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Social Preferences and the Variability of Conditional Cooperation

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Social Preferences and the Variability of Conditional Cooperation

Abstract

We experimentally examine how the incentive to defect in a social dilemma affects conditional cooperation. In our first study we conduct online experiments in which subjects play eight Sequential Prisoner's Dilemma games with payoffs systematically varied across games. We find that few second movers are conditionally cooperative (i.e., cooperate if and only if the first mover cooperates) in all eight games. Instead, most second-movers change strategies between games. The rate of conditional cooperation is higher when the own gain from defecting is lower and when the loss imposed on the first mover from defecting is higher. This pattern is consistent with both social preference models and stochastic choice models. To explore which model explains our findings we employ a second study to jointly estimate noise and social preference parameters at the individual level. The majority of our subjects place significantly positive weight on others' payoffs, supporting the underlying role of social preferences in conditional cooperation.

JEL-Codes: A130, C910.

Keywords: sequential prisoner's dilemma, conditional cooperation, social preferences.

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1. Introduction

Conditional cooperation is widely observed in social dilemmas. Whereas the pursuit of narrowly defined selfish interests would result in a lack of cooperation, many people are willing to forgo their selfish interests and cooperate, but only if others do so as well. This pattern of behavior is particularly clear in controlled experiments investigating contributions to public goods.¹ These experiments also reveal substantial heterogeneity: for example, in some of these studies (see Thöni and Volk (2018) for a review) some group members are classified as "free-riders" (i.e., defecting regardless of the behavior of others), others as "conditional cooperators" (i.e., cooperating if others do so), and still others as "unconditional cooperators" (i.e., cooperating independently of the behavior of others). Identifying these heterogeneities is crucial when trying to understand what makes individuals cooperate and which measures to take to further enhance cooperation.

Despite this commonly applied classification, not much is known, however, about whether it reflects stable personality traits whereby the participant would exhibit similar behavioral patterns in similar situations, or whether the classification applies only to the specific experimental setting and parameters. There is also surprisingly little evidence on how the specific material payoffs of the game affect conditional cooperation. In case that the degree of conditional cooperation varies with game parameters, it is fundamental to understand the mechanisms and account for them when studying group cooperation. To provide first insights into this dimension, in this study, we examine whether the behavioral pattern exhibited by a given participant, such as conditional cooperation, varies in response to changes in the material incentives.

Examining the within-subject variability of conditional cooperation across payoff variations is important for at least two reasons. First, it allows us to understand the nature of conditional cooperation: whether conditional cooperation reflects underlying social preferences, or whether conditional cooperation reflects a desire to reciprocate the cooperation of others in a way that is robust to changes in material incentives.² Social preference models,

¹ See, e.g., Bilancini, et al. (2022); Brandts and Schram (2001); Chaudhuri and Paichayontvijit (2006); Croson (2007); Cubitt, et al. (2017); Fischbacher, et al. (2001); Fischbacher and Gächter (2010); Furtner, et al. (2021); Gächter, et al. (2017b); Gächter, et al. (2022); Isler, et al. (2021); Keser and van Winden (2000); Kocher, et al. (2008). For reviews see Chaudhuri (2011); Fehr and Schurtenberger (2018); Gächter (2007); and Thöni and Volk (2018).

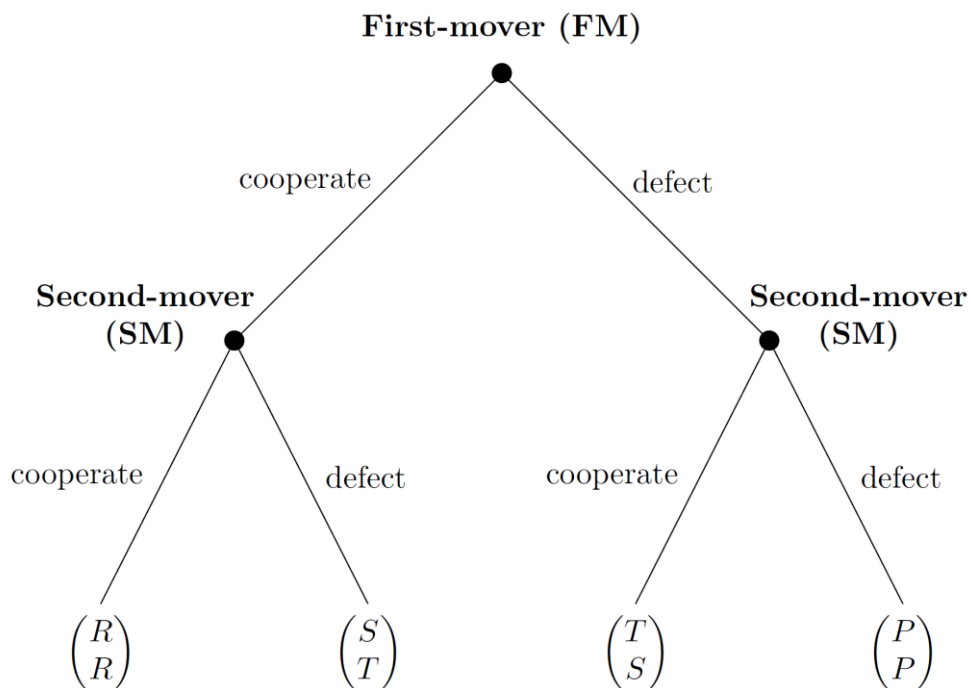
² As discussed by Bardsley and Sausgruber (2005), Fehr and Fischbacher (2004), Gächter, et al. (2017a), and Katuščák and Miklánek (2018), conformity to what is perceived as "socially appropriate" and willingness to sacrifice material payoffs in order to follow such norms could also be a candidate explanation for conditional cooperation.

which define preferences over one's own and other's material payoffs (e.g., Andreoni and Miller (2002); Bolton and Ockenfels (2000); Charness and Rabin (2002); Cox, et al. (2007); Cox, et al. (2008); Fehr and Schmidt (1999)), are capable of explaining conditional cooperation, but at the same time these models predict that it will be influenced by material incentives. In contrast, if conditional cooperation reflects a principled stand against free-riding, eschewing material gains to reciprocate the cooperation of others, then conditional cooperation is expected to be robust across payoff variations.

Second, the efficacy of interventions to promote cooperation depends on whether conditional cooperation is influenced by payoff variations. For example, leading by example would be an effective mechanism to achieve cooperative outcomes if followers are generally conditionally cooperative (e.g., Gächter, et al. (2012)). On the other hand, if conditional cooperation is sensitive to payoffs, then this implies that there are settings where leading by example is ineffective.

We study within-subject variability of conditional cooperation using two experimental designs. Our first experimental design is based on the sequential prisoner's dilemma shown in Figure 1.

FIGURE 1. The Sequential Prisoner's Dilemma (SPD)



Note : $T > R > P > S$; $2R > T + S$

In this game First-mover (FM) chooses either cooperate or defect, and, after observing this choice, Second-mover (SM) chooses either cooperate or defect. Combined earnings are maximized when both cooperate, resulting in each player receiving R . However, if FM cooperates, SM maximizes own earnings by defecting, in which case FM receives S and SM receives T . If FM defects, SM maximizes own earnings by also defecting, so that each player receives P . Thus, a selfish SM who maximizes own earnings should defect regardless of FM's choice.

In our experiments, subjects make decisions in the role of both FM and SM for eight different games with varying payoffs. We elicit SM strategies by asking how the subject would respond to defect and how they would respond to cooperate, with their actual decision being determined by their response to their opponent's actual FM choice. To rule out confounding factors, such as belief updating, no feedback on any of the individual games is provided until the end of the experiment. This simple experimental design allows us to examine whether conditional cooperation is stable across varying payoffs, and, if not, how conditional cooperation is affected by changes in incentives.

In our first study, we conducted two online experiments, the first using Amazon Mechanical Turk (AMT) and to explore the robustness of our findings, we replicated the study using a University of Nottingham (UoN) student subject pool. AMT workers are demographically more diverse and older than typical student subject pools. From the results of related research studying cooperation rates in simultaneous PDs (Gächter, et al. (2021)) and public goods games (Arechar, et al. (2018)) we expect AMT workers to exhibit a higher level of cooperativeness than the younger UoN student subject pool. Comparing AMT workers and UoN students thus provides us with an opportunity to gauge variability of conditional cooperation across subject pools.

For our AMT experiment we find that the proportion of conditional cooperators varies between 27% and 48% across games, while for our UoN experiment the proportion varies between 28% and 48%. Fractions of free rider strategies range from 40% to 55% in AMT and from 43% to 59% in UoN. Moreover, in both experiments more than 70% of subjects change their SM strategy at least once across games. An implication of this is that any classification of individuals as “conditional cooperators” or “free-riders” in one game should not be generalized to other games with different material payoffs: a conditional cooperator in one game may be a free-rider in another, and vice versa. Additionally, we also find that changes in behavior are systematically related to payoffs: SM are more likely to conditionally cooperate when they

have less to gain from free-riding, and when free-riding has a larger negative impact on the FM's earnings.

This pattern is consistent with the predictions of several social preference models (e.g., Charness and Rabin (2002); Fehr and Schmidt (1999)), but it is also consistent with stochastic choice models where subject choices are determined by selfish preferences plus noise (e.g., Anderson, et al. (1998)). Thus, we developed a second experimental study to jointly estimate individual-level noise and social preference parameters. In this study, which we conducted as a laboratory experiment using our UoN student subject pool and a modified version of the SPD, subjects make choices either as FM or as SM in sixty-four games with varying payoffs,

As in Study 1, in Study 2 we find substantial heterogeneity across individuals. Some SMs consistently respond to cooperation by maximizing their own payoff (12%), while others consistently respond by cooperating (6%). However, most SMs vary their responses to cooperation across games in a way that is systematically, though not deterministically, related to payoffs. For 72% of SMs we estimate a random utility model incorporating social preferences and find that most of these (representing 66% of all SMs) have significantly positive social preference parameters that place a positive weight on their opponent's payoff. Thus, our results support the view that conditional cooperation reflects underlying social preferences.

The remainder of the paper is organized as follows. In Section 2, we place our contributions in the related literature that examines the variability of conditional cooperation and the relationship between social preferences and conditional cooperation. In Section 3 we describe the design and results of our online experiments, and in Section 4 we present the design and results of our lab experiment. In Section 5 we conclude.

2. Related literature and our contributions

A number of previous papers have examined the variability of conditional cooperation over time, by measuring conditional cooperation repeatedly but keeping payoff functions constant. The results are mixed. Brosig, et al. (2007) conducted similar SPDs to us three times within three months using the same subjects and random-matching and found that the rate of conditional cooperation diminished across repetitions. This finding is supported by Andreozzi, et al. (2020) that also found conditional cooperation diminished with repetition. Exploring public goods games, Muller, et al. (2008) elicited subjects' strategies across five repetitions. Although only 37% of subjects always chose the same strategy across all five games, previous

choices were useful predictors of subsequent choices. For example, 69% of subjects who conditionally cooperated in any of the first four games also conditionally cooperated in the fifth game. Volk, et al. (2012) elicited subjects' strategies in a public goods game three times over the course of five months and observed that conditional cooperation was remarkably stable over time. Half of their subjects chose the same strategy in all three games, and 71% of these conditionally cooperated. In a closely related analysis, Gächter, et al. (2022) report stability rates of 66% and 59% in their provision and maintenance versions of public goods games played four months apart.³

Our approach differs from this previous literature because we examine robustness whilst varying the payoffs across the eight SPDs people play. We are not aware of any study examining how within-subject variation of payoffs affects conditional cooperation.⁴ We are only aware of three studies that examine whether payoff variation affects conditional cooperation between subjects. Thöni and Volk (2018) found that the proportion of conditional cooperators is similar across 17 public goods experiments, which employ different parameters (i.e., MPCRs, group size). In contrast, Clark and Sefton (2001), using a between-subjects SPD experiment in which subjects played repeatedly against changing opponents with feedback on the outcomes of each play, found that doubling the temptation payoff, T , resulted in a significantly lower rate of conditional cooperation. Our studies differ from these in that we ask subjects to make decisions in multiple games with systematically varying payoffs and without feedback across games. This within-subject design allows us to examine how changes in payoffs affect conditional cooperation at the individual level.

Our paper also contributes to the literature of social preferences explaining decisions in experimental public goods games. One of the first papers in this literature is Blanco, et al. (2011). They measure parameters of disadvantageous and advantageous inequality aversion (Fehr and Schmidt (1999)) using ultimatum and modified dictator games and then have the same subjects play among others an SPD and a public good. They find that the elicited preference parameters predict decisions at the aggregate level but not so much at the individual

³ Two further studies (Eichenseer and Moser (2020) and Mullett, et al. (2020)) examine the variability of conditional cooperation across different contexts by comparing behavior in a public goods game and a SPD. Both studies report that subjects who are conditionally cooperative in a SPD are also conditionally cooperative in a public goods game.

⁴ Several studies examine how decisions in the simultaneous prisoner's dilemmas are influenced by payoff variations (e.g., Ahn, et al. (2001); Au, et al. (2012); Charness, et al. (2016); Engel and Zhurakhovska (2016); Mengel (2018); Ng and Au (2016); Schmidt, et al. (2001); Vlaev and Chater (2006)). See Gächter, et al. (2021) for a discussion of these papers and a systematic experimental analysis of the role of payoff parameters for cooperation in prisoner's dilemma experiments.

level. Hedegaard, et al. (2021) elicit distributional preferences in a representative Danish sample and then use them to explain behavior in trust and public goods games. Our approach differs from these papers. Unlike them, we do not elicit preference parameters in some games to predict behavior in others. Instead, we estimate preference parameters using a series of SPDs that systematically vary the payoff parameters.

Our approach therefore directly relates to an experimental literature testing models of social preferences and estimating social preference parameters (see Cooper and Kagel (2016), for a review). Many experiments in this area are based on designs where individuals are randomly assigned to different treatments and tests of models are based on making treatment comparisons. It is typically the case that there are too few observations on individual subjects to estimate individual preference parameters, and so estimations are based on population regressions (e.g., Charness and Rabin (2002)). We take a fundamentally different approach by having subjects make many choices in a modified version of the SPD game with varying payoffs, enabling us to estimate preference parameters at the individual level. In this regard, our Study 2 experiment is most closely related to a literature initiated by Palfrey and Prisbrey (1997) who estimate altruism and warm glow parameters in public goods games, and Andreoni and Miller (2002), and Fisman, et al. (2007), who estimate individual preferences for giving by having subjects make choices in modified dictator games with varying endowments/prices of giving. A more recent related paper is Bruhin, et al. (2019), who estimate structural social preference models from binary choices, although their emphasis is on finite mixture models.⁵

3. Study 1: Measuring the variability of conditional cooperation

3.1. Experimental design

Our first experimental design is based on the sequential prisoner's dilemma game of Figure 1. Our main interest concerns how changes in payoffs affect conditional cooperation focusing on two factors. First, $LOSS := (R - S)/R$ refers to FM's loss when SM responds to cooperation by defecting rather than cooperating. Second, $GAIN := (T - R)/R$ refers to SM's gains from responding to cooperation by defecting rather than cooperating. We also manipulate the efficiency gains from cooperation, $EFF := (R - P)/R$.

⁵ Our approach is also similar to that used in a considerable literature on individual choice experiments where individual risk preferences are estimated from responses to a battery of lottery choices (see, for example, Hey and Orme (1994), Andersen, et al. (2008)).

Table 1 shows the payoff parameterization used in our experiment and the resulting values of EFF, LOSS and GAIN.⁶ Payoffs were chosen to be strictly positive multiples of ten in order to avoid zero or non-rounded payoffs. All games satisfy the conditions $T > R > P > S$ and $2R > T + S$, so that mutual cooperation maximizes combined earnings, but, assuming players are selfish, own-earnings maximizers, the Nash equilibrium is always mutual defection. R (500) is constant across all games while there are two distinct values of P (200, 400). Thus, we study games with two different levels of efficiency. There are also two distinct values of T (600, 800) and four distinct values of S (20, 90, 40, 180). Note that with this parameterization we study a 2×2 variation in LOSS and GAIN for each level of efficiency.

TABLE 1. Payoff parameters for Sequential Prisoner’s Dilemma Games

Game	R	P	S	T	EFF	LOSS	GAIN
G1	500	200	90	600	0.60	0.82	0.20
G2	500	200	20	600	0.60	0.96	0.20
G3	500	200	90	800	0.60	0.82	0.60
G4	500	200	20	800	0.60	0.96	0.60
G5	500	400	180	600	0.20	0.64	0.20
G6	500	400	40	600	0.20	0.92	0.20
G7	500	400	180	800	0.20	0.64	0.60
G8	500	400	40	800	0.20	0.92	0.60

Note: $\text{EFF} = (R - P)/R$; $\text{LOSS} = (R - S)/R$; $\text{GAIN} = (T - R)/R$.

