shows the rate of cooperation in round one over supergames, split up by treatments. A subject's cooperation choice in the first round is a proxy for her or

[10]Similar to Blonski et al. (2011), unless noted otherwise, all p-values reported in this paper refer to a one-sided Wilcoxon-Mann-Whitney test with continuity correction and graph-level clustering. The continuity correction accounts for the discontinuity in small sample sizes and produces more conservative p-values.

Table 2: The critical discount factors, the mean belief and the mean cooperation rate in the first round split up by treatments.

Treatment	Critical discount factor			Belief		Cooperation					
	δ^{spe}	δ^{+}	δ^{rd}	Supergame		Supergame					All
				1	5	1	2	3	4	5	
Comm70	0.50	0.53	0.67	0.82 (0.24)	0.82 (0.23)	0.90 (0.09)	1.00 (0.00)	1.00 (0.00)	0.93 (0.15)	1.00 (0.00)	0.97 (0.04)
Comm0	0.50	0.65	0.90	0.85 (0.18)	0.69 (0.38)	0.87 (0.14)	0.83 (0.24)	0.73 (0.19)	0.77 (0.28)	0.70 (0.34)	0.78 (0.22)
NoComm70	0.50	0.67	0.67	0.55 (0.31)	0.41 (0.28)	0.53 (0.08)	0.43 (0.15)	0.50 (0.26)	0.53 (0.27)	0.53 (0.27)	0.51 (0.17)
NoComm0	0.50	0.90	0.90	0.35 (0.29)	0.16 (0.26)	0.36 (0.24)	0.21 (0.27)	0.19 (0.20)	0.17 (0.22)	0.19 (0.26)	0.22 (0.23)

Note: Standard deviations in brackets. See Appendix D for more details on the data.

his strategy choice in that supergame. This is why we focus on the first round in this section. The results look very similar if we instead examine all rounds.

From Table 2, we can see that the rate of cooperation in Comm70 is higher than in Comm0 in late supergames. A test shows that the rate of cooperation in round one in the final supergame in Comm70 is significantly higher than in Comm0: $p = 0.03$. The result is similar over all supergames: $p = 0.05$. The rate of cooperation in round one in the first supergame, however, is not significantly higher in Comm70 than in Comm0: $p = 0.41$.[11] The result is very much the same if we instead look at all rounds. See Table 5b in Appendix D for support. Thus, in late supergames, our data supports Hypothesis 2a that changes in the sucker's payoff S affect the rate of cooperation in games with communication.

As can be seen from Table 2, in round one, the rate of cooperation in NoComm70 is higher than in NoComm0 across supergames. We find that the rate of cooperation in the first round in the final supergame in NoComm70 is significantly higher than in NoComm0: $p = 0.03$. Checking all supergames ($p = 0.03$), we find comparable results. In the first supergame, however, the rate of cooperation is not significantly ($p = 0.37$) higher in NoComm70 than in NoComm0.[12] The results are almost the same if we alternatively examine the rate of cooperation in all rounds. To back this up, see Table 5b in Appendix

[11] Also if we compare first round actions in supergame three (two), the rate of cooperation is (marginally) significantly higher in Comm70 than in Comm0: $p = 0.01$ ($p = 0.09$). While the result in the fourth supergame in Comm70 is higher than in Comm0, it is not statistically significant ($p = 0.14$).

[12] A test shows that the rate of cooperation in round one in supergame three (four) in NoComm70 is significantly higher than in NoComm0: $p = 0.02$ ($p = 0.03$). While this is not the case in the second supergame ($p = 0.13$), the mean rate of cooperation points in the predicted direction.

D. Ergo, in late supergames, our data supports Hypothesis 2b that changes in the sucker's payoff S affect the rate of cooperation in games without communication.

It is apparent from Table 2 that the rate of cooperation in treatments with communication is higher than in ones without communication across supergames. A test shows that the rate of cooperation in round one of the final supergame (over supergames) in Comm70 is significantly higher than in NoComm70, $p = 0.01$ ($p < 0.01$). The result is very much the same if we rather consider the rate of cooperation in round one of the final supergame (over supergames) between Comm0 and NoComm0: $p = 0.01$ ($p < 0.01$). Even if we look at round one of the first supergame, the rate of cooperation in Comm70 (Comm0) is significantly higher than in NoComm70 (NoComm0): $p < 0.01$ ($p < 0.01$).[13] The result is almost identical if we instead consider the rate of cooperation in all rounds. See Table 5b in Appendix D for support. Thus, our data clearly supports Hypothesis 3a and Hypothesis 3b that the rate of cooperation in treatments with communication is higher than in ones without communication in games with a sucker's payoff of 70 and a sucker's payoff of 0, respectively.

Strategies Table 3 presents the estimation of the proportions for each strategy discussed in Dal Bó and Fréchette (2011).[14] From the data in this table, we can see that a substantial fraction of subjects focuses on the finite subset of strategies Z, namely, always defect and grim trigger, in both games with and without communication The fraction of subjects choosing grim trigger is significant in Comm70 ($p = 0.02$), Comm0 ($p < 0.01$) and NoComm70 ($p = 0.02$), but not in NoComm0 ($p = 0.26$). Yet, the fraction of subjects choosing always defect is significant in NoComm0 ($p < 0.01$).[15] The results look similar if we instead estimate the proportions for each strategy discussed in Fudenberg et al. (2012). To back this up, see Table 6 in Appendix D. Ergo, our data supports the intuition that a substantial fraction of subjects focuses on the finite subset of strategies Z in both games with and without communication.

