

How Intelligent Players Teach Cooperation

Eugenio Proto *

Aldo Rustichini†

Andis Sofianos‡§

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Abstract

We study cooperation rates in a repeated Prisoner’s Dilemma game, focusing on whether and how subjects of higher intelligence affect the behavior of others, and the evolution over time of the rate. In Proto, Rustichini, and Sofianos (2019) we established that participants of higher intelligence have a higher cooperation rate than otherwise similar participants of lower intelligence, when they play in two separate groups (*split treatment*). Here we study how cooperation rates change over time in mixed groups (*combined treatment*): players are not informed of the intelligence level of the others. We test the main hypothesis that higher intelligence players operate as leaders and increase the cooperation rate of the lower intelligence players; we also want to determine how they achieve this.

The first main finding is that cooperation rates in the combined treatment is substantially higher than the rate of the lower intelligence players (with IQ 76-106), and slightly smaller loss for the high intelligence players (with IQ 102-127), when we compare them to the split treatment. The important question is then “what is the path of the effect?”, in other words, how do the higher intelligence players “teach” the others to cooperate?

Teaching subjects could become more forgiving in the hope that other subjects understand that is in their best interests to mutually cooperate (which would be a form of *active teaching*) or they just consistently best respond to their beliefs— for example by punishing any deviation with Tit for Tat or a Grim trigger strategy—, providing an example of behaviour for the other that can then learn to play more efficiently.

We find support for the latter hypothesis: higher intelligence players use retaliatory strategies (grim trigger or TFT) more often when they are in the combined treatment. They do so more consistently than lower intelligence players, enforcing punishment when it is due, thus providing the low intelligence players in later encounters with the appropriate incentives to cooperate. In conclusion in our environment Tough Love establishes cooperation, and Tender Loving Care is not needed.

JEL classification: C73, C91, C92, B83

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*University of Bristol, CEPR, IZA and CesIfO; email: eugenio.proto@gmail.com

†University of Minnesota; email: aldo.rustichini@gmail.com

‡University of Heidelberg; email: andis.sofianos@uni-heidelberg.de

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1 Introduction

Establishing cooperation under repeated interactions is a complex process because many factors are involved and many skills are necessary. Even in a stylized experimental setting, players need to choose the right strategy, have correct beliefs about the opponent, have to be able to follow coherently a strategy after it has been chosen. Yet, experimental evidence (e.g. Dal Bó, 2005; Dreber et al., 2008; Duffy and Ochs, 2009; Dal Bó and Fréchette, 2011; Blonski, Ockenfels, and Spagnolo, 2011) show how subjects, when gains from cooperation are sufficiently large, tend to cooperate under repeated interactions.

An important characteristic determining the levels of cooperation in the different strategic environment is the intelligence of players. Proto, Rustichini, and Sofianos (2019) (PRS henceforth) found that in a *split treatment* where the subjects are allocated in two groups on the base of their intelligence, only the higher intelligence groups converge to full cooperation. This result identifies an important factor affecting cooperation; however, such separation of individuals in distinct classes does not occur in the real life, so it is important to establish a clear comparison of the cooperation rates occurring when higher and lower Intelligence players interact and when they do not. We also need to understand how the effect operates in combined environments. For example, recent literature has also begun to investigate the way in which different cognitive skills affect learning in strategic environments. For example, recent findings indicate that lower intelligence is associated to more reliance on social learning through imitation (e.g. Muthukrishna, Morgan, and Henrich, 2016; Vostroknutov, Polonio, and Coricelli, 2018).

To answer these questions we adopt in this paper an experimental design where such separation does not occur. The first main finding is that cooperation rates in the combined treatment increases for the lower intelligence players, and decreases only slightly for the higher intelligence ones. Specifically, the cooperation rate is substantially higher for lower intelligence players (those with IQ in the range 76-106) when we compare them to the split treatment. Instead, the cooperation rate is slightly smaller for the high intelligence players (range IQ 102-127), again compared to the split treatment. We then identify the way in which the beneficial effect of the interaction with higher intelligence players occurs.

Our second main finding is that lower intelligence subjects play better strategies and implement them with fewer mistakes when play with high intelligence subjects, because in the early stages they face a response to defection that is more retaliatory than in the split sessions. The teachers, who are the higher intelligence players, when they interact in combined sessions, face a defection rate higher than the one observed by their corresponding high intelligence subjects in the split treatment; they are of course unaware of the different nature of the pool of partners. They respond to this by adopting the punishment implicit in their strategies (whether “grim trigger” or “tit for tat”). They do so at a rate higher than the corresponding lower intelligence partners in the split treatment. This comparatively higher punishment has an educational effect, because lower intelligence subjects learn that retaliation is consistently associated with defection, and thus they learn to exercise more care in their choice. In the evolution of the session, this, in turn, has the surprising effect of benefiting the low intelligence, which would cooperate and earn less otherwise.

There is evidence that subjects teach other subjects how to play efficiently. In particular Hyndman et al. (2012) show that some participants act as teachers and play a forward looking strategy trying to influence the action of the other players. Their design adopts a finitely repeated game, where the stage game has a unique pure strategy Nash equilibrium with outcome on the Pareto frontier. They show that subjects do not best respond to their beliefs about the choice of the other players, presumably with the intent of teaching the others (*active teaching*).

However, in the repeated prisoners’ dilemma, subjects have typically short-term incentive to

deviate from the cooperative outcome, thus other mechanisms of teaching are possible. Specifically, Proto, Rustichini, and Sofianos (2019) show that is the existence of a tension between short-term and long-term objective that lead the less intelligent to inefficiently reach non cooperative outcomes. Along the lines of the active teaching hypothesis, teaching subjects in our setup could become more forgiving, and hope that other subjects understand that is in their best interests to mutually cooperate. What we find, instead is that they just consistently best respond to their beliefs– for example by punishing any deviation with at Tit for Tat or a Grim trigger strategy–, providing an example of behaviour for the other that can then learn to play more efficiently; we can call this *passive teaching*.

Fudenberg, Rand, and Dreber (2012) analyse the effect of uncertainty in the implementation of the different strategies in games of cooperation under repeated interaction, and show how subjects factor-in this noise when playing and become more lenient and forgiving. In our setting the noise is endogenous, and is mostly due to the mistakes of the less intelligent. We show that more intelligent being less lenient and forgiving than the less intelligent reduces the noise and improving efficiency and payoffs.

The paper is organized as follows: In section 2 we formulate the broad question on the effect of mixing subjects with different levels of intelligence. In section 3 we present the experimental design. We then present the result by answering the previously formulated questions in section 4. In section 5 we investigate the difference in the process of beliefs updating and learning to best response between the different groups of subjects and treatments. Section 6 presents our conclusions. Additional technical analysis, robustness checks, details of the experimental design and descriptive statistics are in the appendix.

2 Main research questions and hypotheses.

Our first question examines how interacting in common pools affects the cooperation rates of players, as compared to environments where they play in separate pools:

Question 2.1. *In an environment where cooperation can be sustained as a subgame perfect equilibrium, do the less intelligent cooperate and earn more than when they play separately and do the more intelligent cooperate and earn less?*

The other natural question, in the same environment, is:

Question 2.2. *Are the aggregate payoffs when higher and lower intelligent subjects are mixed together higher than when they play separately?*

We next turn to identifying the pathways of the effects. Proto, Rustichini, and Sofianos (2019) found that less intelligence subjects make mistakes in the implementation of the strategies and, in part, also choose sub-optimal strategies. Accordingly, we will address the following:

Question 2.3. *If mixed together, will less intelligent learn from the more intelligent to play the optimal strategies and to be more consistent with their implementations?*

There is evidence that subjects teach other subjects how to play efficiently. In particular Hyndman et al. (2012) show that some participants act as teachers and play a forward looking strategy trying to influence the action of the other players. Their design adopts a finitely repeated game, where the stage game has a unique pure strategy Nash equilibrium with outcome on the Pareto frontier. They show that subjects do not best respond to their beliefs about the choice of the other players, presumably with the intent of teaching the others (*active teaching*).

However, in the repeated prisoners’ dilemma setup we are considering, subjects have short-term incentive to deviate from the cooperative outcome, thus other mechanisms of teaching are possible. Specifically, Proto, Rustichini, and Sofianos (2019) show that is the existence of a tension between short-term and long-term objective that lead the less intelligent to inefficiently reach non cooperative outcomes. Along the lines of the active teaching hypothesis, teaching subjects in our setup could become more forgiving, and hope that other subjects understand that is in their best interests to mutually cooperate. But they might just consistently best respond to their beliefs– for example by punishing any deviation with at Tit for Tat or a Grim trigger strategy–, providing an example of behaviour for the other that can then learn to play more efficiently; we can call this *passive teaching*. We will investigate these two hypotheses investigating the following question:

Question 2.4. *How the two groups (i.e. more or less intelligent) change their strategies when the play combined and when they play separately?*

3 Experimental Design

Our design involves a two-part experiment administered over two different days separated by one day in between. Participants are allocated into two groups according to cognitive ability that is measured during the first part, and they are asked to return to a specific session to play several repetitions of a repeated game. Each repeated game is played with a new partner. We have two treatments: one where participants are separated according to cognitive ability and one where participants are allocated into sessions where cognitive ability is similar across sessions. We call the former the *IQ-split* treatment and the latter the *Combined* treatment. The subjects were not informed about the basis upon which the split was made.¹

3.1 Experimental Details

Day One

On the first day of the experiment, the participants were asked to complete a Raven Advanced Progressive Matrices (APM) test of 36 matrices. They had a maximum of 30 minutes for all 36 matrices. Before initiating the test, the subjects were shown an example of a matrix with the correct answer provided below for 30 seconds. For each item a 3×3 matrix of images was displayed on the subjects’ screen; the image in the bottom right corner was missing. The subjects were then asked to complete the pattern choosing one out of 8 possible choices presented on the screen. The 36 matrices were presented in order of progressive difficulty as they are sequenced in Set II of the APM. Participants were allowed to switch back and forth through the 36 matrices during the 30 minutes and change their answers.

The Raven test is a non-verbal test commonly used to measure reasoning ability and general intelligence. Matrices from Set II of the APM are appropriate for adults and adolescents of higher average intelligence. The test is able to elicit stable and sizeable differences in performances among this pool of individuals. This test was among others implemented in PRS and Gill and Prowse (2016) and has been found to be relevant in determining behaviour in cooperative or coordinating games.

Subjects are usually not rewarded for completing the Raven test. It has though been reported that Raven scores slightly increase after a monetary reward is offered to higher than average intelligence subjects (e.g. Larson, Saccuzzo, and Brown, 1994). With the aim of measuring intelligence

¹During the de-briefing stage we asked the participants if they understood the basis upon which the allocation to sessions was made. Only one participant mentioned intelligence as the possible determining characteristic.

with minimum confounding with motivation, we decided to reward our subjects with 1 Euro per correct answer from a random choice of three out of the total of 36 matrices. During the session we never mentioned that Raven is a test of intelligence or cognitive abilities.

Following the Raven test, the participants completed an incentivised Holt-Laury task (Holt and Laury, 2002) to measure risk attitudes. Finally, participants were asked to respond to a standard Big Five personality questionnaire together with some demographic questions, a subjective well-being question and a question on previous experience with a Raven’s test. No monetary payment was offered for this section of the session and the subjects were informed about this. We used the Big Five Inventory (BFI); the inventory is based on 44 questions with answers coded on a Likert scale. The version we used was developed by John, Donahue, and Kentle (1991) and has been recently investigated by John, Naumann, and Soto (2008).

All the instructions given on the first day are included in the supplementary material.²

Day Two

On the second day, the participants were asked to come back to the lab and they were allocated to two separate experimental sessions. The basis of allocation depends on the treatment. In the IQ-split treatment, participants were invited back according to their Raven scores: subjects with a score higher than the median were gathered in one session, and the remaining subjects in the other. We will refer to the two sessions as *high-IQ* and *low-IQ* sessions.^{3,4} In the combined treatment, we made sure to create groups of similar Raven scores across sessions. To allocate participants to second day sessions, we ranked them by their Raven scores and split by median. Instead of having high- and low-IQ groups though, we alternated in allocating participants in one session or the other.⁵

The task they were asked to perform was to play an induced infinitely repeated Prisoner’s Dilemma (PD) game. Table 1 reports the stage game that was implemented.

Table 1: **Prisoner’s Dilemma.** *C*: Cooperate, *D*: Defect.