3.2. Experimental procedures

We conducted our initial online interactive experiment in Spring 2019 using Amazon MTurk across five sessions with a total of 138 participants. We refer to this as our AMT experiment. To further examine the robustness of our first data collection, we replicated the AMT experiment with a different subject pool in Summer 2021, referred to as our UoN experiment, using students from the University of Nottingham who had signed up to a subject database for participating in experiments. For this experiment we used ORSEE (Greiner (2015)) to recruit subjects and conducted an additional three sessions with a total of 152 participants. Between both data sets we observe significant differences in demographics, such as age, gender and ethnic composition, allowing us to explore potential treatment effects for a range of individual

⁶ This is the same parameterization used in Gächter, et al. (2021) for studying cooperation in simultaneous PDs.

characteristics (see Appendix A for the details). Both online experiments were programmed using LIONESS Lab (Giamattei, et al. (2020)), and the same program was used for both experiments, with only minimal changes to the instructions related to the subject pools (for the instructions, see Appendix B).

Each participant was paired with another subject after they had read the instructions and passed some control questions. Each pair then played all eight games of Table 1 with no feedback between games. For each game, subjects had to answer eight additional control questions about the payoffs before making decisions. These additional control questions were intended to ensure that subjects understood the implications of their decisions and recognized the payoff changes across games. Subjects then made decisions as FM as well as SM. Both decision tasks were presented on the same screen. For the FM decision, they simply chose whether to cooperate or to defect. For the SM decision, we asked subjects to decide in the following two situations: i) if FM cooperates, and ii) if FM defects. Therefore, we elicited SM strategies using the strategy method (Selten (1967)).⁷ Rather than use the terms "cooperate" or "defect", we labeled options neutrally as A or B, with labeling randomly chosen at the pair level in each game. To control for potential order effects, we randomized the sequence of games and the order of tasks (i.e., placing the FM or SM decision at the top of the screen) at the pair level. Once subjects completed the tasks for all games, we asked them to complete a short post-experimental questionnaire eliciting basic demographic information.

We paired subjects with another participant on a real-time basis, and they made decisions in each game at the same time. That is, they could not proceed to the next game until both had completed their decisions for the current game.⁸

To elicit subjects' responses in an incentive-compatible way, we implemented the following payment scheme. At the end of the session, one of the eight games was randomly chosen at the pair-level for payment. If both subjects completed the entire experiment, they

⁷ Regarding potential differences between responses elicited using the strategy method and those using a direct response method, previous studies found no statistical differences in subjects' responses between these two methods (see Brandts and Charness (2000), and Brandts and Charness (2011) for a review and Keser and Kliemt (2021) for a recent discussion). See also Fischbacher and Gächter (2010); Fischbacher, et al. (2012); Gächter, et al. (2017b); Isler, et al. (2021); Gächter, et al. (2022) who all find that combining strategies with beliefs explains contributions in direct response public goods games supporting the behavioral validity of the strategy method.

⁸ To reduce the risk of decreased attention due to long waiting times as subjects waited for their opponent to decide, we took the following measures. Before participants entered the experiment, we told them to avoid distractions during the experiment. In addition, participants who were inactive for more than 30 seconds (i.e., no mouse movement or no keyboard input) got an alert voice message and a blinking text on their browser. If an inactive participant did not respond to the alert message for a further 30 seconds, such an inactive participant was removed from the experiment and the remaining person was able to continue the experiment.

were paid according to the outcome of this game as follows. One of the pair was randomly chosen to be FM, and the other was selected to be SM. Then, subjects were reminded of their decisions and informed about the outcome for this game. As mentioned above, for SM's decision we used their conditional response to FM's decision. If one of the pair had dropped out during the experiment, the computer randomly selected the payoff-relevant game for the remaining subject. Then the computer randomly selected one out of four monetary outcomes (i.e., T , R , P , or S) of the chosen game for payment to the remaining subject. We explained this payment scheme clearly in the instructions. This payment procedure gives subjects a monetary incentive to take both FM decisions and SM decisions seriously in all games as any of these decisions can become payoff relevant.

In line with other online experiments, there was a non-negligible attrition rate: 32 out of 138 AMT subjects (23%) and 9 out of 152 UoN subjects (6%) dropped out during the experiment.⁹ For subjects who completed the AMT experiment, the average age was 34.2 years (s.d. 10.2 years) and 37% were female, while for the UoN experiment the average age was 22.5 years (s.d. 4.6 years) and 58% were female. AMT subjects' earnings ranged from \$1.20 to \$9.00, averaging \$4.59, while UoN subjects' earnings ranged from £1.20 to £9.00, averaging £4.53. On average, the experiment lasted about 30 minutes and subjects were informed of their payment immediately upon completion of the experiment and were paid within 24 hours.

3.3 Results

For our analysis, we only include the decisions of subjects who completed the experiment: thus, our data set consists of 848 AMT observations (106 subjects \times eight games) and 1144 UoN observations (143 subjects \times eight games). In line with our research question, our focus is on SM decisions as these provide a direct measure of conditional cooperation. These conditionally cooperative strategies, where SM responds to cooperation with cooperation and defection with defection, make up 38% of the strategies elicited in the AMT experiment, and 37% of the strategies elicited in the UoN experiment. Free-riding strategies (i.e., unconditional defection) make up 45% of the AMT strategies and 53% of the UoN strategies. There are relatively few unconditionally cooperative strategies (AMT: 12%; UoN: 7%) and even fewer strategies that respond to defection with cooperation and cooperation with defection (AMT: 5%; UoN: 3%)

⁹ The dropout rate in our AMT sessions is similar to that of related interactive online experiments. For example, Arechar, et al. (2018) report a 20% dropout rate in their interactive four-player public goods game, and Gächter, et al. (2021) reports a 24% dropout rate in their interactive eight simultaneous prisoner's dilemma games.

Thus, as in other social dilemma experiments (e.g., Fischbacher, et al. (2001); Fallucchi, et al. (2019); Gächter, et al. (2022); Isler, et al. (2021); Miettinen, et al. (2020); Muller, et al. (2008); Thöni and Volk (2018)), conditional cooperation and free-riding make up the bulk of elicited strategies (87% in aggregate).

However, we find that most subjects cannot be unambiguously classified as a ‘free-rider’ or ‘conditional cooperator’ because they vary their strategy between games. Of AMT subjects, 13% always free-ride, 13% always conditionally cooperate, and the remainder change strategies at least once across games. For the UoN experiment, 19% always free-ride, 10% always conditionally cooperate, and the remainder change strategies at least once across games.

Table 2 reports the proportion of conditionally cooperative strategies, broken down by game, for the AMT and UoN experiments. Panel (a) gives the proportion in the AMT experiment depending on the levels of LOSS and GAIN for the high efficiency games, while panel (b) does the same for the UoN experiment. Results for low efficiency games are reported in panels (c) and (d) in a similar fashion. Table 2 also reports changes in proportions, and McNemar tests of significance of these, for pairwise comparisons between games where LOSS or GAIN varies and other payoffs are held constant.¹⁰

We find a consistent pattern in both experiments, where for all four possible combinations of efficiency and GAIN, conditional cooperation is higher in the high than the low LOSS game, and for all four possible combinations of efficiency and LOSS conditional cooperation is higher in the low than the high GAIN game. To test whether conditional cooperation varies significantly across games, we conduct pairwise comparisons using McNemar's test. In the AMT experiment, subjects are significantly less likely to conditionally cooperate when GAIN increases in the low efficiency games. In the UoN experiment the effect of GAIN is significant except when efficiency is low and LOSS is low, and the effect of LOSS is significant in the low efficiency game with low GAIN. For other cases the differences are not statistically significant.

¹⁰ We conducted a similar analysis for the other strategies. For free-riding the results mirror those shown in Table 2 very closely: where conditional cooperation increases between games free-riding increases, and vice versa. The proportions of the other two strategies are small and do not vary across games in a systematic way (only 1 of 32 pairwise comparisons is significant at the 5% level). See Appendix A, Table A3-5 for details.

TABLE 2. Proportions of Conditionally Cooperative Strategies

(a) High Efficiency Games (EFF = 0.6) – AMT

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	35.8%	42.5%	+6.7%
	<i>High</i> (= 0.60)	33.0%	38.7%	+5.7%
	Δ (<i>H-L</i>)	-2.8%	-3.8%	

(b) High Efficiency Games (EFF = 0.6) – UoN

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	37.8%	44.1%	+6.3%
	<i>High</i> (= 0.60)	28.0%	32.9%	+4.9%
	Δ (<i>H-L</i>)	-9.8% **	-11.2% **	

(c) Low Efficiency Games (EFF = 0.2) – AMT

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	44.3%	48.1%	+3.8%
	<i>High</i> (= 0.60)	27.4%	34.9%	+7.5%
	Δ (<i>H-L</i>)	-16.9% ***	-13.2% **	

(d) Low Efficiency Games (EFF = 0.2) – UoN

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	36.4%	48.3%	+11.9% ***
	<i>High</i> (= 0.60)	32.2%	38.5%	+6.3%
	Δ (<i>H-L</i>)	-4.2%	-9.8% **	

Note: EFF = $(R - P)/R$, LOSS = $(R - S)/R$, GAIN = $(T - R)/R$. * $p < 0.1$;
 ** $p < 0.05$; *** $p < 0.01$ indicate p -values based on McNemar's test.

To summarize how incentives affect conditional cooperation, controlling for demographic characteristics, we present the marginal effects from logit regressions for our AMT and UoN experiments in Table 3. The dependent variable is 1 if the subject conditionally cooperated and 0 otherwise. Our experiments manipulate LOSS and GAIN across two levels of EFF, and so we report how conditional cooperation varies with the indices of LOSS and GAIN separately for our two levels of efficiency. These regressions control for individual and task characteristics, round, and session effects. A full set of results is given in Table A3 in Appendix A.

TABLE 3. Determinants of Conditional Cooperation

	AMT	UoN
LOSS*EFF _{high}	0.175 (0.120)	0.289*** (0.089)
LOSS*EFF _{low}	0.294** (0.118)	0.332*** (0.089)
GAIN*EFF _{high}	-0.150 (0.092)	-0.234*** (0.072)
GAIN*EFF _{low}	-0.335*** (0.089)	-0.159** (0.076)
Observations	800	1,104

Notes: Average marginal effects from logit regression with robust standard errors clustered at the individual level. Dependent variable = 1 if SM conditionally cooperated, 0 otherwise. LOSS = $(R - S)/R$, GAIN = $(T - R)/R$, EFF_{high}: indicator variable for $(R - P)/R = 0.6$, EFF_{low}: indicator variable for $(R - P)/R = 0.2$. Regressions include controls for individual characteristics, task characteristics, round and session effects.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

As in Table 2, we see consistent patterns in the sign of the effects of GAIN and LOSS on conditional cooperation. As GAIN increases and it becomes more profitable for a SM to free-ride, we observe lower levels of conditional cooperation, and as LOSS increases and free-riding has a larger negative impact on FM's earnings we observe more conditional cooperation. These effects are significant at the 5% level or lower in the UoN experiment, while for the AMT experiment the effects are significant at the 5% level or lower for the low EFF games, but not so for the high EFF games.

Including controls allows us to explore how conditional cooperation is affected by the heterogeneity in demographics across our two experiments. More detailed results are given in Appendix A Table A5, but here we note a significant effect of age and gender for the UoN sample, where older and female students are more likely to conditionally cooperate. In contrast

to our expectation, we do not observe the same result on age in the AMT sample even though we have more age variation in the AMT data. We do, however, find significant heterogeneity in conditional cooperation between ethnicities in the AMT sample.

These results also control for task characteristics (whether cooperation was labelled A or B, and whether FM or SM decision fields were presented first), round effects, and session effects. In the UoN experiment neither round dummies ($\chi^2(7) = 9.75$, $p = 0.203$) nor session dummies ($\chi^2(2) = 2.13$, $p = 0.344$) are jointly significant. For AMT, however, there are significant round effects ($\chi^2(7) = 15.47$, $p = 0.030$), reflecting a higher rate of conditional cooperation in the first round compared to later rounds, and significant session effects ($\chi^2(4) = 10.38$, $p = 0.035$) effects. In neither experiment are the task characteristics significant.

In summary, across our online experiments we find that conditional cooperation varies across games. Most subjects change strategies across games, and this switching between strategies varies systematically with the distributional consequences of free-riding relative to conditionally cooperating. Subjects are more likely to conditionally cooperate when free-riding imposes larger losses on the FM, or when free-riding provides smaller gains for oneself. Our finding that strategies are sensitive to the cost imposed on the opponent as well as the gain to self suggests that a substantial proportion of subjects care not only about their own material payoffs but also about the other's material payoffs. Moreover, the way conditional cooperation varies with LOSS and GAIN is consistent with the predictions of several distributional preference models. For example, consider the Fehr and Schmidt (1999) model of inequality aversion or the “distributional preference” model by Charness and Rabin (2002). According to these models the SM maximizes utility by defecting in response to defection, while the optimal response to cooperation depends on how much weight the SM places on the disadvantaged FM's payoff (Charness and Rabin's ρ parameter) or the marginal disutility from earning more than the FM (Fehr and Schmidt's β parameter). Applied to our game SM will conditionally cooperate if ρ (or β) $>$ $GAIN/(GAIN + LOSS)$, and free-ride otherwise. Thus, given a distribution of preference parameters in the population, more individuals in the population will conditionally cooperate when GAIN is lower, or LOSS is higher.

However, it should be noted that behavior is not perfectly aligned with these models: we observe some individuals sometimes unconditionally cooperate, some individuals sometimes switch from free riding to conditionally cooperating when GAIN increases, and so

on. At best, our data is consistent with noisy versions of these models.¹¹ In fact, the systematic effects of GAIN and LOSS are also consistent with stochastic choice models in which subjects maximize selfish utility with error. For example, in Appendix C we present a quantal response equilibrium analysis and show that the QRE probability of conditional cooperation increases with LOSS and decreases with GAIN. Since our data does not allow us to distinguish which of these alternative models drives our results, we designed a further experiment to separately estimate the effects of social preferences and noise.

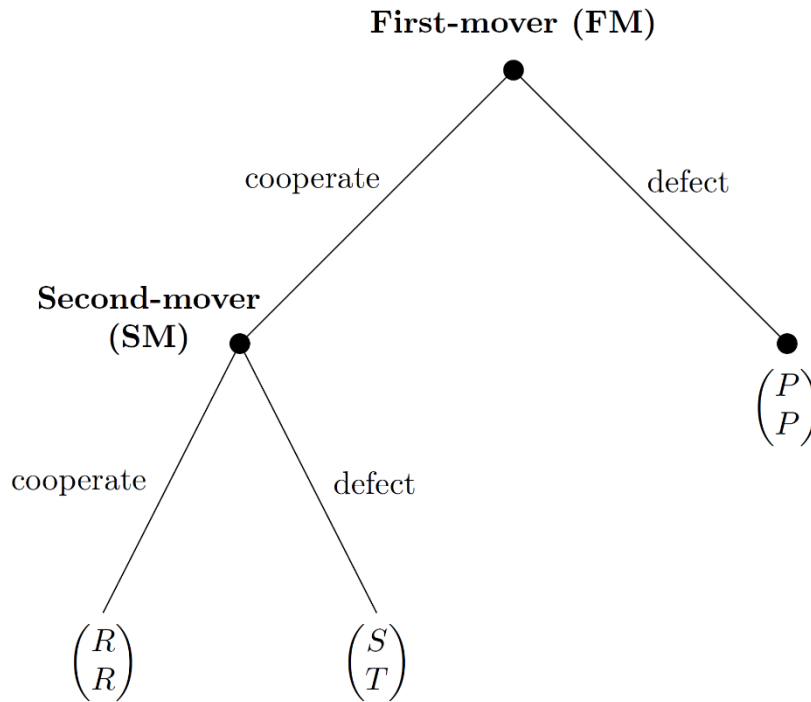
4. Study 2: Explaining the variability of conditional cooperation

Our second experimental design attempts to jointly estimate noise and preference parameters at an individual level. To obtain meaningful estimates it is necessary to have a subject play many games and so we modified our initial design in a number of ways. First, we used an in-person lab experiment to avoid problems of attrition and to enhance control. Second, we simplified the task by having subjects play in fixed roles. Third, we simplify the SM decision by having second movers only make a choice in response to cooperation – effectively, we hardwire defection as a response to defection (based on the results from our earlier design, where the response to defection is defect in over 85% of cases, we think not much is lost from this simplification). The game implemented in our lab experiment is shown in Figure 2.

Despite these changes, we kept most of the features identical to our first experiment. To elicit SM responses to cooperation we retained the contingent choice element of our earlier design. That is, FM and SM made choices at the same time and a SM choice was only relevant for payoffs if the FM cooperated. Thus, both players make binary choices in each game.