[13] It is apparent from this analyses, that the rate of cooperation in round one in Comm70 (Comm0) is significantly higher than in NoComm70 (NoComm0) in the second, third and fourth supergame: $p < 0.01$, $p < 0.01$ and $p = 0.02$ ($p < 0.01$, $p < 0.01$ and $p < 0.01$), respectively.

[14] We use the strategy frequency estimation method to assess the proportions for each strategy. This method has been proven particularly useful for the estimation of the proportions of strategies in the infinitely repeated prisoner's dilemma (see Dal Bó and Fréchette, 2019; Dvorak, 2023, and the literature therein). The strategy set discussed by Dal Bó and Fréchette (2011) includes in addition to Z the tit for tat, win stay loose shift, punishment 2 and always cooperate strategy. Tit for tat is a strategy that starts by cooperating $\sigma_i^1(C) = 1$ and, in the following rounds, $\sigma_i^t(h^{t-1})(a_j^{t-1}) = 1$. Win stay loose shift starts by cooperating $\sigma_i^1(C) = 1$ and then, if either $h^{t-1} = ..., (C, C)$ or $h^{t-1} = ..., (D, D)$, then this strategy $\sigma_i^t(h^{t-1})(C) = 1$ and otherwise it $\sigma_i^t(h^{t-1})(D) = 1$. Punishment 2 starts by cooperating $\sigma_i^1(C) = 1$ and then $h^{t-1} = (C, C), ..., (C, D)$ triggers $\sigma_i^t(h^{t-1})(D) = 1$ and $\sigma_i^{t+1}(h^{t-1})(D) = 1$, after which the strategy $\sigma_i^{t+2}(h^{t-1})(C) = 1$. Always cooperate is a strategy σ_i that chooses cooperation C for every history h^t.

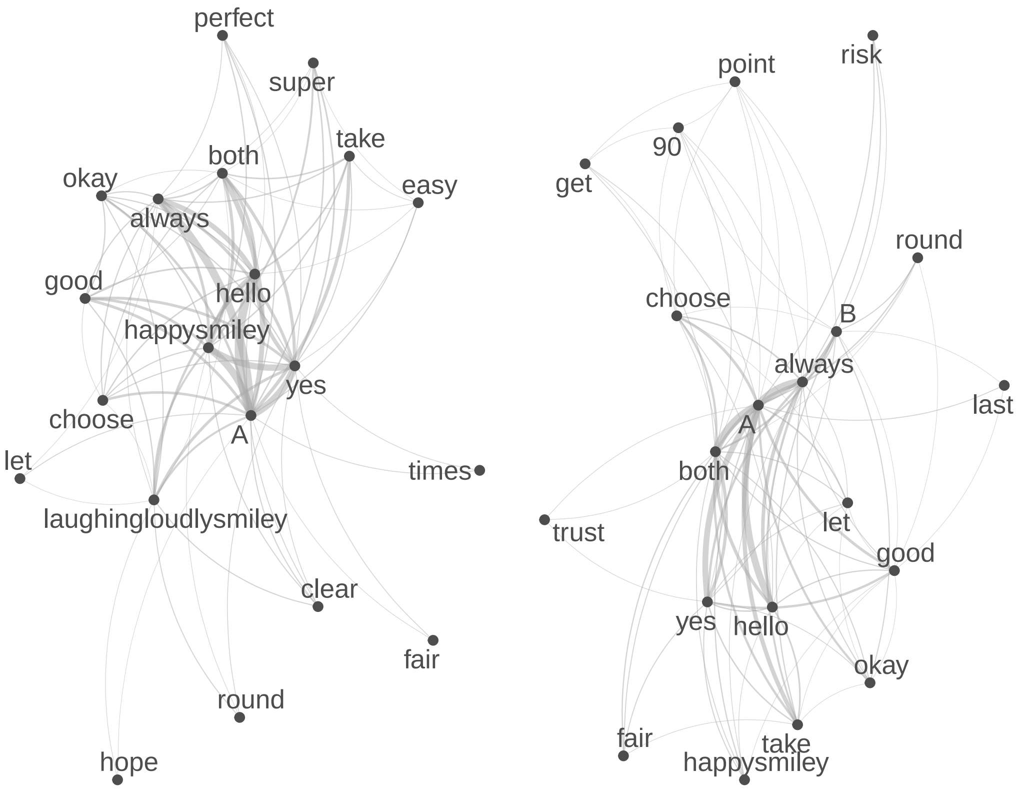
[15] The fraction of subjects choosing always defect is also significant in Comm0 ($p = 0.03$) and in NoComm70 ($p < 0.01$).

Table 3: Estimation of strategies used split up by treatments.

Treatment	Strategy					
	Always defect	Grim trigger	Tit for tat	Win stay loose shift	Punishment 2	Always cooperate
Comm70	0.00 (0.00)	0.39 (0.16)	0.31 (0.16)	0.01 (0.07)	0.07 (0.09)	0.23 (0.13)
Comm0	0.13 (0.06)	0.54 (0.18)	0.28 (0.19)	0.00 (0.00)	0.00 (0.00)	0.05 (0.06)
NoComm70	0.37 (0.10)	0.26 (0.11)	0.25 (0.11)	0.00 (0.00)	0.00 (0.00)	0.12 (0.06)
NoComm0	0.79 (0.06)	0.07 (0.06)	0.14 (0.07)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)

Note: Standard errors in brackets.

