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Testing the level of consistency between choices and beliefs in games using eye-tracking

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A B S T R A C T

We use eye-tracking to identify possible causes of inconsistency between choices and beliefs in games. Participants play a series of two-player 3 × 3 one-shot games (choice task) and state their beliefs about which actions they expect their counterpart to play (belief elicitation task). We use a model-based clustering method to group participants according to the pattern of visual analysis they use to make their decisions in the two tasks. We find that heterogeneity in the lookup patterns reflects the adoption of different models of choice. Our results suggest that there are two main reasons why participants do not best respond to their beliefs in games. First, many of them take into account the incentives of the counterpart when stating their beliefs, but not when choosing their actions. Second, some participants have other-regarding preferences and attempt to find a cooperative solution of the game.

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1. Introduction

In strategic interactions, optimal decisions depend on beliefs about other players' decisions, which in turn depend on others' expectations about one's own decisions, and so on. Beliefs are crucial for many behavioral game-theoretic solution concepts and also for many behavioral models of game play. Standard equilibrium models assume that players best respond to their beliefs about other players' strategies. In level-k (Stahl and Wilson, 1994, 1995; Nagel, 1995; Costa-Gomes et al., 2001; Costa-Gomes and Crawford, 2006) and cognitive hierarchy models (Camerer et al., 2004) it is also assumed that players best respond to their beliefs about others,[1] even if they might use limited cognition in forming beliefs and have incorrect assumptions about the rationality of other players.[2] Thus, the consistency between choice and beliefs (i.e., when players best respond to their beliefs about other players' choices) is relevant for both equilibrium theories and bounded rationality models with incorrect beliefs.

A common method used in behavioral game theory to study the level of consistency between choices and beliefs is to elicit individuals' beliefs about the expected action of the counterpart.[3] Belief elicitation procedures have been extensively applied to normal form games with finite action sets in both one-shot (Costa-Gomes and Weizsäcker, 2008; Rey-Biel, 2009;

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1 See Crawford et al. (2013) for a survey of the applications of level-k and cognitive hierarchy models in economics.

2 In this case they would best respond to "incorrect" beliefs.

3 See Manski (2004) for a survey on elicitation of probabilistic expectations. See Armantier and Treich (2013), Manski and Neri (2013), Schotter and Trevino (2014), and Trautmann and Kuilen (2015) for exhaustive discussions of different methods of belief elicitation in the lab.

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Dufwenberg et al., 2011) and finitely-repeated settings (Nyarko and Schotter, 2002; Palfrey and Wang, 2009; Rutström and Wilcox, 2009; Danz et al., 2012; Hyndman et al., 2012), as well as to games with continuous action sets (Dufwenberg and Gneezy, 2000; Neri, 2015).

It is generally accepted that in repeated games, players form beliefs over time about the likely behavior of the counterpart, and that these beliefs contribute to the process of converging to equilibrium. However, experimental evidence clearly indicates that in games without clear precedents (one-shot games), players often make choices that are not best responses to their own stated beliefs.[4] These results raise the question of the determinants of this general inconsistency. In this paper, we try to answer this question by studying the decision process that leads players to choose their actions and state their beliefs about the expected action of the counterpart (probabilistic first-order beliefs) in a series of two-player 3×3 one-shot games. To study the decision process, we record the eye movements of the participants. The analysis of the lookup patterns allows us to make the decision process visible and reveal possible causes of inconsistent behavior.