¹¹ There is considerable evidence that errors and confusion play a significant role for behavior in public goods games. See, for instance, Andreoni (1995), Bayer, et al. (2013), Burton-Chellew, et al. (2016); Ferraro and Vossler (2010); Houser and Kurzban (2002); Palfrey and Prisbrey (1997). Errors may also affect conditional cooperation to some extent (e.g., Fosgaard, et al. (2017); Gächter, et al. (2022)).

FIGURE 2. The Modified Sequential Prisoner's Dilemma Game



Additionally, as in our earlier design, we kept R (500) constant in all games and used the same four values of S (20, 40, 90, 180). We expanded the set of values of P (100, 200, 300, 400), and T (400, 600, 800, 1000), to obtain 64 games. These include the 8 games of our original design, and 22 more games satisfying the PD conditions $T > R > P > S, 2R > T + S$. In addition, there are 15 games where $T > R > P > S$, but $T + S > 2R$, so that the Nash equilibrium outcome is mutual defection, while combined earnings are maximized when FM cooperates and SM defects. In addition, there are 16 games where $R > T$, so that the SM maximizes own earnings by cooperating. For these games the Nash equilibrium outcome is mutual cooperation (and in one of these $S > P$ so the FM has a dominant strategy to cooperate). Finally, there are 3 more games where $S > P$ and so a FM has a dominant strategy to cooperate. (A complete list of games and parameters is provided in Appendix F, Table F1.) Thus, most of our games are dilemmas but the inclusion of other games means that a subject motivated to maximize own earnings cannot achieve this by using a simple heuristic of always defecting, and similarly a subject motivated to maximize combined earnings cannot use a simple heuristic of always cooperate. This feature of our experimental design provides us with an additional opportunity to examine the attentiveness of subjects and gain some insights into the rationalizability of choices.

4.2 Experimental procedures

We conducted our experiment in June 2022 in the CeDEX lab using University of Nottingham students. We conducted 13 sessions with a total of 194 participants (97 SMs). Subjects were recruited using ORSEE (Greiner, 2015) and the experiment was conducted with the software LIONESS Lab (Giamattei, et al. (2020)). 42% of the subjects were female and the average age was 22.1 yrs (s.d. 3.69 years). The experiment was pre-registered (AEARCTR-0009536).¹²

At the beginning of the session each participant was given a set of instructions, and these were read aloud by the experimenter. Subjects then answered control questions before beginning the decision-making part of the session. As in the online experiments, subjects were anonymously paired with another subject and then played all 64 games with no feedback between games.

In contrast to our online study, we asked subjects to make their choices on a graphical implementation of the decision tree as outlined in Figure 2 (see instructions in Appendix D). We again utilized neutral labels, where for each game, the FM was Person A and chose between options A1 and A2, while the SM was described as Person B and chose between options B1 and B2. In addition, we elicited beliefs about the other person's choice. As before, to control for potential order effects, we randomized the sequence of games at the pair level. Once subjects completed the tasks for all games, we asked them to complete a short post-experimental questionnaire eliciting basic demographic information.

At the end of the session two games were randomly chosen for each pair. One of these games was used to determine additional earnings based on game choices, based on an exchange rate of £0.02 per point. The other game was used to determine additional earnings based on beliefs. Subjects were rewarded in lottery tickets using a binarized scoring rule (Hossain and Okui (2013)), and these determined their chances of winning a prize of 200 points (i.e., £4). The instructions did not describe the precise binarized scoring rule to subjects. Instead, they were told that they maximized their chances of winning the prize by reporting their beliefs as accurately as possible. The instructions also offered to reveal the precise mechanism after the experiment to interested subjects (only one subject took up the offer). We adopted this procedure following Danz, et al. (2022) who show that despite a potential centrality bias using the binarized scoring rule, not outlining the details of the incentive mechanism results in most accurate belief elicitations.

¹² <https://www.socialscicenter.org/trials/9536>. We aimed for 200 participants but due to show-up problems we ended up with 194.

Subjects received a £5 show up fee and earnings ranged from £5.40 to £25.00, averaging £16. On average, the experiment lasted about 60 minutes, including the completion of a post-experimental questionnaire. Subjects were informed of their payment immediately upon completion of the experiment and were paid within 24 hours.

4.3 Econometric model

To jointly estimate the effects of noise and social preferences we use a random utility model incorporating social preferences. First, following Fehr and Schmidt (1999) and Charness and Rabin (2002) we assume SM's utility depends on both own-earnings and other's earnings as follows:

$$u_{SM}(\pi_{FM}, \pi_{SM}) = \rho\pi_{FM} + (1 - \rho)\pi_{SM} = \pi_{SM} - \rho(\pi_{SM} - \pi_{FM})$$

The parameter ρ is the weight that SM places on FM's payoff when SM earns at least as much as FM in the Charness-Rabin model. It can also be interpreted as the marginal disutility from advantageous inequality in the Fehr-Schmidt model (their β parameter). In all 64 games SM earns at least as much as FM, and so we do not need to distinguish between the weights placed on the other's payoff when ahead and when behind, or between advantageous and disadvantageous inequality.

Second, we assume SM holds beliefs about FM's choice and assigns probability q to FM cooperating. Given these assumptions and our payoff parameterization, SM's expected utility from cooperating is

$$V_c = qR + (1 - q)P$$

and the expected utility from defecting is

$$V_d = q(T - \rho(T - S)) + (1 - q)P.$$

We assume SM follows a stochastic choice rule and cooperates if and only if

$$V_d - V_c < Z, \text{ where } Z \sim N(\mu, \sigma^2).$$

Thus, SM cooperates unless the expected utility gain from defecting exceeds a normally distributed noise term with mean μ . A positive parameter μ thus results in a bias toward cooperation that is independent of payoffs. That is, even if the choice rule is deterministic ($\sigma = 0$), and even if the expected payoff from defection exceeds the expected payoff from cooperation, SM may choose to cooperate if the expected utility difference is less than μ . The higher is μ , the more likely it is that SM will cooperate even when expected payoff maximization points toward defecting. Including μ in our econometric specification therefore

accounts for potential individual bias and provides us with more robust estimates of the social preference parameter.

From this choice rule, letting $\Phi(\cdot)$ denote the standard normal distribution function, the probability of cooperating as a function of the payoffs, beliefs, preference, and noise parameters is:

$$\Pr\{SM \text{ cooperates}\} = \Phi(\mu/\sigma + q(R - T)/\sigma + \rho q(T - S))/\sigma).$$

We then estimate μ, σ and the preference parameter ρ for each subject using maximum likelihood probit, providing us with individual estimates corresponding to our key dimensions of interest, social preferences (ρ) as well as noise (σ).

Prior to estimation we conducted Monte Carlo simulations to explore the properties of the estimators under alternative data generating processes (see Appendix E). The main take-aways from our simulations are, first, that sometimes the model fails to produce sensible estimates. Partly this reflects the familiar under-identification problem in discrete choice models, whereby maximum likelihood parameters cannot be estimated when the data is perfectly predicted by the regressors. This occurs if a subject cooperates in every decision, or defects in every decision. But it also occurs, for example, if choices follow deterministically from the social preference model so that a subject cooperates if and only if $\rho > (T - R)/(T - S)$ for some value of ρ . Another reason for failure to produce sensible estimates is that estimates of σ may be negative. Related to this, when estimates of σ are very close to zero, corresponding estimates of ρ can vary wildly. Thus, in our data analysis we treat individuals with $\hat{\sigma} < 0$ or $|\hat{\rho}| > 1$ as outliers.

Second, controlling for potential bias in choices, $\mu \neq 0$, by including a constant in the regression, and controlling for variability in beliefs across games by including beliefs in the regression, are important parts of our estimation strategy. When the data generating process includes a bias term, $\mu \neq 0$, estimates from a model without a constant are severely biased, whereas when the data generating process does not include a bias term, $\mu = 0$, estimating a model with a constant comes at a small price (mainly, adding a constant term increases the chance of running into identification problems). Similarly, when choices are based on expected utility differences and depend on q , estimating a model assuming $q = 1$ leads to severely biased estimates.

Third, standard errors can be very large, particularly when σ is large. An implication of this is that point estimates may be very imprecise estimates of underlying parameters. On the

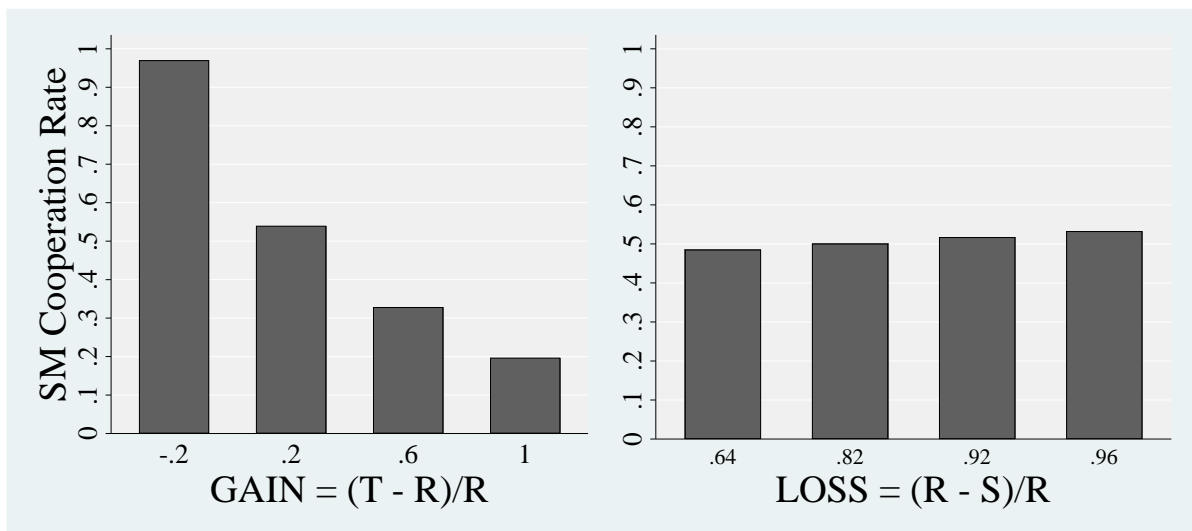
other hand, the finite-sample bias in the estimate of ρ is small, and so the average estimate of ρ across many individuals gives a useful estimate of the underlying mean parameter in the population.

4.4 Results

4.4.1 Descriptive statistics

Before estimating our model, we give some summary information on choices and beliefs.¹³ Figure 3 shows how cooperative choices relate to GAIN and LOSS. As in our online experiment, the effect of GAIN is very clear: the higher is gain, the lower is the cooperation rate. Recall, that in our design SM's payoff from defecting is lower than the payoff from cooperating in 16 games (i.e., in the $T = 400$ games, which implies $\text{GAIN} = -0.2$). As it turns out, SM almost always cooperates in these games. Note also that in these games the private gain from cooperating is quite small (100 points), and the same as the private gain from defecting when $T = 600$. The fact that the cooperation rate in the $T = 400$ games is almost 100% while the cooperation rate in the $T = 600$ games is substantially above zero is a first hint that cooperation reflects more than just selfish motives plus error.¹⁴

FIGURE 3. SM Cooperation Rate by GAIN and LOSS



¹³ See Appendix F, Table F1, for a complete table of average beliefs and average choices for each of the 64 games.

¹⁴ This is not conclusive evidence because it ignores the role of beliefs. SM may have a higher expectation that FM cooperates when $T = 400$ than when $T = 600$, and so the expected private gain from cooperating when $T = 400$ may be higher than the expected private gain from defecting when $T = 600$.

With respect to LOSS, as in our online experiment, there is a positive relationship, although much less pronounced than for the case of GAIN. These results are further confirmed in a logit regression model that examines how SM cooperation varies with GAIN and LOSS for the four levels of efficiency. The results are reported in Table 4 and replicate previous results from the online experiment: SM cooperation increases with LOSS and decreases with GAIN, though the effect size of GAIN is substantially greater (c.f. Table 3).

TABLE 4. Determinants of SM Cooperation (64 games)

LOSS*EFF _{=0.8}	0.145*** (0.040)
LOSS*EFF _{=0.6}	0.152*** (0.041)
LOSS*EFF _{=0.4}	0.131*** (0.042)
LOSS*EFF _{=0.2}	0.146*** (0.041)
GAIN*EFF _{=0.8}	-0.561*** (0.020)
GAIN*EFF _{=0.6}	-0.560*** (0.018)
GAIN*EFF _{=0.4}	-0.512*** (0.020)
GAIN*EFF _{=0.2}	-0.556*** (0.020)
Observations	6,016

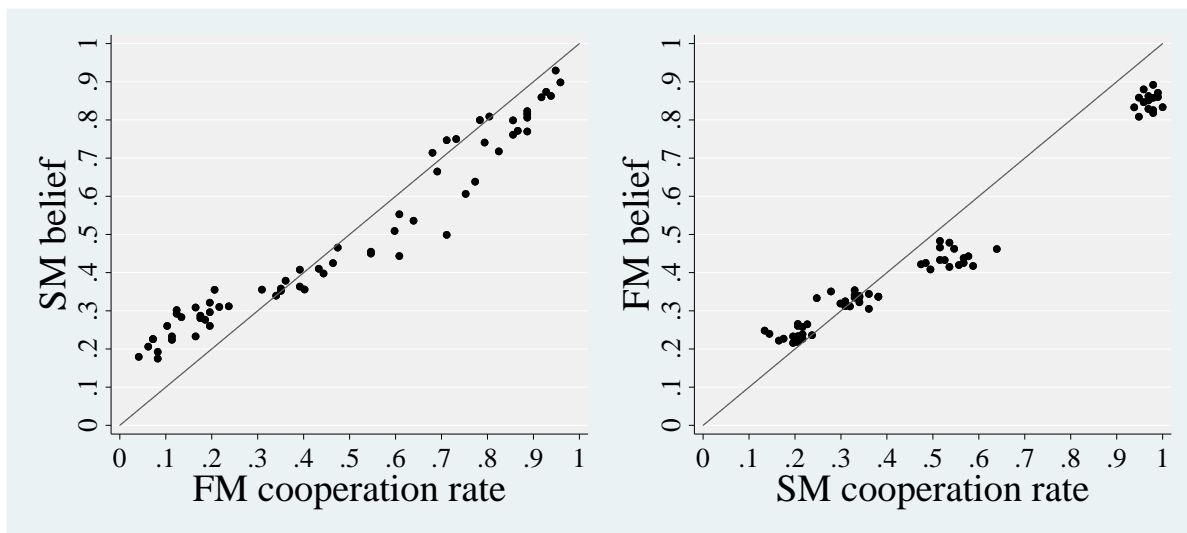
Notes: Average marginal effects from logit regression with robust standard errors clustered at the individual level. Dependent variable = 1 if SM conditionally cooperated, 0 otherwise. LOSS = $(R - S)/R$, GAIN = $(T - R)/R$, EFF = $(R - P)/R$. Controls: demographic variables, round and session effects. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Next, we examine how *beliefs* relate to choices in our 64 games. Figure 4 shows how beliefs about the other player's choice are related to the other player's actual choice. The left panel shows SM beliefs against the actual cooperation rates of FMs. The Spearman correlation is 0.984 ($p < 0.001$), suggesting that SM beliefs are quite well-calibrated, although there is a tendency for SM to somewhat over-estimate low FM cooperation rates and under-estimate FM high cooperation rates.

In the right panel of Figure 4 we present FM beliefs about SM choices. Again, there is a high correlation across the 64 games: the Spearman correlation coefficient is 0.949 ($p < 0.001$). For FMs, there is a clear clustering of beliefs, and it reflects differences in GAIN. Thus, for the $T = 400$ games FMs expect SMs to cooperate at a

high rate (the average belief is 85%), although the actual SM cooperation rate is in fact even higher than this (97%). At $T = 1000$ on average FM expect SMs to cooperate 24% of the time (slightly over-estimating the cooperation rate of 20%).