Figure 1: The 20 most frequent tokens in each cluster and their co-occurrence coefficient $\phi > 0.5$.



(a) *Talk about A* (b) *Talk about A and B*

Note: Figure 3 in Appendix E.5 provides the tokens in German.

Communication Figure 1 depicts the 20 most frequent words and their co-occurrences in each communication cluster. To identify the clusters, we use an unsupervised machine learning algorithm.[16] This algorithm identifies two key distinguishing clusters of chats, the *Talk about A* cluster shown in Figure 1a and the *Talk about A and B* cluster shown in Figure 1b. The co-occurrences of words in each cluster are shown using gray lines. See Appendix E for more details.

From this figure, we can see that the key distinguishing feature between chats is whether subjects are uncertain about the cooperation of the other subject or not. In the *Talk about A and B* cluster, the tokens 'B', 'risk' and 'trust' often appear together with the token 'A', indicating that subjects mainly discuss the riskiness of action choices. In the *Talk about A* cluster, the token 'A' often appears together with tokens related to agreeableness ('perfect', 'super' and 'clear'), indicating that subjects mainly talk about an agreement to choose the cooperative action. The fact that words like 'risk', 'trust' and the defection action 'B' are present in one cluster, but not in the other one, indicates that subjects are uncertain about the action of the other subject before choosing an action – at least in one cluster.[17] Ergo, the communication analysis supports the intuition that subjects are uncertain about the cooperation of the other subject before choosing an action.

6 Conclusion

This paper addressed the important question of how we can predict cooperation in infinitely repeated games where players can communicate before choosing their strategies. To answer this question, we studied an infinitely repeated prisoner's dilemma between two players. Each player is uncertain whether the other will cooperate, but less so if they can agree to cooperate before choosing either to cooperate or to defect. In this game, the sub-game perfect critical discount factor δ^{spe} predicts cooperation well only if communication entirely eliminates the players' uncertainty. However, if communication reduces but does *not* entirely eliminates the players' uncertainty, a novel critical discount factor δ^{+} predicts cooperation much better. To clarify whether the sub-game perfect critical discount factor δ^{spe} or our novel critical discount factor δ^{+} predicts cooperation better, we run laboratory experiments. In the laboratory experiments, for payoff changes where the sub-game perfect δ^{spe} and our novel critical discount factor δ^{+} make different predictions, changes in the cooperation rate follow predictions based on δ^{+}. Thus, we conclude that only examining changes in the sub-game perfect critical discount factor δ^{spe} for applied

[16]This algorithm has the distinct advantage that it does not rely on pre-defined clusters, which are typically introduced through a process of human hand-coding. We find qualitatively similar results between human hand-coding and our machine learning algorithm. See Table 8 in Appendix E for support.

[17]In line with the interpretation that the *Talk about A and B* cluster indicates that subjects are uncertain about the action of the other subject before choosing an action, the mean belief and the mean cooperation rate is significantly lower in the *Talk about A and B* cluster than in the *Talk about A* in late supergames. See Table 7 in Appendix D for support.

comparative statics exercises might result in misleading predictions. The present paper suggest that our novel critical discount factor δ^+ predicts cooperation much better in games where players can communicate. Taking this suggestion into account is of central importance for future research, for example, on antitrust policy.

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Appendix

A Proofs

The following section presents the proofs for our game theoretical model.

A.1 Proof for Equation (5)

This section presents the proof for Equation (5).

Proof. Let us first consider how we can re-write $\sum_{t=1}^{\infty} \delta^{t-1}$ and $\sum_{t=2}^{\infty} \delta^{t-1}$. Rewriting $\sum_{t=1}^{\infty} \delta^{t-1}$ and $\sum_{t=2}^{\infty} \delta^{t-1}$ yields Equation (10) and Equation (11), respectively:

$$\sum_{t=1}^{\infty} \delta^{t-1} = \frac{1}{1-\delta} \tag{10}$$

$$\sum_{t=2}^{\infty} \delta^{t-1} = \frac{1}{1-\delta} - 1 = \frac{\delta}{1-\delta} \tag{11}$$

Plug Equation (10) and Equation (11) into Equation (4).

$$p \cdot \left(R \cdot \frac{1}{1-\delta}\right) + (1-p) \cdot \left(S + P \cdot \frac{\delta}{1-\delta}\right) \geq p \cdot \left(T + P \cdot \frac{\delta}{1-\delta}\right) + (1-p) \cdot \left(P \cdot \frac{1}{1-\delta}\right) \tag{12}$$

Simplify Equation (12).

$$p \cdot \frac{R}{1-\delta} + S - p \cdot S + P \cdot \frac{\delta}{1-\delta} - p \cdot P \cdot \frac{\delta}{1-\delta} \geq p \cdot T + p \cdot P \cdot \frac{\delta}{1-\delta} + \frac{P}{1-\delta} - p \cdot \frac{P}{1-\delta} \tag{13}$$

Subtract $p \cdot \frac{R}{1-\delta}$ and $\frac{P}{1-\delta}$, add $p \cdot S$ and $p \cdot \frac{P}{1-\delta}$ and multiply the results by $(1-\delta)$:

$$S \cdot (1-\delta) + P \cdot \delta - P \geq p \cdot T \cdot (1-\delta) + p \cdot P \cdot \delta - p \cdot P - p \cdot R + p \cdot S \cdot (1-\delta) + p \cdot P \cdot \delta \tag{14}$$

