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GAME PERCEPTION AND HARMONY IN 3 X 3 GAMES

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Abstract

The experiment presented in this paper employs 3×3 games to analyze how perception of a game affects behavior in the presence or absence of a minimal framing effect and of uncertainty about the values of some game payoffs. We vary the harmony of practice stage games, and explain how this changes later behavior. We employ techniques, such as payoff integration and similarity evaluations, that could be used in further research to open the black box of framing effects. Game harmony is a measure summarizing how harmonious the interests of the players are in the game. It is associated with cooperation.

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Game Perception and Harmony in 3×3 Games

1. Introduction

This paper is based on the intuition that how an economic agent perceives a game is important for her to decide how to play it. Whether, for example, an agent perceives a Prisoner's Dilemma as such or as a Chicken or perhaps even a coordination game may make a difference between whether she decides to cooperate or not. Framing effects can have pervasive, and yet poorly understood, effects on cooperation rates (e.g. Cookson, 2000): we argue that framing effects can be understood as being due to differences in the way that decision problems are perceived, and we provide tools to make progress in understanding how they operate. Further, one can shed light on how certain perceived game features, such as 'game harmony', affect cooperation in games.

Game harmony is identified as a scalar measure summarizing how harmonious or disharmonious the interests of the players are in the game (Zizzo, 2003). A pure coordination game is an example of perfectly harmonious game, and a zero-sum game one of a perfectly disharmonious game: most games are somewhere in the middle.

Our experiment finds a strong correlation between game harmony and cooperation in games. In addition, we employ the same "minimal framing" manipulation used with 2×2 games by Zizzo and Tan (2003): practice stage games can be of different average levels of *game harmony* across games (high, medium or low). Hence, in the practice stage subjects faced games entailing different levels of "cooperativeness". The simplest framing effect prediction is that subjects should play more cooperatively in later game play the more harmonious the games they have faced in the practice stage.

Agents often face incomplete and ambiguous decision problems in economic transactions. These sources of complexity may derive from a variety of sources, from lack of information to contract incompleteness to cognitive limitations in processing information. If there is any residual of incompleteness in the specification of a game for any reason, agents will have to form their own mental models of the decision problem and, in so doing, they may use any clue they can get. The clues may be provided by *game antecedents*, i.e. by anything that may have happened before the game. For example, subjects may have been asked to do some task inducing a 'cooperative frame' or an 'entrepreneurial frame': much experimental evidence suggests that this or other framing effects have an impact on cooperation (e.g., Elliott et al., 1998; Morris et al., 1998; Cookson, 2000).

Framing effects might be thought to operate more the more the ambiguity about the game. Yet, game ambiguity may affect game play also in another way: by increasing its complexity, behavior in it might be better describable by simpler, less cognitively demanding algorithms. Our experiment uses 3×3 games in order to enable or facilitate the identifiability of play according to different non-cooperative algorithms. For example, if we had 2×2 games one would not be able to distinguish D1 (defined as one round of strict iterated dominance) from D2 (defined as two rounds of strict iterated dominance).

We develop methods to better understand how subjects deal with uncertainty about the game payoff values and how this interacts with framing effects: these methods are based on the incentive-compatible elicitation of payoff guesses and of similarity evaluations between games. We believe that the development of tools to understand framing effects is an important task, since all too often framing effects are noted but not explained, notwithstanding their potentially large effect on behavior (for example, on cooperation in social dilemmas).

The rest of this paper is organized as follows. Section 2 describes the concept of game harmony and otherwise presents the experimental background. Sections 3, 4 and 5 present the experimental design, hypotheses and results, respectively. Section 6 concludes. Appendices A and B contain the experimental instructions and a list of regression variables (as referred to in Section 5.3), respectively.

2. Experimental Background

This section briefly clarifies the concept of game harmony as discussed in Zizzo (2003) and reviews the evidence on game harmony and game perception.

2.1 Game harmony

Following Zizzo (2003), let Γ be a finite n -person game in normal form, and let N be the set of players such that $|n| = N$. Denote W_i the actions available to player i , so $W = W_1 \times W_2 \times \dots \times W_n$ is the set of possible outcomes or states of the world, each of which we label by w in W . Payoffs are defined by $x_{iw}: W \rightarrow \mathbb{R}$, a standard Von Neumann-Morgenstern utility function, and so x_{iw} is the payoff for player i ($i \in N$) in state of the world w . For n players, there are $C = \frac{1}{2} n (n - 1)$ player pairs. Let us label the payoffs x_{iw} for each pair c as a_{cw}, b_{cw} for $w \in W$. We can then define the cardinal harmony $G(\Gamma)$ of game Γ as the arithmetic mean of the Pearson correlations between the C pairs of Γ :

$$G(\Gamma) = G(x_i, W) = \frac{1}{C} \sum_{c=1}^C r_c(a_{cw}, b_{cw}) = \frac{1}{C} \sum_{c=1}^C \frac{\text{Cov}(a_{cw}, b_{cw})}{\sigma_a \sigma_b}$$

(1)

In the case of 3×3 games, $C = 1$, so $G(\Gamma) = r(a_w, b_w)$, which is obviously bounded between -1 and +1. An equivalence result can be shown to hold between perception of a game as more or less harmonious and payoff transformation. The payoff transformation could be psychological (e.g., altruism) or it could just reflect the relationship that may hold, at least at a first approximation, between any two given payoff matrices. Let the payoff transformation for agent i be defined by the function:

$$V_{iw} = x_{iw} + \sum_{j \neq i}^n \beta_i x_{jw}$$

(2)

where $\beta_i \in [-1, 1]$ is the weight on j 's utility component. In the non-psychological interpretation, (2) would just state an operator mapping game Γ^u with payoffs x_{iw} (the untransformed payoff matrix) into a game Γ^v with payoffs V_{iw} (the transformed payoff matrix) $\forall i, w$. The greater game harmony associated to a positive payoff transformation will imply greater cooperation in all games where such simple payoff transformation will help to attain it (such as in the Prisoner's Dilemma).

A closely related measure of game harmony can be obtained by considering payoff orderings rather than cardinal values. Let X_i be the set of all payoff values for player i in W , and let $x_{iw}^p = \text{rank}(x_{iw} | X_i)$, which can be mapped into rank payoff pairs a_{cw}^p, b_{cw}^p . Then:

$$G_p(\Gamma) = G_p(x_i, W) = \frac{1}{C} \sum_{c=1}^C r_c(a_{cw}^p, b_{cw}^p)$$

(3)

In the case of 2×2 games, this reduces to $G_p(\Gamma) = r_c(a_{cw}^p, b_{cw}^p)$. While undoubtedly not the only possible measures of game harmony, $G(\Gamma)$ and $G_p(\Gamma)$ have the virtues of general applicability, simplicity and lack of degrees of freedom.

Kelley and Thibaut (1978) devised a more complex “index of correspondence” (IC) applying only to 2-player games, and which multiplies $G(\Gamma)$ by a function of the variances among the payoffs. Conceptually, their measure mixes pure game harmony concerns with how much each agent stands to gain from cooperation. However, in the set of games played in the main part of our

experiment, the correlation between $G(\Gamma)$ ($G_p(\Gamma)$) and IC was as high as 0.999 (0.998), and as a result there is no value added in using the more complex and less general measure rather than just $G(\Gamma)$ or $G_p(\Gamma)$.