FIGURE 4. Beliefs and Choices



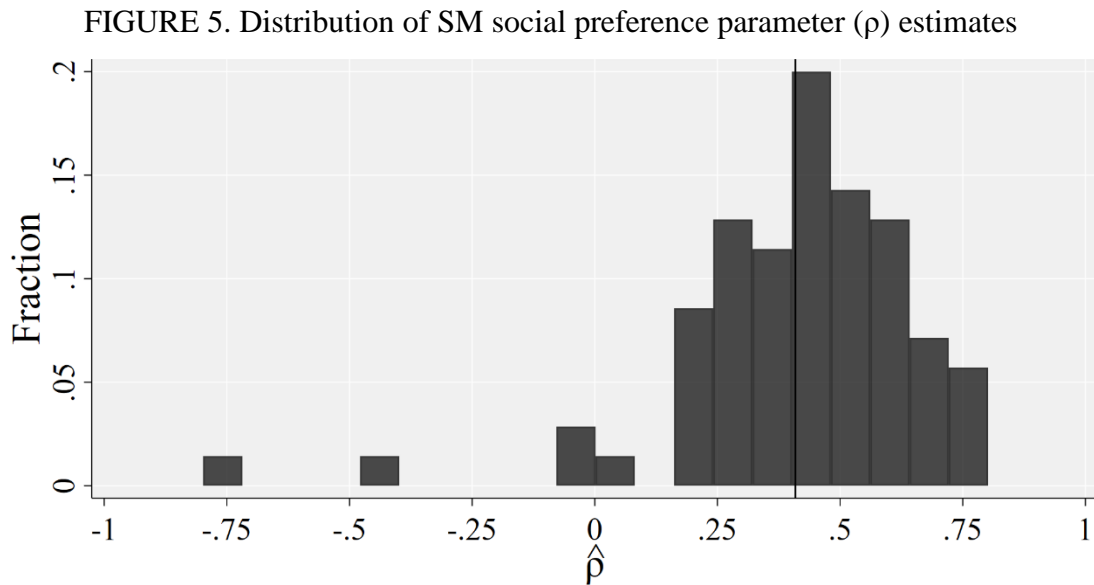
4.4.2 Estimation results

Next, we turn to the estimation of our social preferences model using maximum likelihood probit regressions. We are unable to estimate parameters for 26 of 97 SMs for whom a linear combination of regressors perfectly predict choices. For example, 6 SMs always chose to cooperate, and 12 SMs always chose to maximise own-earnings (i.e., defect when $T > R$ and cooperate when $T < R$). Of the remaining 71 SMs for whom we can estimate parameters, one is estimated with $|\hat{\rho}| > 1$, which we exclude as an outlier. The rest of our analysis of SMs is based on the remaining sub-sample of 70 SMs. A complete list of the individual estimates is provided in Table F2 in Appendix F.

Figure 5 presents a histogram of the 70 ρ parameter estimates. The average estimate is 0.41 (s.d. 0.25), and using this to estimate the mean ρ parameter in the population we conclude the mean parameter is statistically significantly different from zero ($p < 0.001$).¹⁵ Of the 70 subjects, 64 have significantly positive estimates of ρ . Thus, the majority of our second movers have significantly positive social preference parameters and place positive weight on FM's

¹⁵ To test this hypothesis, we use the average estimate in our sample, 0.41, as our estimate of the population mean, and for a standard error of this estimate we use $se(\sum \hat{\rho}_i / n) = (1/n)\sqrt{(\sum se(\hat{\rho}_i)^2)} = 0.1137$.

payoff. This presents clear evidence in line with models of social preferences to explain variability in conditional cooperation under changing payoff parameters. It is interesting to compare these results with previous experiments that use modified dictator games to estimate the Fehr-Schmidt β parameter. In line with our results, Blanco et al. (2011) give an average estimate of β of 0.47 (s.d. 0.31), while Beranek, et al. (2015) (using UoN students) find an average estimate of $\beta = 0.48$ (s.d. 0.29).



For the noise parameters, the average estimate of μ is 5.36 (s.d. 289.76) and the average estimate of σ is 62.48 (s.d. 109.93). Note, the average bias estimate is very small, and we cannot reject the hypothesis that the mean bias in the population is zero ($p = 0.978$).¹⁶ However, there is substantial variability in the sample: many subjects have a large estimated bias and 38 estimates are significantly negative (i.e., displaying a bias toward defection). Both of these additional pieces of evidence further support that social preferences are in fact the main driver of our previously established results.

For our sub-sample of 70 subjects Table 5 summarizes the predictive accuracy of our model and compares it with the predictive accuracy of two alternative models. For our first alternative, we simply predict cooperation using a probit model with a constant. That is, for each SM we predict cooperation (defection) in all games if that subject cooperates (defects) in most games). Note that this model must successfully predict at least 50% of an SM's choices.

¹⁶ We again follow the same approach as before, using our average estimate, $\sum \hat{\mu}/n = 5.36$, as our estimate of the mean bias and for a standard error we use $se(\sum \hat{\mu}/n) = (1/n)\sqrt{(\sum se(\hat{\mu}_i)^2)} = 195.77$.

Across our sub-sample we find it predicts 67% of choices correctly. For a second alternative, we predict cooperation using a random utility model with ρ constrained to be zero (i.e., for each SM we predict decisions based on a constant and expected utility differences, where utility depends only on own-payoff). This increases predictive success considerably, and correctly predicts 80% of SM's choices, on average. Adding social preferences to the model increases the predictive success to 89%. We also report another widely used measure of predictive success, the pseudo R^2 measure. Since these measures of predictive success generally increase with the number of predictors in the model, we also report McFadden's adjusted Pseudo R^2 , which penalizes for the number of predictors. Even using this measure, the model with social preferences improves predictive success relative to the other models.

TABLE 5. Measures of Predictive Success

Model	Average Hit Ratio	Average Pseudo R^2	Average adjusted Pseudo R^2
Constant	0.67	0	-0.03
Random utility with selfish preferences	0.80	0.31	0.25
Random utility with social preferences	0.89	0.56	0.47

4.4.3 Reciprocity

Our social preference model as outlined above is based on preferences defined over the distribution of payoffs. This means that when deciding how to respond to cooperation by FM, SM weighs up the utility of cooperation, which depends on R , and the utility from defection, which depends on S and T . The payoff parameter P does not directly enter SM's utility. However, it is possible that P does in fact matter for SM choices if subjects have reciprocal preferences. That is, SM considers that FM is being kind by cooperating (see, e.g., Falk, et al. (2003)), and so SM cooperates to reward this act. How kind FM is to SM could be measured in alternative ways that depend on P , the payoff that FM forgoes by choosing to cooperate. One can argue that $P - S$ is a relevant measure of kindness, as by cooperating FM forgoes P and risks getting S . Alternatively, one could argue that $R - P$ is a more relevant measure of kindness from cooperating as these are the cooperative gains being offered to SM.

To test whether some form of reciprocation is playing a role in our setting, we do not model reciprocal preferences explicitly, but rather we simply test whether the weight SM places on FMs payoff changes with P . That is, we suppose that SM's probability of cooperating is given by:

$$\Pr\{SM \text{ cooperates}\} = \Phi\left(\mu/\sigma + q(R - T)/\sigma + q \sum_k \rho_k \mathbb{I}_{P=P_k}(T - S)/\sigma\right)$$

where $\mathbb{I}_{P=P_k}$ is the indicator function for the four possible values of P . We estimate separate ρ_k parameters for each value and test the hypothesis that all four are equal.

We can estimate this model for 68 subjects (70%). Of these, there are only four subjects for whom the weights significantly vary with P at the 10% level. Thus, in our specification, we can only find limited evidence of reciprocity as an explanation of conditional cooperation. It appears that most of the variation in cooperation we observe can be explained by heterogeneity in social preferences rather than due to additional reciprocal concerns.

4.4.4 First Mover choices

Although our main focus is on SM's response to cooperation, FM cooperation rates also vary substantially across the 64 games, ranging from as little as 4.1% up to 95.9% in another.¹⁷ To further examine a potential explanation behind FM cooperation, we can also apply the random utility model with social preferences to FM choices. Let FM's utility be given by

$$u_{FM}(\pi_{FM}, \pi_{SM}) = \tau\pi_{SM} + (1 - \tau)\pi_{FM} = \pi_{FM} + \tau(\pi_{SM} - \pi_{FM}).$$

Here, the parameter τ is the weight FM places on SM's payoff when SM earns more than FM (the Charness-Rabin σ parameter). (Recall, in our games SM always earns at least as much as FM.) It can also be interpreted as minus one times Fehr-Schmidt's disadvantageous inequality aversion parameter.

With this utility function, FM's utility from defecting is P , and since this determines the outcome with certainty FM's expected utility from defecting is

$$V_d = P.$$

FM's expected utility from cooperating is

$$V_c = qR + (1 - q)(S + \tau(T - S))$$

where q is the probability FM assigns to SM cooperating. Using the random utility choice rule, FM cooperates if and only if

¹⁷ Table F1 in Appendix F reports average FM cooperation rates for each of the 64 games

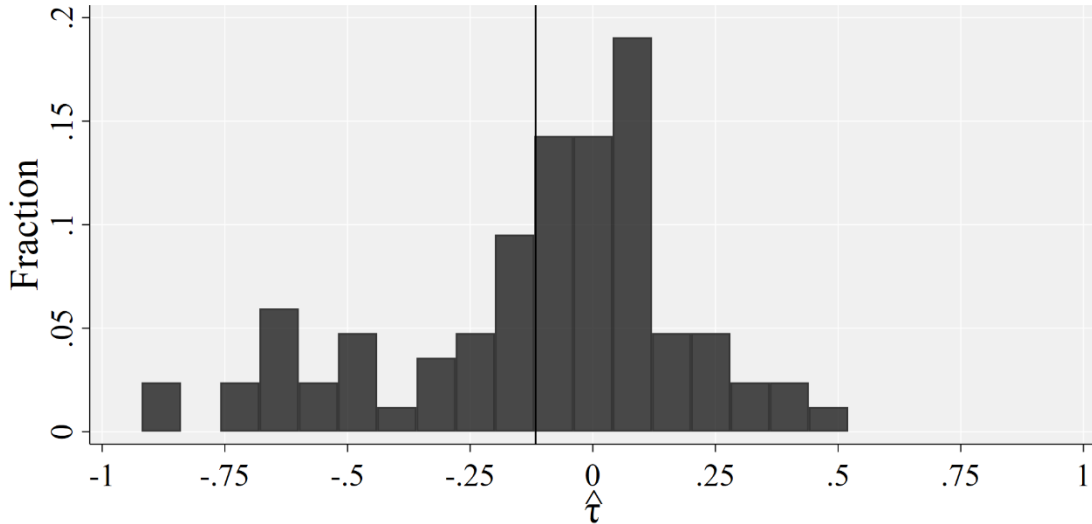
$$V_d - V_c < Z, \text{ where } Z \sim N(\mu, \sigma^2),$$

and from this it follows that FM cooperates with probability:

$$\Pr\{FM \text{ cooperates}\} = \Phi(\mu/\sigma + (qR + (1 - q)S - P)/\sigma + \tau(1 - q)(T - S)/\sigma).$$

As before, we estimate the parameters μ, σ and τ using maximum likelihood probit regressions. We are able to estimate individual parameters for 84 of 97 FMs. The average estimate of τ is -0.11 (s.d. 0.30). Sixty-two of the estimates are insignificantly different from zero. Eleven are significantly negative and 13 are significantly positive. Despite this heterogeneity we find that the population mean of τ is significantly different from zero ($p = 0.010$) providing evidence for other-regarding preferences.¹⁸ Figure 6 shows a histogram of the estimates.

FIGURE 6. Distribution of FM social preference parameter (τ) estimates



Most notably, we find that the weight FM places on SM's payoff tends to be lower than the weight SM places on FM's payoff. This is consistent with the assumption in Charness and Rabin (2002) that the weight placed on the other's payoff depends on whether a player is ahead or behind. Note also that a substantial proportion of FMs put a positive weight on SM's payoff, even when SM earns more – these subjects are not consistent with difference aversion models since only those subjects with $\tau < 0$ are averse to disadvantageous inequality in the sense of Fehr and Schmidt. Lastly, as in the case for SM, for the FM we also find large heterogeneity in

¹⁸ In line with the SM analysis, we compute the standard error of our estimate as $se(\sum \hat{\tau}/n) = (1/n)\sqrt{\sum se(\hat{\tau}_i)^2} = 0.044$.

our estimated bias with a small and insignificant population mean of $\hat{\mu} = -0.18$ (s.d. 126.84; $p = 0.980$).¹⁹

5. Discussion and conclusion

To our knowledge, our study is the first to empirically examine the within-subject variability of conditional cooperation when payoffs vary. To do this, we have subjects play eight one-shot sequential prisoner's dilemma games with varying payoff parameters. We find that conditional cooperation varies across games, and most subjects change strategies at least once across games. This switching between strategies varies systematically with the distributional consequences of free-riding relative to conditionally cooperating. Subjects conditionally cooperate more often when free-riding imposes larger losses on the FM, or when free-riding provides smaller gains for oneself. Further, in a second study, we jointly estimate social preference parameters and noise parameters at the individual level and find that the majority of our subjects place a significantly positive weight on others' payoff.

These findings provide two important implications. First, the within-subject variation of conditional cooperation with payoffs suggests that conditional cooperation should be viewed as an endogenous behavior arising from interaction between underlying motives and payoff variations, rather than a preference itself (Arifovic and Ledyard (2012)). A majority of subjects change their SM strategy when material payoffs change, and so classifications of individuals as conditional cooperators or free-riders should not be generalized to other games with different material payoffs. Moreover, identical payoffs could be internalized differently by individuals implying that across samples it is possible to observe different classifications in types even whilst maintaining the same game parameters. Lastly, it must be noted that other studies have elicited "conditional cooperation preferences" at the individual level and found them to be predictive of behavior in another, related, game (e.g. Eichenseer and Moser, 2020, Mullet et al., 2020). Our view is that these findings are not in conflict with ours, but we suggest a different interpretation whereby subjects classified as conditional cooperators can be viewed as subjects with sufficiently strong preference parameters, and it is these parameters that explain behavior in the related game.

Second, our findings support the underlying role of social preferences in conditional cooperation. We find that simple distributional preferences, where preferences depend on the

¹⁹Following our previous approach, we use the following to compute the standard error of our estimate: as $se(\sum \hat{\mu}/n) = (1/n)\sqrt{(\sum se(\hat{\mu}_i)^2)} = 10.70$.

distribution of payoffs, can explain a lot of conditional cooperation, and we find little support for reciprocity augmented models. This may reflect our particular focus on a sequential dilemma game in which only positive reciprocity can play a role, and the well-known evidence that positive reciprocity concerns are generally weaker than negative reciprocity (e.g., Abbink, et al. (2000); Offerman (2002)). We also find that weights placed on other's payoffs vary substantially between first movers and second movers. Since, in our games, second movers earn at least as much as first movers in any outcome, this finding is consistent with individuals placing less weight on other's payoff when others are ahead and more weight on other's payoffs when others are behind. These results are also qualitatively consistent with those reported in Bruhin, et al. (2019) in that they also find subjects place more weight on other's earnings when others are behind.

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Online Appendix for

Social Preferences and the Variability of

Conditional Cooperation

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Appendix A. Additional Data from Study 1

Table A1: Comparison of demographic characteristics in Study 1 subject pools

	(1) Total	(2) AMT	(3) UoN	(4) Difference
Age	27.46 (9.50)	34.19 (10.22)	22.47 (4.64)	11.72*** (0.97)
Female	0.49 (0.50)	0.37 (0.48)	0.58 (0.50)	-0.21*** (0.06)
Male	0.50 (0.50)	0.62 (0.49)	0.41 (0.49)	0.21*** (0.06)
Other	0.01 (0.09)	0.01 (0.10)	0.01 (0.08)	0.00 (0.01)
Asian	0.23 (0.42)	0.11 (0.31)	0.32 (0.47)	-0.21*** (0.05)
Black or African	0.06 (0.23)	0.02 (0.14)	0.09 (0.28)	-0.07** (0.03)
Latin American	0.02 (0.13)	0.03 (0.17)	0.01 (0.08)	0.02 (0.02)
Native Hawaiian	0.00 (0.06)	0.01 (0.10)	0.00 (0.00)	0.01 (0.01)
White	0.62 (0.49)	0.80 (0.40)	0.49 (0.50)	0.31*** (0.06)
Other	0.07 (0.26)	0.04 (0.19)	0.10 (0.30)	-0.06* (0.03)
Political Orientation	4.06 (2.50)	4.33 (3.04)	3.86 (2.00)	0.47 (0.32)
Never	0.21 (0.41)	0.32 (0.47)	0.13 (0.33)	0.19*** (0.05)
Once or Twice	0.37 (0.48)	0.32 (0.47)	0.41 (0.49)	-0.09 (0.06)
3-10 Times	0.31 (0.46)	0.15 (0.36)	0.43 (0.50)	-0.28*** (0.06)
11-50 Times	0.09 (0.29)	0.17 (0.38)	0.03 (0.18)	0.13*** (0.04)
More than 50 Times	0.02 (0.13)	0.04 (0.19)	0.00 (0.00)	0.04** (0.02)
Observations	249	106	143	249

Note. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ based on t-test of whether the difference between columns (2) and (3) is zero.