Simplify Equation (14).

$$S - S \cdot \delta + P \cdot \delta - P \geq p \cdot T - p \cdot T \cdot \delta + p \cdot P \cdot \delta - p \cdot P - p \cdot R + p \cdot S - p \cdot S \cdot \delta + p \cdot P \cdot \delta \tag{15}$$

Multiply δ and p out results in Equation (16).

$$\delta \cdot (p \cdot (T - 2 \cdot P + S) + P - S) \geq p \cdot (T - P - R + S) + P - S \tag{16}$$

Deviate Equation (16) by $p \cdot (T - 2 \cdot P + S) + P - S$ establishes Equation (17).

$$\delta \geq \frac{p \cdot (T - R - P + S) + P - S}{p \cdot (T - 2 \cdot P + S) + P - S} \tag{17}$$

Equation (17) describes that Condition (4) holds if the discount factor δ is larger than or equal to the value on the right hand side of Equation (17). This establishes the critical discount factor δ^* shown in Equation (5). ■

A.2 Proof for Equation (8)

This section presents the proof for Equation (8).

Proof. The partial derivative of $\delta^*(T, R, P, S, p)$ with respect to S equals:

$$\frac{\partial \delta^*\big(T, R, P, S, p\big)}{\partial S} = \frac{\partial}{\partial S}\left(\frac{p \cdot (T - R - P + S) + P - S}{p \cdot (T - 2 \cdot P + S) + P - S}\right) \tag{18}$$

Use the quotient rule.

$$\Leftrightarrow \frac{(p-1) \cdot \Big(p \cdot (T - 2 \cdot P + S) + P - S\Big) - \Big(p \cdot (T - R - P + S) + P - S\Big) \cdot (p-1)}{\Big(p \cdot (T - 2 \cdot P + S) + P - S\Big)^2} < 0 \tag{19}$$

Equation (19) yields that changes in the sucker's payoff S do not affect $\delta^*(T, R, P, S, p)$ as long as $p = 1$ or 0 because, for those values, $\frac{\partial \delta^*\left(T,R,P,S,p\right)}{\partial S}$ equals 0.

For $1 > p > 0$, however, multiply Equation (19) by the squared and, hence, positive denominator $((p \cdot (T - 2 \cdot P + S) + P - S))^2 > 0$ and divide by $(p-1)$ where $(p-1) < 0$ yields Equation (20).

$$\Big(p \cdot (T - 2 \cdot P + S) + P - S\Big) - \Big(p \cdot (T - R - P + S) + P - S\Big) > 0 \tag{20}$$

Add $p \cdot (T - R - P + S) + P - S$ to Equation (20).

$$p \cdot (T - 2 \cdot P + S) + P - S > p \cdot (T - R - P + S) + P - S \tag{21}$$

Subtract P from, add S to and, then, divide by p yields Equation (22)

$$T - 2 \cdot P + S > T - R - P + S \tag{22}$$

Simplify Equation (22) by subtracting T and S.

$$-2 \cdot P > -R - P \tag{23}$$

Finally, adding $2 \cdot P$ and R to Equation (23) results in Equation (24).

$$R > P \tag{24}$$

This proof documents that for every stage game, the critical discount factor $\delta^*(T, R, P, S, p)$ decreases in S because $R > P$ as long as $1 > p > 0$. For $p = 1$ and $p = 0$, we find that changes in the sucker's payoff S do not affect $\delta^*(T, R, P, S, p)$. Thus, changes in the sucker's payoff S affect δ^{rd} and our novel critical discount factor δ^+, but do not affect the sub-game perfect critical discount factor δ^{spe}, because $p = 0.5$ in δ^{rd}, $1 \geq p^+ \geq 0.5$ in δ^+ and $p = 1$ in δ^{spe}. ∎

A.3 Proof for Equation (9)

This section presents the proof for Equation (9).

Proof. The partial derivative of $\delta^*(T, R, P, S, p)$ with respect to p equals:

$$\frac{\partial \delta^*\big(T, R, P, S, p\big)}{\partial p} = \frac{\partial}{\partial p}\left(\frac{p \cdot (T - R - P + S) + P - S}{p \cdot (T - 2 \cdot P + S) + P - S}\right) \tag{25}$$

Use the quotient rule.

$$\begin{aligned} \Leftrightarrow\ & \frac{\big(T - R - P + S\big) \cdot \big(p \cdot (T - 2 \cdot P + S) + P - S\big)}{\big(p \cdot (T - 2 \cdot P + S) + P - S\big)^2} \\ & - \frac{\big(p \cdot (T - R - P + S) + P - S\big) \cdot \big(T - 2 \cdot P + S\big)}{\big(p \cdot (T - 2 \cdot P + S) + P - S\big)^2} < 0 \end{aligned} \tag{26}$$

Simplify the nominator of Equation (26).

$$\frac{P^2 - P \cdot S + S \cdot R - P \cdot R}{\big(p \cdot (T - 2 \cdot P + S) + P - S\big)^2} < 0 \tag{27}$$

Multiply Equation (27) by the positive denominator.

$$P^2 - P \cdot S + S \cdot R - P \cdot R < 0 \tag{28}$$

Simplify Equation (28).

(29) $$(P - S) \cdot (P - R) < 0$$

Divide Equation (29) by $(P - S)$.

(30) $$P - R < 0$$

Simplify Equation (30).