Zizzo and Tan (2003) found that simple game harmony measures could explain between 31 and 45% of the variance in mean cooperation rate in a sample of randomly generated 2×2 games, and between 57 and 93% of the variance in a sample of mostly well-known 2×2 games, such as the Prisoner's Dilemma (PD), the Stag-Hunt, the Chicken, a coordination game and three variants of trust games. They also had the minimal framing manipulation discussed in the introduction and found that it was ineffective in changing the mean cooperation rate.

2.2 Game perception

The experiment presented in this paper differs from that of Zizzo and Tan (2003) in at least two important respects. First, the game samples are different: we employ 3×3 games and, with two exceptions (two 3×3 variants of the PD), we only use randomly generated games. Second, while in Zizzo and Tan (2003) payoff matrices are always displayed in their complete form, our experiment has treatments where some payoff cells are hidden and in relation to which subjects are asked to guess incentive-compatibly what the payoff values are, before playing each game. There are also treatments where some payoff cells are hidden but there is no guessing task or where, conversely, subjects are simply asked to guess random numbers.

There has been only limited work in experimental economics trying to address how agents perceive the game they are playing. In Mitropoulos' (2001) experiment, subjects were unaware about the structure of the game except that payoffs cells were either 0 or 1, and unaware of the actions by the other player: they were actually playing a very simple 2×2 game (the mutual fate control game), and Mitropoulos was interested in how subjects got to coordinate on the equilibrium. Costa-Gomes et al. (2001) worked experimentally with a variety of normal-form games: they collected useful information on the cognitive process guiding agents to action by allowing only one payoff cell to be open for the subjects to see at any one time, with a click of the mouse. Oechssler and Schipper (2000) were also interested in how agents learn to know about the structure of the game: subjects know their normal form game matrix payoffs, but not those of the other player. They could infer information about the structure of the game from the feedback on the actual payoff received after each round. They were also asked, and knew they would be asked, questions on the payoff structure (ordering between payoffs), so that there was an actual incentive for guessing the

correct structure of the game. One interesting aspect of these papers is that cognitive processes were studied by *hiding away*, one way or another, information about the payoff structure at any given time. We followed the lead, but expanded it in a new direction by asking subjects directly to make guesses on the payoff values.

3. Experimental Procedure

3.1 Design overview

The experimental sessions were run in the Department of Economics in the University of Oxford in May 2001 (Treatments 4-7), December 2001 (Treatment 8) and May 2002 (Treatments 1-3). Treatments 1 through 7 had 16 subjects each, for a total of 112 subjects;¹ treatment 8 was a control task at the start of a different experiment involving 61 subjects. Subjects were mostly undergraduate or postgraduate students, but not exclusively so. All treatments were computerized and partitions were used between subjects to ensure the anonymity of their decisions. An overview of the treatments is provided by Table 1.

(Insert Table 1 about here).

Treatments 1 through 7 had a common structure. Four subjects participated to each session. There were three stages.²

In Stage 1, subjects did practice by choosing actions in fully displayed 3×3 games, one game at a time in six rounds. Subjects were matched with the same coplayer throughout the stage, and received feedback on game outcomes after each round. The practice games set varied across treatments, as analyzed shortly.

In Stage 2, subjects were presented with ten 3×3 games in sequence, and never received any feedback on the outcome of their choices after each game in the sequence. They knew they were matched with a different coplayer from the one of the practice stage. What subjects saw on the computer screen and had to do varied across treatments, but, whatever the treatment, subject always had to choose an action in relation to the game.

¹ We later discovered that in Treatment 7 a subject was a (heavily game-theory-trained) Oxford M.Phil. Economics student, and another one had done the Zizzo and Tan (2003) experiment just a few weeks earlier. Their choices are removed from all the analysis below (and from the sample size as reported in Table 1).

² In order to check understanding of the instructions, subjects filled questionnaires at the start of each stage. Their answers were checked by experimenters, and, if any was incorrect or missing, the relevant points were explained individually.

Stage 3 involved no interaction and this was known in advance: subjects were simply asked to assess incentive-compatibly the similarity of sixteen game matrices presented in sequence on the computer screen to a comparison game they had in print (the “comparison decision table”, CDT for short). The focus of this paper is on Stage 2, but we shall refer briefly to some result from Stage 3.

3.2 Stage 1 (Treatments 1-7)

There were three different experimental conditions in Stage 1, according to whether subjects faced a sample of games with mean high, medium or low game harmony (High, Medium and Low condition, respectively), as measured by $G(\Gamma)$ and $G_p(\Gamma)$: Low corresponded to Treatments 1 and 4, Medium to Treatments 2, 5 and 7, and High to Treatments 3 and 6 (see Table 1).

Games were chosen drawing payoff values randomly from a uniform distribution between 0 and 100, under the restriction that they all had to have a unique pure Nash equilibrium; this was to guarantee that games would be of not too widely different strategic complexity.³ Mean $G(\Gamma)$ was -0.890, 0.159 and 0.902 in the Low, Medium and High condition, respectively: Table 2 lists the games used.

(Insert Table 2 about here).

Subjects played for six rounds with the same player. Each round they faced a different game, and after the decisions were made they would receive feedback on the game outcome. Subjects did not play the practice stage for real money.

3.3 Stage 2 (Treatments 1-7)

Subjects played ten different games, this time not receiving any feedback on the game outcome. They were matched with a different coplayer from the one they had faced in Stage 1. They also knew that this was the last stage in which they would interact with other participants.

Treatments 1-3 (Visible condition). In Treatments 1-3, subjects simply had to choose an action each round. Game matrices were fully visible on the computer display. They were games with randomly generated payoffs, except those in rounds 9 and 10, which were variants on the PD.

In the payment stage at the end of the experiment, a round would be picked up randomly by the computer to determine the *action payment* on the basis of the action payoff points earned in that round. The resulting payoffs were converted in UK pounds at the rate of £ 0.05 per experimental point.

³ We also checked that the game samples were not otherwise meaningfully different in other undesired respects (e.g., in the distribution of mean payoff values or in that of equilibria according to non-Nash algorithms).

Treatments 4-6 (Guess condition). In Treatments 4-6, the right diagonal of the game matrix was “hidden” by question marks (see Figure 1).

(Insert Figure 1 about here).

Subjects were first asked incentive-compatibly to replace the question marks with their best guesses of the expected payoffs (“to replace the question marks with the point numbers that you guess correspond to each hidden cell”) and then they had to choose actions. The guesses were just such, and had no effect on the actual payoff values hidden in each cell. Subjects knew that payoffs had to be between 0 and 100. At the end of the experiment, the *guess payment* was determined on the basis of the guess made in a randomly chosen round, different from the one determining the action payment. In relation to this round, subjects were paid £ 3 to get the guess exactly right, with a penalty of £ 0.12 per each point of error (subjects were paid zero for getting the guess wrong by 25 points or more). Thus, a standard absolute difference incentive-compatibility mechanism was implemented (e.g., Croson, 2000). The instructions contained a table with details on the amount of payment for any given level of error, and so subjects were not required to make any significant computation.

Treatment 7 (Frozen condition). Treatments 1 through 6 crossed two factors: practice stage game harmony and need for payoff integration. However, the Guess condition differed from the Visible condition not in one but in two ways: subjects faced the payoff cells covered by the question marks (the “hidden cells”) *and* they had to guess what payoff values were hidden by the question marks. We had a control condition that had the first change but not the second: in Treatment 7, the right diagonal of the game payoff matrix was hidden by question marks, but these were “frozen”, i.e. they could not be replaced with numbers. Subjects simply had to choose game action on the basis of the incompletely displayed payoff matrix.