In light of previous studies, which show that heterogeneity in lookup patterns is associated with the use of different models of choice (for a detailed review, see Section 3), we hypothesize that players' behavior in one-shot games is heterogeneous (Weizsäcker, 2003) and depends on two features: the level of sophistication of the decision model adopted and the motives that drive players' choices. According to level-k and cognitive hierarchy models, players differ from one another in their depth of reasoning: each player's behavior is determined by her cognitive type and reflects the extent to which the player takes the game structure and other players' incentives into account.[5] A second type of heterogeneity is related to the existence of different types of other-regarding preferences (Rabin, 1993; Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Dufwenberg and Kirchsteiger, 2004; Falk and Fischbacher, 2006; Cox et al., 2008). Indeed, a number of studies have reported a significant proportion of participants whose behavior is motivated by fairness considerations (Fehr et al., 1997; Isaac and Walker, 1988; Andreoni and Miller, 2002; Fisman et al., 2007; Iriberri and Rey-Biel, 2013). Starting from this theoretical framework we use a model-based clustering method to classify participants according to their patterns of visual analysis and identify the decision model that most accurately predicts their behavior. Finally, we test whether the level of consistency between choices and beliefs depends on the coherence between the decision model used in the choice task and the one attributed to the counterpart in the belief elicitation task.

Our results show that approximately one third of the participants devotes a considerable amount of attention to the incentives of the counterpart in both choice and belief elicitation tasks. These participants play according to the *Level-2* model and believe it is highly probable that their counterpart play the *Level-1* action. A similar proportion of participants focuses their attention predominantly on their own payoffs when choosing their actions, and almost exclusively on the payoffs of their counterpart when stating their beliefs. These participants follow the predictions of the *Level-1* model in the choice task, but expect the counterpart to play the *Level-1* action in the belief elicitation task. We also find that there are participants whose analysis in the two tasks is based on the comparison between their own payoffs and those of the counterpart for each possible outcome of the game. Their choices and belief statements are in accordance with the prediction of a model of *Prosociality*. This model assigns a positive weight to the total payoff of the two players and a negative weight to the inequality in payoffs.

Our findings show that participants allocate a considerable amount of attention to the payoffs of the counterpart when stating their beliefs but only some of them based their analysis on the prediction of the other player's action in the choice task. We find that the number of best responses to participants' own stated beliefs is related to the amount of attention that they pay to the payoffs of the counterpart in the choice task: the more participants focus their attention on the incentives of the counterpart, the more they best respond to their beliefs. We thus observe consistency between choices and beliefs only when the information acquisition pattern of the participants in the choice task is centered on the prediction of the other player's action. Any deviation from this pattern leads to inconsistency between choices and beliefs.

2. Related literature on belief elicitation

Elicitation of first-order beliefs has recently become a common practice in experimental economics to predict choice behavior and infer decision processes in interactive decision making (Manski, 2004). This procedure was used by Costa-Gomes and Weizsäcker (2008) to investigate the level of consistency between choice data and belief data using 3×3 matrix games.[6] They estimated players' beliefs from their choices in a choice task and compared them with those reported in a belief elicitation task. Analyzing choices game by game, they tested the hypothesis that behavior in the two tasks was based on the same beliefs. However, their participants best responded to their stated beliefs only slightly more than 50% of the time (18% more than predicted by random behavior), and the consistency hypothesis was rejected for most of the games. In a subsequent analysis, Costa-Gomes and Weizsäcker assumed the existence of five different types of players: *Nash*, *Level-2*, *Level-1*, *Dominance-1* and *Optimistic*. Among these five models, the *Level-1* model provides the best description of the choice data. However, when the players stated their first-order beliefs, they attributed their own level of sophistication to the other

[4] We will discuss the related literature on belief elicitation methods in detail in section 2.

[5] For example, in level-k models, *Level-0* types choose randomly with uniform probability among the available options. *Level-1* players best respond to the belief that all other players are *Level-0*. *Level-2* players best respond to the belief that all other players are *Level-1*, and so on for higher levels.