(31) $$R > P$$

Equation (31) documents that for every stage game, the critical discount factor $\delta^*(T, R, P, S, p)$ decreases in p because $R > P$. Thus, $\delta^{rd} > \delta^+ > \delta^{spe}$ as $p = 0.5$ in δ^{rd}, $1 \geq p^+ \geq 0.5$ in δ^+ and $p = 1$ in δ^{spe}. ■

B Instructions

In the following, we present our instructions for participants in the Comm0 treatment. Parts that appear only in the instructions of a particular treatment are clearly marked as such. Text in *italics* only appears in the instructions if people can communicate. Numbers in square brackets appear in the instructions inherent a sucker's payoff S of 0 as 0 and of 70 as 70. The (original) instructions for the participants were in German.

Instructions

Today you are taking part in a decision-making experiment. If you read the following explanations carefully, you can earn money. The amount you receive depends on your decisions and the decisions of other participants.

You are not allowed to communicate with other participants for the entire duration of the experiment. We therefore ask you not to talk to each other. Violation of this rule will result in exclusion from the experiment and payment.

If there is anything you do not understand, please refer to these experiment instructions again or give us a hand signal. We will then come to you and answer your question personally.

During the experiment we do not talk about euros, but about points. The number of points you score during the experiment will be converted into euros as follows:

180 Points = 1 Euro

At the end of today's experiment, you will receive the points you have achieved from the experiment converted into euros plus 5 euros in **cash** as basic equipment.

The instructions are the same for all participants. On the following pages, we will explain the exact procedure of the experiment.

The Experiment

The experiment consists of 5 independent sub-experiments. All sub-experiments have the same structure. Each sub-experiment consists of several rounds. All rounds have the same structure. In each round you have the opportunity to choose an action.

For each sub-experiment, the participants are randomly assigned into groups of 2 persons each. The grouping remains the same within a sub-experiment. Neither you nor the other people learn anything about the identity of the participants in the groups - neither before nor after the experiment.

The grouping changes after each sub-experiment. It is ensured that you will meet the same person in a group at most once during the entire experiment. In each new sub-experiment, you will meet a new person whom you have not met before or will meet after the experiment.

At the beginning of each sub-experiment, you can communicate with the other person in your group in writing via chat on the computer. The duration of the chat is limited to 60 seconds. You can write whatever you like in the chat, with the only restriction that you may not give any hint of your identity.

The Sub-Experiment

A sub-experiment consists of several rounds.

Exactly how many rounds there are depends on chance. Before each round, a number between 0 and 100 is drawn. For technical reasons, the computer does this. Each number has the same probability of being drawn. If the number is less than 75, a new round starts, if the number is greater than or equal to 75, the sub-experiment is finished and if necessary a new sub-experiment with a new person follows. The random numbers are drawn independently of each other.

In each round you can earn points depending on your decision and the decision of the other person you interact with. The points earned in each round are added up and paid out in **cash** at the end of today's experiment.

The Round

In each round, you and the other person are simultaneously asked to decide between the two actions **A** and **B**. You make your decision for the action **A** or **B** by clicking the corresponding red button on the screen with the mouse. After clicking, the decision is irrevocably made. You should make your decision within 30 seconds if possible. After that you will be warned by a flashing display.

Your payoff in the round depends on your action and the action of the other person you interact with. The payoff's are as follows:

My decision	Payoff if the other person chooses	
	A	B
A	For me **90 Points** For the other person **90 Points**	For me [**0**] **Points** For the other person **100 Points**
B	For me **100 Points** For the other person [**0**] **Points**	For me **80 Points** For the other person **80 Points**

At the end of each round, you will learn the decision of the other person you are interacting with, your scored points in that round, and the sum of the scored points in the current sub-experiment. The information remains visible for 30 seconds. However, you can exit the information screen before that by clicking the gray OK button. When all participants have left the screen by clicking the gray OK button, but after 30 seconds at the latest, the next round will begin, if applicable.

We will ask you to answer some comprehension questions on the computer in a moment. This is to make sure that all participants have understood this instructions well.

After the experiment, we will ask you to fill out a short questionnaire on the computer. After that you will receive your payout.

C Quiz

In the following, we present our comprehension questions. After the instructions are read, subjects are asked comprehension questions on the screen to ensure and to make it common knowledge they all understand the important parts of the experiment. The comprehension questions are:

(1) How many people (including you) are in a group?

(2) What payoff do you get in a round if you and the other person choose "B"?

(3) What payoff do you get in a round if you and the other person choose "A"?

(4) If the random number is less than what number, a new round starts?

(5) The random numbers are drawn independently?

(6) What is the total payoff you would get in a sub-experiment if the sub-experiment lasted 4 rounds and you and the other person always chose "A"?

(7) In each new sub-experiment, you will meet a new person whom you have not met before or will meet after the experiment?

(8) What payoff do you get in a round if you choose "A" and the other person chooses "B"?

D Data

In the following, we present the data discussed in this article in more detail.

D.1 Belief split up by Treatments

Table 4 presents additional data on the belief split up by treatments. It is apparent from this table, that the median belief is around 0.9 across supergames in treatments where subjects can communicate. We argue that this result is in line with the game theoretical model in at least two ways. First, the belief in treatments where subjects can communicate is higher than in ones where they can not communicate. Second, the belief in treatments where subjects can communicate is below one. This is why we use this focal belief to derive the critical discount factor presented in Table 2.