3.4 Stage 3 (Treatments 1-7)

Subjects were asked to assess incentive-compatibly the similarity of sixteen game matrices presented in sequence on the computer screen to another game, the “comparison decision table” (CDT in what follows, see Figure 2), they had in print.⁴

(Insert Figure 2 about here).

⁴ This methodology is well-known in cognitive psychology (e.g., Hahn and Chater’s, 1997, review). In economics, Buschena and Zilberman (1999) asked subjects to evaluate the similarity between standard binary lottery choices. Gilboa and Schmeidler’s (2001) case-based decision theory is a possible formalization of reasoning by similarity.

The games were different from those of Stage 2, and the payoffs were chosen drawing numbers between 0 and 100 from a uniform distribution, with eight games out of the sixteen having unique Nash equilibria. The order of presentation of the games was randomized across subjects. Another incentive-compatibility mechanism was in place to determine the *similarity payment*: one round out of sixteen was chosen randomly, and an absolute difference incentive-compatibility mechanism was in place, with £ 6 as maximum payment, and £ 0.24 deducted for every point off the mark. Payment was determined at the end of the experiment and subjects received no feedback on the outcome of their choices during Stage 3. For this reason, the determination of the “correct” similarity answer was an issue that had to be practically addressed in order to ensure financial motivation and determine payments, but not one with serious bearing on the experiment. This was important since any choice of “correct” similarity values was bound to be somewhat arbitrary, and a potential source of distortions in the experiment if learning feedback had been provided.⁵ In total, payments could range between £ 4 and (depending on the treatment) £ 15 or 18; actual mean payments were in the order of 8-9 pounds for about 45-75 minutes of work (a short questionnaire was administered at the end).

As the Stage 3 games were different from those of Stage 2, the similarity choices will be only limitedly useful for the analysis of this paper. Nevertheless, we shall mention one result from Stage 3 that is directly relevant to how Stage 2 games were perceived.

3.5 Treatment 8

Treatment 8 was an individual choice experiment, and this was known in advance. It worked as a control condition with respect to the guessing task of Treatments 4 through 6. In each session, between 13 and 18 subjects had to guess a number between 0 and 100 in each of six cells. One of the six cells was then chosen at random. The number chosen in this cell was compared by the computer to a randomly determined “correct” answer and subjects were paid according to the same absolute difference payment scheme used for the guess payment in Treatments 4-6: they got a guess payment equal to 3 UK pounds minus 12 pence for every point by which the guess was incorrect (with a minimum of 0 if the guess was wrong by 25 points or more).

⁵ The “correct” similarity value was determined giving equal weight to the absence of a unique pure Nash equilibrium (as in both the CDT) and to the Euclidean distance between the payoffs (*EDP*). Let *Unique* be equal to 1 when there is a unique pure Nash equilibrium, and let $\max(EDP)$ and $\min(EDP)$ the maximum and minimum *EDP* values in relation to the 16 games. Then the “correct” answer was determined as $50 \times \text{Unique} + 50 \times [(EDP - \min(EDP)) / (\max(EDP) - \min(EDP))]$.

4. Experimental Hypotheses

We can now define our experimental hypotheses with more precision; all hypotheses are defined in relation to Stage 2 games when not specified otherwise.

H1 (Game harmony). Higher game harmony is associated to higher mean cooperation rates (as in Zizzo and Tan, 2003). In Treatments 1 through 3, where subjects are faced with complete payoff matrices and hence can compute the harmony of the game, we should expect a positive correlation between game harmony and mean cooperation rate.

H2 (Assimilation effect). The framing effect induced by the game harmony in the practice stage operates by *assimilation* to the harmony of the practice stage games. If so, mean cooperation is greater, and in the Guess condition δ (as defined below) is smaller, the higher the harmony of the practice stage games.

A framing effect could also operate by *contrast* of a game with a previous game: for example, an agent who has had experience with very harmonious games might notice how different, in terms of harmony, those games appear relative to the game she is now playing, and so, by contrast, cooperate less than she otherwise would.⁶ Any contrast effect works in the opposite direction to the assimilation effect, and the two could cancel each other out. It may be difficult to discriminate between the absence of framing effects and existence of a contrast effect. One way of doing so is to look at the guesses in Stage 2: define a variable, δ , as the root mean square of the difference between one's own guess of one's own and the coplayer's gains - a_{ij}^g and b_{ij}^g (respectively) -, averaged out across the three right diagonal outcomes:

$$\delta = \left[\frac{(a_{13}^g - b_{13}^g)^2 + (a_{22}^g - b_{22}^g)^2 + (a_{31}^g - b_{31}^g)^2}{3} \right]^{\frac{1}{2}} \quad (4)$$

δ measures how different a subject guesses her payoff relative to that of her coplayer. If there is an assimilation effect, we would expect δ to be smaller the greater the harmony of the practice

⁶ Contrast effects are well known in psychophysics (see Kahneman and Varey, 1991).

stage games. This would not happen if a contrast effect were to dominate. An alternative possible way is by analyzing Stage 3 similarity choices: if a subject is being liable to a contrast effect, then we would expect a significantly lower similarity rating between games than if (only) an assimilation effect were operative.

H3 (Contrast effect). The framing effect induced by game harmony in the practice stage also operates by *contrast* to the harmony of the practice stage games. It would be evidence for this if we found that (a) δ does not vary as predicted by H2 and (b) the mean similarity rating in Stage 3 is lower while the Stage 2 cooperation rate is not higher.

H4 (Interaction effect). If we accept that the Guess condition presents more ambiguous decision problems for the subjects than those in the Visible condition, then subjects might rely more on past experience, i.e. we would expect a greater effect of practice stage game harmony on Stage 2 cooperation in the Guess condition than in the Visible condition.

Whether *H4* holds or not will depend on the counterbalancing of assimilation and contrast effects. The last two hypotheses are related to how the guesses are formed and to how the problem complexity affects decision-making.

H5 (Guesses as non-random). Guesses give an indication of the expected payoff values by the subjects in the hidden cells of Treatments 4-6. Thus: 1) subjects do not choose payoff guesses at random; 2) they take guesses into account in choosing what action to play.

H6 (Problem complexity). Under the assumption that H5 holds, subjects appear to rely on simpler algorithms when dealing with incomplete payoff matrices than otherwise. The cooperation rate may also change.

5. Experimental Results

We shall organize the presentation of our data around the experimental hypotheses listed in the previous section.

5.1 Test of H1: Cooperative Outcomes and Game Harmony

In order to test for the association between $G(\Gamma)$ [or $G_p(\Gamma)$] and cooperation, we need to define what we mean by a “cooperative action”: while this is uncontroversial in the two variants of the PD, it may not be so in the other games. We define a cooperative action as the action associated to the utilitarian solution, i.e. the combination of actions yielding the highest sum of payoffs. This is clearly not the only possibility. An alternative that gives similar results is to employ the Nash bargaining solution, i.e. to refer to the combination of actions yielding the highest *product* of payoffs. Zizzo and Tan (2003) used a narrower notion with a generic and much larger ($n = 30$) dataset of (2×2) games: they considered an outcome cooperative if (a) the cooperative outcome does not coincide with a strictly dominant solution and if (b) the utilitarian and Nash bargaining solutions coincide. Appendix A discusses the implications of using this narrower notion for the hypotheses of this paper.