TABLE A2. Proportions of Free Riding Strategies

(a) High Efficiency Games (EFF = 0.6) – AMT

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	42.5%	39.6%	-2.8%
	<i>High</i> (= 0.60)	49.1%	43.4%	-5.7%
	Δ (<i>H-L</i>)	6.6%	3.8%	

(b) High Efficiency Games (EFF = 0.6) – UoN

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	49.0%	44.8%	-4.2%
	<i>High</i> (= 0.60)	58.7%	55.9%	-2.8%
	Δ (<i>H-L</i>)	9.8% **	11.2% ***	

(c) Low Efficiency Games (EFF = 0.2) – AMT

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	43.4%	42.5%	-0.9%
	<i>High</i> (= 0.60)	54.7%	43.4%	-11.3%*
	Δ (<i>H-L</i>)	11.3% **	0.9%	

(d) Low Efficiency Games (EFF = 0.2) – UoN

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	55.9%	43.4%	-12.6% ***
	<i>High</i> (= 0.60)	58.7%	53.8%	-4.9%
	Δ (<i>H-L</i>)	2.8%	10.5% **	

Note: EFF = $(R - P)/R$, LOSS = $(R - S)/R$, GAIN = $(T - R)/R$. * $p < 0.1$;
 ** $p < 0.05$; *** $p < 0.01$ indicate p -values based on McNemar's test.

TABLE A3. Proportions of Unconditionally Cooperative Strategies

(a) High Efficiency Games (EFF = 0.6) – AMT

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	17.9%	12.3%	-5.7%
	<i>High</i> (= 0.60)	13.2%	9.4%	-3.8%
	Δ (<i>H-L</i>)	-4.7%	-2.8%	

(b) High Efficiency Games (EFF = 0.6) – UoN

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	8.4%	9.1%	0.7%
	<i>High</i> (= 0.60)	7.7%	9.1%	1.4%
	Δ (<i>H-L</i>)	-0.7%	0.0%	

(c) Low Efficiency Games (EFF = 0.2) – AMT

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	8.5%	6.6%	-1.9%
	<i>High</i> (= 0.60)	13.2%	17.0%	3.8%
	Δ (<i>H-L</i>)	4.7%	10.4%**	

(d) Low Efficiency Games (EFF = 0.2) – UoN

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	5.6%	4.9%	-0.7%
	<i>High</i> (= 0.60)	7.0%	4.9%	-2.1%
	Δ (<i>H-L</i>)	1.4%	0.0%	

Note: EFF = $(R - P)/R$, LOSS = $(R - S)/R$, GAIN = $(T - R)/R$. * $p < 0.1$;
 ** $p < 0.05$; *** $p < 0.01$ indicate p -values based on McNemar's test.

TABLE A4. Proportions of Mismatching Strategies

(a) High Efficiency Games (EFF = 0.6) – AMT

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	3.8%	5.7%	1.9%
	<i>High</i> (= 0.60)	4.7%	8.5%	3.8%
	Δ (<i>H-L</i>)	0.9%	2.8%	

(b) High Efficiency Games (EFF = 0.6) – UoN

		LOSS		
		<i>Low</i> (= 0.82)	<i>High</i> (= 0.96)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	4.9%	2.1%	-2.8%
	<i>High</i> (= 0.60)	5.6%	2.1%	-3.5%
	Δ (<i>H-L</i>)	0.7%	0.0%	

(c) Low Efficiency Games (EFF = 0.2) – AMT

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	3.8%	2.8%	-0.9%
	<i>High</i> (= 0.60)	4.7%	4.7%	0.0%
	Δ (<i>H-L</i>)	0.9%	1.9%	

(d) Low Efficiency Games (EFF = 0.2) – UoN

		LOSS		
		<i>Low</i> (= 0.64)	<i>High</i> (= 0.92)	Δ (<i>H-L</i>)
GAIN	<i>Low</i> (= 0.20)	2.1%	3.5%	1.4%
	<i>High</i> (= 0.60)	2.1%	2.8%	0.7%
	Δ (<i>H-L</i>)	0.0%	-0.7%	

Note: EFF = $(R - P)/R$, LOSS = $(R - S)/R$, GAIN = $(T - R)/R$. * $p < 0.1$;
 ** $p < 0.05$; *** $p < 0.01$ indicate p -values based on McNemar's test.

Table A5: Detailed Regression Results for Study 1.

	AMT	UoN
LOSS*EFF _{high}	0.175 (0.120)	0.289*** (0.089)
LOSS*EFF _{low}	0.294** (0.118)	0.332*** (0.089)
GAIN*EFF _{high}	-0.150 (0.092)	-0.234*** (0.072)
GAIN*EFF _{low}	-0.335*** (0.089)	-0.159** (0.076)
<i>Round dummies</i>		
2 nd round	-0.067 (0.050)	-0.076 (0.048)
3 rd round	-0.142*** (0.054)	-0.103** (0.044)
4 th round	-0.169*** (0.055)	-0.062 (0.050)
5 th round	-0.130** (0.058)	-0.060 (0.049)
6 th round	-0.107** (0.052)	-0.041 (0.051)
7 th round	-0.172*** (0.050)	-0.079* (0.046)
8 th round	-0.132** (0.056)	-0.127** (0.050)
<i>Demographics</i>		
Age	0.004 (0.003)	0.017** (0.007)
Politics	-0.016 (0.010)	0.013 (0.016)
<i>Gender (Reference group: Female)</i>		
Male	-0.000 (0.070)	-0.110* (0.058)
Other	0.246* (0.129)	-
<i>Ethnicity (Reference group: Asia)</i>		
Black or African	0.220 (0.354)	0.163 (0.122)
Latin American	-	-
Native Hawaiian	-	-
White	0.192** (0.079)	0.042 (0.067)
Other	0.435*** (0.079)	0.004 (0.098)
<i>Study experience (Reference group: Never)</i>		
Once or Twice	0.158* (0.082)	0.046 (0.088)
3-10 Times	0.299*** (0.092)	0.056 (0.090)
11-50 Times	0.094 (0.085)	0.035 (0.103)
More than 50 Times	0.247 (0.193)	-
<i>Task Characteristics</i>		
B is Cooperation	-0.040 (0.032)	-0.040 (0.030)

The sequence of SM/FM decision (1 if SM decision is shown above the screen)	-0.038 (0.035)	0.039 (0.028)
<i>Session effects (Reference group: Session 1)</i>		
Session 2	0.153* (0.089)	0.093 (0.087)
Session 3	-0.122 (0.083)	0.019 (0.092)
Session 4	-0.106 (0.092)	-
Session 5	0.113 (0.123)	-
Observations	800	1,104
Log-Likelihood	-464	-685
BIC	1,115	1,544

Notes: Average marginal effects from logit regression with robust standard errors clustered at the individual level. Dependent variable = 1 if SM conditionally cooperated, 0 otherwise. LOSS = $(R - S)/R$, GAIN = $(T - R)/R$, EFF_{high}: indicator variable for $(R - P)/R = 0.6$, EFF_{low}: indicator variable for $(R - P)/R = 0.2$.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix B. Instructions for Study 1

These are the instructions for the AMT experiment. Instructions for UoN online experiment were identical except that the terms 'HIT', 'dollar' and \$ were replaced with 'experiment', 'pound', and '£', respectively.

Welcome

Thank you for accepting this HIT. To complete this HIT, you must make some decisions. Including the time for reading these instructions, the HIT will take about 30 minutes to complete. If you are using a desktop or laptop to complete this HIT, we recommend that you maximize your browser screen (press F11) before you start.

It is important that you complete this HIT without interruptions. During the HIT, please **do not close this window or get distracted from the task**. If you close your browser or leave the task, you will not be able to re-enter and we will not be able to pay you.

In this HIT, you will be matched with one other participant. Each of you will make decisions for 8 decision situations. In each situation, each of you will earn Tokens depending on your decisions.

At the end of the HIT, one of the decision situations will be randomly chosen. Your earnings from this situation will be converted from Tokens to Dollars at a rate of **100 Tokens = \$ 1**. This will be added to **your participation fee of \$1.00**. Depending on your decisions, you may make up to \$8.00 more in addition to the \$1.00 participation fee. In the same way, Tokens earned by the person matched with you in that same situation will also be converted to Dollars at a rate of 100 Tokens = \$ 1.

You will receive a code to collect your payment via MTurk upon completion.

Please click "Continue" to start the HIT.

Instructions

The HIT consists of 8 decision situations.

Each decision situation will be presented on a screen like the **example screen** below.

		Other's Choice	
		A	B
Your Choice	A	200 (green), 200 (blue)	0 (green), 300 (blue)
	B	300 (green), 0 (blue)	100 (green), 100 (blue)

You and the other person will be making choices between **A** and **B**. Your earnings are the values in the green circle, and the other person's earnings are the values in the blue circle. The table is read as follows:

- If you choose A and the other person chooses A, you will earn 200 Tokens and the other person will earn 200 Tokens.
- If you choose A and the other person chooses B, you will earn 0 Tokens and the other person will earn 300 Tokens.
- If you choose B and the other person chooses A, you will earn 300 Tokens and the other person will earn 0 Tokens.
- If you choose B and the other person chooses B, you will earn 100 Tokens and the other person will earn 100 Tokens.

Please note that the values in the table will differ in each decision situation.

Tasks

In each decision situation, you must complete **two types** of tasks, which we will refer to below as the “FIRST MOVER’s decision” and “SECOND MOVER’s decision”. The FIRST MOVER

decides first whether to choose A or B. The SECOND MOVER is then informed of the FIRST MOVER's decision. The SECOND MOVER then decides whether to choose A or B.

We want to know what you would do in the role of the FIRST MOVER and what would you do in the role of the SECOND MOVER. Thus you will be prompted to make decisions in both roles.

- For the “FIRST MOVER's decision” task, you will see the following screen and you must choose A or B:

Suppose you are the FIRST MOVER. The other person decides after observing your decision. Your choice is:

- For the “SECOND MOVER's decision” task, You will see the following screen and you must choose A or B in two possible cases: (1) if the FIRST MOVER chooses A (2) if the FIRST MOVER chooses B

Suppose you are the SECOND MOVER, and the other person is the FIRST MOVER. Make your choice for each possible decision of the FIRST MOVER.

If the FIRST MOVER chooses A, your choice is:

If the FIRST MOVER chooses B, your choice is:

During the HIT, you will not receive any feedback on the other person's choice or the outcomes of the decision situations.

Your dollar earnings

On completion of the HIT, you will be paid your participation fee of \$ 1.

In addition, one of the decision situations will be randomly chosen for your additional dollar earnings. The computer will randomly choose either you or the other person to be the first-mover. If you are chosen to be the first-mover, your first-mover's decision will be matched with the second-mover's decision of the other person. If the other person is chosen to be the first-mover, your second-mover's decision will be matched with the first-mover's decision of

the other person. Your earnings and the other person's earnings will be determined depending on choices of you and the other person in that situation. Two examples should make this clear.

Example 1. Assume that **the computer randomly selects you to be the first-mover. This implies that your payoff relevant decision will be your first-mover's decision.** Assume that you choose A as the first-mover's decision in the above example screen. Assume that the other person matched with you makes the following second-mover's decisions: he/she chooses A if you choose A, and chooses B if you choose B. As a consequence, you will earn 200 Tokens and the other person will earn 200 Tokens.

Example 2. Assume that **the computer randomly selects the other person to be the first-mover. This implies that your payoff relevant decision will be your second-mover's decision.** Assume that you make the following second-mover's decisions: you choose B if the FIRST MOVER chooses A, and choose B if the FIRST MOVER chooses B in the above example screen. Assume that the other person matched with you chooses A as the first-mover's decision. As a consequence, you will earn 300 Tokens and the other person will earn 0 Tokens.

At the end of the HIT

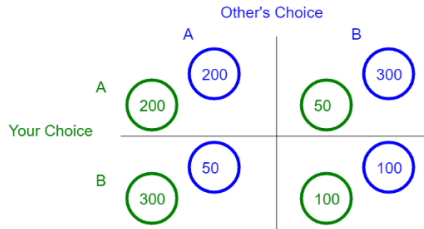
On completion of the HIT, one of the decision situations will be randomly chosen as explained above. You will be informed of your choices and earnings for that decision situation, and you will be paid these earnings in addition to your participation fee.

Note that we will not be able to pay you if you do not complete the HIT. If the person you are matched with does not complete the HIT, the computer will randomly select one of the four possible earnings in the randomly chosen decision situation, and you will be paid these earnings in addition to your participation fee.

Your participation fee and the additional earnings will be paid to you within two working days.

Comprehension Questions

Control Questions (1/2)



Please answer all questions. They serve as a test for your understanding of the HIT.

Question 1. Suppose you are the **FIRST MOVER** and you choose **A**. Suppose the other person makes the following decisions: The other person chooses **A** if you choose **A**, and chooses **B** if you choose **B**.

What will be Your Earnings?

What will be Other's Earnings?

Question 2. Suppose you are the **FIRST MOVER** and you choose **B**. Suppose the other person makes the following decisions: The other person chooses **A** if you choose **A**, and chooses **A** if you choose **B**.

What will be Your Earnings?

What will be Other's Earnings?

Question 3. Suppose you are the **SECOND MOVER** and you make the following decisions: You choose **A** if the other person chooses **A**, and choose **A** if the other person chooses **B**. Suppose the other person chooses **B**.

What will be Your Earnings?

What will be Other's Earnings?

Question 4. Suppose you are the **SECOND MOVER** and you make the following decisions: You choose **A** if the other person chooses **A**, and choose **B** if the other person chooses **B**. Suppose the other person chooses **B**.

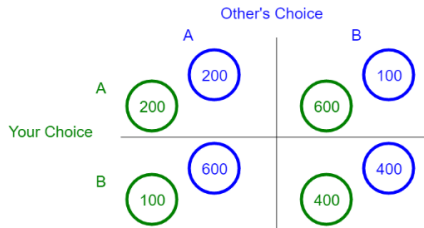
What will be Your Earnings?

What will be Other's Earnings?

Back to the Instructions

Continue

Control Questions (2/2)



Please answer all questions. They serve as a test for your understanding of the HIT.

Question 1. Suppose you are the **FIRST MOVER** and you choose **B**. Suppose the other person makes the following decisions: The other person chooses **A** if you choose **A**, and chooses **A** if you choose **B**.

What will be Your Earnings?

What will be Other's Earnings?

Question 2. Suppose you are the **FIRST MOVER** and you choose **A**. Suppose the other person makes the following decisions: The other person chooses **A** if you choose **A**, and chooses **B** if you choose **B**.

What will be Your Earnings?

What will be Other's Earnings?

Question 3. Suppose you are the **SECOND MOVER** and you make the following decisions: You choose **A** if the other person chooses **A**, and choose **B** if the other person chooses **B**. Suppose the other person chooses **B**.

What will be Your Earnings?

What will be Other's Earnings?

Question 4. Suppose you are the **SECOND MOVER** and you make the following decisions: You choose **A** if the other person chooses **A**, and choose **A** if the other person chooses **B**. Suppose the other person chooses **B**.

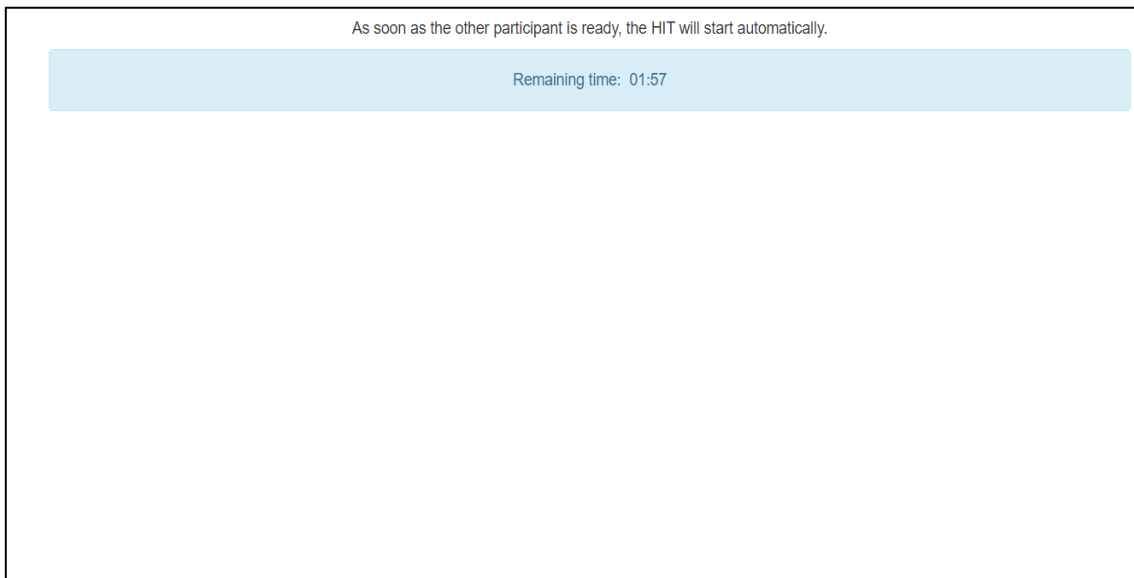
What will be Your Earnings?

What will be Other's Earnings?