Table 4: Mean and median belief as well as above- and below-median cooperation count split up by treatment in the first and final supergame.

(a) First supergame

		Treatment			
		NoComm70	NoComm0	Comm70	Comm0
Belief	Mean	54.59 (31.16)	35.42 (29.37)	81.51 (23.83)	84.99 (17.45)
	Median	64.69	30.47	89.94	88.66
>Median	Cooperation	14	14	15	15
	Defection	1	7	0	0
<Median	Cooperation	2	1	12	11
	Defection	13	20	3	4

Note: Standard deviations in brackets.

(b) Final supergame

		Treatment			
		NoComm70	NoComm0	Comm70	Comm0
Belief	Mean	40.56 (28.08)	15.88 (25.51)	81.80 (23.25)	68.33 (37.76)
	Median	43.30	20.73	90.99	84.75
>Median	Cooperation	13	8	15	13
	Defection	2	13	0	2
<Median	Cooperation	3	0	15	8
	Defection	12	21	0	7

Note: Standard deviations in brackets.

D.2 Cooperation per Supergame split up by Treatments

Table 5 presents the cooperation rate per supergame split up by treatments in more detail. It is apparent from this table that the results look similar if we instead focus on all rounds. The p-value between NoComm70 and NoComm0 in all rounds is 0.01, 0.04, 0.02, 0.02, 0.02 and < 0.01 in the first, second, third, fourth, fith and over all supergames, respectively. The p-value between Comm70 and Comm0 in all rounds is 0.37, 0.09, < 0.01, 0.02, 0.19 and 0.07 in the first, second, third, fourth, fith and over all supergames, respectively. The p-value between Comm70 and NoComm70 in all rounds is < 0.01, < 0.01, < 0.01, 0.01, 0.02 and < 0.01 in the first, second, third, fourth, fith and over all supergames, respectively. The p-value between Comm0 and NoComm0 in all rounds is < 0.01, < 0.01, < 0.01, < 0.01, 0.01 and < 0.01 in the first, second, third, fourth, fith and over all supergames, respectively.

Table 5: The rate of cooperation in the first round and all rounds over supergames split up by treatments.

(a) First round

Supergame	Treatment			
	NoComm70	NoComm0	Comm70	Comm0
1	0.53 (0.08)	0.36 (0.24)	0.90 (0.09)	0.87 (0.14)
2	0.43 (0.15)	0.21 (0.27)	1.00 (0.00)	0.83 (0.24)
3	0.50 (0.26)	0.19 (0.20)	1.00 (0.00)	0.73 (0.19)
4	0.53 (0.27)	0.17 (0.22)	0.93 (0.15)	0.77 (0.28)
5	0.53 (0.27)	0.19 (0.26)	1.00 (0.00)	0.70 (0.34)
Mean	0.51 (0.17)	0.22 (0.23)	0.97 (0.04)	0.78 (0.22)

Note: Standard deviations in brackets.

(b) All rounds

Supergame	Treatment			
	NoComm70	NoComm0	Comm70	Comm0
1	0.52 (0.04)	0.25 (0.23)	0.80 (0.60)	0.77 (0.22)
2	0.39 (0.12)	0.15 (0.18)	1.00 (0.00)	0.82 (0.27)
3	0.46 (0.20)	0.12 (0.16)	0.94 (0.09)	0.67 (0.17)
4	0.43 (0.33)	0.11 (0.16)	0.95 (0.08)	0.65 (0.35)
5	0.39 (0.30)	0.10 (0.13)	0.89 (0.13)	0.67 (0.40)
Mean	0.44 (0.18)	0.15 (0.16)	0.92 (0.04)	0.72 (0.26)

Note: Standard deviations in brackets.

D.3 Strategy Estimation

Table 6 presents the estimation of the proportions for each strategy discussed in Fudenberg et al. (2012). From the data in this table, we can see that a majority of subjects focuses on always defect and versions of grim trigger. The fraction of subjects choosing grim trigger is significant in Comm70 ($p < 0.01$), but not in Comm0 ($p = 0.17$), in NoComm70 ($p = 0.11$) and in NoComm0 ($p = 0.26$). Yet, the fraction of subjects choosing always defect is significant in Comm0 ($p = 0.03$), in NoComm70 ($p < 0.01$) and in NoComm0 ($p < 0.01$). Thus, the estimation supports the intuition that a substantial fraction of subjects focus on the finite subset of strategies Z.

Table 6: Estimation of strategies used split up by treatments discussed by Fudenberg et al. (2012).

Treatment	Strategies										
	Always cooperate	Tit for tat	Tit for 2 tat	Tit for 3 tat	Tit 2 for tat	Tit 2 for 2 tat	Grim trigger	Grim 2 trigger	Grim 3 trigger	Always defect	Defect tit for tat
Comm70	0.00 (0.00)	0.13 (0.12)	0.22 (0.15)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.43 (0.14)	0.00 (0.00)	0.22 (0.14)	0.00 (0.00)	0.00 (0.00)
Comm0	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.12 (0.66)	0.22 (0.18)	0.45 (0.32)	0.08 (0.26)	0.00 (0.00)	0.13 (0.06)	0.00 (0.00)
NoComm70	0.13 (0.06)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.17 (0.12)	0.00 (0.00)	0.21 (0.13)	0.00 (0.00)	0.00 (0.00)	0.29 (0.09)	0.20 (0.08)
NoComm0	0.00 (0.00)	0.11 (0.06)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.06 (0.05)	0.00 (0.00)	0.02 (0.02)	0.77 (0.07)	0.04 (0.04)

Note: Standard errors in brackets.