We focus on Treatments 1-3, not just because they are the only ones where subjects had full knowledge of the material payoff matrix: after all, in Treatments 4-6 we could rely on the subjective guesses by the subjects to “complete” the payoff matrix and obtain a subjective (“guess-integrated”) payoff matrix. We use this method in the next subsection. However, it is inapplicable here since no two guess-integrated payoff matrices are exactly the same, and so we are not able to estimate a mean cooperation rate, for each guess-integrated payoff matrix, over a sample sufficiently large to be informative.

Let us define c_g as the mean cooperation rate in each game in Treatments 1-3, those where subjects had full knowledge of the material payoff matrix. H1 predicts a positive correlation between $G(\Gamma)$ [or $G_p(\Gamma)$] and c_g : this is indeed the case, since Pearson $r[G(\Gamma), c_g] = 0.627$ and Spearman $\rho[G(\Gamma), c_g] = 0.579$, while Pearson $r[G_p(\Gamma), c_g] = 0.601$ and Spearman $\rho[G_p(\Gamma), c_g] = 0.603$ (in both cases, $P < 0.05$, $n = 10$). This correlation is illustrated in Figure 3, where game 4 is the noteworthy outlier.

(Insert Figure 3 about here).

It is striking to find that the cooperation rates in the PD variants were below 10% in our experiment, definitely below those found in psychological experiments (e.g., Pruitt and Kimmel, 1977). Since the game is a 3×3 variant of the PD, it is possible for the agent to cooperate *partially*, and this is not captured by c_g . This might bias downwards an eventual finding of correlation between cooperation rate and game harmony measures.

A more detailed analysis would recognize that, due to the asymmetric nature of all the games (with the exception of the PD variants), we should really analyze the cooperation rate by player role, rather than just by game. This is bound to decrease the correlation coefficient, since this within-game cooperation rate variance cannot be explained by a measure that applies at the level of the game rather than at that of the single player.⁷ Let c_r be the mean cooperation rate by player role rather than just by game. The correlation coefficients drop by about 0.1-0.15, which is comparable to the equivalent analysis for one of the samples of Zizzo and Tan (2003): $r[G(\Gamma), c_r] = 0.485$ and Spearman $\rho[G(\Gamma), c_r] = 0.456$; $[G(\Gamma), c_r] = 0.466$ and Spearman $\rho[G(\Gamma), c_r] = 0.500$ (in all cases, $P < 0.05$, $n = 20$).

Notwithstanding the qualifications, there is strong support for *H1*:

RESULT 1. *Simple game harmony measures are strongly associated with cooperation, as predicted by H1.*

5.2 Test of H2-H4: Framing and Game Perception

The mean cooperation rates by treatment c_t are listed in Table 1. In the Frozen condition, the cooperative outcome was defined over the visible payoff cells. In the Guess condition, it was defined over the guess-integrated payoff matrix, the game matrix that replaces the question marks with the guesses by the subject.⁸

c_t generally increases with the practice stage game harmony, as for *H2*, but with one exception: in the Guess condition, Low and Medium (i.e., Treatments 4 and 5) both have $c_t \approx 0.47$. A *F* test employing game harmony condition *H* and game matrix incompleteness condition *I* as factors yields significance for *I* [$F(1, 1093) = 5.921$, $P < 0.01$], marginal significance for *H* [$F(2, 1093) = 2.791$, $P < 0.07$], and insignificance for the interaction effect [$F(2, 1093) = 0.594$, *n.s.*]. By lumping Low and Medium together, we get significance not only on *I* [$F(2, 1095) = 6.121$, $P < 0.01$] but also on *H* [$F(2, 1095) = 5.359$, $P < 0.05$]; the interaction effect remains insignificant [$F(1, 1095) = 0.780$, *n.s.*].

How do we reconcile our finding of marginal significance of *H* with the insignificance with 2×2 games pointed out by Zizzo and Tan (2003)? The answer comes from doing separate *F* tests on

⁷ One could devise less parsimonious measures of game harmony that are subject-specific: see Zizzo (2003) for details.

⁸ This method implicitly relies on *H5*, the evidence for which is discussed in section 5.3.

H in the Visible condition and in the Guess condition: in the Visible condition, $F(2, 467) = 0.827$ ($P = 0.438$, *n.s.*); in the Guess condition, $F(2, 477) = 2.570$ ($P = 0.078$). Thus, even though there is not a significant interaction effect with the more global F tests, the marginal significance of H in them appears driven by the Guess treatments.

By lumping Low and Medium we are increasing the significance of H since we are neglecting that c_t is the same in Treatments 4 and 5. The existence of a counterbalancing contrast effect, as for $H3$, may explain this finding. To verify whether this is so, we now look at the Stage 2 δ values and at the Stage 3 similarity choices.

Table 1 lists the mean δ and similarity values by treatment s_t . A F test on δ using H as factor is significant [$F(2, 477) = 21.970$, $P < 0.001$]: Scheffé' and Tukey post-hoc tests indicate a significance of the difference between High and the other two conditions ($P \leq 0.001$). While this supports $H2$, the finding that δ is lower, or at least the same, in Medium relative to High is a strong indication that a contrast effect is at work (as for $H3$).

The lowest similarity value is for Treatment 4, the Low, Guess condition. A F test of I and H on s_t yields insignificance for I [$F(2, 1753) = 0.585$, *n.s.*], significance for H [$F(2, 1753) = 3.427$, $P < 0.05$] and more so for the interaction effect [$F(2, 1753) = 14.844$, $P < 0.001$]. In the light of the significance of the interaction effect, there is therefore evidence that subjects tend to evaluate games as less similar to one another in Treatment 4, as a contrast effect would predict.

We can summarize our results as follows:

RESULT 2. There is a contrast effect (as for H3) when game matrices are incomplete and the practice stage game harmony is low.

RESULT 3. Controlling for Result 2, cooperation is increasing in the practice stage game harmony because of an assimilation effect (as for H2).

RESULT 4. Result 3 is significant only because of the Guess condition: this suggests that this assimilation may be stronger when game matrices are incomplete, although the evidence for H4 is otherwise unfavourable.

5.3 Test of H5: Forming Payoff Guesses

Do subjects make payoff guesses entirely at random? A question in the final questionnaire asked subjects to state how much they agreed with a statement that they had picked up numbers at a random, on a scale between 0 (minimum) and 10 (maximum): the mean valuation was just 2.660 (this was not significantly different across treatments). This contrasts with other answers in the final questionnaire, with much higher ratings: for example, a question asking how clear the instructions were received a mean rating of 8.266.

We can compare the histogram of mean random guesses by subject given in Treatment 8 ($n = 60$) to the mean guesses of the comparable first Stage 2 round of the Guess condition (Treatments 4-6, $n = 48$).

(Insert Figure 4 about here).

A non-parametric Epps-Singleton test shows that the two distributions are significantly different from one another [$\chi^2(4) = 15.932$, $P < 0.05$]. The same result holds if we compare the mean random guesses in Treatment 8 with the mean guesses for all rounds in Treatments 4-6 ($n = 480$): in an Epps-Singleton test, $\chi^2(4) = 33.242$ ($P < 0.001$). Whatever they were doing, subjects in Treatments 4-6 were not just generating numbers at random.

If subjects do not make payoff guesses at random, we would expect that they use past and current information about the game to formulate guesses about the expected payoff values in each payoff cell. Three subjects do not: they just always chose 50.⁹ If we exclude them from the sample, we can use regression analysis to explore the determinants of δ .¹⁰ We started with a model with a large set of independent variables, and iteratively eliminated those that failed to pass a significance test.¹¹ Details on the set of independent variables used in the most general model are included in Appendix B. Table 3 presents the final model.