[6] They studied dominance solvable games and games with pure Nash equilibria.

players. This behavior is inconsistent, because if players believe their counterpart to be *Level-1*, they should best respond to this belief, acting like a *Level-2* player. The authors explained this inconsistency by stating that the perception of the games, and/or of how players' counterparts play the games, is significantly different when players choose their actions and state their beliefs.[7]

A low level of consistency between choices and stated beliefs was also found by Nyarko and Schotter (2002) in a series of two-person constant sum game experiments. The authors tested the explanatory power of different belief learning models and found that they do not predict stated beliefs well. A higher level of consistency between choices and stated beliefs was found by Rey-Biel (2009). He also used one-shot two-person 3×3 normal form games but with a simpler payoff structure compared to Costa-Gomes and Weizsäcker.

There are also a number of studies which elicit second-order beliefs: for example, Bhatt and Camerer (2005) recorded the brain activity of participants while eliciting first and second-order beliefs in one-shot normal form games. They found that players have similar brain activations when their choices and belief statements are both consistent with Nash equilibrium. Vanberg (2008) elicited first and second-order beliefs in a mini dictator game with random dictatorship, showing that people do not simply dislike going against the other's payoff expectations, but that they dislike the act of lying *per se*. Bellemare et al. (2011) measured the willingness to pay to avoid guilt in a simple sequential game similar to the trust game. They found that willingness to pay, estimated using stated belief data, is overestimated when the correlation between preferences and beliefs is not accounted for.

In the three studies we have just mentioned, the second-order beliefs were measured as point forecasts even though subjective expectations in games were usually elicited probabilistically to allow the forecaster to convey her degree of uncertainty about her own forecast (Offerman et al., 1996; Nyarko and Schotter, 2002; Costa-Gomes and Weizsäcker, 2008; Rey-Biel, 2009; Blanco et al., 2010; Ziegelmeyer et al., 2010).[8] Only recently, Manski and Neri (2013) proposed a method to probabilistically elicit both first- and second-order beliefs in a hide-and-seek game. The object of their study was to investigate whether the observed choices coincide with the optimal one, given elicited beliefs. They found that 89% of the choices are best responses to first-order beliefs and 75% of them are best responses to second-order beliefs.[9]

In line with the literature on probabilistic elicitation of subjective beliefs in games, we elicit first-order beliefs by asking participants to assign a probability to each possible action of the counterpart. Belief elicitation is incentivized with a quadratic scoring rule (described below).

3. Related literature on process data

Many process tracing studies support the idea that players differ in their level of sophistication and have different beliefs about the other player's actions. In this regard, Costa-Gomes et al. (2001) used a computer mouse-tracking method to investigate information search processes in normal form games. The authors tested the cognitive implications of alternative models of choice combining choice data and patterns of information search. In order to explain players' behavior, nine possible types of players were specified *a priori*. Five types were strategic and required players to form beliefs about the expected action of their counterpart, and the remaining four types were non-strategic (or alternatively had diffused beliefs). To describe the link between decision process and choice, the authors assigned each player type with one (or more than one) search pattern(s). They observed that most of their participants exhibited lookup and choices consistent with the predictions of the level-k model.

Mouse-tracking was used also by Costa-Gomes and Crawford (2006) in a study where they elicited players' initial responses to a series of two-person guessing games. The authors assumed that each player's behavior is determined (with error) by a unique type, which determines their information search patterns and guesses in all games. They inferred participants' beliefs from their guesses and/or information search and, similarly to Costa-Gomes et al. (2001), classified players into types using an econometric analysis. They found that deviation from the equilibrium could be predicted and explained assuming a hierarchy of boundedly rational types. In particular, they found that half of their participants were following a decision rule (*Level-1*, *Level-2*, *Level-3* or *Equilibrium*) that included a precise specification of beliefs.[10]

Brocas et al. (2014) investigated the link between information search and decision strategy in games with private information. The authors used mouse-tracking to study strategic thinking in two-person betting games with three states and two-sided private information. The authors used a model-based clustering method to group participants according to their lookup patterns and choices. They identified three clusters which corresponded approximately to *Level-1*, *Level-2* and *Level-3* thinking, and a fourth cluster of players who analyzed the game exhaustively but made inferential mistakes. Their results showed that deviations from Nash equilibrium were associated with a failure to look at relevant information.