	C	D
C	48,48	12,50
D	50,12	25,25

We induced infinite repetition of the stage game using a random continuation rule: after each round the computer decided whether to finish the repeated game or to have an additional round depending on the realization of a random number. The continuation probability used was $\delta = 0.75$. We used a pre-drawn realisation of the random numbers; this ensures that all sessions across both treatments are faced with the same experience in terms of length of play at each decision point. As usual, we define as a supergame each repeated game played; period refers to the round within a specific supergame; and, finally, round refers to an overall count of number of times the stage game has been played across supergames during the session. The length of play of the repeated game during the second day was either 45 minutes or until the 151st round was played depending on which came first.

²This is available online at X

³The attrition rate was small, and is documented in table A.1.

⁴In cases where there were participants with equal scores at the cutoff, two tie rules were used based on whether they reported previous experience of the Raven task and high school grades. Participants who had done the task before (and were tied with others who had not) were allocated to the low-IQ session, while if there were still ties, participants with higher high school grades were put in the high session.

⁵Again, the attrition rate was small, and is documented in table A.2.

The parameters used are identical to the ones used by DBF and PRS. The payoffs and continuation probability chosen entail an infinitely repeated Prisoner’s Dilemma game where the cooperation equilibrium is both subgame perfect and risk dominant.⁶

The matching of partners is done within each session under an anonymous and random re-matching protocol. Participants played as partners for as long as the random continuation rule determines that the particular partnership is to continue. Once each match was terminated, the subjects were again randomly and anonymously matched and started playing the game again according to the respective continuation probability. Each decision round for the game was terminated when every participant had made their decision. After all participants made their decisions, a screen appeared that reminded them of their own decision, indicated their partner’s decision while also indicated the units they earned for that particular round. The group size of different sessions varies depending on the numbers recruited in each week.⁷ The participants were paid the full sum of points they earned through all rounds of the game. Payoffs reported in table 1 are in terms of experimental units; each experimental unit corresponded to 0.003 Euros.

Upon completing the PD game, the participants were asked to respond to a short questionnaire about any knowledge they had of the PD game, some questions about their attitudes towards cooperative behaviour and some strategy-eliciting questions.

Implementation

The recruitment was conducted through the Alfred-Weber-Institute (AWI) Experimental Lab subject pool based on the Hroot recruitment software. A total of 214 subjects participated in the experimental sessions. They earned on average around 23 Euros each; the show-up fee was 4 Euros. The software used for the entire experiment was *Z-Tree* (Fischbacher, 2007).

We conducted a total of 8 sessions for the IQ-split treatment; four-high IQ and four low-IQ sessions. There were a total of 108 participants, with 54 in the high-IQ and 54 in the low-IQ sessions. For the combined treatment we conducted a total of 8 sessions with a total of 106 participants. The dates of the sessions and the number of participants per session, are reported in tables A.1 and A.2 in the appendix. The recruitment letter circulated is in the supplementary material.⁸

4 Results

4.1 Cooperation rates and payoffs

We first address two simple descriptive questions, comparing cooperation rates and payoffs across the two treatments for the two groups. We will then answer to question 2.1: *Do the less intelligent earn more than when they play separately and do the more intelligent earn less?*

The top left panel of figure 1 shows that when separated the two groups behave differently. In the group with more intelligent subjects cooperation goes up until to almost full cooperation; the lower intelligence participants have a substantially and persistently lower cooperation rate. These results replicate, in a different group and in a different country, the results in Proto, Rustichini, and Sofianos (2019).⁹

⁶See DBF, p. 415 for more details

⁷The bottom panels of tables A.1 and A.2 in the appendix list the sample size of each session across both treatments.

⁸See note 2.

⁹In figure A.2 of the appendix we present the cooperation rates disaggregates by single session and supergame

The behavior is very different in the combined treatment. The top right panel shows that when participants of different intelligence are combined together, the cooperation rate increases to almost full cooperation and the two groups cooperate in average in the same way. The bottom panels of figure 1 show that payoffs are higher for high IQ subjects when they play separately than when they play in the combined sessions. On the contrary, low IQ earn considerably more when they play with the high IQ in the combined sessions.

In the following we define a supergame each repeated game played; period refers to the iteration within a specific supergame. We use the term round to denote an overall count of the number of times the stage game has been played across supergames during the session.

Table 2 shows that, as in Proto, Rustichini, and Sofianos (2019), IQ is not significant in determining cooperation in the first round of each session. Interestingly, risk aversion is the only significant determinant of cooperation at the beginning of each session hence the learning in the different environments seem key in determining the level of cooperation.

Moreover, table 3 shows that in the high IQ sessions subjects earn 2.5 unit and cooperate 10% more than in the combined sessions in the 1st 20 supergames, while in low IQ sessions they cooperate about 20% and earn 5.5 unit less than in the combined sessions. While there is no significant difference between high IQ and combined sessions in the second part, suggesting that low IQ learn to play as efficiently as the high IQ in the second part of the sessions. While in the low IQ sessions the differences in both cooperation and payoffs remain constant.

Overall, living with the lower intelligence participants is slightly detrimental for higher intelligence participants, and very advantageous for lower intelligence ones.

The second simple descriptive statistic we consider is the comparison of the average payoffs for the two treatments (split and combined). We will then provide an answer to question 2.2: *Are the aggregate payoffs when higher or lower intelligent subjects are mixed higher than when they play separately?*

Figure 2 shows that the average payoff per interaction is *consistently higher in the combined sessions than in the low IQ sessions.*

4.2 Learning process of lower IQ subjects

The evidence provided up to now suggests that in the mixed treatment less intelligent learn to play more efficiently more than in the split treatment. Accordingly, we will now provide an answer to the first part of question 2.3: *If mixed together, will less intelligent learn from the more intelligent to play the optimal strategies*

Figure 3 shows that subjects increasingly open with cooperation in every treatments and groups. High IQ subjects converge faster to almost 1, while for low IQ this pattern is slower, especially in the low IQ sessions, where they seem to converge to a level below 1. Accordingly, table 4 shows that– in the first 20 supergames– subjects in the high IQ sessions and in the combined sessions increasingly open with cooperation at faster speed than in the combined treatment, while in the low IQ session the cooperation increase less than in the combined sessions (columns 1 and 2); subjects in the low IQ sessions tend to catch-up with the others in the in the second part (column 3 and 4).

This represents evidence that lower IQ learn to play more cooperative strategies when mixed with higher IQ faster than when they play together. This is confirmed by tables 5 and 6, where we estimated the probability of the different strategies subjects adopt in the split treatments.¹⁰ In table 5 we note that high IQ play always defect (then open with a defection) the 20% of time in the first 5 supergames, this probability goes essentially to zero in the last 5 supergames. The low

¹⁰We followed Dal Bó and Fréchette (2011) for this estimation, the details are provided in the online appendix of their paper.

IQ the probability of always defect is close to 50% in the first 5 supergames but is still sizeable in the last 5 supergames (about 24%). This behaviour needs to be compared with the strategies played by the low IQ groups in the combined sessions– displayed in table 6. Already, in the 1st 5 supergames low IQ play non cooperative strategy about 19% of time and this probability decreases even more in the last 5 supergames (about 13%), so they learn quickly to cooperate when they play with the high IQ in the combined treatments.

Why this increase in cooperation in the opening rounds in session where there is a larger number of high IQ subjects occurs?

If this increase in cooperation is driven by subjects beliefs about the other subjects play in period 1 of each supergame, we should observe that subjects whose partners opened with cooperation in the past more often should increase the probability of opening with cooperation in the present. This is what we observe in column 2 and 4 of table 4, where the coefficients of the partners’ pasts cooperation in the 1st rounds are positive and significant. In column 2, however, the other coefficients show a positive trend and a significant difference in the sessions with more high IQ subjects, suggesting that the increase in 1st period cooperation is not entirely due to the past behaviour of the subjects in period 1.¹¹

Figures 6, 7 and 8 provide further insights about this learning process. In figure 6, it is evident that high IQ learn to reciprocate with cooperation faster than low IQ, and low IQ players learn faster when they play in the mixed sessions and can observe that high IQ are more keen to reciprocate cooperation. This learning mechanism is even clearer in figures 7 and 8, where we report the percentage of defections a subject face in period $t+1$ after cooperating at t : this is a situation that clearly discourages cooperation. For the high IQ (figure 7) there is a declining pattern both when they play separately and when they play combined with low IQ. Although there seems to be a difference when they play separately in the first part of the sessions. In the second part the rate of defection after cooperation is similar whether high IQ play separately or not, suggesting a learning pattern for the low IQ. From figure 8, we observe that the low IQ face defection after cooperation more when they play separately then when they play combined and the decline of this pattern when they play separately is less clear than when they play combined with the high IQ. Therefore, it is also the behaviour of the partners after cooperation rather than the 1st period cooperation which seems to drive the patterns of cooperation in the different groups and treatments that we observe in figures 1 and 3.

But are the low IQ learning to play the optimal strategy when they are mixed with the high IQ? In other words, is opening with cooperation an optimal choice from the low IQ point of view?

In tables 7 and 8 we analyze the optimality of the the most frequent strategies subjects plays in the different treatments. As we can see in table 7, when they play in the split sessions, the low IQ play Grim, Tit for Tat, Win stay Lose Shift (that we define “sophisticated cooperation” (SC)) only an estimated 28% of time, despite this being the strategy yielding the highest expected payoffs (41.33). From table 8 we notice that in the combined treatment the probability of SC is already about 42% in the 1st 5 supergames and goes up until 92% in the last 5 supergames. *Hence, the low IQ learn to play more optimal strategies when mixed with the high IQ*

We will now address the second part of question 2.3: *If mixed together, will less intelligent learn from the more intelligent to be more consistent with their implementations?*

We define deviation from former cooperation the event in which a player chooses defection after a round of mutual cooperation. We may classify a choice of D after a last period action profile (C, C) an error (as in Proto, Rustichini, and Sofianos (2019)) because such choice provides a total

¹¹In section 5, we will formally investigate the process of beliefs formation and updating for the first periods of each supergame.

payoff smaller than the alternative, since for none of the strategies that we have identified choosing D at that history is optimal.

Figure 4 reports the evolutions of the deviations from a former (in previous round) mutual cooperation. In all cases (that is, both low and high IQ, and split and combined sessions) the trend is a decrease in the frequency of defect choice over time. However, for the low IQ in the split sessions the frequency of defect is substantially higher in the early supergames, and declines to a rate of approximately 10 per cent, which is higher than the frequency for low IQ subjects in the combined sessions.

Figure 5 shows that in split sessions the frequency of deviations monotonically declines as the IQ of the subjects increase suggesting a direct link between errors and intelligence. This pattern does not exist in the combined sessions. Therefore, we can conclude that *low intelligence participants learn to be more consistent when they play with the high intelligence participants.*

4.3 The teaching of the high IQ subjects

Less intelligent learn to play more efficient when mixed with high intelligent, our last question (question 2.4 is then: *How the two groups (i.e. more or less intelligent) change their strategies when the play combined and when they play separately?*

As we said in reference to figure 7, high IQ face defection after cooperation more often when they play in the mixed sessions, but the likelihood of this situation decline in the second part of this session. How this decline has been achieved? if the high IQ is patient and forgive the 1st defection, will the partner revert back to cooperation?

Figure 9 suggests that this is NOT the case. After forgiving a 1st round of defection high IQ face more defection when they play in the combined session than when they play separately, especially in the second part of the session. High IQ, when matched with other subjects with similar IQ, after forgiving one defection in the last period their partners revert to cooperation at with 50% chance. When they are matched in a combined session, this chance declines to less than 25%. Patience then pay more when high IQ are matched with other high IQ, but less so when they are matched with low IQ. An effect of this can be observed in table 5, the high IQ play AC about 35% of time in the last 5 supergames when the play separately. While, in the combined sessions, AC is essentially 0 as we can see in table 6.

In what comes next, we analyse this change of behaviour between combined and split treatments in a more systematic way. There is widespread evidence that subjects overwhelmingly play *memory one* strategies in repeated prisoners' dilemma games (see Dal Bó and Fréchet (2018)). This is consistent with the results presented in tables 5 and 6, which show that AC, AD, Grim Trigger and TfT cover between 85% and 100 % of the strategies played by all subjects. As in the previous simulation we assume that every subject choose a strategy that applies for a number of supergames. Accordingly, we assume that choices in every round are determined by the past outcome (hence by both his and his partner's choice in the match), according to a model, where the dependent variable $ch_{i,t}$ represents the subjects' choice (1 for Cooperate and 0 for Defect). We will estimate separately using the first part of each session (i.e. first 20 supergames) and then the second part. We will estimate using a logit estimator.