(Insert Table 3 about here).

The variables in Table 3 can be classified in four groups. First, there are some personal variables (*DAge*, *HardSciences* and *AmbiguityAv*). *HardSciences* is a dummy equal to 1 for students

⁹ One of these three subjects put 40 in one hidden cell out of the sixty faced between round 1 and 10.

¹⁰ A random-effects regression model was used to handle individual-specific effects, as each subject made ten choices and there is evidence suggesting their existence (using a Bresch-Pagan Lagrange multiplier test) and the adequacy of a random-effects specification (using a Hausman specification test).

¹¹ Some variables were constructed using questionnaires given at the end of the experiment. Since these questionnaires were given only from the second session, the regression models do not use the observations from the first session (and so $n = 410$).

in the hard sciences. *AmbiguityAv* is an index of ambiguity aversion built using the final questionnaire (see Appendix B): the larger *AmbiguityAv*, the smaller the measured ambiguity aversion.

Second, there are variables based purely on game features: *MeanNRD* and *SdNRD* respectively refer to the mean and standard deviation of payoffs not on the right diagonal. The coefficient on *SdNRD* is interpretable as an assimilation effect: a larger standard deviation of available payoffs can be interpreted as a larger variability of right-diagonal payoffs, which may produce a larger DI value.

Third, there are variables based purely on game antecedents: *St1Payoff*, *St1NegDiff* and *High*. *St1Payoff* is the average payoff obtained by the subject in Stage 1.¹² *St1NegDiff* is the average difference between own own's and the coplayer's gains in Stage 1, if negative (otherwise it is equal to zero). The coefficients on these variables suggest that having earned more fictional money in Stage 1 made the subject more likely to perceive things as entailing scope for cooperation, but lagging behind worked as powerful negative reinforcement. *High* (*Low*) is equal to 1 in the High (*Low*) condition, and 0 otherwise. The coefficient on *High* is indicative of the assimilation effect, and that on *Low* of the contrast effect at work.

Fourth, there are interaction variables between experimental condition and game harmony outside the right diagonal; a main effect variable for game harmony outside the right diagonal was removed in the reduction process. *Medium* $\times$ *GHnRD* is equal to *Medium* $\times$ $G(\Gamma)$ computed over the visible part of the payoff matrix; similarly for *HighGH* $\times$ *GHnRD*. While the largest coefficient is on *MediumGH* $\times$ *GHnRD*, the coefficient on *HighGH* $\times$ *GHnRD* is also significant. Not only does experience with high game harmony in the practice stage lead to a cooperative frame, interpreted as a perception of more harmonious interests in subsequent game playing, but also the effect is stronger when what is known about the game lends itself better to a cooperative interpretation.

Clearly, the data is noisy, as shown by the low within-subject R^2 . One obvious source of noise is likely to be rounding: 0.253 of the guesses involved multiples of 10, over twice as many as we would expect with a uniform distribution of guesses between 0 and 100 ($P < 0.001$), while 0.433 involved multiples of 5, versus a null of 21% ($P < 0.001$). Equally clearly, though, subjects did not simply choose numbers at random. Further, δ values agree with data on cooperation and similarity

¹² Note that practice stage gains were not convertible in real money, and everybody knew it, so the significance of the coefficient on *St1Payoff* cannot be interpreted as a wealth effect.

rating suggesting that in the Low, Guess condition a contrast effect was at work, and a small but significant correlation can be found between δ values and cooperative choices: lower perceived payoff inequalities between oneself and the coplayer were associated to greater cooperation (Pearson $r = -0.118$, Spearman $\rho = -0.124$, $d.f. = 449$, $P < 0.01$).

RESULT 5. *As for H5, subjects do not make payoff guesses entirely at random. It is possible to explain about half of the between-subject variance.*

RESULT 6. *The practice stage game harmony affected δ 1) either by contrast (in moving from Medium to Low) or by assimilation (in moving from Medium to High); 2) in the Medium and High conditions, by making agents more sensitive to the level of game harmony as emerging from the visible part of the payoff matrix.*

RESULT 7. *As for H5, payoff guesses were related to actual cooperation.*

5.4 Test of H6: Problem Complexity

We found in section 5.2 that a F test using H and I as factors is significant for I .

RESULT 8. *Cooperation increases in the complexity of the decision problem. This is compatible with H6.*

How does problem complexity affect the use of non-cooperative algorithms by the subjects? Define $P(e_m)$ as the frequency with which a unique action prescribed by the algorithm m is identifiable in a given sample over the visible or guess-integrated payoff matrix (in the Visible and Guess conditions, respectively). Define $P(m | e_m)$ as the (conditional) frequency that the unique m action is followed given that a unique e_λ exists, and $P(m)$ as the (unconditional) frequency that the unique m action is followed. Table 4 displays the values of $P(e_m)$, $P(m | e_m)$ and $P(m)$ for the following non-cooperative algorithms: 1) Nash; 2) minmax; 3) “0-level strict dominance” (D0); 4) “1-level strict dominance” (D1); 5) rationalizability (D2); 6) “pure sum of payoff dominance” (L1); 7) “best response to pure sum of payoff dominance” (L2); 8) “maximum payoff dominance” (MPD). 1 and 2 are well known, and 3 and 4 are simply levels of reasoning in the rationalizability process,

with rationalizability equating to “2-level strict dominance” in a 3×3 game. MPD corresponds to going for the highest conceivable payoff for itself; L1 to choosing the best action against a uniformly randomizing opponent; L2 to choosing the best action against a L1 player. A fuller description of these algorithms can be found in Zizzo and Sgroi (2000). The values are displayed for the Visible and the Guess conditions only (Treatments 1-6), as non-cooperative solutions cannot be found with the incomplete and uncompleted payoff matrices of the Frozen condition.

(Insert Table 4 about here).

The interesting result from Table 4 is that, whereas by construction all Visible game matrices have a unique Nash equilibrium, $P(e_{Nash})$ drops by over half over the payoff-integrated game matrices, and the dominance-based algorithms also do not fare well.¹³ Conversely, simpler algorithms, such as L1 and L2, remain basically stable in their $P(e_m)$ values.

$P(m | e_m)$ mostly tend to be lower. This could be for two reasons. First, even with guesses perfectly corresponding to the expected payoff values, in making decisions subjects may rely not just on the expected values but also on higher moments of their subjective distribution of possible payoff values in each cell. Second, subjects may simply tremble more with greater problem complexity.

$P(m)$ values are widely different in ways that reflect the differential success of the more complex and the simpler algorithms in prescribing a unique action in the Guess condition. Nash can only explain about one fourth of the choices, whereas algorithms such as MPD, Maxmin, L2 and especially L1 hover at about or above the 50% success rate.

RESULT 9. As subjects face more uncertain decision problems, their behavior can be better described by simpler, less cognitively demanding strategies, as for H6, as long as they are not based on strict dominance.

These results appear roughly compatible with the experimental findings of Costa-Gomes et al. (2001) and the computer simulations of Zizzo and Sgroi (2000), which suggest that L1 and L2 are the strategies that best correspond to what people do when facing new normal-form games: indeed, we find that this is truer when subjects face incompletely determined games than otherwise.

¹³ The drops are statistically significant at $P < 0.001$.