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[7] They also performed additional tests to exclude the possibility that inconsistency among choice data and belief data was due to risk-aversion or other-regarding preferences. These hypotheses were ruled out.

[8] Bhatt and Camerer (2005) measured both first- and second-order beliefs as point forecasts. Other examples of non-probabilistic elicitation of first-order beliefs are in Croson (2000), Dufwenberg and Gneezy (2000) and Sapienza et al. (2013).

[9] They also found evidence of heterogeneity across participants.

[10] The behavior of the other half of the participants was still coherent (with only few violations of dominance for most of them) but less well described by their specification of possible types. In their analysis, the authors rejected the possibility that the observed behavior might be explained by other factors such as altruistic behavior, risk aversion or confusion.

Altogether, these findings support the idea that individuals differ from one another in their level of sophistication. There is also a growing body of evidence that even social preferences systematically affect individual decision making in games. In Johnson et al. (2002), the authors used mouse-tracking in three-stage Rubinstein bargaining games to test whether players deviate from the equilibrium because of their limited cognition or other-regarding preferences. They ran an experiment in which players bargained with self-interested robots and one in which they bargained with other players. Their results showed that participants' offers in the two experiments were greater than what would be expected if they were using game-theoretic reasoning. This is in line with the hypothesis that individuals are boundedly rational. However, they found that social preferences also matter, because about a third of the difference between the equilibrium prediction and the observed mean offer disappeared when participants switched from bargaining with individuals to bargaining with robots.

Polonio et al. (2015) recorded participants' eye movements while playing a series of two-player 2×2 one-shot games. The authors first grouped participants into types according to the information-search patterns observed in a single class of games and then predicted their choices in different classes based on their type. They found three groups of participants: the first group of participants used an iterative step-by-step procedure to form beliefs about the other players' actions and best respond to them (*Level-2* players). The second group of participants took into account their own incentives, but largely neglected the incentives of their counterpart (*Level*-1 players). The third group of participants based their analysis on the comparison between their own payoffs and those of their counterpart (players with other-regarding preferences).

The role of social preferences in games was highlighted by another eye-tracking study conducted by Devetag et al. (2016). In their study, the authors showed that, in two-person three-by-three one-shot-games, players adopted simplified strategies such as choosing the action leading to an attractive and symmetric payoff. They found that many players did not take into account the other players' incentives and chose according to focal payoffs, as expected for players with social preferences.

Overall, these studies suggest that there are two main causes of heterogeneity in strategic interactions: the level of sophistication of the individual; and her social preferences. This, in turn, suggests that the level of consistency between choices and beliefs in games might differ based on the player type.[11]

4. Experimental design

4.1. The games

Our main goal is to shed light on the determinants of the general inconsistency observed in the literature between choices and beliefs in one-shot games. In particular, we hypothesize that the level of consistency between choices and beliefs is related to the coherence between the model of choice used in the choice task and the one attributed to the counterpart in the belief elicitation task. To test this hypothesis we selected 18 games, including the 14 games used in Costa-Gomes and Weizsäcker (2008), plus four games with multiple equilibria. 10 of our games are solvable in two, three, or four steps of iterated elimination of dominated actions, four games have a unique Nash equilibrium without dominant strategies, and four games are weak-link games (a 3×3 version of the stag-hunt game) with three equilibria, one of which is Pareto optimal. In games with a unique pure-strategy equilibrium, there are no salient payoffs. Conversely, weak-link games include possible equilibria that may act as attractors. The games with a unique pure-strategy equilibrium (games 1 to 14) are organized into pairs of isomorphic games. Isomorphic games are equivalent in the sense that the second game of each pair is identical to the first except for transposing the players' roles, changing the order of the three actions (for both players), and adding or subtracting a small constant amount from the payoffs of each game.[12] Using pairs of isomorphic games, all participants face the same set of games regardless of the role they play (row or column). In coordination games, we do not need to have pairs of isomorphic games, because each game has a symmetric structure. Fig. 1 reports the 18 games and Table 1 shows their strategic structure.