Let $p_{i,t}$ the probability of $ch_{i,t} = 1$ conditioned on the set of independent variables

$$p_{i,t} = \Lambda(\alpha_i + \beta[Ch_{i,t-1}; Partn.Ch_{i,t-1}] + \epsilon_{i,t}) \quad (1)$$

where $[Ch_{i,t-1}; Partn.Ch_{i,t-1}]$ is a 3-dimensional vector of dummy variables representing the different outcomes, where (1,0,0) represents $Ch_{i,t-1} = 0; Partn.Ch_{i,t-1} = 1$, (0,1,0) represents

$Ch_{i,t-1} = 1; Partn.Ch_{i,t-1} = 0$ and $(0,0,1)$ represents $Ch_{i,t-1} = 0; Partn.Ch_{i,t-1} = 0$; with mutual cooperation, $Ch_{i,t-1} = 1; Partn.Ch_{i,t-1} = 1$, being the baseline category. α_i is the time-invariant individual fixed-effect (taking into account time-invariant characteristics of both individuals and sessions); finally $\epsilon_{i,t}$ represent the error terms.

In table 9, we present the estimates of model 1 separately for the supergames belonging to the first and the second part of each sessions. Results are presented in odds ratios using the outcome $(C, C)_{t-1}$ as baseline. From Panel A, we note that the odd of cooperating at time t by high IQ are higher after that at least one in the match has defected (i.e. after $(D, D)_{t-1}$ $(D, C)_{t-1}$ $(C, D)_{t-1}$) when they play among themselves than when they play in the combined sessions. This difference is, if anything, even larger in the second part of the sessions as we can notice from Panel B of table 9.¹² In table 10 we directly test whether high IQ are more forgiving when they play amongst each other than when play in combined sessions. We note that the high IQ are significantly less likely to cooperate whenever the other subject unilaterally defect. Interestingly, the low IQ do not seem to play systematically differently whether they play with with other low IQ or in the combined sections. Hence we can summarise this section by saying that *High IQ are less likely to cooperate after a unilateral deviation of the partner when they play in combined session than when play separately. The low IQ do not play in a systematically different way in the two treatments*

5 A formal analysis of beliefs' updating

In section 4.2, we showed that less intelligent subjects play less efficiently in the split treatments and learn how to play more efficiently when mixed with more intelligent. There are essentially three ways cognitive abilities can affect the way subjects play: i) through more precise beliefs; ii) by best responding to their beliefs (in other words correctly calculating the expected payoffs of their choices); iii) and, after choosing a strategy, by being consistent with its implementation. We already saw that low IQ learn iii) when playing with high IQ and argued that this might be due to the fact that high IQ choose less forgiving strategies when matched with low IQ and this makes any mistake of the latter more costly. In what follows we will try to disentangle i) from ii) and understand better the mechanism by which low IQ learn from high IQ.

We assume that subjects in the first repeated game hold beliefs that other players either use AD or a cooperative strategy that we already defined SC (sophisticated cooperation = essentially corresponding to Tft + Grim). Closely following Dal Bó and Fréchette (2011), let the probability of player i in supergame s to play AD be $\beta_{i,s}^{AD} / (\beta_{i,s}^{AD} + \beta_{i,s}^{SC})$. In the first supergame, $s = 1$, subjects have beliefs characterized by $\beta_{i,s}^{AD}$ and $\beta_{i,1}^{SC}$, from the second supergame onward, $s > 1$, the they update their beliefs as follows:

$$\beta_{i,s+1}^k = \theta_i \beta_{i,s}^k + 1(a_j^k), \quad (2)$$

where k is the action (AD or SC) and $1(a_j^k)$ takes the value 1 if the action of the partner j is k . The discounting factor of past belief, θ_i , equals 0 in the so-calleld *Cournot Dynamics* and is 1 in the *fictitious play*. Therefore the closer is θ to 1 the slower will player update their beliefs. Since we assume that subjects chose a strategy at the beginning of the supergame, they will play cooperation, C, in period 1 of supergame if they expect that the partner plays SC, defect, D, otherwise. The expected utility each player obtains for each action, a , is

$$U_{i,s}^a = \frac{\beta_{i,s}^{AD}}{\beta_{i,s}^{AD} + \beta_{i,s}^{SC}} u^a(a_j^{AD}) + \frac{\beta_{i,s}^{SC}}{\beta_{i,s}^{AD} + \beta_{i,s}^{SC}} u^a(a_j^{SC}) + \lambda_{i,s} \epsilon_{i,s}^a \quad (3)$$

¹²for example, considering $(C, D)_{t-1}$, $0.03468 - 0.01485 > 0.01039 - 0.01450$

where $u^a(a_j^k)$ is the payoff from taking action a when j takes the action k . The estimation of the model above generates choices of the first period of each supergame that in average fits well our data as it is shown in figure 10. We now analyse the two parameters we are interested: θ_i , measuring the inverse of the speed by which subjects update their beliefs and $\lambda_{i,s}$, measuring the inverse of the capacity of best responding given the beliefs.¹³

In table 12, we show the correlation between IQ and the parameters of interest. IQ significantly negatively correlated with θ_i , implying that higher IQ subjects update faster their beliefs. While do not affect the capacity of best responding, λ_s . In the top panels of figure 11 we can compare the cumulative distribution of the θ_i in the different treatments. θ_i seem to be smaller for high IQ than for low IQ, confirming that low IQ update they beliefs slower than high IQ (top left panel). When combined the differences seem to be drastically reduced (top right panel). From panel A of table 11, we note that the differences between high IQ and low IQ in the split treatment is statistically significant, while the same difference in the combined treatment is only weakly significant at the best. The bottom left panel of figure 11 shows that low IQ improve their speed (i.e. θ_i is lower) when combined with the high IQ, while there is no much difference among high IQ subjects in the different treatments. Panel B of 11 confirm that the differences among the low IQ in the combined and in the split treatments are statistically significant. We can summarise this discussion saying *Less intelligent learn to update their beliefs faster when they are mixed with more intelligent, while the way the subjects best respond to their beliefs is not depended on their IQs*. A possible explanation of why lower IQ subjects update their first period beliefs faster when mixed with the higher IQ might be that in the latter environment they receive a clearer signal from the other players playing more consistent strategies of cooperation.

6 Conclusions

In spite of the many forces operating in the direction of segregation of individuals along similarity of individual characteristics, a large part of social interaction occur across very diverse individuals. This occurs in particular across different levels of intelligence. So once it is clear that higher cognitive skills may favor a higher rate of cooperation, the natural question arises: what are the outcomes of strategic interactions among heterogeneous individuals. We have proved two main results.

The first is that cooperation rates in heterogeneous groups are close to the high cooperation rates, although the more intelligent makes a small loss. The entire aggregated surplus is higher when heterogeneous groups play than together than when they play separately, but the interaction in heterogeneous pooling is more advantageous to lower intelligence players.

The second result is that the higher cooperation rates of lower intelligence players in mixed groups is due to the influence of the choices of high intelligence players, who are more consistent in punishing defection when they play combined with less intelligent than when they play with subjects of a similar level of intelligence.

¹³The details on how the model is estimated are in the online appendix of Dal Bó and Fréchette (2011) at p. 6-8., the main parameter of the simulation are presented in table A.14 of the appendix

7 Figures and Tables

Figure 1: **Cooperation and payoffs per period in Split and Combined sessions** The four panels report the averages, computed over observations in successive blocks of five supergames, of all high and all low IQ sessions, aggregated separately. The black and grey lines report the average cooperation and payoffs for high and low IQ subjects in the Split and Combined treatment respectively. Bands represent 95% confidence intervals.

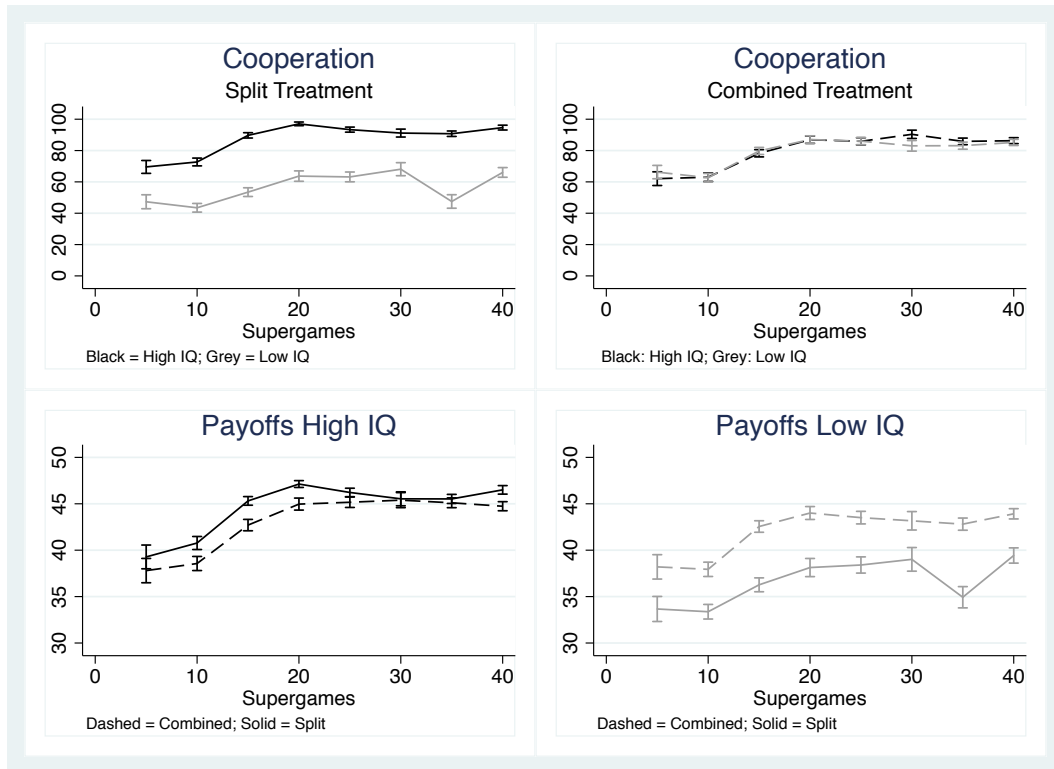


Figure 2: **Average payoffs per interaction in the Split and Combined sessions** The average is computed over observations in successive blocks of five supergames, of all Split and Combined sessions, aggregated separately. Bands represent 95% confidence intervals.

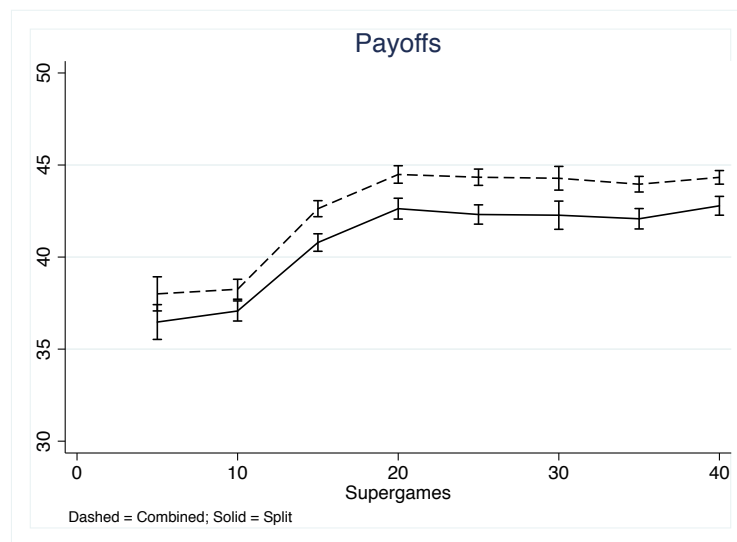


Figure 3: **Cooperation in period 1 in the different groups of the Split and Combined sessions** Average cooperation, computer over each supergames. High and all low IQ treatments correspond to the the black and grey solid lines, high and all low IQ groups in the combined treatment correspond to the the black and grey dashed lines.