6. Conclusions

This paper presented an experimental exercise in cognitive game theory: we employed techniques, such as payoff integration and similarity evaluations, that could be used in further research to open the black box of framing effects. This is worthwhile since framing effects are poorly understood by economists, and yet they can have a significant impact on cooperation. We analyzed the effect of one specific and minimal framing effect: the manipulation of the harmony of the games faced in the practice stage. We analyzed this framing effect as affecting the way the game is perceived, and thus within a more general framework of a study of how game perception affects behavior. Zizzo (2003) provides a theoretical example of how this framework can be formalized, in relation to the concept of game harmony with normal form games. We used 3×3 games, as these better allow to discriminate among non-cooperative algorithms.

We found a strong association between game harmony and cooperation, if weaker than the one identified by Zizzo and Tan (2003). Higher game harmony in the practice stage tends to induce more cooperative behavior later on, by *assimilation* to the harmony of the previous games, but we show how this assimilation effect can be moderated by a counteracting *contrast* effect. Framing effects depend upon the balance between the two. Further, the framing effect would be smaller, and insignificant, were it not for the treatments where the game is ambiguous, i.e. when the payoff matrix is presented in an incomplete form. The framing effect operates not only by changing the *level* of cooperation, but also the *sensitivity* of cooperation to the harmony of the game. Cooperation increases in the complexity of the decision problem, and so does the descriptibility of behavior with simpler algorithms than Nash and rationalizability, such as the L1 and L2 that were so successful in Costa-Gomes et al. (2001). Asking subjects to guess the payoff values, or to evaluate the similarity between games, can be a way of gathering information about how the game is perceived, and on how this affects behavior.

Appendix A – Cooperation indices

This appendix analyzes the implications of using a narrow cooperative solution restricted to games where the Nash bargaining solution coincides with the utilitarian solution but not with a strictly dominant solution. There are two reasons why using the narrow solution is inconvenient in our sample of just ten 3×3 games.

First, in 2×2 games strictly dominant strategies are likely to be obvious to most players, since they require at most just one level of iteration in the deletion of strictly dominated strategies; conversely, with respect to 3×3 games agents may need two levels of iteration; this leads us to consider two narrow indices, one defined as a function of just one level of iteration of deletion of strictly dominated strategies (N1) and the other defined as a function of any strictly dominant strategies (N2). Since our experiment did not measure levels of reasoning, it is unclear which one we should prefer.

Second, N1 (N2) is defined only in seven (eight) games out of the ten 3×3 games. This creates a serious problem of statistical power. (As a way of comparison, the narrow solution is defined over as many as 19 2×2 randomly generated games of Zizzo and Tan, 2003).

With these qualifications in mind, we can check the robustness of the results of section 5 to the use of N1 and N2 in place of the utilitarian solution as algorithm to define cooperative actions:

H1: the use of N1 provides mostly equally strong evidence, and N2 mostly weaker evidence, for *H1* than if the utilitarian solution is used. In the data classified by game, Pearson correlation coefficients between game harmony and N1 or N2 tend to be lower and insignificant or only marginally significant (they range between 0.369 and 0.552), with N1 performing better. Spearman correlation coefficients are comparable with those obtained with the utilitarian solution, and are in the 0.523-0.635 range (though insignificant for lack of power with N2). In the data classified by role (see section 5.1 for an explanation), correlation coefficients are consistently lower for N2 (in the 0.36-0.409 range) and about as high for N1 (in the 0.458-0.635 range, with $P < 0.05$ always).

H2-H4: results are insensitive to the kind of measure used;

H5: results are mildly stronger with both N1 and N2 than with the utilitarian solution; for example, while the Spearman correlation between δ and utilitarian solution play is - 0.124, the corresponding values with N1 and N2 are - 0.154 and - 0.176, respectively ($P < 0.01$).

H6: in a F test using H and I as factors, there is a stronger effect of I using N1 or N2 than using the utilitarian solution ($P < 0.001$). The result on cooperation is insensitive to the kind of measure effect.

Appendix B – Variables used in most general model

i) Personal Variables

DAge: age minus mean age.

Sex: 1 for males, 0 for females.

Economics, Humanities, HardSciences: 1 for subjects with an Economics, humanities, hard sciences background (respectively), 0 otherwise.

QAverage: final questionnaire evaluation by subject on their agreement (from 0 to 10) with the statement about the payoff guess task “I was not sure about the number, so I chose the likely average each time”.

QRandom: same as *QAverage* in relation to statement “I just picked numbers at random”.

QSimilarity: same as *QAverage* in relation to statement: “I chose numbers on the basis of the similarity of the Decision Table to previous Decision Tables”.

RiskAv: risk aversion index. The final questionnaire had five hypothetical binary choices between A) 50 pounds per choice and B) 100 pounds with probability $k\%$ and 0 pounds with probability $(1 - k)\%$, for $k = 50, 60, 70, 80$ and 90 , which we can respectively map into the index $K = 1, 2, 3, 4$ and 5 . Let the answer to the question concerning K be $a(K)$, and let $a(K) = 1$ if B (the risk-loving choice) is chosen (0 if not). Then $RiskAv = K \times a(K)$: the lower the *RiskAv*, the more risk averse the agent is likely to be.

AmbiguityAv: ambiguity aversion index. The final questionnaire had five hypothetical binary Ellsberg choices where the subject wins if she picks a green ball out of one of two bags with 100 balls of one of two colors, green and blue. She does not know how many green or blue balls there are in Bag 2, but she knows that Bag 1 has k green balls and $(1 - k)$ blue balls, for $k = 35, 40, 45, 50, 55$, which we can respectively map into the index $K = 1, 2, 3, 4$ and 5 . Let the answer to the question concerning K be $a(K)$, and let $a(K) = 1$ if Bag 2 (the ambiguity-loving choice) is chosen (0 if not). Then $AmbiguityAv = K \times a(K)$: the lower the *AmbiguityAv*, the more ambiguity averse the agent is likely to be.

ii) Game-Specific Variables

MeanNRD: mean of the visible payoffs (i.e. those not on the right diagonal).

SdNRD: standard deviation of the visible payoffs (i.e. those not on the right diagonal).

iii) Game Antecedents Variables

High: 1 in High condition, 0 otherwise.

Low: 1 in Low condition, 0 otherwise.

Round: Stage 2 round a game is played in.

St1Payoff: mean payoff obtained by the subject in Stage 1.

St1PayoffOther: mean payoff obtained by the subject's coplayer in Stage 1.

St1NegDiff: mean difference between own and coplayer's payoff in Stage 1, if negative; otherwise 0.

iv) Interaction Variables

Low $\times$ *GHnRD*: *Low* $\times$ $G(\Gamma)$ computed over the visible payoff matrix

Medium $\times$ *GHnRD*: *Medium* $\times$ $G(\Gamma)$ computed over the visible payoff matrix

High $\times$ *GHnRD*: *High* $\times$ $G(\Gamma)$ computed over the visible payoff matrix

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Fig. 1. A computer display from the Guess and Frozen conditions in Stage 2.