Back to the Instructions

Continue

Screenshots of Online Experiment



Screenshot 1: Matching stage

Decision Situation 1

		Other's Choice	
		A	B
Your Choice	A	500 (Your), 500 (Other)	90 (Your), 600 (Other)
	B	600 (Your), 90 (Other)	200 (Your), 200 (Other)

Before making your decision, you need to answer the following questions for Situation 1.
You will make actual decisions in Situation 1 once you complete these questions.

Question 1. You choose A and the other person chooses A.
What will be Your Earnings? What will be Other's Earnings?

Question 2. You choose B and the other person chooses A.
What will be Your Earnings? What will be Other's Earnings?

Question 3. You choose A and the other person chooses B.
What will be Your Earnings? What will be Other's Earnings?

Question 4. You choose B and the other person chooses B.
What will be Your Earnings? What will be Other's Earnings?

Screenshot 2: Comprehension Question before Decision Screen

Decision Screen (Situation 1)

		Other's Choice	
		A	B
Your Choice	A	500 (500)	90 (600)
	B	600 (90)	200 (200)

Suppose you are the **FIRST MOVER**, and the other person is the **SECOND MOVER**. Your choice is:

Suppose you are the **SECOND MOVER**, and the other person is the **FIRST MOVER**.
Make your choice for each possible decision of the **FIRST MOVER**.

If the **FIRST MOVER** chooses A, your choice is:

If the **FIRST MOVER** chooses B, your choice is:

Screenshot 3: Decision screen

Appendix C. Effect of GAIN and LOSS in stochastic choice models

In this appendix we examine the comparative static effects of GAIN and LOSS on the probability of second-mover conditional cooperation in a sequential prisoner's dilemma using a stochastic choice model without social preferences. In our experiment R is constant and so the effect of changes in $\text{GAIN} = (T - R)/R$ on the probability of conditional cooperation has the same sign as the effect of changes in T . The effect of $\text{LOSS} = (R - S)/R$ has the opposite sign as the effect of S .

Let q denote the probability that the first-mover cooperates, and let V_j denote SM's expected (selfish) payoff from strategy j . Thus, the expected payoff from conditional cooperation (cc) is

$$V_{cc} = qR + (1 - q)P,$$

the expected payoff from free riding (fr) is

$$V_{fr} = qT + (1 - q)P,$$

the expected payoff from unconditional cooperation (uc) is

$$V_{uc} = qR + (1 - q)S,$$

and the expected payoff from mis-matching FM's choice (mm), is

$$V_{mm} = qT + (1 - q)S.$$

Let $Z_j = V_j + \varepsilon_j$ be the perturbed payoff from strategy j , where the ε_j error terms are independent draws from an extreme value distribution with scale parameter $1/\lambda$. Assuming the individual chooses the strategy giving the largest perturbed payoff, this induces a multinomial logit choice structure where the probability of conditional cooperation, p_{cc} , is given by

$$\begin{aligned} p_{cc} &= \frac{\exp\{\lambda V_{cc}\}}{\sum \exp\{\lambda V_j\}} = \frac{1}{1 + \exp\{\lambda(V_{fr} - V_{cc})\} + \exp\{\lambda(V_{uc} - V_{cc})\} + \exp\{\lambda(V_{mm} - V_{cc})\}} \\ &= \frac{1}{1 + \exp\{\lambda q(T - R)\} + \exp\{\lambda(1 - q)(S - P)\} + \exp\{\lambda q(T - R) + \lambda(1 - q)(S - P)\}} \\ &= (1 + \exp\{\lambda q(T - R)\})^{-1} (1 + \exp\{\lambda(1 - q)(S - P)\})^{-1} \end{aligned}$$

For fixed q the first term is decreasing in T and so p_{cc} decreases with T and decreases with GAIN. For fixed q the second term is decreasing in S and so p_{cc} decreases with S and increases with LOSS.

In order to sign the comparative statics with endogenous q , we need a model of FMs choice. Using a QRE model (McKelvey and Palfrey (1995)), the choice probabilities are given by the solution to the system of equations:

$$\begin{aligned}
p_{cc} &= (1 + \exp \{\lambda q(T - R)\})^{-1} (1 + \exp \{\lambda(1 - q)(S - P)\})^{-1} \\
p_{fr} &= (1 + \exp \{\lambda q(R - T)\})^{-1} (1 + \exp \{\lambda(1 - q)(S - P)\})^{-1} \\
p_{uc} &= (1 + \exp \{\lambda q(T - R)\})^{-1} (1 + \exp \{\lambda(1 - q)(P - S)\})^{-1} \\
p_{mm} &= (1 + \exp \{\lambda q(R - T)\})^{-1} (1 + \exp \{\lambda(1 - q)(P - S)\})^{-1} \\
q &= \left((1 + \exp \{\lambda \left((P - S)p_{fr} + (P - R)p_{cc} + (T - S)p_{mm} + (T - R)p_{uc} \right)\}) \right)^{-1}
\end{aligned}$$

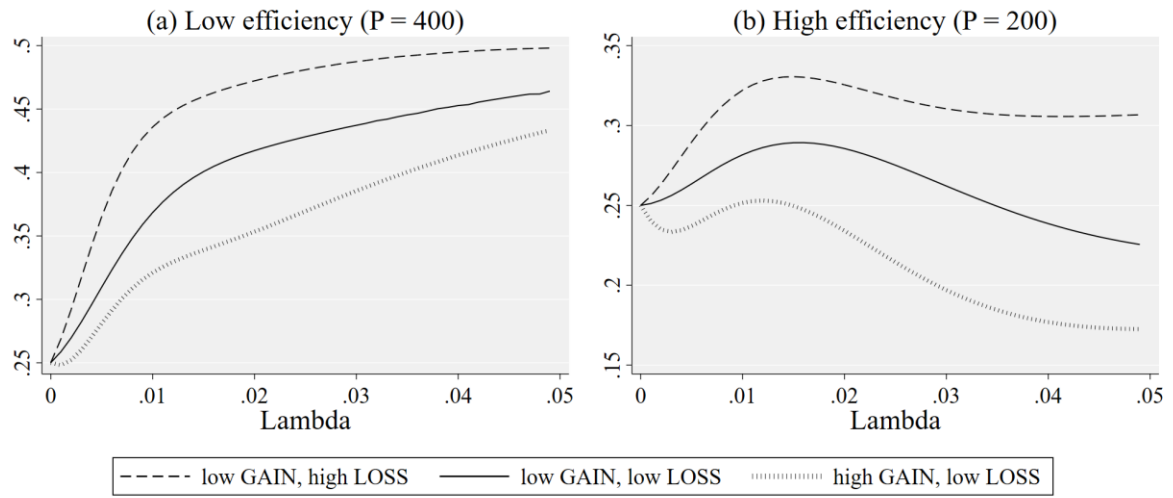
The solution gives the QRE probabilities as functions of the payoff parameters and precision parameter λ . We use numerical methods to solve these equations for our payoff parameters.

Figure C1(a) below shows the QRE probability of conditional cooperation as a function of λ for the *low efficiency* games ($R = 500, P = 400$). As a baseline take the low GAIN and low LOSS game ($T = 600, S = 180$). The QRE probability of conditional cooperation in this baseline is shown in Figure C1(a) as the middle line. Keeping $S = 180$ and increasing T to 800 gives the high GAIN and low LOSS game, and this results in a lower probability of conditional cooperation, as shown by the lowest line. Keeping $T = 600$ and reducing S to 40 gives the low GAIN and high LOSS game, and this results in a higher probability of conditional cooperation, as shown by the uppermost line.

Figure C1(b) shows the QRE probability of conditional cooperation for the *high efficiency* games ($R = 500, P = 200$). Again, take the low GAIN and low LOSS game ($T = 600, S = 90$) as a baseline. The QRE probability of conditional cooperation is the middle line in Figure C1(b). Keeping $S = 90$ and increasing T to 800 gives the high GAIN and low LOSS game, and this results in the lowest line. Keeping $T = 600$ and reducing S to 20 gives the low GAIN and high LOSS game, and results in the uppermost line.

In summary, for any given λ , the QRE probability of conditional cooperation increases with LOSS and decreases with GAIN.

Figure C1. QRE probability of conditional cooperation for low EFF (left panel) and high EFF (right panel) games



Reference

McKelvey, R. D., & Palfrey, T. R. (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior*, 10, 6-38.

Appendix D. Instructions for Study 2

Welcome

Thank you for participating in this experiment. At the end of this experiment you will receive £5 for your participation, in addition to other money to be paid as a result of decisions made in the experiment. These instructions explain how the additional money depends on decisions, so please read them carefully. If you have a question at any time, please raise your hand and an experimenter will come to you to answer it. During the session, please do not use mobile phones or try to communicate with any of the other participants. If you do not follow these rules, you will be excluded from the study and will not be paid.

General Instructions

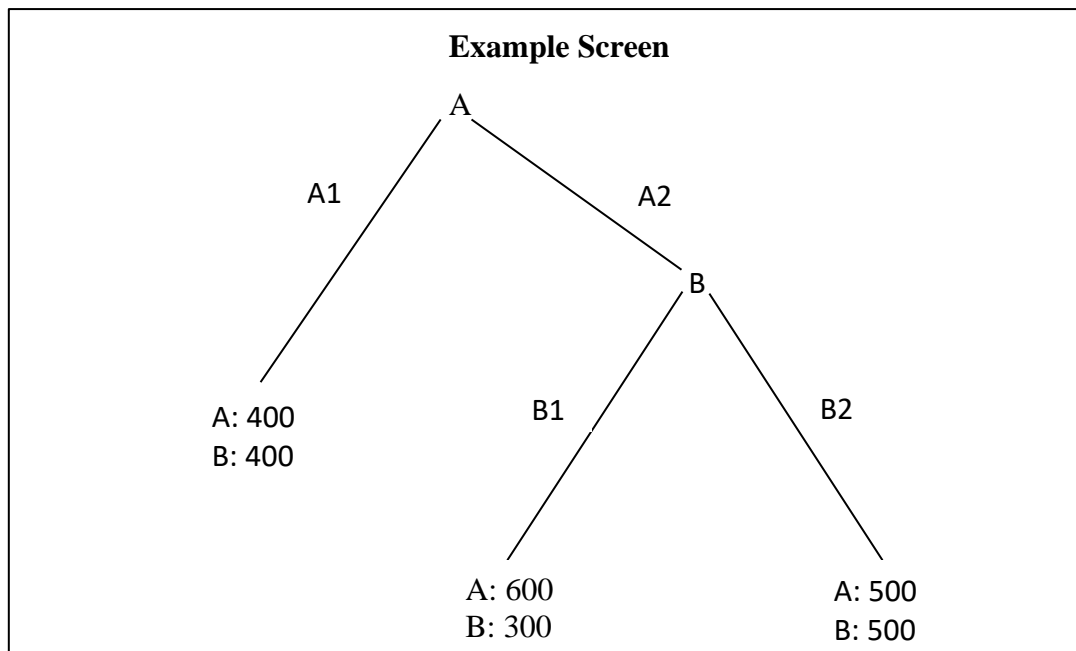
In this session, you will be anonymously matched with one other participant. Each of you will make decisions for 64 decision situations. In each situation, each of you will earn Tokens depending on your decisions.

At the end of the session, one of the decision situations will be randomly chosen. Your earnings from this situation will be converted from Tokens to pounds at a rate of 1 Token = £0.02. This will be added to your participation fee of £5.00. In the same way, Tokens earned by the person matched with you in that same situation will also be converted to pounds at a rate of 1 Tokens = £0.02, and they will earn this amount in addition to their £5 participation fee. Payments will be made individually and privately via PayPal.

The Decision Situation

In each decision situation there are two "roles", Person A and Person B. You will either be assigned the role of Person A or Person B at the beginning of the first decision situation and you will keep this role for all 64 situations. The person you are matched with will be assigned the other role for all 64 situations.

Each decision situation will be presented on a screen like the example screen below. The choices available to each player are represented by lines and the earnings are given by the numbers at the end of the lines. The earnings values will differ in each decision situation. Neither your choices, nor the choices of the person you are matched with, will affect the earnings values in each decision situation.



Person A will be making choices between A1 and A2. Person B will be making choices between B1 and B2. Earnings will depend on the choices as follows.

If Person A chooses A1 the token earnings are as shown at the end of the leftmost branch: Person A will earn 400 Tokens and Person B will earn 400 Tokens.

If Person A chooses A2 then Person B's choice will determine the outcome. If Person B chooses B1, Person A will earn 600 tokens and Person B will earn 300 Tokens. If Person B chooses B2, Person A will earn 500 Tokens and Person B will earn 500 Tokens.

Person A and Person B will make their choices at the same time. Thus, Person B will make a choice in every decision situation, even though Person B's choice only affects the outcome if Person A chooses A2.

You will not receive any feedback on the other person's choice or the outcomes of the decision situations until the end of the session.

To make a choice on the experimental screen, you can simply click on the line that you wish to choose. Once selected the chosen line will be highlighted.

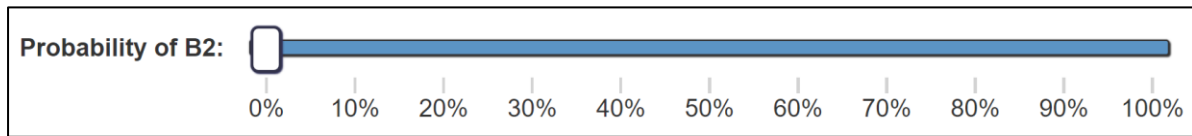
Probability task

For each decision situation you are also asked to provide your best guess that the other Player selects A2 or B2.

This means, Player A is asked to guess the likelihood that Player B chooses B2 and Player B is asked to guess the likelihood that Player A chooses A2.

Your guess is a percentage probability from 0 to 100 - with 0 indicating a 0-out-of-100 chance that the other Player chose A2/B2, and 100 indicating a 100-out-of-100 chance.

You choose Your Guess by clicking a response bar on your screen as can be seen below.



The width of the bar represents 100% and you can select the probability corresponding to Your Guess by clicking on the bar. Larger values represent a greater chance that the other Player chooses A2/B2 and smaller values represent a smaller chance that the other Player chooses A2/B2.

Your guess and the actual choice of the other Player will be used to determine your chance of winning an additional 200 Tokens. Your chance of winning the Tokens is set so that more accurate guesses lead to a higher chance of winning.

The payment rule is designed so that you can secure the largest chance of winning the additional 200 Tokens by reporting your most-accurate guess. That is, if you think there is a 20% chance the other Player chooses A2/B2, you maximise your chances of winning the additional 200 Tokens by submitting a guess of 20%; if you think there is a 78% chance the other player chooses A2/B2, you maximise your chances of winning the additional 200 Tokens by submitting a guess of 78%. Etc. The precise payment rule details are available by request at the end of the experiment.

Ending the Session

At the end of the session, two different decision situations will be randomly chosen as explained above.

You will be informed of the choices and token earnings of you and the person you are matched with for the first chosen decision situation.

You will also be informed about the choices of the person you are matched with in the second chosen decision situation. This will determine the chance of winning the 200 additional Tokens in the probability task.

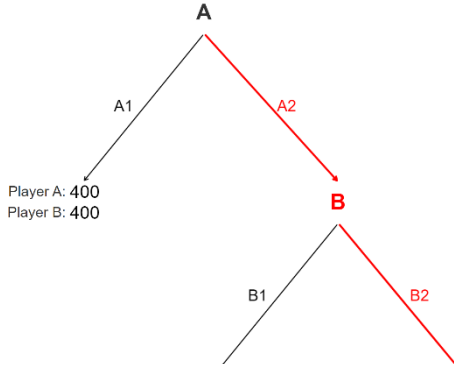
For both decisions you will be paid £0.02 per token in addition to your £5 participation fee.

Comprehension Questions

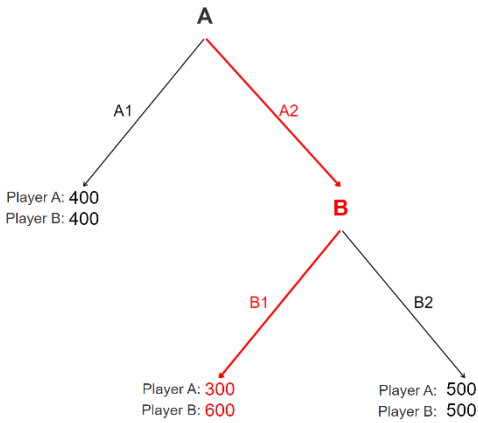
1. With whom are you grouped for each decision situation?
 - a. With the same participant for the whole experiment.
 - b. Each situation with a different participant.
2. Which “role” are you playing as?
 - a. A different “role” each decision situation.
 - b. The same “role” for the entire experiment

The following 4 images show possible decisions made by **Person A and Person B**.