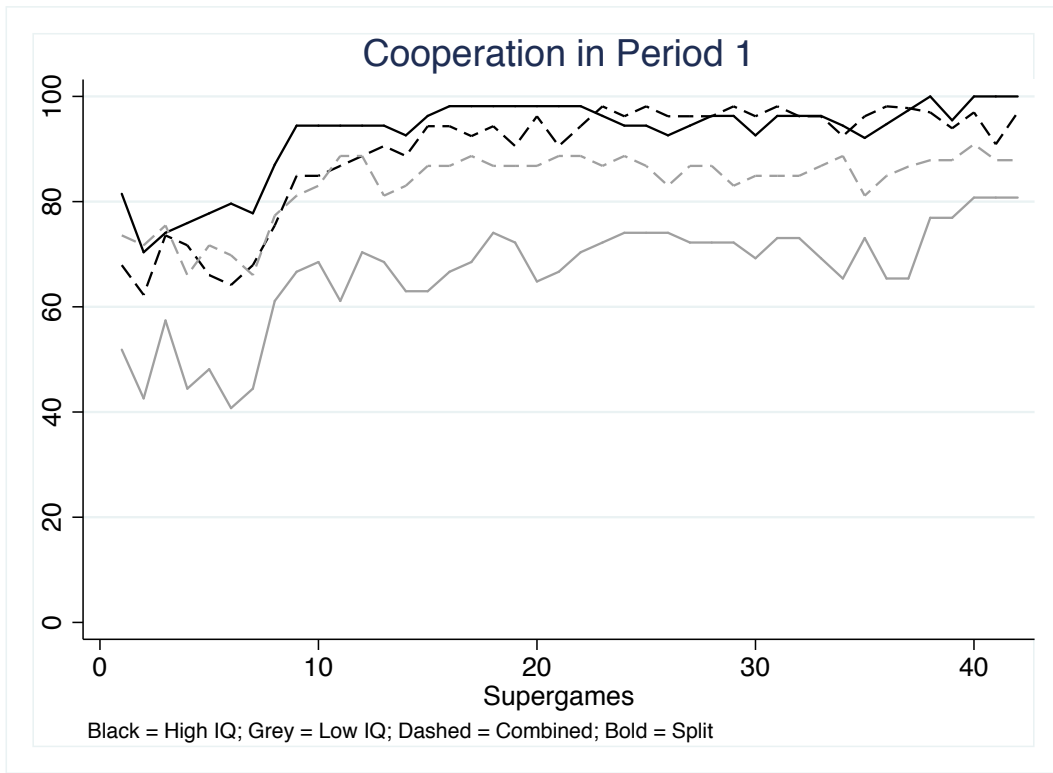


Figure 4: **Deviations from former cooperation over time.** A deviation from former cooperation is a choice of defect (D) at t following a round of mutual cooperation (C, C) at $t - 1$. Bands represent 95% confidence intervals.

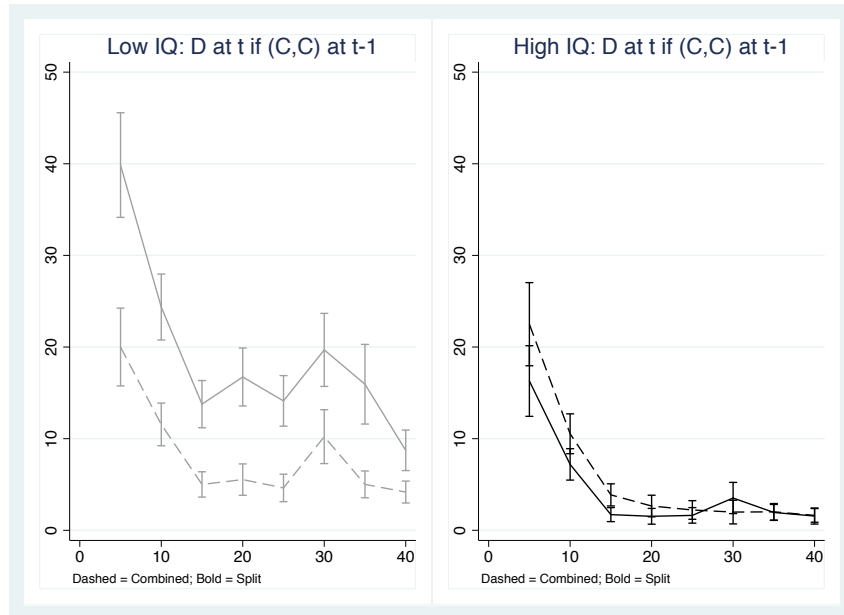


Figure 5: **Deviations from former cooperation across IQ classes.** Variability of the deviation from former cooperation in the two treatments, by quintile of IQ. Bands represent 95% confidence intervals.

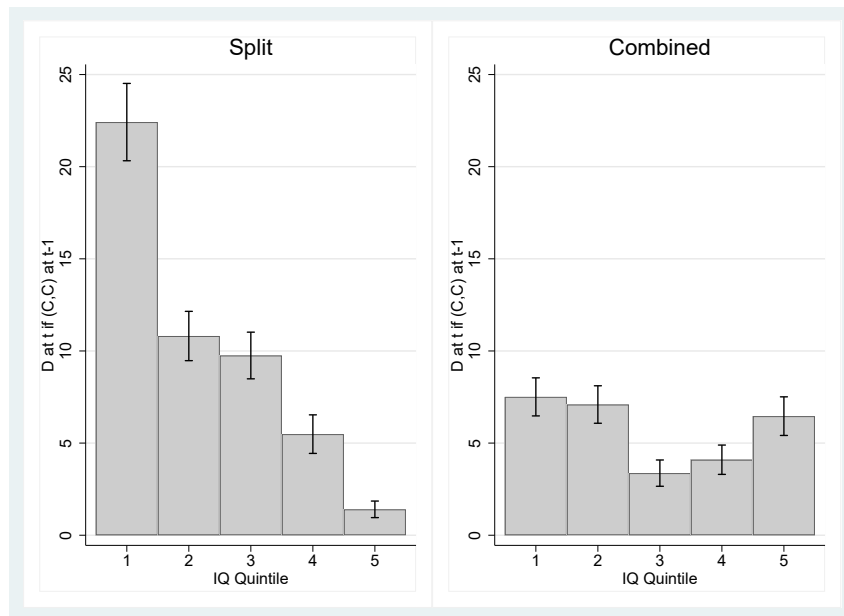


Figure 6: **Conditional Cooperation in the different groups and treatments.** Averages computed over observations aggregated by supergames

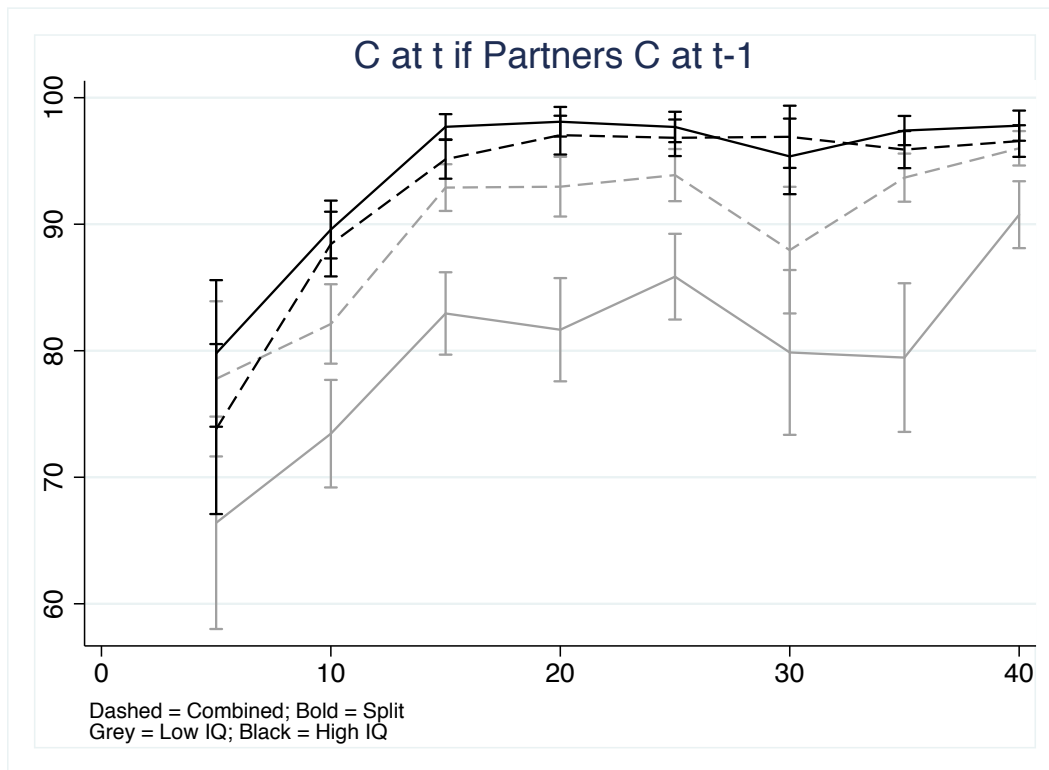


Figure 7: **Learning strategies for high-IQ subjects.** Averages computed over observations aggregated by supergames.

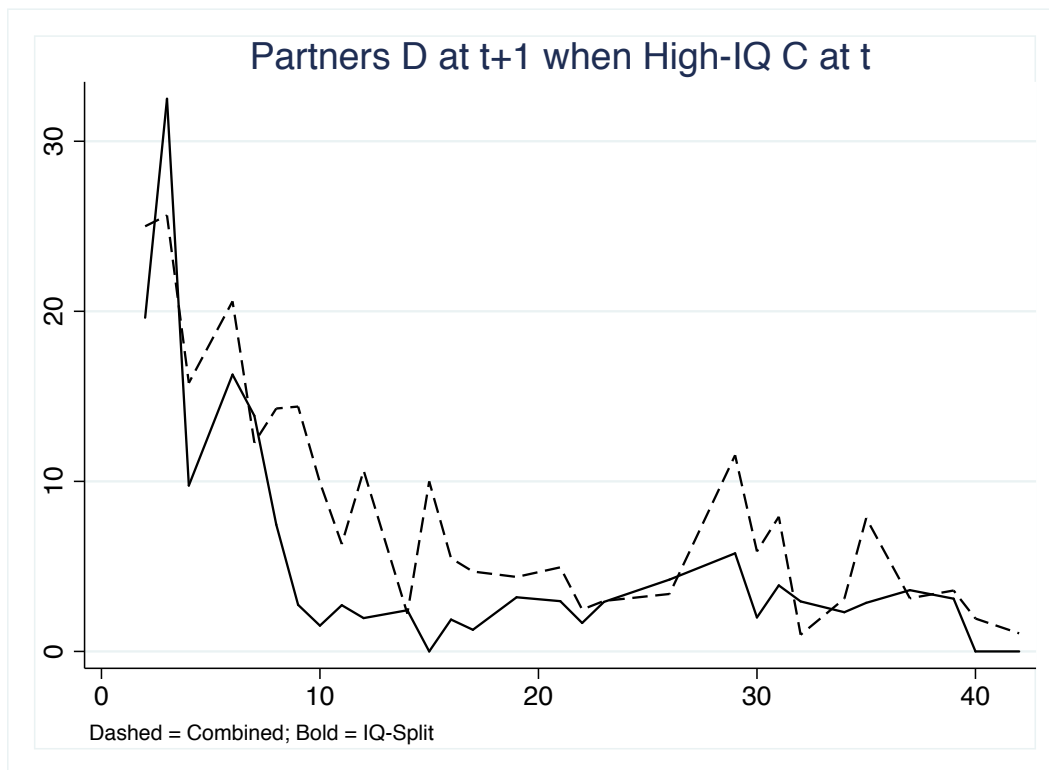


Figure 8: **Learning strategies for low-IQ subjects.** Averages computed over observations aggregated by supergames

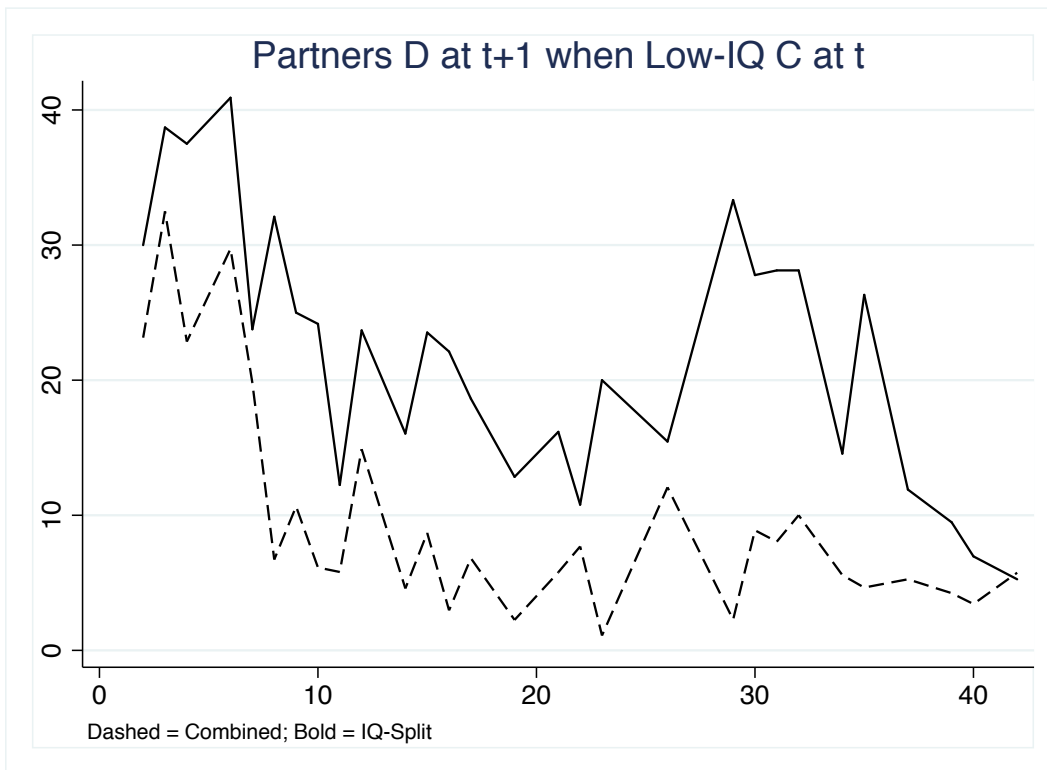


Figure 9: **Partners Defect at $t+1$ when High-IQ forgives Defection at t** The bars report percentage of (C, D) after a sequence (C, D) at period t . The vertical lines show the 10% confidence intervals