D.4 Cooperation and Beliefs per Supergame split up by Communication Cluster

Table 7 shows the mean cooperation rate in all rounds and the mean belief in the first round in the first and final supergame split up per communication cluster in COMM0. It is apparent from this table that mean belief and the mean cooperation rate in the final supergame is lower in the *Talk about A and B* cluster than in the *Talk about A* cluster. A test shows that the mean belief in the final supergame in *Talk about A and B* is significantly lower than in *Talk about A*: $p = 0.02$. The result is very similar if we instead consider the mean cooperation rate in the final supergame: $p = 0.04$. Thus, we conclude that subjects in the *Talk about A and B* cluster are indeed uncertain about the action of the other subject before choosing an action.

Table 7: Mean cooperation rate and mean belief in the first and final supergame split up per communication cluster in COMM0.

Cluster	Cooperation		Belief	
	Supergame		Supergame	
	1	5	1	5
Talk about A	0.72 (0.41)	1.00 (0.00)	0.89 (0.13)	0.95 (0.08)
Talk about A and B	0.79 (0.35)	0.56 (0.48)	0.83 (0.15)	0.59 (0.34)

Note: Standard deviations in brackets.

E Communication Analysis

In the following, we present the communication analysis discussed in this article in more detail.

E.1 Natural Language Processing

Our analysis starts by looking at the entire communication content across supergames and treatments. Thus, the corpus consists of 150 chats, i.e. 150 documents. This corpus is subject to a systematic natural language procedure, which includes the correction of spelling mistakes, the reduction of words to their dictionary form, and the elimination of words that are not meaningful.

The processed corpus can be represented in a matrix Λ, where the element (μ, θ, ω) shows the word embedding value ω of the novel token θ that appears in the document μ. A token θ can be a word or, for example, a number. A word embedding $\vec{\omega_\theta}$ of a token θ is a real-valued vector of length Ω, which encodes the meaning of the token θ such that tokens that have similar vectors should have similar meaning (see Joulin et al., 2016).

The matrix Λ is then transformed into a matrix $\overline{\Lambda}$ by averaging: the element $(\mu, \overline{\omega})$ is the mean of the word embedding ω, i.e. $\overline{\omega}$, for each token θ in each document μ. This representation $\overline{\Lambda}$ has been proven particularly useful to cluster documents with similar meaning (see Ash and Hansen, 2023, and the literature therein).

E.2 k-means

To cluster documents with similar meaning, we use the k-means algorithm. This unsupervised machine learning algorithm is especially suitable for separating a corpus into k clusters (see Steinbach et al., 2000). Documents within the same cluster are as similar as possible, whereas documents from different clusters are as dissimilar as possible. The idea behind this algorithm is to define clusters such that the total within-cluster variation is minimized.

Formally, this is

$$\arg\min_{\psi} \sum_{i=1}^{k} \mid \psi_i \mid \, Var\, \psi_i \tag{32}$$

which entails that, given an initial set of k means σ_1^1, ..., σ_k^1, the algorithm alternates between assigning each document μ to the cluster with the least squared Euclidean distance

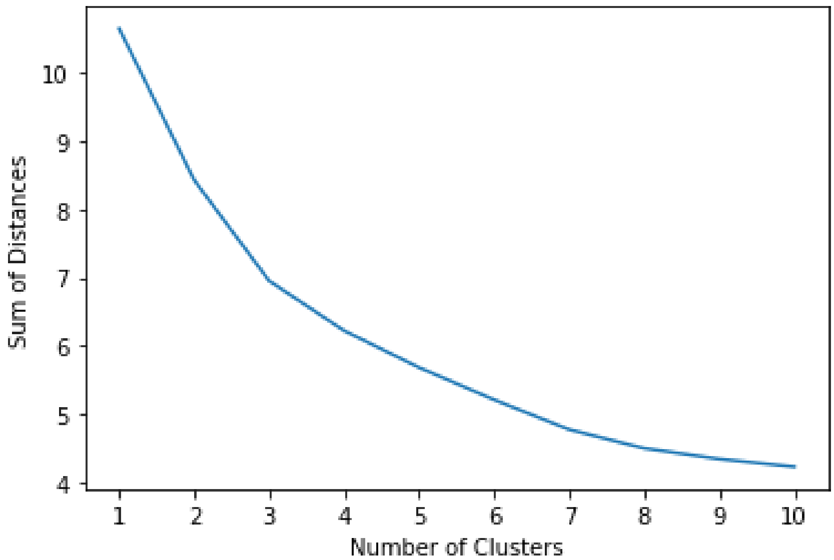
$$\psi_i^t = \{\mu_p : \|\mu_p - \sigma_i^t\|^2 \leq \|\mu_p - \sigma_j^t\|^2 \forall j, 1 \leq j \leq k\} \tag{33}$$

and updating the means for documents assigned to each cluster accordingly:

$$\sigma_i^{t+1} = \frac{1}{\mid \psi_i^t \mid} \cdot \sum_{x_j \in \sigma_i^t} x_j \tag{34}$$

A need for any k-means algorithm lies in choosing the number of cluster k. To choose the number of cluster k, we rely on the total-within clusters sum of square. Figure 2 shows the total-within clusters sum of square per number of cluster k. It is apparent from this figure that an increasing number of cluster k led to a lower total-within clusters sum of square. The statistically optimal number of cluster lies at the point where choosing one more cluster does not reduce the the total-within clusters sum of square much further. In Figure 2, this is the number of cluster k where the elbow lies. It is apparent from this figure, that the number of cluster k that we consider for the k-means algorithm is 3.[18] Two of those cluster are meaningful: they consider a conversation. In the third cluster, both subjects only greet each other without further intention. Thus, for the analysis of the communication content, we just consider the two meaningful cluster.