Stage 2

Other Participant

A B C

You	A	40 1	67 59	? ?
	B	32 69	? ?	60 86
	C	? ?	82 26	50 88

Round 6

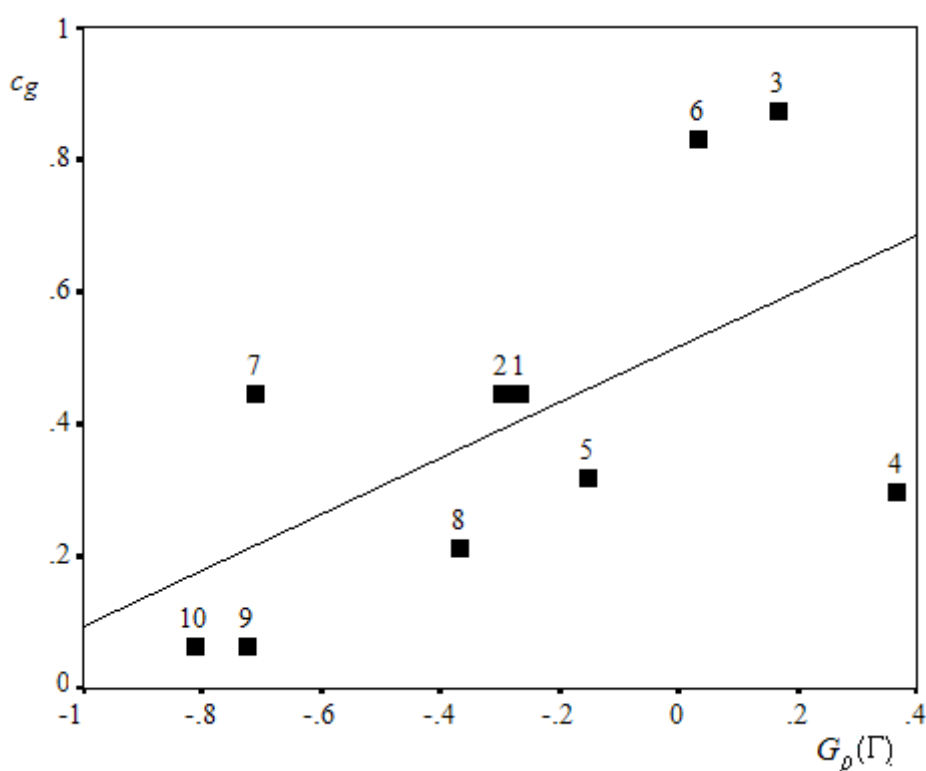
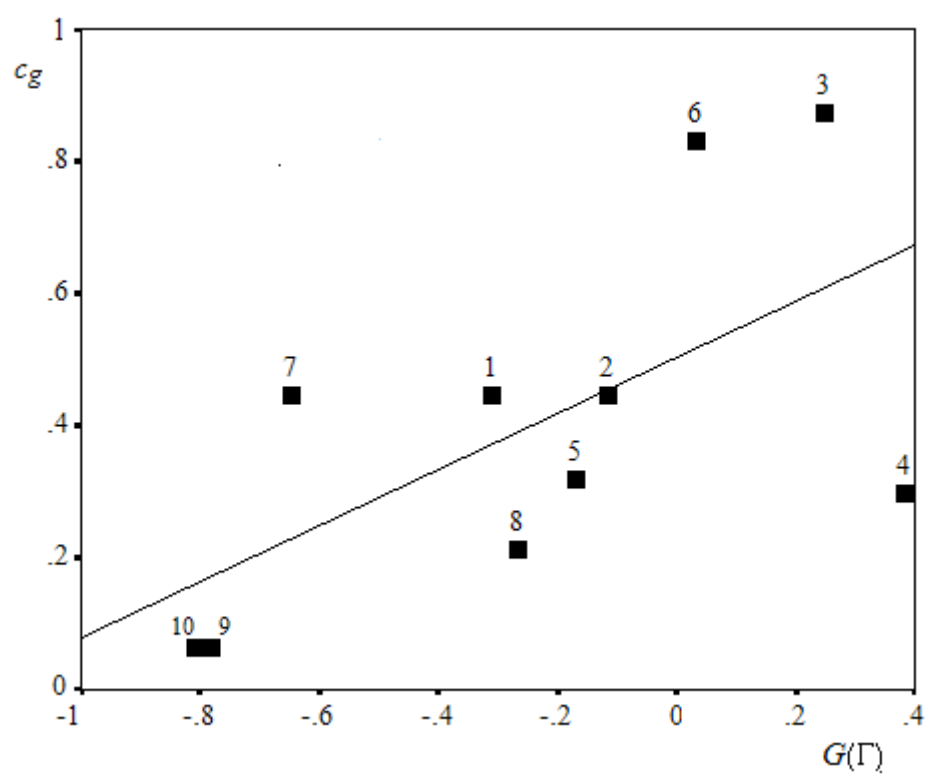
There is a YELLOW cell (YOUR gain) and a BLUE cell (THE OTHER PARTICIPANT'S gain) for each combination of ACTIONS (A, B and C) by you and the other participant.

You are Participant 1

Confirm Cancel

Fig. 2. The Comparison Decision Table as presented on paper to the subjects.

		Your coparticipant					
		A		B		C	
You	A	5	56	88	52	72	43
	B	36	61	15	25	57	41
	C	86	22	23	23	77	28

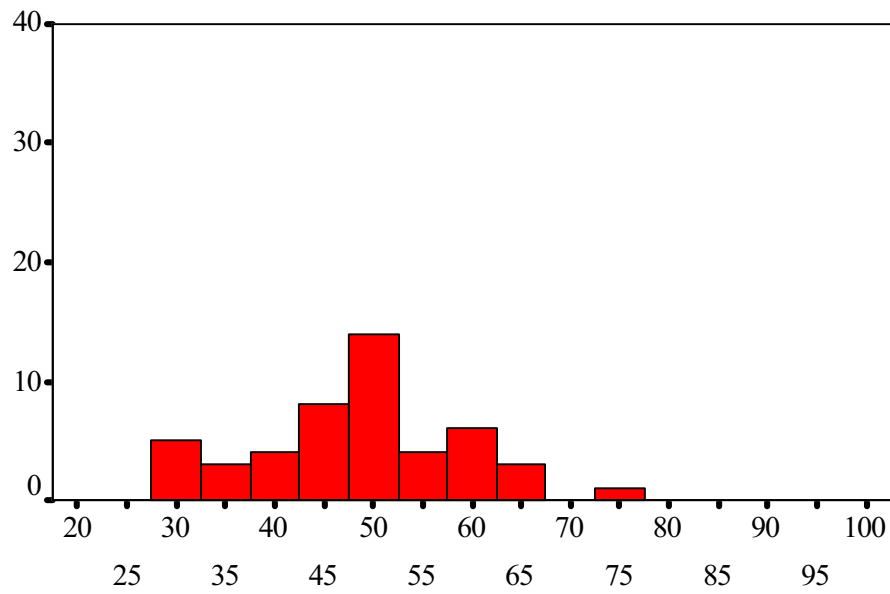
Fig. 3. Scatterplots of game harmony on cooperation rate by game.^a

^a The observation labels correspond to the games, as specified by the round of presentation in Table 2.

Fig. 4. Histograms of mean guesses by subject.