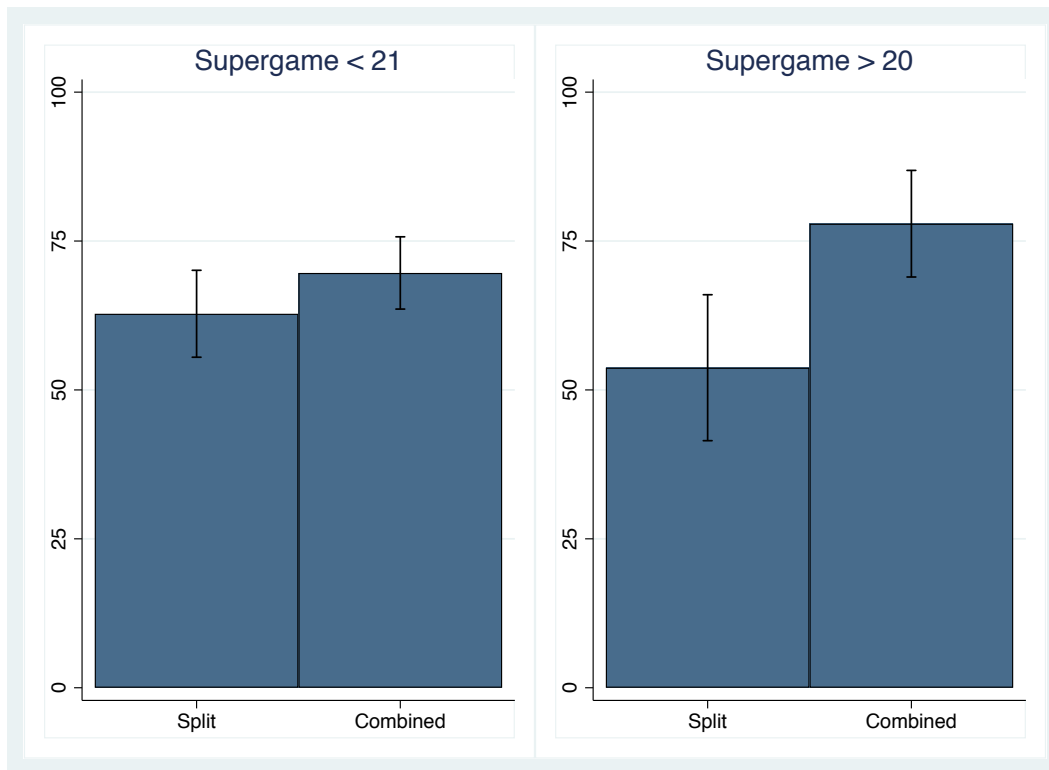


Figure 10: **Simulated Evolution of Cooperation Implied by the Learning Estimates** Solid lines represent experimental data, dashed lines the average simulated data, and dotted lines the 90 percent interval of simulated data.

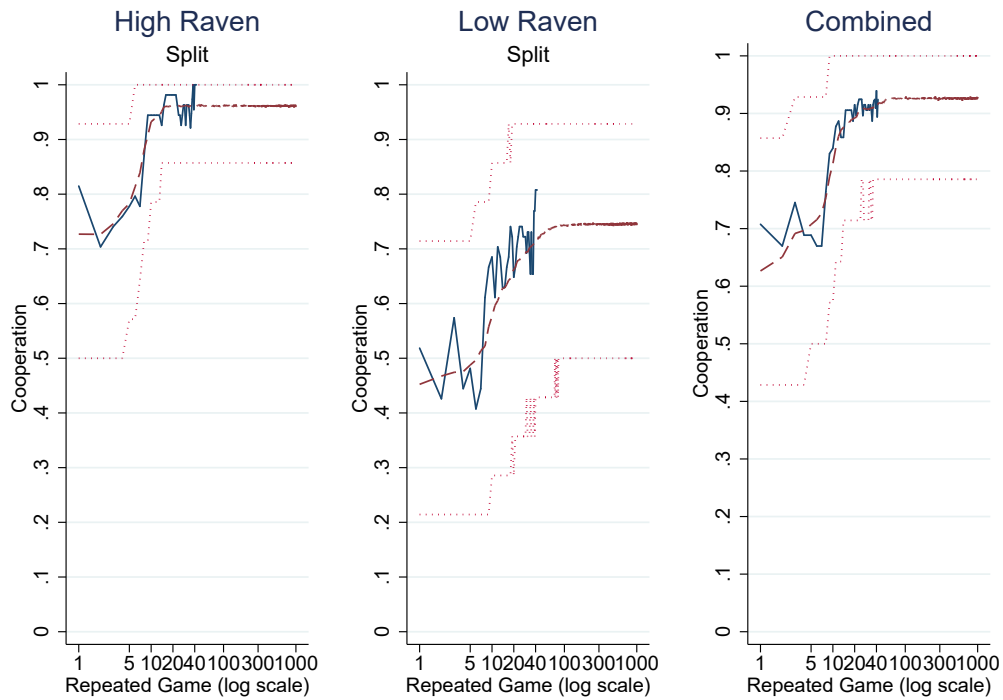


Figure 11: **Distribution of the beliefs' updating speed within the different groups and treatments.** Distribution of the parameter θ_i as defined in equation 2, where 1 correspond to slowest speed (fictitious play) and 0 to the fastest speed (Cournot dynamics)

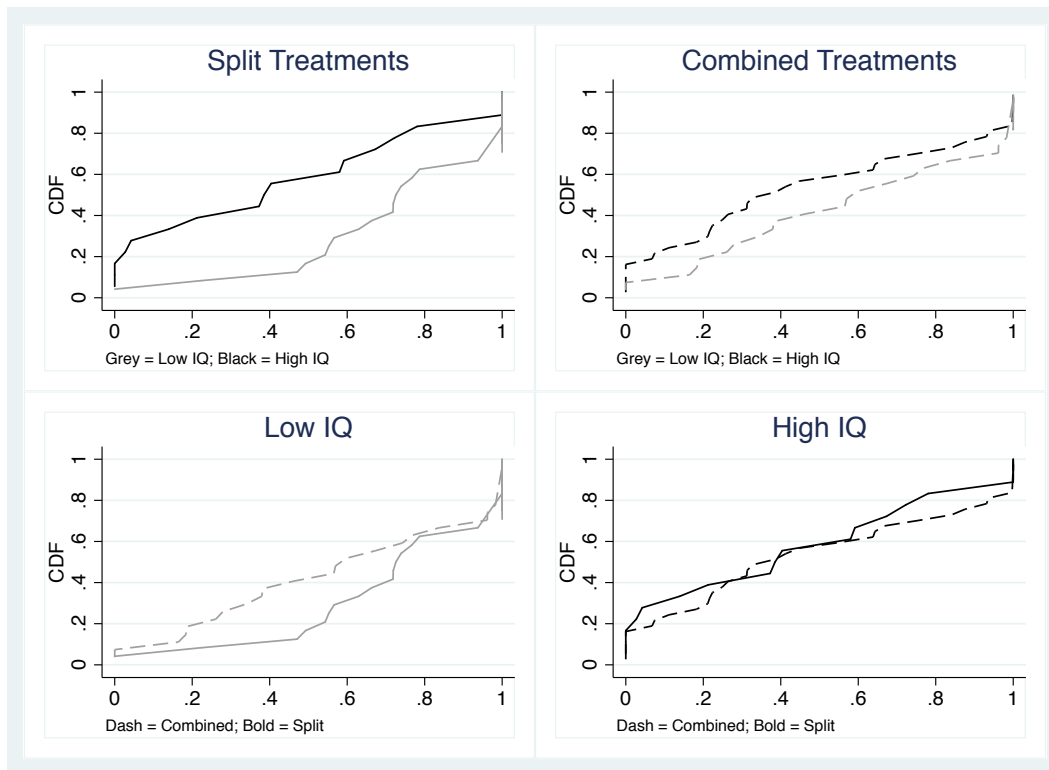


Table 2: **Effects of IQ and other characteristics on cooperative choice in round 1 of each session** The dependent variable is the choice of cooperation in round 1. Logit estimator. **Note that coefficients are expressed in odds ratios.** Robust standard errors clustered at the session level; *p* – values in brackets; * *p* – value < 0.1, ** *p* – value < 0.05, *** *p* – value < 0.01.

	Round 1 Cooperate b/p	Round 1 Cooperate b/p	Round 1 Cooperate b/p	Round 1 Cooperate b/p
choice				
IQ	1.00889 (0.6444)	1.00948 (0.6297)	1.00955 (0.6247)	1.00965 (0.6260)
Extraversion		0.92863 (0.7340)	0.92137 (0.7214)	0.91548 (0.6918)
Agreeableness		0.68282 (0.1061)	0.68450 (0.1048)	0.68554 (0.1059)
Conscientiousness		1.23365 (0.4109)	1.22652 (0.4500)	1.21807 (0.4513)
Neuroticism		0.79055 (0.4737)	0.79114 (0.4740)	0.78215 (0.4462)
Openness		1.27695 (0.4814)	1.28830 (0.4851)	1.32470 (0.4510)
Risk Aversion		0.78425*** (0.0028)	0.78629*** (0.0042)	0.78555*** (0.0037)
Age		0.99583 (0.9262)	0.99667 (0.9396)	0.99871 (0.9762)
Female		1.07444 (0.8257)	1.07153 (0.8317)	1.07728 (0.8186)
German		1.46620 (0.2866)	1.44473 (0.3230)	1.47173 (0.3129)
Combined Treatment			1.11679 (0.7745)	1.12642 (0.7536)
Size Session				1.03944 (0.5771)
N	214	214	214	214

Table 3: **Effect of high IQ and low IQ session on choice of cooperation and payoffs**
The dependent variables are average cooperation and average payoff across all interactions. The baseline are the combined sessions. OLS estimator. Robust standard errors clustered at the session levels in brackets; * p - value < 0.1, ** p - value < 0.05, *** p - value < 0.01

	Supergame \leq 20		Supergame $>$ 20	
	Cooperate b/se	Payoff b/se	Cooperate b/se	Payoff b/se
High IQ Session	0.0990** (0.0354)	2.5238** (0.9217)	0.0691 (0.0542)	1.7259 (1.4115)
Low IQ Session	-0.2180*** (0.0524)	-5.5977*** (1.3339)	-0.2152*** (0.0612)	-5.7067*** (1.5712)
# Subjects	-0.0112 (0.0071)	-0.3063 (0.1815)	-0.0062 (0.0107)	-0.1812 (0.2766)
r2	0.203	0.407	0.152	0.320
N	214	214	214	214

Table 4: **Effects of split treatment on the evolution of cooperative choice in the first periods of all repeated games** The dependent variable is the choice of cooperation in the first periods of all repeated games. The baseline are the combined sessions. Logit with individual fixed effect estimator. Note that in the second part of each session many subjects made the same choices throughout, and for this reason their observations needed to be excluded from the estimations of the model in columns 3 and 4. Similar regressions with random effect (which does not need variability of choices at the individual levels avoiding this loss of observations) would deliver similar results. Std errors in brackets; * p - value < 0.1, ** p - value < 0.05, *** p - value < 0.01.