The experimental design consists of two treatments with two sessions each. The treatments are defined as follows: in treatment *AB*, participants first choose their actions in the 18 games and then state their first-order beliefs. In treatment *BA*, players state their first-order beliefs in the 18 games and then make their choices. Participants are randomly assigned to a role, row or column player, and are randomly paired. Eye movements are recorded in both treatments and in both sessions.

4.2. Experimental procedure

All sessions were run at the EPL lab (Experimental Psychology Laboratory) of the University of Trento. Participants were 72 undergraduate students from the University of Trento (19 males, 53 females), the mean age was 23 (SD 2.95). Presentation of the stimuli was performed using a custom-made program implemented using Matlab Psychophysical toolbox.

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[11] Eye tracking was used also to study non-interactive decision making. For example, Krajbich et al. (2010) developed a computational model of value-based binary choice in which the evolution of the relative decision value depends on the allocation of attention. Arieli et al. (2011) showed that participants choosing between two lotteries often compare prizes and probabilities separately, rather than taking into account the whole structure of each lottery, as suggested by expected utility theory. Reutskaja et al. (2011) studied individual choice of consumption goods under time pressure and option overload.

[12] The payoffs of Game 2 are generated by subtracting 2 points from the payoffs of Game 1. The payoffs of Game 4 are generated by adding 2 points to the payoffs of Game 3. The payoffs of Game 6 are generated by adding 1 point to the payoffs of Game 5. The payoffs of Game 8 are generated by subtracting 1 point from the payoffs of Game 7. The payoffs of Game 10 are generated by adding 2 points to the payoffs of Game 9. The payoffs of Game 13 are generated by adding 2 points to the payoffs of Game 11. The payoffs of Game 14 are generated by subtracting 3 points from the payoffs of Game 12.

Game 1	L	M	R
T	78,73	69,23	12,14
M	67,52	59,61	78,53
B	16,76	65,87	94,79

Game 2	L	M	R
T	21,67	59,57	85,63
M	71,76	50,65	74,14
B	12,10	51,76	77,92

Game 3	L	M	R
T	74,38	78,71	46,43
M	96,12	10,89	57,25
B	15,51	83,18	69,62

Game 4	L	M	R
T	73,80	20,85	91,12
M	45,48	64,71	27,59
B	40,76	53,17	14,98

Game 5	L	M	R
T	78,49	60,68	27,35
M	10,82	49,10	98,38
B	69,64	42,39	85,56

Game 6	L	M	R
T	39,99	36,28	57,86
M	83,11	50,79	65,70
B	11,50	69,61	40,43

Game 7	L	M	R
T	84, 82	33, 95	12, 73
M	21, 28	39, 37	68, 64
B	70, 39	31, 48	59, 81

Game 8	L	M	R
T	47, 30	94, 32	36, 38
M	38, 69	81, 83	27, 20
B	80, 58	72, 11	63, 67

Game 9	L	M	R
T	57, 58	46, 34	74, 70
M	89, 32	31, 83	12, 41
B	41, 94	16, 37	53, 23

Game 10	L	M	R
T	60, 59	34, 91	96, 43
M	36, 48	85, 33	39, 18
B	72, 76	43, 14	25, 55

Game 11	L	M	R
T	43, 91	38, 81	92, 64
M	39, 27	79, 68	68, 19
B	69, 10	66, 21	74, 54

Game 12	L	M	R
T	25,27	90, 43	38, 60
M	49, 39	53, 73	78, 52
B	64, 85	20, 46	19,78

Game 13	L	M	R
T	83, 40	23, 68	70, 81
M	93, 45	12, 71	29, 41
B	66, 94	56, 76	21, 70