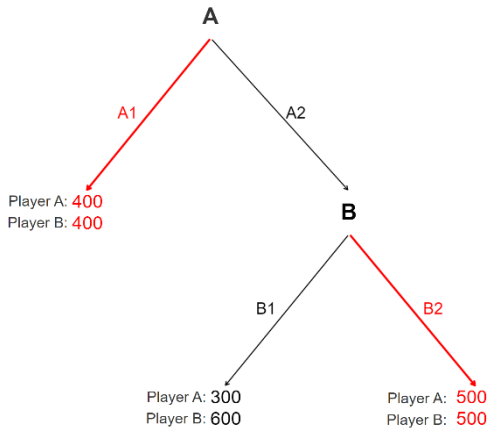
For each image, please use the boxes on the right to insert how many tokens Person A and Player B would receive with the decisions shown in the image.



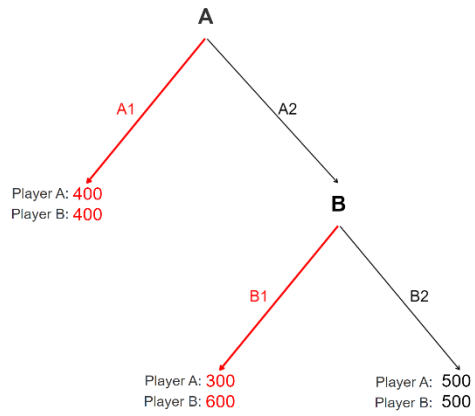
3a) How many Tokens would Person A receive?
3b) How many Tokens would Person B receive?



4a) How many Tokens would Person A receive?
4b) How many Tokens would Person B receive?

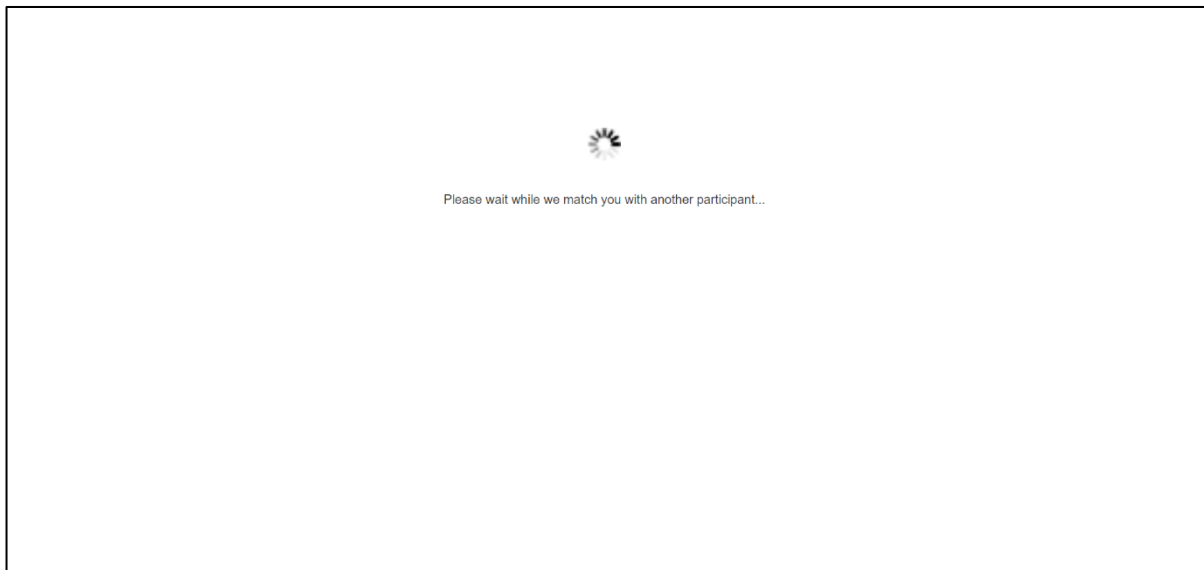


5a) How many Tokens would Person A receive?
5b) How many Tokens would Person B receive?

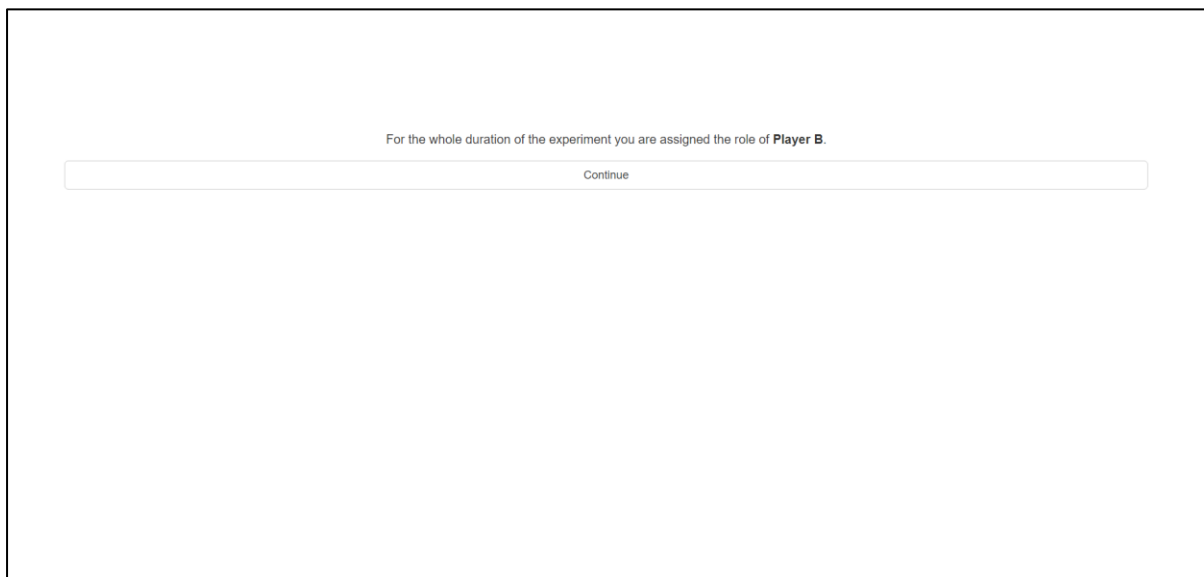


6a) How many Tokens would Person A receive?
 6b) How many Tokens would Person B receive?

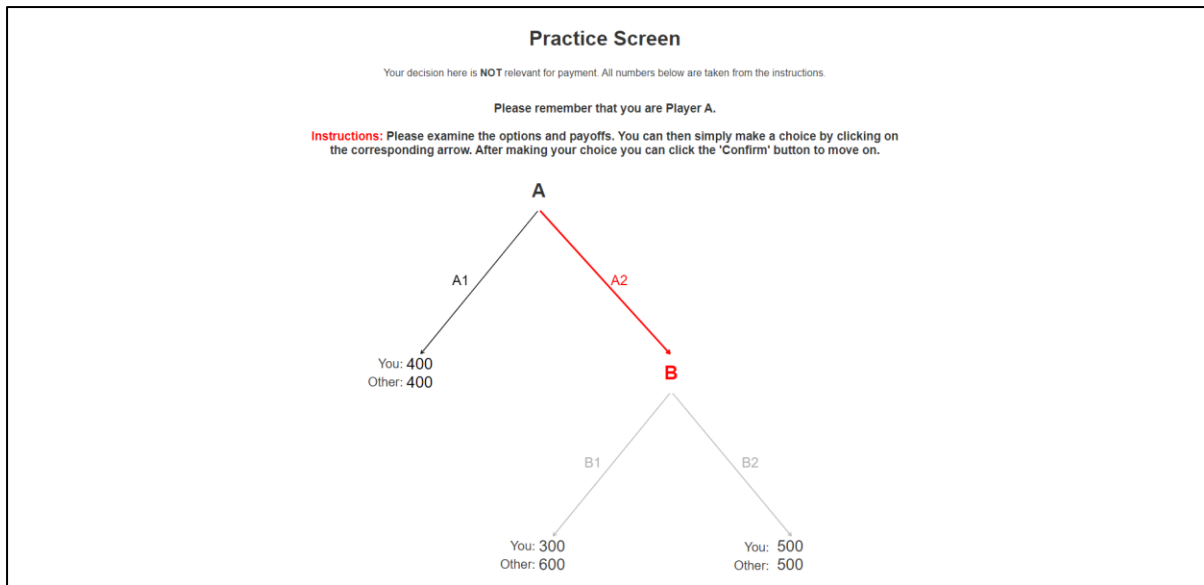
Screenshots of Lab Experiment



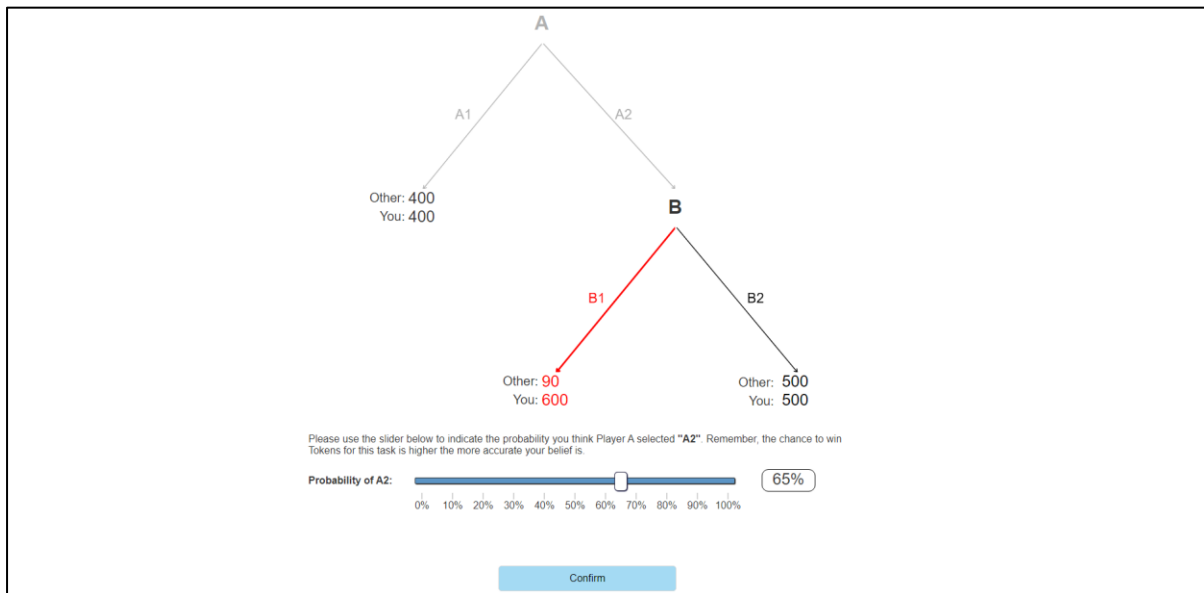
Screenshot 1: Matching stage



Screenshot 2: Role assignment



Screenshot 3: Practice screen



Screenshot 4: Decision screen

Questionnaire

1. How often have you previously participated in the experiments including similar decision problems (e.g. dividing an amount of money between yourself and another person)?
 - a. Never
 - b. Once or Twice
 - c. 3-10 times
 - d. 11-50 times
 - e. More than 50 times
 - f. Prefer not to say
2. What is your gender
 - a. Female
 - b. Male

- c. Other
 - d. Prefer not to say
3. What is your age?
 4. What is your nationality?
 5. What is your citizenship?
 - a. United Kingdom
 - b. European Union
 - c. United States
 - d. Latin American Countries
 - e. African Countries
 - f. Asian Countries
 - g. Other
 - h. Prefer not to say
 6. Which of the following describes you best?
 - a. Asian
 - b. Native Hawaiian or Other Pacific Islander
 - c. Black or African
 - d. Middle Eastern
 - e. Latin American
 - f. White
 - g. Mixed background
 - h. Other
 - i. Prefer not to say
 7. What is your current year of university?
 - a. Year 1
 - b. Year 2
 - c. Year 3
 - d. MA/MSc
 - e. PhD
 - f. Diploma
 - g. Foundation Programme
 - h. International Exchange Programme
 - i. Other
 - j. Prefer not to say
 8. What is your major in the university?
 9. How much do you spend per month, excluding rent?
 - a. Less than £200
 - b. £200 to £399
 - c. £400 to £599
 - d. £600 to £799
 - e. £800 to £999
 - f. £1,000 or more
 - g. Prefer not to say
 10. In politics, people sometimes talk about the 'left' and the 'right'. Where would you place your own views on a scale from 0 to 10? (0 means the most left and 10 means the most right)

Appendix E. Monte Carlo Simulations

Prior to estimation we conducted Monte Carlo simulations to explore the properties of the estimators under alternative data generating processes. First, we generated data from model 1:

$$\Pr\{\text{cooperate}\} = \Phi(\mu/\sigma + (R - T)/\sigma + \rho(T - S))/\sigma).$$

using our Study 2 payoff parameters and various combinations of μ , σ and ρ . We used values of $\rho \in \{0, 0.2, 0.4\}$ corresponding to no, low and high weights on other's payoff. Low and high noise processes are represented by $\sigma \in \{100, 200\}$, and negative, zero, and positive bias toward cooperation are represented by $\mu \in \{-100, 0, 100\}$.

We generated 1000 replications for each parameter combination, where a replication generates a sequence of 64 choices for our games. For each replication we ran two regressions. The first is a probit regression without a constant, estimating $\Phi(\beta_1(R - T) + \beta_2(T - S))$. Our estimate of ρ is $\hat{\rho} = \widehat{\beta}_2/\widehat{\beta}_1$ and standard errors are determined using the delta method. The second regression includes a constant and estimates $\Phi(\beta_0 + \beta_1(R - T) + \beta_2(T - S))$. Our estimate of μ is $\hat{\mu} = \widehat{\beta}_0/\widehat{\beta}_1$ and we again estimate ρ as $\hat{\rho} = \widehat{\beta}_2/\widehat{\beta}_1$, using the delta method to calculate standard errors.

Table E1 reports results. *%id* gives the proportion of 1000 replications in which we obtain 'sensible' estimates. We exclude cases where the model fails to converge due to underidentification and cases where $\hat{\sigma} < 0$ or $|\hat{\rho}| > 1$. *Av $\hat{\rho}$* is the average estimate of ρ over the remaining cases, and *Av se($\hat{\rho}$)* is the average of the associated standard errors. *Power* gives the proportion of 1000 replications that resulted in a significantly positive estimate of ρ (i.e. $\hat{\rho} < 1.96, se(\hat{\rho}) > 0$).

Note that neither the data generation process nor the regression models examined in Table E1 use beliefs and are essentially based on the model in the text with $q = 1$.

We studied the role of beliefs by generating data from an additional, belief-augmented, model

$$\Pr\{\text{cooperate}\} = \Phi(\mu/\sigma + q(R - T)/\sigma + \rho q(T - S))/\sigma).$$

We wanted to use beliefs that vary with game payoffs in a reasonable way, and so to fix beliefs we use Rapoport's K-index, $q = (R - P)/(T - S)$, which has been shown to be systematically related to cooperation rates in prisoner's dilemma experiments (Rapoport and Chammah, 1965). We generated 1000 replications for each combination of parameters and ran two regressions for each replication. The first regression estimates $\Phi(\beta_0 + \beta_1(R - T) + \beta_2(T - S))$,

i.e., ignoring beliefs. The second model estimates $\Phi(\beta_0 + \beta_1 q(R-T) + \beta_2 q(T-S))$ using the belief data. In both models we estimate μ as $\hat{\mu} = \widehat{\beta}_0/\widehat{\beta}_1$ and ρ as $\hat{\rho} = \widehat{\beta}_2/\widehat{\beta}_1$, using the delta method to calculate standard errors. Results are given in Table E2.

Reference

Rapoport, A., & Chammah, A. M. (1965). Prisoner's dilemma: A study in conflict and cooperation. Ann Arbor: University of Michigan Press.

Table E1. Monte Carlo Results: Model 1

μ	ρ	Σ	No constant in regression				With constant in regression			
			%id	Av $\hat{\rho}$	Av se($\hat{\rho}$)	power	%id	Av $\hat{\rho}$	Av se($\hat{\rho}$)	Power
-100	0	100	.278	-.340	.213	0	.219	-.011	.675	.033
-100	0	200	.889	-.320	.269	0	.723	.113	.677	.156
-100	.2	100	.954	-.054	.087	.009	.885	.164	.397	.254
-100	.2	200	.989	-.072	.181	.044	.84	.214	.579	.246
-100	.4	100	.988	.210	.051	.909	.966	.337	.278	.506
-100	.4	200	.999	.196	.105	.613	.891	.359	.490	.398
0	0	100	.866	-.003	.065	.017	.72	.009	.474	.1
0	0	200	.998	-.026	.128	.061	.779	.048	.686	.124
0	.2	100	.845	.198	.045	.806	.786	.161	.386	.232
0	.2	200	1	.191	.077	.709	.845	.186	.590	.245
0	.4	100	.989	.398	.030	.989	.973	.342	.276	.511
0	.4	200	1	.400	.054	.996	.888	.357	.487	.392
100	0	100	.509	.187	.044	.487	.428	-.007	.515	.06
100	0	200	.998	.180	.065	.753	.762	.048	.661	.133
100	.2	100	.952	.349	.029	.952	.902	.141	.390	.243
100	.2	200	1	.349	.047	.998	.826	.184	.589	.244
100	.4	100	.978	.517	.025	.978	.94	.334	.300	.472
100	.4	200	1	.520	.049	1	.885	.354	.512	.381

1000 replications from the data generating process $\Pr\{\text{cooperate}\} = \Phi(\mu/\sigma + (R - T)/\sigma + \rho(T - S)/\sigma)$; %id is proportion of replications where parameters satisfying $\hat{\sigma} < 0$ or $|\hat{\rho}| > 1$, $\hat{\sigma} < 0$ can be estimated. power is the proportion of replications with significantly positive $\hat{\rho}$ is at the 5% level.