	Superg. \leq 20		Superg. $>$ 20	
	Cooperate b/se	Cooperate b/se	Cooperate b/se	Cooperate b/se
choice				
High IQ Sessions*Supergame	0.14861*** (0.0502)	0.15670*** (0.0521)	-0.03499 (0.0666)	0.01662 (0.0679)
Low IQ Sessions*Supergame	-0.06502** (0.0277)	-0.04342 (0.0285)	0.08965** (0.0428)	0.09945** (0.0456)
Supergame	0.12697*** (0.0249)	0.09194*** (0.0257)	-0.00911 (0.0298)	-0.05359 (0.0372)
1st Per. Partners' Coop. at s-1		0.22917 (0.1713)		1.16616*** (0.3479)
1st Per. Part. Coop. Rates until s-1		3.13168*** (0.5400)		5.96293 (6.1902)
Partner Coop Rates until t-1		-0.24866 (0.3303)		12.10323** (5.0114)
Average lenght Supergame	0.69441*** (0.1199)	0.78908*** (0.1312)	1.74103** (0.8026)	1.79204** (0.8556)
N		2280	2280	654 654

Table 5: **Split Treatment: Individual strategies in the different IQ sessions in the last 5 and first 5 subgames.** Each coefficient represents the probability estimated using ML of the corresponding strategy. Std error is reported in brackets. Gamma is the error coefficient that is estimated for the choice function used in the ML and beta is the probability estimated that the choice by a subject is equal to what the strategy prescribes.⁽¹⁾ Tests equality to 0 using the Wald test: * p - values < 0.1, ** p - values < 0.05, *** p - values < 0.01

IQ Session	High	Low	High	Low
Repeated Games	Last 5	Last 5	First 5	First 5
Strategy				
Always Cooperate	0.3415** (0.1728)	0.1948** (0.0850)	0.1792** (0.0824)	0.1989** (0.0991)
Always Defect	0.0302 (0.0310)	0.2389*** (0.0668)	0.1933*** (0.0708)	0.4652*** (0.0915)
Grim after 1 D	0.3463 (0.2295)	0.1855 (0.1318)	0.2606** (0.1203)	0.0501 (0.0836)
Tit for Tat (C first)	0.2820 (0.2352)	0.2599 (0.1800)	0.3209** (0.1608)	0 (0.0830)
Win Stay Lose Shift	0 (0.0326)	0 (0.0181)	0.0460 (0.0890)	0.0420 (0.0642)
Tit For Tat (after D C C) ⁽²⁾	0	0.1207	0	0.2439**
Gamma	0.2794*** (0.0495)	0.2911*** (0.0444)	0.4662*** (0.0468)	0.5578*** (0.0708)
beta	0.973	0.969	0.895	0.857
Average Rounds	4.82	4.52	1.8	1.8
N. Subjects	54	54	54	54
Observations	1,240	980	540	540

1. When beta is close to 1/2, choices are essentially random and when it is close to 1 then choices are almost perfectly predicted.
2. Tit for Tat (after D C C) stands for the Tit for Tat strategy that punishes after 1 defection but only returns to cooperation after observing cooperation twice from the partner.

Table 6: **Combined Treatment: Individual strategies in the different treatments in the last 5 and first 5 SGs.** Each coefficient represents the probability estimated using ML of the corresponding strategy. Std errors are reported in brackets. Gamma is the error coefficient that is estimated for the choice function used in the ML and beta is the probability estimated that the choice by a subject is equal to what the strategy prescribes.⁽¹⁾ Tests equality to 0 using the Waldtest: * $p - values < 0.1$, ** $p - values < 0.05$ ***, $p - values < 0.01$ ***

IQ Partition	High	Low	High	Low
Repeated Games	Last 5	Last 5	First 5	First 5
Strategy				
Always Cooperate	0.0507 (0.0807)	0.0545 (0.0689)	0.0775 (0.0765)	0.3158*** (0.1036)
Always Defect	0.0189 (0.0288)	0.1321** (0.0638)	0.2623*** (0.0703)	0.1858** (0.0810)
Grim after 1 D	0.6289*** (0.1927)	0.4580* (0.2392)	0.3949*** (0.1480)	0.1564 (0.1064)
Tit for Tat (C first)	0.2452 (0.1618)	0.3554 (0.2797)	0.2654* (0.1378)	0.2068* (0.1125)
Win Stay Lose Shift	0.0563 (0.0909)	0 (0.0064)	0 (0.0581)	0.1353 (0.1166)
Tit For Tat (after D C C) ⁽²⁾	0	0	0	0
Gamma	0.2353*** (0.0263)	0.2722*** (0.0430)	0.5270*** (0.0655)	0.5236*** (0.0766)
beta	0.986	0.975	0.870	0.871
Average Rounds	5.12	5.12	1.8	1.8
N. Subjects	53	53	53	53
Observations	1,296	1,296	530	530

1. When beta is close to 1/2, choices are essentially random and when it is close to 1 then choices are almost perfectly predicted.
2. Tit for Tat (after D C C) stands for the Tit for Tat strategy that punishes after 1 defection but only returns to cooperation after observing cooperation twice from the partner.

Table 7: **IQ-Split: Payoffs at empirical frequency** The *Frequency* column reports the empirical frequency of each strategy in the set $\{AC = \textit{Always Cooperate}, AD = \textit{Always Defect}, SC = \textit{Grim} + \textit{TfT}\}$. The *Payoff* column reports the expected payoff using the strategy against the empirical frequency.

High IQ		Low IQ			
payoff	frequency	payoff	frequency		
AC	37.46	0.03	33.40	0.24	Last 5 Supergames
AD	46.91	0.34	26.00	0.19	
SC	47.49	0.63	43.99	0.57	

High IQ		Low IQ			
payoff	frequency	payoff	frequency		
AC	31.96	0.19	30.76	0.46	First 5 Supergames
AD	38.83	0.18	29.24	0.20	
SC	42.55	0.58	38.19	0.29	

Table 8: **Combined: Payoffs at empirical frequency**. The *Frequency* column reports the empirical frequency of each strategy in the set $\{AC = \textit{Always Cooperate}, AD = \textit{Always Defect}, SC = \textit{Grim} + \textit{TfT}\}$. The *Payoff* column reports the expected payoff using the strategy against the empirical frequency.

High IQ		Low IQ			
payoff	frequency	payoff	frequency		
AC	30.88	0.02	30.88	0.13	Last 5 Supergames
AD	43.93	0.05	43.93	0.05	
SC	45.38	0.87	45.38	0.81	

High IQ		Low IQ			
payoff	frequency	payoff	frequency		
AC	31.42	0.26	31.42	0.18	First 5 Supergames
AD	36.69	0.08	36.69	0.31	
SC	41.00	0.66	41.00	0.36	

Table 9: **Outcomes at period $t-1$ as determinants of cooperative choices at period t** The dependent variable is the cooperative choice at time t ; the baseline outcome is mutual cooperation at $t-1$, $(C, C)_{t-1}$. Panel A relates to the first 20 supergames, panel B to the last 22 supergames. Logit with individual fixed effect estimator. **Coefficients are expressed in odds ratios p -values in brackets;** * p -value < 0.1, ** p -value < 0.05, *** p -value < 0.01.

Panel A: #Supergame ≤ 20				
	Low IQ Split b/p	High IQ Split b/p	Low IQ Combined b/p	High IQ Combined b/p
choice				
$(C, D)_{t-1}$	0.00860*** (0.0000)	0.01038*** (0.0000)	0.00885*** (0.0000)	0.00533*** (0.0000)
$(D, C)_{t-1}$	0.01069*** (0.0000)	0.01485*** (0.0000)	0.00731*** (0.0000)	0.01039*** (0.0000)
$(D, D)_{t-1}$	0.00353*** (0.0000)	0.00339*** (0.0000)	0.00397*** (0.0000)	0.00172*** (0.0000)
N	2499	2448	2499	2448
Panel B: #Supergame > 20				
	Low IQ Split b/p	High IQ Split b/p	Low IQ Combined b/p	High IQ Combined b/p
choice				
$(C, D)_{t-1}$	0.00301*** (0.0000)	0.00527*** (0.0000)	0.00426*** (0.0000)	0.00153*** (0.0000)
$(D, C)_{t-1}$	0.00402*** (0.0000)	0.03468*** (0.0000)	0.00270*** (0.0000)	0.01450*** (0.0000)
$(D, D)_{t-1}$	0.00121*** (0.0000)	0.00318*** (0.0000)	0.00157*** (0.0000)	0.00044*** (0.0000)
N	1718	1201	1771	1379

Table 10: **Outcomes at period $t-1$ as determinants of cooperative choices at period t** The dependent variable is the cooperative choice at time t ; the baseline outcome is mutual cooperation at $t-1$, that is (C, C) at $t-1$. Combined is a dummy indicating the combined treatments. Logit with individual random effect estimator. Standard errors in brackets; * p -value < 0.1 , ** p -value < 0.05 , *** p -value < 0.01 .

	High IQ All b/se	Low IQ All b/se
choice		
Combined* $(C, C)_{t-1}$	0.30868 (0.5137)	0.39098 (0.3606)
Combined* $(D, D)_{t-1}$	-0.55593 (0.3414)	0.32614 (0.4283)
Combined* $(D, C)_{t-1}$	-0.21615 (0.2557)	-0.03074 (0.3078)
Combined* $(C, D)_{t-1}$	-0.52167** (0.2580)	0.38201 (0.3406)
$(D, D)_{t-1}$	-6.56678*** (0.4456)	-6.41848*** (0.4022)
$(D, C)_{t-1}$	-4.69152*** (0.4560)	-5.21715*** (0.2068)
$(C, D)_{t-1}$	-5.15376*** (0.2549)	-5.27280*** (0.3545)
N	10343	10003

Table 11: **Differences in the beliefs' updating speed within the different groups and treatments.** Tests of the differences of the estimated parameter θ_i as defined in equation 2, where 1 correspond to slowest speed (fictitious play) and 0 to the fastest speed (Cournot dynamics)
* p -value < 0.1 , ** p -value < 0.05 , *** p -value < 0.01 .

Panel A: Tests between IQ groups

Treatment		Split $\theta_{LowIQ} - \theta_{HighIQ}$	Combined $\theta_{LowIQ} - \theta_{HighIQ}$
t test	t	-2.9623***	-1.3777*
Mann-Witney	z	-2.488**	-1.411

Panel B: Tests between treatments

Treatment		Split vs Combined θ_{LowIQ}	Split vs Combined θ_{HighIQ}
t-test	t	1.9647**	-0.3909
Mann-Witney	z	1.849*	-0.350

Table 12: **Correlation between IQ, beliefs updating and capacity of best responding to own beliefs** Correlations between IQ, updating speed, θ_i (as defined in equation 2), capacity of best responding to beliefs in supergame s , λ_s (as defined in equation 3). p – values in brackets

Variables	IQ	θ_i	λ_0	λ_{20}	λ_{40}
IQ	1.000				
θ_i	-0.345 (0.000)	1.000			
λ_0	-0.032 (0.746)	-0.242 (0.006)	1.000		
λ_{20}	-0.047 (0.635)	-0.196 (0.026)	0.887 (0.000)	1.000	
λ_{40}	0.001 (0.992)	-0.205 (0.020)	0.899 (0.000)	0.988 (0.000)	1.000

Table 13: **Determinants of the response time** The dependent variable is the response time at period t ; the baseline outcome are cooperative choice at t (for the choice of the player) and mutual cooperation at $t-1$, $(C, C)_{t-1}$ (for the history). (D_t) indicates the choice of defection by the player. Panel A relates to the first 20 supergames, panel B to the last 22 supergames. OLS with individual fixed effect estimator. Standard Errors in brackets; * p -value < 0.1, ** p -value < 0.05, *** p -value < 0.01.

Panel A: #Supergame ≤ 20				
	Low IQ IQ-Split b/se	High IQ IQ-Split b/se	Low IQ Combined b/se	High IQ Combined b/se
$(C, D)_{t-1}$	0.79349*** (0.1957)	1.73748*** (0.2183)	1.31364*** (0.2216)	1.59534*** (0.2507)
$(D, C)_{t-1}$	0.66904*** (0.2185)	2.52979*** (0.2292)	1.09927*** (0.2357)	2.13791*** (0.2717)
$(D, D)_{t-1}$	1.46417*** (0.1670)	1.86581*** (0.1777)	1.55534*** (0.1742)	1.57749*** (0.2094)
N	2754	2754	2703	2703

Panel B: #Supergame > 20				
	Low IQ IQ-Split b/se	High IQ IQ-Split b/se	Low IQ Combined b/se	High IQ Combined b/se
$(C, D)_{t-1}$	0.04307 (0.1470)	-0.13543 (0.1753)	0.03826 (0.1474)	-0.18413 (0.1410)
$(D, C)_{t-1}$	0.28546* (0.1709)	-0.20279 (0.1925)	-0.04097 (0.1780)	0.18021 (0.1476)
$(D, D)_{t-1}$	0.61658*** (0.1148)	-0.02195 (0.1528)	0.30837** (0.1232)	-0.15412 (0.1080)
N	1956	2296	2590	2590

A Design and Implementation: Additional Details

Table A.9 summarises the statistics about the Raven scores for each session in the IQ-split treatment and table A.10 for the Combined treatment. In the IQ-split treatment, the cutoff Raven score was 24 and 25. In sessions 7 and 8 the cutoff was 23 because the participants in these sessions scored lower on average than the rest of the participants in all the other sessions. Top-left panel of figure A.1 presents the overall distribution of IQ scores across both treatments. The bottom row of figure A.1 presents the distribution of the IQ scores across low- and high-IQ sessions for the IQ-split sessions, while top-right panel presents the distribution of the IQ scores for the Combined treatment sessions. Tables A.11 until A.13 present a description of the main data in the low- and high-IQ sessions in the IQ-split treatment and the Combined treatment sessions. Table A.15 shows the correlations among individual characteristics.