Game 14	L	M	R
T	82, 61	36, 46	24, 22
M	43, 17	70, 50	40, 87
B	75, 16	49, 75	57, 35

Game 15	L	M	R
T	73, 73	34,22	17, 55
M	22, 34	68, 68	54, 57
B	55, 17	57, 54	63, 63

Game 16	L	M	R
T	68, 68	62, 22	60, 59
M	39, 62	78, 78	22, 27
B	59, 60	27, 39	73, 73

Game 17	L	M	R
T	25, 37	71,71	57,60
M	58, 20	60, 57	66,66
B	76,76	37,25	20,58

Game 18	L	M	R
T	62, 61	64, 24	70, 70
M	75, 75	61, 41	29, 62
B	24, 29	80, 80	41, 64

Fig. 1. The games used in the experiment. The underlined payoffs indicate the Nash equilibria in pure strategies. Games 15 to 18 are coordination games with multiple equilibria.

Table 1
Structures of the games and their Nash equilibria (Top = T, Middle = M, Bottom = B, for the row players and Left = L, Middle = M, Right = R for the column players). The number of rounds of elimination of dominated actions required by row and column players to reach the equilibrium is shown in the third row of the table. In games with multiple equilibria (games 15 to 18) we report the actions consistent with the Pareto optimal equilibrium.

Game	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
N° of equilibria	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3	3	3	3
Rounds of elimination (row, column)	2,3	3,2	2,3	3,2	2,3	3,2	2,3	3,2	3,4	4,3	No	No	No	No	No	No	No	No
EQ (*Pareto*) (*row, column*)	T, L	M, L	B, R	M, M	T, M	B, M	M, R	B, R	T, R	B, L	M, M	B, L	T, R	T, L	*T, L*	*M, M*	*B, L*	*B, M*

Before the experiment started, a copy of preliminary instructions that described a 3×3 strategic game was given to the participants and read aloud by the experimenter. Control questions were administered to assure that participants understood the rules of the choice task and the rules of the belief elicitation task.[13] When participants failed to answer the control

[13] A translated copy of the instructions and the control questions are included as supplementary material (see online Appendices A and B).

questions, instructions were repeated, and then the control questions were administered again. Participants who failed to answer one of the control questions for the second time were excluded from all analyses. 36 participants were included in each treatment.[14] Participants in treatments *AB* were provided with the instructions for the choice task and were told how their choices would be incentivized. Then, after they completed the control questions, and the eye-tracking system was calibrated, participants underwent two practice games and then played the 18 games.[15] At the end of the choice task, participants were provided with the instructions on how to state their beliefs and how their reward in this task would be determined based on the scoring rule. Next, they underwent two practice games and then stated their beliefs in 18 games without knowing in advance the outcome of their choices. No time limit was imposed on participants to give their response.

In treatment *BA*, we inverted the order of the two tasks. First, participants were provided with the instructions for the choice task and how they would be incentivized. Then, they were provided with the instructions for the belief elicitation task and were informed on how they would be paid for the accuracy of their beliefs. Next, they stated their beliefs for all 18 games and finally they played the games.

Since one of our priorities was to compare the patterns of visual analysis used by the participants when they chose their actions and when they stated their beliefs, the structure of the choice task and the belief elicitation task were kept as similar as possible. In the choice task, the participants chose their actions by pressing the corresponding button. In the belief elicitation task, the participants were asked to assign a probability to each possible action of their counterpart. In particular, they were told to think about the probabilities they would assign to the three actions while observing the game matrix. Then, once they had decided on the three probabilities, they had to press the spacebar to move to the response screen where they could select their probabilities and confirm their response (see Appendix A in the online supplementary material for an exhaustive description of the belief elicitation task).