Figure 2: The total-within clusters sum of square per number of cluster k.



[18]The human-coders, as described in the Appendix, find a similar third cluster that contains greetings between the participants only.

E.3 Co-occurrence Coefficient

The most frequent tokens in each cluster present the key distinguishing communication content between both clusters. Their phi coefficient ϕ records the co-occurrences of tokens in each cluster.

$$\phi = \frac{\nu_{11} \cdot \nu_{00} - \nu_{10} \cdot \nu_{01}}{\sqrt{\nu_{1\bullet} \cdot \nu_{0\bullet} \cdot \nu_{\bullet 0} \cdot \nu_{\bullet 1}}} \tag{35}$$

$\nu_{\alpha,\beta}$ are non-negative counts of numbers of occurrences, where α and β represent whether the token is present, and where $\nu_{\alpha,\bullet}$ and $\nu_{\bullet,\beta}$ represent the sum for a given α and given β respectively.

E.4 Human Coding

Compared to our machine learning algorithm, we find qualitatively similar results using human hand-coding. The hand-coding was realized as follows. First, two student research assistants, independently from each other, read the corpus to note clusters present in the data. Then, they met and agreed on two relevant clusters: agreement and discussion. The first cluster—agreement—captures chats where the subjects purely agree to choose action ‘A’, i.e. to cooperate. In the second cluster—discussion—subjects communicate on both actions, ‘A’ and ‘B’, and the dilemma-aspect of the game. Second, the student assistants independently clustered every chat to the respective clusters: Their work across all clusters is consistent ($\kappa = 0.71$) with each other.

Table 8 shows the frequency of each cluster in approach machine learning or human coding, and the corresponding Cohen’s κ. The mean Cohen’s κ across all clusters between the human raters and our machine learning approach is above 0.74, indicating a substantial agreement. See Table 8 for support. Thus, the data supports our machine learning approach, indicating that subjects are uncertain about the cooperation of the other subject before choosing an action.

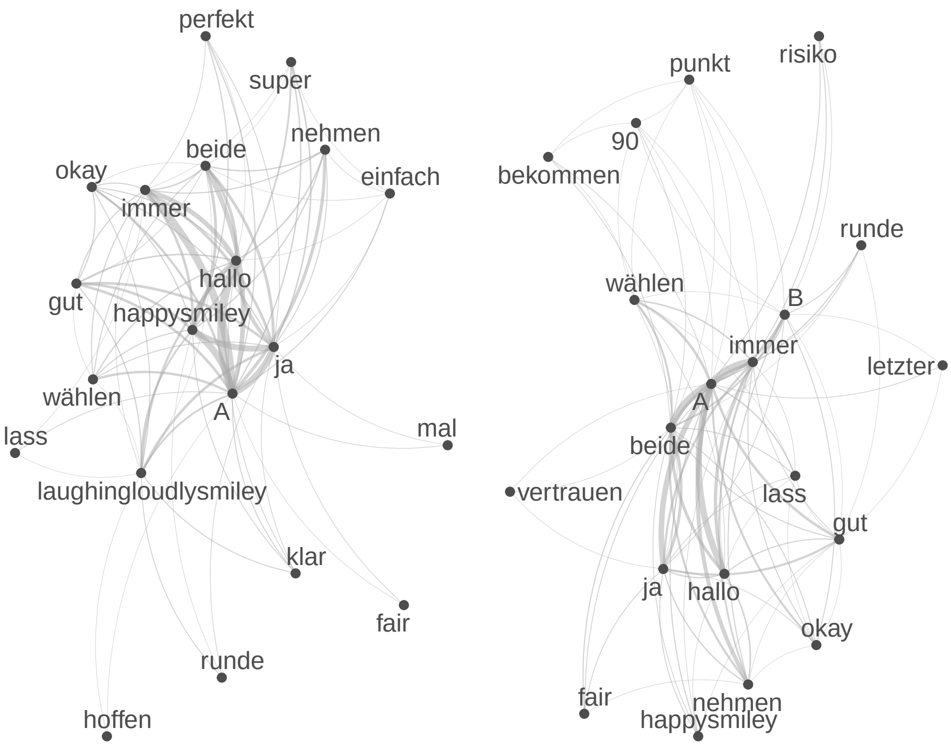
Table 8: Frequency of each cluster in approach machine learning or human coding, and the corresponding Cohen's κ.

Cluster	Frequency in approach		Cohen's κ
	Machine learning	Hand coding	
Agreement	0.49 (0.50)	0.59 (0.49)	0.61
Discussion	0.50 (0.50)	0.41 (0.49)	0.62
Greetings	0.01 (0.12)	0.01 (0.12)	1.00
Average			0.74

E.5 Original German Tokens in their corresponding Figure

Here, we show the original German tokens in their corresponding figure. We translated the tokens only after the analyzes of the chats.

Figure 3: The 20 most frequent tokens in German in each cluster and their co-occurrence coefficient $\phi > 0.5$.



(a) *Talk about A*

(b) *Talk about A and B*