Table A.3 compares participant characteristics across the two treatments. Only the proportion of German participants is found to be significantly different across the two treatments, but as is obvious from tables A.4 and A.5 this is not significantly different across intelligence groups. Overall subjects are similar across the two treatments. In table A.4 participant characteristics across intelligence groups in the IQ-split treatment are contrasted where only differences in the IQ scores are statistically different. Finally, table A.5 contrasts participant characteristics across intelligence groups across both treatments. As in table A.4 the only statistically significant difference is for IQ. Extraversion is found to be significantly different across intelligence groups but that cannot be reasonably seen as a driver of the results.

A timeline of the experiment is detailed below and all the instructions and any other pertinent documents are available online in the supplementary material.¹⁴

A.1 Timeline of the Experiment

Day One

1. Participants were assigned a number indicating session number and specific ID number. The specific ID number corresponded to a computer terminal in the lab. For example, the participant on computer number 13 in session 4 received the number: 4.13.
2. Participants sat at their corresponding computer terminals, which were in individual cubicles.
3. Instructions about the Raven task were read together with an explanation on how the task would be paid.
4. The Raven test was administered (36 matrices with a total of 30 minutes allowed). Three randomly chosen matrices out of 36 tables were paid at the rate of 1 Euro per correct answer.
5. The Holt-Laury task was explained verbally.
6. The Holt-Laury choice task was completed by the participants (10 lottery choices). One randomly chosen lottery out of 10 played out and paid
7. The questionnaire was presented and filled out by the participants.

¹⁴See note 2.

Between Day One and Two

1. Allocation to second day sessions made. An email was sent out to all participants listing their allocation according to the number they received before starting Day One.

Day Two

1. Participants arrived and were given a new ID corresponding to the ID they received in Day One. The new ID indicated their new computer terminal number at which they were sat.
2. The game that would be played was explained using an example screen on each participant's screen, as was the way the matching between partners, the continuation probability and how the payment would be made.
3. The infinitely repeated game was played. Each experimental unit earned corresponded to 0.004 GBP.
4. In the combined treatment participants completed a decoding task and a one-shot dictator game.
5. A de-briefing questionnaire was administered.
6. Calculation of payment was made and subjects were paid accordingly.

B Session Dates and Sizes

Tables A.1 and A.2 below illustrate the dates and timings of each session across both treatments.

Table A.1: **Dates and details for IQ-split**

Day 1: Group Allocation				
	Date	Time	Subjects	
1	23/04/2018	10:00	17	
2	23/04/2018	11:00	19	
	Total		36	
3	07/05/2018	14:45	15	
4	07/05/2018	16:00	11	
	Total		26	
5	12/06/2018	09:45	14	
6	12/06/2018	11:30	19	
	Total		33	
7	20/11/2018	14:00	17	
8	20/11/2018	15:15	19	
	Total		36	
Day 2: Cooperation Task				
	Date	Time	Subjects	Group
Session 1	25/04/2018	10:00	16	High IQ
Session 2	25/04/2018	11:30	14	Low IQ
	Total Returned		30	
Session 3	09/05/2018	14:00	10	High IQ
Session 4	09/05/2018	15:30	10	Low IQ
	Total Returned		20	
Session 5	14/06/2018	10:00	12	High IQ
Session 6	14/06/2018	11:30	14	Low IQ
	Total Returned		26	
Session 7	22/11/2018	14:00	16	High IQ
Session 8	22/11/2018	15:30	16	Low IQ
	Total Returned		32	
Total Participants			108	

Table A.2: Dates and details for Combined

Day 1: Group Allocation			
	Date	Time	Subjects
1	30/04/2018	09:45	7
2	30/04/2018	11:00	13
	Total		20
3	15/05/2018	10:00	6
4	15/05/2018	11:30	16
	Total		22
5	18/06/2018	14:45	17
6	18/06/2018	16:00	9
	Total		26
7	10/07/2018	09:45	7
8	10/07/2018	11:00	13
	Total		20
9	02/10/2018	09:45	7
10	02/10/2018	11:00	11
	Total		18
11	15/10/2018	09:45	6
12	15/10/2018	11:00	6
	Total		12
Day 2: Cooperation Task			
	Date	Time	Subjects
Session 1	02/05/2018	10:00	14
Session 2	17/05/2018	14:00	10
Session 3	17/05/2018	15:30	12
Session 4	20/06/2018	14:00	12
Session 5	20/06/2018	15:30	12
Session 6	12/07/2018	10:00	18
Session 7	04/10/2018	11:30	16
Session 8	17/10/2018	11:30	12
	Total Participants		106

Table A.3: Comparing Variables across the IQ-Split and the Combined Sessions

Variable	Split	Combined	Differences	Std. Dev.	N
IQ	103.4069	103.1394	.2674614	1.349413	214
Age	23.84259	23.06604	.7765549	.6392821	214
Female	.4907407	.5	-.0092593	.0686773	214
Openness	3.767593	3.678302	.0892907	.0730968	214
Conscientiousness	3.358025	3.431866	-.0738411	.0883303	214
Extraversion	3.228009	3.371462	-.143453	.1024118	214
Agreeableness	3.591564	3.612159	-.0205955	.0850711	214
Neuroticism	3.016204	2.879717	.1364867	.0995567	214
Risk Aversion	5.518519	5.386792	.1317261	.233456	214
German	.6481481	.754717	-.1065688	.0624657**	214
Total Profit	5167.87	5957.415	-789.5447	141.8649***	214
Rounds Played	126.8519	139.8302	-12.97834	2.591088***	214
Payoff per Round	40.19059	41.89426	-1.703675	.6099137***	214
Total Profit (Equal SGs Played)	3858.296	4021.849	-163.5528	57.84501**	214
Payoff per Round (Equal SGs Played)	40.19059	41.89426	-1.703675	.6025522**	214

Note: * p - value < 0.1, ** p - value < 0.05, *** p - value < 0.01

Table A.4: Comparing Variables across IQ-split Sessions

Variable	Low IQ	High IQ	Differences	Std. Dev.	N
IQ	95.94193	110.8718	-14.92987	1.232502***	108
Age	24.14815	23.53704	.6111111	1.142875	108
Female	.462963	.5185185	-.0555556	.0969619	108
Openness	3.824074	3.711111	.112963	.0975451	108
Conscientiousness	3.376543	3.339506	.037037	.1160422	108
Extraversion	3.386574	3.069444	.3171296	.1456155**	108
Agreeableness	3.609054	3.574074	.0349794	.1201571	108
Neuroticism	2.949074	3.083333	-.1342593	.1357823	108
Risk Aversion	5.666667	5.37037	.2962963	.3627447	108
German	.6111111	.6851852	-.0740741	.0924877	108
Final Profit	4481.481	5854.259	-1372.778	184.8242***	108
Rounds Played	122.4815	131.2222	-8.740741	4.266736**	108
Payoff per Round	36.68508	44.50096	-7.815882	.5747042***	108
Total Profit (Equal SGs Played)	3480.667	4235.926	-755.2593	55.6599***	108
Payoff per Round (Equal SGs Played)	36.25694	44.12423	-7.867284	.5797906***	108

Note: * p - value < 0.1, ** p - value < 0.05, *** p - value < 0.01

Table A.5: Comparing Variables across IQ-split Groups Across both Treatment Sessions

Variable	Low IQ	High IQ	Differences	Std. Dev.	N
IQ	95.68959	110.8592	-15.1696	.8576931***	214
Age	23.83178	23.08411	.7476636	.6394164	214
Female	.4672897	.5233645	-.0560748	.0685692	214
Openness	3.741122	3.705607	.035514	.0733099	214
Conscientiousness	3.425753	3.363448	.0623053	.0883684	214
Extraversion	3.398364	3.199766	.1985981	.1019719**	214
Agreeableness	3.613707	3.589823	.0238837	.0850633	214
Neuroticism	2.925234	2.971963	-.046729	.0999411	214
Risk Aversion	5.448598	5.457944	-.0093458	.2336202	214
German	.7102804	.6915888	.0186916	.0628772	214
Final Profit	5177.28	5940.626	-763.3458	142.5326***	214
Rounds Played	131.0748	135.486	-4.411215	2.723199*	214
Payoff per Round	39.30087	43.82866	-4.527786	.5416761***	214
Total Profit (Equal SGs Played)	3729.673	4148.944	-419.271	51.40749***	214
Payoff per Round (Equal SGs Played)	38.85076	43.21817	-4.367407	.5354947***	214

Note: * p - value < 0.1, ** p - value < 0.05, *** p - value < 0.01

Figure A.1: **Distribution of IQ Scores.** Top-left panel shows IQ distribution for all participants across both treatments, top-right shows IQ distribution in Combined treatment and bottom panels show IQ distribution in low- and high-IQ sessions from IQ-split treatment.

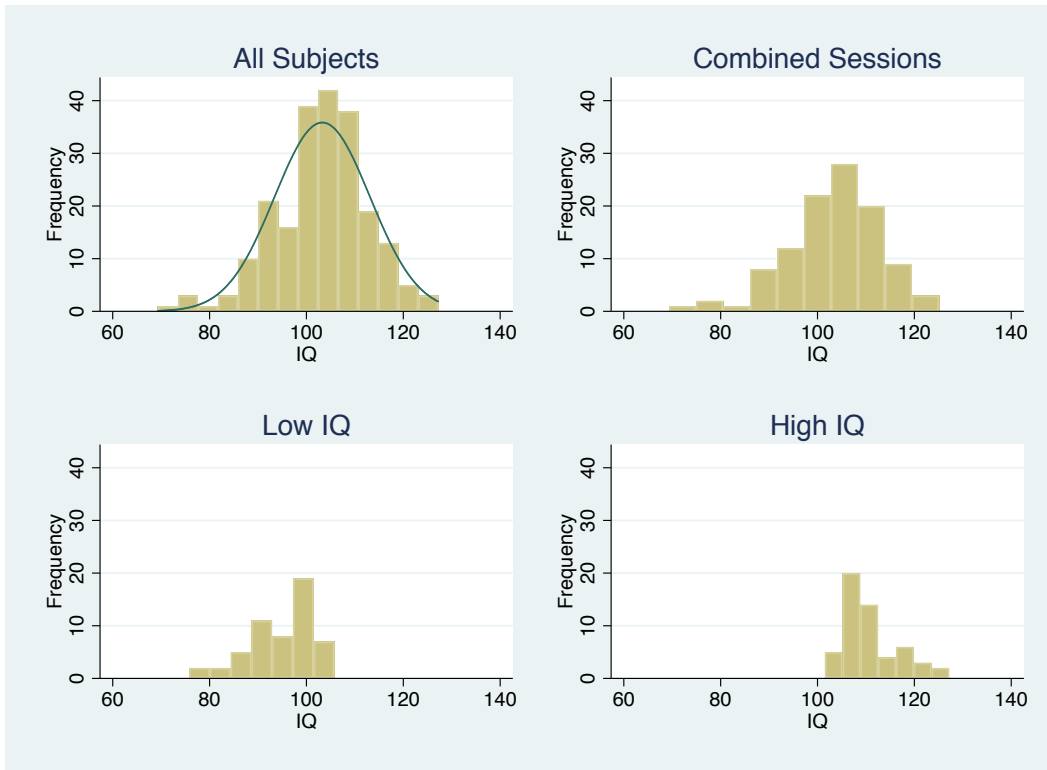


Table A.6: Countries of Origin of Participants

Country	Number	Percentage
Albania	2	0.93
Belarus	1	0.47
Bulgaria	2	0.93
Canada	1	0.47
China	9	4.21
Denmark	1	0.47
Egypt	3	1.40
France	1	0.47
Germany	150	70.09
Hungary	1	0.47
India	3	1.40
Indonesia	1	0.47
Italy	4	1.87
Japan	1	0.47
Kazakhstan	1	0.47
Kosovo	1	0.47
Moldova	2	0.93
Peru	1	0.47
Poland	1	0.47
Romania	1	0.47
Russia	7	3.27
Serbia	1	0.47
Spain	3	1.40
Switzerland	2	0.93
Syria	1	0.47
Taiwan	1	0.47
Turkey	4	1.87
UK	1	0.47
USA	2	0.93
Ukraine	4	1.87
Vietnam	1	0.47
Total	214	100.00