Table E2. Monte Carlo Results: Belief-augmented model

M	P	Σ	No Beliefs in regression				With Beliefs in regression			
			<i>%id</i>	<i>Av $\hat{\rho}$</i>	<i>Av se($\hat{\rho}$)</i>	<i>power</i>	<i>%id</i>	<i>Av $\hat{\rho}$</i>	<i>Av se($\hat{\rho}$)</i>	<i>power</i>
-100	0	100	0.541	0.069	0.916	0.067	0.996	-0.025	0.232	0.007
-100	0	200	0.614	0.311	1.021	0.188	0.960	-0.007	0.399	0.016
-100	.2	100	0.737	0.108	0.761	0.120	1.000	0.195	0.198	0.164
-100	.2	200	0.642	0.306	0.995	0.195	0.959	0.184	0.340	0.070
-100	.4	100	0.783	0.153	0.747	0.178	0.997	0.391	0.176	0.625
-100	.4	200	0.652	0.322	0.976	0.192	0.940	0.367	0.341	0.186
0	0	100	0.754	0.148	0.794	0.179	1.000	0.005	0.178	0.046
0	0	200	0.655	0.348	0.925	0.229	0.964	-0.000	0.358	0.029
0	.2	100	0.799	0.197	0.713	0.217	1.000	0.203	0.165	0.327
0	.2	200	0.653	0.337	0.977	0.213	0.974	0.171	0.345	0.097
0	.4	100	0.806	0.239	0.758	0.243	0.997	0.402	0.162	0.706
0	.4	200	0.671	0.356	0.960	0.239	0.930	0.372	0.346	0.251
100	0	100	0.801	0.238	0.696	0.229	0.999	-0.012	0.200	0.057
100	0	200	0.670	0.348	0.915	0.221	0.971	0.008	0.356	0.047
100	.2	100	0.788	0.300	0.698	0.273	0.999	0.196	0.206	0.293
100	.2	200	0.662	0.384	0.947	0.252	0.964	0.209	0.367	0.150
100	.4	100	0.732	0.375	0.795	0.292	0.975	0.397	0.238	0.558
100	.4	200	0.664	0.378	1.015	0.228	0.923	0.361	0.381	0.286

1000 replications from the data generating process $\Pr\{\text{cooperate}\} = \Phi(\mu/\sigma + q(R - T)/\sigma + \rho q(T - S)/\sigma)$, where $q = (R - P)/(T - S)$; *%id* is proportion of replications where parameters satisfying $\hat{\sigma} < 0$ or $|\hat{\rho}| > 1$, $\hat{\sigma} < 0$ can be estimated. *power* is the proportion of replications in which the estimate of ρ is significantly positive at the 5% level.

Appendix F. Study 2 Data

Table F1. Cooperation Rates and Beliefs in Cooperation by Game

R	P	S	T	GAIN	LOSS	EFF	FM_C	SM_C	FM_q	SM_q	R	P	S	T	GAIN	LOSS	EFF	FM_C	SM_C	FM_q	SM_q
500	100	20	400	-.2	.64	.2	0.711	0.969	0.829	0.747	500	100	20	400	.6	.64	.2	0.134	0.309	0.312	0.283
500	200	20	400	-.2	.64	.4	0.887	0.969	0.863	0.770	500	200	20	400	.6	.64	.4	0.206	0.340	0.322	0.355
500	300	20	400	-.2	.64	.6	0.938	0.959	0.880	0.863	500	300	20	400	.6	.64	.6	0.608	0.278	0.351	0.553
500	400	20	400	-.2	.64	.8	0.948	0.990	0.860	0.929	500	400	20	400	.6	.64	.8	0.887	0.247	0.333	0.806
500	100	40	400	-.2	.82	.2	0.825	0.948	0.858	0.718	500	100	40	400	.6	.82	.2	0.072	0.320	0.312	0.226
500	200	40	400	-.2	.82	.4	0.784	0.979	0.818	0.800	500	200	40	400	.6	.82	.4	0.216	0.299	0.319	0.310
500	300	40	400	-.2	.82	.6	0.887	0.969	0.851	0.823	500	300	40	400	.6	.82	.6	0.351	0.309	0.325	0.358
500	400	40	400	-.2	.82	.8	0.959	0.979	0.892	0.898	500	400	40	400	.6	.82	.8	0.691	0.330	0.341	0.665
500	100	90	400	-.2	.92	.2	0.732	0.959	0.846	0.750	500	100	90	400	.6	.92	.2	0.113	0.340	0.336	0.233
500	200	90	400	-.2	.92	.4	0.794	0.948	0.808	0.741	500	200	90	400	.6	.92	.4	0.175	0.381	0.337	0.287
500	300	90	400	-.2	.92	.6	0.856	0.938	0.833	0.761	500	300	90	400	.6	.92	.6	0.361	0.330	0.335	0.379
500	400	90	400	-.2	.92	.8	0.918	0.990	0.871	0.859	500	400	90	400	.6	.92	.8	0.474	0.361	0.344	0.466
500	100	180	400	-.2	.96	.2	0.680	1.000	0.834	0.714	500	100	180	400	.6	.96	.2	0.072	0.340	0.339	0.226
500	200	180	400	-.2	.96	.4	0.804	0.979	0.826	0.809	500	200	180	400	.6	.96	.4	0.175	0.361	0.305	0.281
500	300	180	400	-.2	.96	.6	0.866	0.969	0.853	0.772	500	300	180	400	.6	.96	.6	0.392	0.381	0.337	0.364
500	400	180	400	-.2	.96	.8	0.887	0.979	0.858	0.815	500	400	180	400	.6	.96	.8	0.546	0.330	0.354	0.455
500	100	20	600	.2	.64	.2	0.165	0.495	0.409	0.309	500	100	20	600	1	.64	.2	0.103	0.216	0.258	0.260
500	200	20	600	.2	.64	.4	0.392	0.515	0.433	0.408	500	200	20	600	1	.64	.4	0.196	0.206	0.261	0.321
500	300	20	600	.2	.64	.6	0.753	0.515	0.483	0.606	500	300	20	600	1	.64	.6	0.598	0.144	0.240	0.509
500	400	20	600	.2	.64	.8	0.928	0.474	0.422	0.874	500	400	20	600	1	.64	.8	0.856	0.134	0.248	0.799
500	100	40	600	.2	.82	.2	0.196	0.557	0.420	0.296	500	100	40	600	1	.82	.2	0.082	0.175	0.227	0.192
500	200	40	600	.2	.82	.4	0.351	0.485	0.425	0.352	500	200	40	600	1	.82	.4	0.165	0.216	0.227	0.233
500	300	40	600	.2	.82	.6	0.546	0.526	0.433	0.450	500	300	40	600	1	.82	.6	0.237	0.196	0.233	0.312
500	400	40	600	.2	.82	.8	0.773	0.515	0.466	0.638	500	400	40	600	1	.82	.8	0.639	0.206	0.265	0.536
500	100	90	600	.2	.92	.2	0.124	0.567	0.438	0.292	500	100	90	600	1	.92	.2	0.041	0.196	0.216	0.179
500	200	90	600	.2	.92	.4	0.309	0.536	0.415	0.355	500	200	90	600	1	.92	.4	0.062	0.216	0.239	0.206
500	300	90	600	.2	.92	.6	0.433	0.567	0.425	0.410	500	300	90	600	1	.92	.6	0.196	0.206	0.230	0.261
500	400	90	600	.2	.92	.8	0.711	0.536	0.479	0.499	500	400	90	600	1	.92	.8	0.443	0.206	0.234	0.398
500	100	180	600	.2	.96	.2	0.124	0.588	0.418	0.302	500	100	180	600	1	.96	.2	0.082	0.165	0.222	0.175
500	200	180	600	.2	.96	.4	0.340	0.577	0.443	0.340	500	200	180	600	1	.96	.4	0.113	0.237	0.236	0.224
500	300	180	600	.2	.96	.6	0.464	0.639	0.462	0.425	500	300	180	600	1	.96	.6	0.186	0.206	0.218	0.277
500	400	180	600	.2	.96	.8	0.608	0.546	0.462	0.444	500	400	180	600	1	.96	.8	0.402	0.227	0.265	0.356

Table F2. SM Parameter Estimates

ID	$\hat{\sigma}$	se($\hat{\sigma}$)	$\hat{\rho}$	se($\hat{\rho}$)	$\hat{\mu}$	se($\hat{\mu}$)	Coop	Comment
4	1.70	1.04	0.22	0.02	-7.01	3.00	0.36	
6	n/a	n/a	n/a	n/a	n/a	n/a	1.00	Always cooperator ^A
7	11.13	9.09	0.58	0.10	-80.14	23.87	0.31	
8	1.47	2.77	0.26	0.01	-10.63	2.68	0.33	
10	61.26	17.29	0.49	0.09	-44.38	30.80	0.53	
12	22.55	5.85	0.45	0.05	-32.89	8.96	0.39	
14	n/a	n/a	n/a	n/a	n/a	n/a	1.00	Always cooperator ^A
16	n/a	n/a	n/a	n/a	n/a	n/a	0.28	underidentified ^C
18	58.44	30.45	0.26	0.18	145.13	101.69	0.84	
21	22.97	16.10	0.69	0.21	-33.11	23.07	0.48	
24	4.48	1.64	0.55	0.01	-6.76	2.98	0.80	
25	n/a	n/a	n/a	n/a	n/a	n/a	0.27	underidentified ^C
26	37.10	15.67	0.42	0.24	-106.41	68.34	0.25	
29	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
30	29.99	7.43	0.69	0.05	-90.13	19.82	0.66	
32	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
34	66.17	15.41	0.44	0.10	-57.57	26.04	0.42	
36	59.28	13.90	0.47	0.09	-130.50	35.24	0.27	
40	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
41	n/a	n/a	n/a	n/a	n/a	n/a	0.23	underidentified ^D
43	55.84	13.35	0.43	0.12	-87.56	36.39	0.33	
44	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
47	48.31	15.76	0.40	0.06	-10.51	14.15	0.53	
48	60.53	17.54	0.49	0.05	7.42	26.50	0.73	
50	57.36	12.97	0.38	0.07	-94.62	28.56	0.31	
52	20.36	5.93	0.73	0.09	-82.24	23.86	0.64	
54	38.83	19.32	0.31	0.08	-65.42	39.66	0.31	
56	15.41	6.86	0.22	0.21	-51.58	25.05	0.20	
58	89.99	46.71	-0.02	0.25	130.00	76.93	0.84	
60	24.83	6.61	0.41	0.04	-16.39	7.73	0.50	
62	n/a	n/a	n/a	n/a	n/a	n/a	0.52	underidentified ^C
64	47.54	11.17	0.52	0.06	-54.32	24.09	0.56	
67	61.25	12.93	0.59	0.06	-105.90	36.96	0.61	
68	11.71	3.01	0.46	0.03	-10.63	4.55	0.55	
71	3.45	1.52	0.26	0.02	-1.22	1.82	0.47	
72	58.30	15.82	0.67	0.09	-108.94	45.18	0.67	
74	34.70	7.98	0.53	0.07	-37.03	27.53	0.67	
76	9.22	3.32	0.40	0.03	2.51	2.59	0.69	
78	224.58	134.04	0.50	0.30	-222.47	100.79	0.25	
80	92.42	25.87	0.75	0.11	-121.75	32.87	0.42	
82	67.57	15.18	0.29	0.09	-33.97	27.15	0.42	
86	n/a	n/a	n/a	n/a	n/a	n/a	0.98	underidentified ^C
88	67.67	15.68	0.57	0.09	-131.87	32.02	0.33	
89	15.33	4.77	0.50	0.03	-6.45	7.64	0.73	
90	41.07	25.40	0.53	0.11	-102.48	58.86	0.25	
93	34.63	9.40	0.61	0.05	-50.47	21.55	0.72	
95	63.57	18.72	0.57	0.14	-54.09	35.65	0.58	
99	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
100	87.77	21.50	0.32	0.11	-85.55	39.44	0.28	
102	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
103	108.11	34.74	0.17	0.18	78.88	54.85	0.66	
104	45.50	15.73	0.36	0.17	-80.41	43.37	0.28	
107	5.03	2.92	0.40	0.01	-2.23	2.31	0.56	
108	n/a	n/a	n/a	n/a	n/a	n/a	0.27	underidentified ^C
112	89.54	58.72	0.36	0.19	127.50	103.22	0.92	
114	n/a	n/a	n/a	n/a	n/a	n/a	1.00	Always cooperator ^A
115	43.05	15.06	0.28	0.08	-2.24	12.13	0.52	
116	867.48	5387.21	-0.46	7.01	2091.30	13444.71	0.98	

121	334.13	766.01	-0.80	3.64	1006.42	2631.20	0.94	
122	0.52	0.40	0.25	0.00	-3.43	0.67	0.41	
124	12.66	4.78	0.45	0.03	-14.22	11.05	0.63	
125	37.86	11.92	0.37	0.11	-63.74	37.19	0.34	
127	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
129	64.16	20.48	0.44	0.07	-47.93	20.53	0.48	
130	n/a	n/a	n/a	n/a	n/a	n/a	1.00	Always cooperator ^A
132	80.39	62.12	0.67	0.21	42.34	162.68	0.97	
134	57.73	14.28	0.54	0.07	-60.84	17.35	0.39	
137	11.35	6.58	0.23	0.03	-14.15	9.60	0.31	
139	64.18	15.60	0.73	0.07	-133.02	28.49	0.39	
142	39.53	10.47	0.60	0.06	-71.42	19.33	0.47	
144	27.01	6.55	0.22	0.08	28.67	18.76	0.55	
145	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
146	16.74	7.24	0.67	0.05	-202.86	19.98	0.27	
149	n/a	n/a	n/a	n/a	n/a	n/a	0.98	underidentified ^D
150	n/a	n/a	n/a	n/a	n/a	n/a	1.00	Always cooperator ^A
152	n/a	n/a	n/a	n/a	n/a	n/a	0.27	underidentified ^C
155	31.06	10.21	-0.05	0.13	-11.57	20.54	0.28	
158	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
159	53.04	13.20	0.07	0.24	-8.88	47.65	0.27	
161	31.92	7.76	0.47	0.08	-61.37	19.37	0.34	
163	31.65	8.03	0.50	0.03	-23.27	13.77	0.67	
164	9.11	3.53	0.21	0.02	-1.26	4.13	0.38	
166	81.22	32.15	0.36	0.12	90.24	59.85	0.83	
168	32.48	9.56	0.64	0.05	-36.33	12.38	0.70	
170	19.18	5.86	0.45	0.05	-3.84	16.91	0.69	
172	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
174	170.96	62.77	0.73	0.19	-122.79	85.22	0.63	
176	61.14	18.38	0.62	0.09	-120.80	37.76	0.28	
181	n/a	n/a	n/a	n/a	n/a	n/a	1.00	Always cooperator ^A
182	16.45	4.59	0.43	0.04	-17.12	10.51	0.53	
184	84.20	24.71	0.46	0.06	-31.14	21.01	0.52	
187	68.89	21.06	0.43	0.08	-4.05	25.20	0.66	
189	33.65	10.21	0.59	0.05	-44.72	17.79	0.70	
190	34.83	20.85	0.30	0.17	-56.78	39.67	0.28	
192	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
193	n/a	n/a	n/a	n/a	n/a	n/a	0.25	Payoff maximizer ^B
194	2714.81	15354.74	-1.10	9.73	511.17	3379.62	0.52	Outlier

Notes. The estimates above are for SM and follow the econometric specification as outlined in the paper. For 26 individuals we cannot obtain maximum likelihood estimates because a linear combination of the regressors perfectly predicts outcomes. Of these cases of underidentification,

A: 6 always cooperate – choices perfectly predicted using a model with only a constant;

B: 12 maximise own payoff – choices perfectly predicted using a model with only $q(R-T)$;

C: 6 further underidentified cases can be perfectly predicted using a model with a constant and $q(R-T)$

D: 2 further underidentified cases can be perfectly predicted using a constant, $q(R-T)$ and $q(T-S)$.

One individual is treated as an outlier as the estimate of $\rho < -1$.