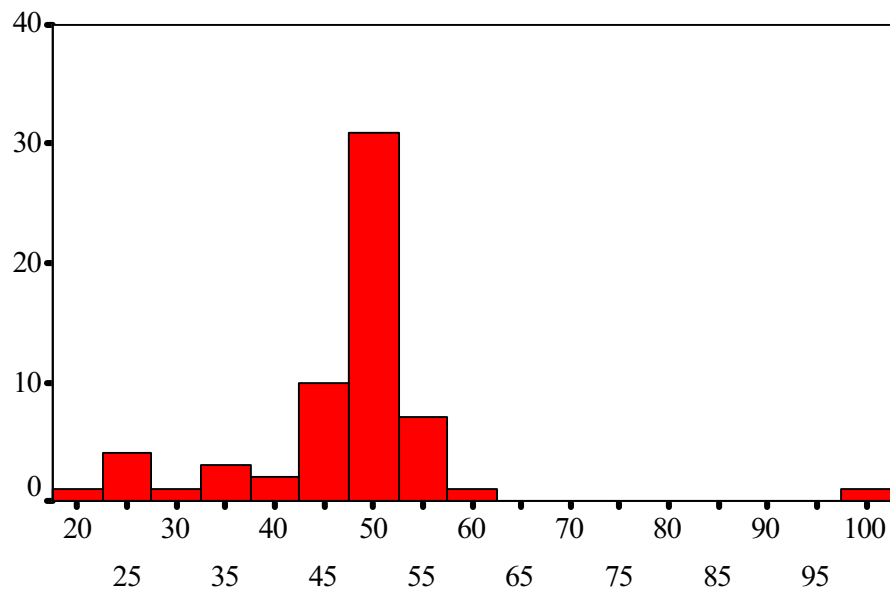
Fig. 4. Histograms of mean guesses by subject.^a

Treatments 4-6, Round 1



Mean Payoff Guess

Treatment 8



Mean Random Guess

^a The vertical axis has the number of observations for every 5 guess points interval.

Table 1
Experimental treatments ^a

Treatment	<i>H</i> Condition	<i>I</i> Condition	<i>n</i>	c_t	δ	s_t
1	Low	Visible	16	0.363	-	39.895
2	Medium	Visible	16	0.406	-	40.109
3	High	Visible	15	0.433	-	35.396
4	Low	Guess	16	0.475	32.989	31.596
5	Medium	Guess	16	0.469	35.123	37.816
6	High	Guess	16	0.581	26.034	42.445
7	Medium	Frozen	15	0.4	-	38.342
8	-	-	61	-	-	-

^a *H* condition refers to whether the treatment had High, Medium or Low game harmony in the practice stage. *I* condition refers to whether the payoff matrix was fully displayed (Visible), incomplete (Frozen), or incomplete and with a request to guess payoff values (Guess). c_t is the mean cooperation rate by treatment. δ is the mean of a summary statistic of the difference between guess of own's own and the coplayer's payoff. s_t is the mean evaluation of similarity between games in Stage 3, by treatment.

Table 2.
Stage 1 and 2 games ^a

		Column Player																	
		Row	A, B	C, D	E, F														
		Pl.	G, H	I, J	K, L														
			M, N	O, P	Q, R														
	Round	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Practice	1	4	87	47	39	19	53	98	8	3	63	42	67	25	53	69	21	38	62
Low	2	22	78	26	64	11	96	63	1	83	18	12	72	16	55	83	1	17	82
Game	3	33	91	72	31	80	16	28	62	52	56	81	7	12	100	32	45	58	12
Harmony	4	36	43	16	77	93	6	43	85	35	56	68	38	16	66	87	17	86	3
Games	5	19	68	46	31	86	15	23	78	43	54	56	24	31	72	29	65	40	59
	6	20	35	96	8	30	40	93	13	90	8	82	1	9	93	10	74	28	42
Practice	1	72	12	11	3	83	95	26	36	94	69	27	1	45	100	36	87	90	27
Medium	2	23	52	18	80	28	74	96	98	98	26	28	46	56	76	26	0	78	59
Game	3	84	80	70	10	23	71	22	54	3	21	50	15	69	97	6	59	63	94
Harmony	4	66	66	72	39	33	19	22	30	18	3	59	95	83	73	66	7	93	92
Games	5	24	68	25	69	16	10	72	19	93	57	42	94	24	21	51	24	84	26
	6	31	92	93	17	51	20	61	4	11	68	69	84	97	69	11	93	2	57
Practice	1	86	96	59	41	44	5	21	4	59	60	24	6	65	85	35	7	42	11
High	2	96	86	4	21	85	65	41	59	60	59	7	35	5	44	6	24	11	42
Game	3	15	19	64	77	88	87	99	96	8	14	95	84	18	65	2	11	11	23
Harmony	4	23	31	96	84	25	20	31	10	91	75	8	24	13	4	61	80	10	12
Games	5	95	95	55	43	22	2	99	60	44	7	71	56	33	8	12	12	63	38
	6	77	82	57	67	27	33	63	85	30	29	64	42	90	97	20	17	89	89
Stage 2	1	60	3	79	11	58	7	20	47	44	52	68	93	6	71	27	59	98	48
Games	2	26	39	30	5	24	99	57	12	28	12	90	59	51	47	10	72	36	55
	3	76	71	83	29	45	3	37	84	15	53	29	51	93	82	42	2	71	68
	4	59	54	40	9	18	85	0	29	79	71	88	57	58	88	20	29	3	43
	5	70	18	24	89	67	75	5	65	67	62	7	10	92	5	7	66	89	75
	6	40	1	67	59	70	77	32	69	44	88	60	86	45	11	82	26	50	88
	7	54	61	72	55	78	67	78	30	68	3	31	96	36	71	48	71	49	100
	8	21	16	14	76	44	10	21	47	31	69	42	65	40	88	22	89	48	30
	9	40	40	61	31	81	21	31	58	48	52	70	40	20	80	40	69	61	62
	10	69	69	39	86	12	100	83	39	55	56	25	69	100	10	69	24	40	41

^a Games are defined row-by-row: to obtain the payoff matrix corresponding to a given round and condition, replace the A, B, C, D... values in the generic payoff matrix with the corresponding value on the row for that round and condition. For the Stage 2 games, the (right diagonal) payoff cells that were hidden in Treatments 4-7 are displayed in italics.

Table 3.
Random effects regression on δ

	Coef.	SE	Sign.
DAge	0.56	0.18	***
HardSciences	5.805	2.868	**
AmbiguityAv	-7.696	3.15	**
SdNRD	0.325	0.136	**
High	-11.167	4.396	**
Low	-12.065	5.458	**
St1Payoff	-0.283	0.139	**
St1PayoffOther	-0.242	0.137	*
St1NegDiff	0.373	0.159	**
Medium x GHnRD	-11.859	3.311	***
High x GHnRD	-6.943	3.087	**
Constant	76.189	15.311	***
<i>Within R^2</i>	0.045		
<i>Between R^2</i>	0.552		
<i>Overall R^2</i>	0.267		

Table 4.^a
Performance of non-cooperative algorithms

Algorithm	Visible Condition			Guess Condition		
	$P(e_m)$	$P(m e_m)$	$P(m)$	$P(e_m)$	$P(m e_m)$	$P(m)$
Nash	1	0.702	0.702	0.463	0.581	0.269
Minmax	1	0.668	0.668	0.929	0.567	0.527
D0	0.353	0.855	0.302	0.098	0.936	0.092
D1	0.502	0.869	0.436	0.154	0.77	0.119
D2	0.651	0.85	0.553	0.223	0.738	0.165
L1	0.951	0.745	0.709	0.971	0.631	0.613
L2	0.949	0.684	0.649	0.969	0.536	0.519
MPD	0.9	0.66	0.594	0.973	0.563	0.548

^a $P(e_m)$ as the rate with which a unique action prescribed by the algorithm m is identifiable. $P(m | e_m)$ is the rate that the unique m action is followed given that a unique e_λ exists. $P(m)$ is the rate that the unique m action is followed.