Table A.7: **SGs and Rounds Played by Session in IQ-Split**

Session	SGs	Rounds
1	37	123
2	29	96
3	42	151
4	42	151
5	40	146
6	29	96
7	34	116
8	42	151

Table A.8: **SGs and Rounds Played by Session in Combined**

Session	SGs	Rounds
1	42	151
2	42	151
3	42	151
4	37	123
5	42	151
6	42	151
7	36	119
8	37	123

Table A.9: Raven Scores by Sessions in IQ-split Treatment

Variable	Mean	Std. Dev.	Min.	Max.	N
High IQ - Session 1	28.063	2.886	25	35	16
Low IQ - Session 2	20.214	3.725	11	24	14
High IQ - Session 3	28	2.539	25	33	10
Low IQ - Session 4	22	2.539	18	25	10
High IQ - Session 5	27.917	3.147	24	34	12
Low IQ - Session 6	19.357	3.671	11	23	14
High IQ - Session 7	25.875	2.029	23	31	16
Low IQ - Session 8	20.5	2.394	15	23	16

Table A.10: Raven Scores by Sessions in Combined Treatment

Variable	Mean	Std. Dev.	Min.	Max.	N
Session 1	23.214	5.754	11	31	14
Session 2	22	6.532	8	31	10
Session 3	22.833	4.859	13	31	12
Session 4	25.333	3.339	20	32	12
Session 5	24.917	2.466	20	29	12
Session 6	24.833	4.19	16	32	18
Session 7	23.375	4.674	16	30	16
Session 8	23	4.533	16	34	12

Table A.11: IQ-split: Low IQ Sessions, Main Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Choice	0.561	0.496	0	1	6614
Partner Choice	0.561	0.496	0	1	6614
Age	23.983	7.876	17	65	6614
Female	0.454	0.498	0	1	6614
Round	64.824	40.281	1	151	6614
Openness	3.85	0.518	2.5	5	6614
Conscientiousness	3.37	0.559	2.333	4.667	6614
Extraversion	3.408	0.683	1.875	4.75	6614
Agreeableness	3.585	0.680	1.667	4.889	6614
Neuroticism	2.969	0.696	1.125	5	6614
Raven	20.552	3.04	11	25	6614
Risk Aversion	5.639	2.016	0	10	6614
Final Profit	4695.723	1037.735	3168	6337	6614
Profit x Period	36.685	3.179	28.669	42.875	54
Total Periods	122.481	27.739	96	151	54

Table A.12: IQ-split: High IQ Sessions, Main Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Choice	0.875	0.331	0	1	7086
Partner Choice	0.875	0.331	0	1	7086
Age	23.518	3.28	18	33	7086
Female	0.523	0.5	0	1	7086
Round	66.91	39.264	1	151	7086
Openness	3.723	0.497	2.6	4.8	7086
Conscientiousness	3.322	0.64	1.444	4.556	7086
Extraversion	3.073	0.816	1.25	4.625	7086
Agreeableness	3.578	0.563	2	5	7086
Neuroticism	3.081	0.707	1.375	4.375	7086
Raven	27.44	2.745	23	35	7086
Risk Aversion	5.386	1.63	2	9	7086
Final Profit	5941.262	864.996	4312	7248	7086
Profit x Period	44.501	2.78	36.382	48	54
Total Periods	131.222	14.615	116	151	54

Table A.13: Combined, Main Variables

Variable	Mean	Std. Dev.	Min.	Max.	N
Choice	0.795	0.404	0	1	14822
Partner Choice	0.795	0.404	0	1	14822
Age	23.048	2.906	18	33	14822
Female	0.496	0.5	0	1	14822
Round	71.156	41.578	1	151	14822
Openness	3.683	0.553	2.4	5	14822
Conscientiousness	3.432	0.684	1.556	4.778	14822
Extraversion	3.378	0.73	1.625	4.625	14822
Agreeableness	3.614	0.61	2.111	4.889	14822
Neuroticism	2.872	0.743	1.375	4.625	14822
Raven	23.759	4.621	8	34	14822
Risk Aversion	5.407	1.508	2	9	14822
Final Profit	6026.931	851.060	3984	7212	14822
Profit x Period	42.555	3.933	30.417	47.762	106
Total Periods	139.83	14.467	119	151	106

Table A.14: IQ and Simulated Parameters

Variable	Mean	Std. Dev.	Min.	Max.	N
IQ	103.516	10.203	69.338	127.231	182
θ_i	0.58	0.357	0	1	129
λ_0	5.67	11.683	0	93.275	129
λ_{20}	7.28	12.941	0.154	93.275	128
λ_{40}	6.846	12.913	0.141	93.275	128

Table A.15: All participants: Correlations Table (p-values in brackets)

Variables	Raven	Female	Risk Aversion	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism
Raven	1.000							
Female	0.003 (0.969)	1.000						
Risk Aversion	0.018 (0.795)	0.148 (0.030)	1.000					
Openness	-0.025 (0.715)	0.016 (0.814)	-0.059 (0.390)	1.000				
Conscientiousness	-0.043 (0.533)	0.070 (0.307)	0.093 (0.175)	0.026 (0.707)	1.000			
Extraversion	-0.151 (0.028)	0.080 (0.243)	0.015 (0.831)	0.298 (0.000)	0.202 (0.003)	1.000		
Agreeableness	-0.024 (0.732)	0.181 (0.008)	0.055 (0.423)	0.068 (0.324)	0.287 (0.000)	0.170 (0.013)	1.000	
Neuroticism	0.041 (0.551)	0.287 (0.000)	-0.002 (0.972)	0.092 (0.178)	-0.192 (0.005)	-0.276 (0.000)	-0.112 (0.102)	1.000

C Design and Implementation: Additional Details

C.1 Supplementary Data Analysis

Figure A.2: **Average cooperation per supergame in all different sessions** The grey lines in each panel represent the average cooperation per period among all subjects of the corresponding low IQ groups and the black lines represent the average cooperation per supergame among all subjects of the corresponding high IQ groups. The dashed lines represent the combined sessions, the bold lines the split sessions, and the dotted straight lines the linear trends.

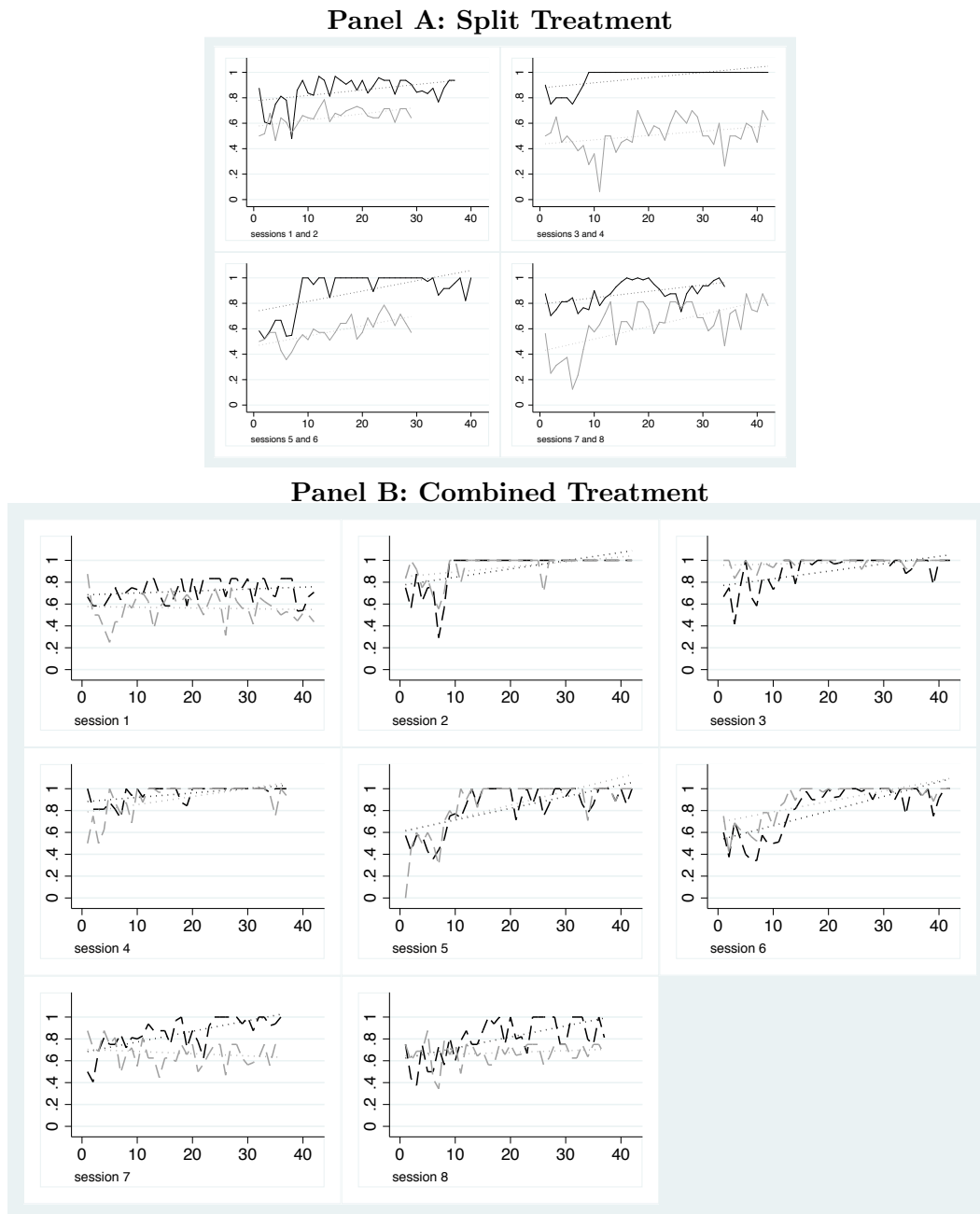


Table A.16: **Determinants of the response time in periods 1 of each supergame** The dependent variable is the response time in period 1. (D_t) indicates the choice of defection by the player. Combined sessions is the baseline in column 1. OLS estimator with random effect. Std errors clustered at the individual levels in brackets; * p - value < 0.1, ** p - value < 0.05, *** p - value < 0.01.

	Periods 1 R. Time b/se	Periods 1 R. Time b/se	Periods 1 R. Time b/se	Periods 1 R. Time b/se
(D_t)	0.66084*** (0.2173)	0.64697*** (0.2170)	0.53450 (2.0029)	0.65654*** (0.2191)
High IQ Session	0.02999 (0.1790)			
Low IQ Session	-0.05748 (0.1710)			
IQ		-0.01150** (0.0058)	-0.01172** (0.0052)	-0.01088* (0.0064)
IQ*(D_t)			0.00111 (0.0190)	
Extraversion	-0.12382 (0.0849)	-0.15458* (0.0826)	-0.15495* (0.0821)	-0.14663* (0.0770)
Agreeableness	0.13042 (0.1170)	0.13081 (0.1179)	0.13106 (0.1177)	0.19555* (0.1089)
Conscientiousness	0.04954 (0.0994)	0.05130 (0.0979)	0.05127 (0.0978)	-0.03450 (0.0926)
Neuroticism	-0.03161 (0.0806)	-0.03375 (0.0833)	-0.03396 (0.0832)	-0.09047 (0.0811)
Openness	-0.10066 (0.1345)	-0.09467 (0.1310)	-0.09424 (0.1298)	0.00687 (0.1203)
Risk Aversion	-0.06234 (0.0461)	-0.06259 (0.0452)	-0.06269 (0.0452)	-0.05126 (0.0433)
Age	-0.00579 (0.0159)	-0.00915 (0.0152)	-0.00915 (0.0152)	-0.01204 (0.0131)
Female	-0.11406 (0.1453)	-0.10646 (0.1412)	-0.10635 (0.1411)	-0.06894 (0.1241)
# Supergame	-0.03156*** (0.0047)	-0.03174*** (0.0047)	-0.03174*** (0.0047)	-0.03087*** (0.0047)
Size Session	0.00551 (0.0237)	0.00597 (0.0237)	0.00594 (0.0236)	
Partner C rates until t-1	-0.89242*** (0.3444)	-0.84457** (0.3303)	-0.84218*** (0.3254)	-0.93145*** (0.3512)
Average Supergame Length	-1.30962*** (0.0967)	-1.31495*** (0.0963)	-1.31488*** (0.0964)	-1.31030*** (0.0972)
Sessions Fixed-Effects	No	No	No	Yes
N	7961	7961	7961	7961

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