All participants were tested individually.[16] At the beginning of the experiment, the experimenter told the participants that their responses would be paired with those of a randomly selected counterpart, and it was made clear that, in the 18 games, the selected counterpart would remain the same both when choosing their actions and when stating their beliefs. No feedback about the result of their decisions was given to the participants until the end of the data collection. At the end of the data collection, participants were anonymously and randomly paired, and their responses were combined.

All participants returned to receive their payments a few days after the end of the experiment, and they each drew two tags from two different jars. Each of the tags in the first and second jars was associated with one of the games used during the experiment. The tag extracted from the first jar determined the payment for the choice task, and the tag extracted from the second jar determined the payment for the belief elicitation task.

For the choice task participants were paid at an exchange rate of 10 cents per point. For the belief elicitation task participants were paid according to a quadratic scoring rule defined as follows: let y_g^i be the stated belief of player i in game g, where y_g^i is a probability distribution over the three actions (L, M, and R) of player j (the counterpart). The probability distribution is $y_g^i \equiv (y_{g,L}^i y_{g,M}^i y_{g,R}^i)$, such that $y_g^i \in \Delta^2 \equiv \{y_g^i \in \Re^3 \mid \Sigma_{c\in\{L,M,R\}} y_{g,c}^i = 1\}$. The action chosen by player j (the counterpart) is defined as $x_g^j \equiv (x_{g,L}^j, x_{g,M}^j, x_{g,R}^j)$, where x_g^j equals 1 for the chosen action and zero otherwise. The payoff v_g of player i is calculated with the following quadratic scoring rule $v_g = A - c[(y_{g,L}^i - x_{g,L}^j)^2 + (y_{g,M}^i - x_{g,M}^j)^2 + (y_{g,R}^i - x_{g,R}^j)^2]$, where A and c are constants ($A = 10$ Euros and $c = 5$ Euros).[17] Before starting the experiment the participants were provided with a clear description of the scoring rule and several examples.

Participants earned between 1.00 and 19.9 Euros in addition to a 4 Euro show-up fee. One participant in treatment *AB* and one in treatment *BA* were discarded for technical reasons; thus in total we collected eye-tracking and behavioral data from 35 participants in each treatment. The ethical committee of the University of Trento approved the study, and all participants gave informed consent prior to admission to the study.

5. Results

In this section, we provide a descriptive analysis of choice and stated beliefs data. The average rate of equilibrium choices in games with a unique Nash equilibrium is equal to 0.37, which is very close to what would be predicted by chance (rate = 0.33). Importantly, this proportion is not affected by the treatment ($AB = 0.34$, $BA = 0.39$). The average probability with which participants estimated that the counterpart is playing the equilibrium strategy (in games with a unique Nash equilibrium) is equal to 0.29 in treatments *AB* and to 0.33 in treatment *BA* (Table 2). These results suggest that participants do not believe their counterpart to play according to the equilibrium, regardless of the treatment group.

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[14] The reasons for choosing a sample size of 72 participants is based on previous results showing that monitoring eye movements in similar experimental settings it is possible to identify three groups of participants associated with three general visual patterns of information acquisition (see Polonio et al., 2015, and Devetag et al., 2016). These studies show that participants are equally distributed among these three groups. Based on these previous results, we wanted to have at least 20 participants for each group. Therefore we decided to collect data from 70 participants.

[15] An extensive description of the eye-tracking procedure is provided in online supplementary material (see Supplementary Fig. 1 Appendix C).

[16] In order to allow the experimenter to carefully set up and control the eye-tracking data acquisition, a high precision eye-tracking device requires a dedicated laboratory. For this reason, and also because of the high cost of the device, in eye-tracking studies (as well as in fMRI experiments) participants are tested one at a time.

[17] The scoring rule is the same as that used by Costa-Gomes and Weizsäcker (2008).

Table 2
The left side of the table shows the Nash equilibria in the choice task (Top = T, Middle = M, Bottom = B, for the row players and Left = L, Middle = M, Right = R for the column players) and the average proportion of choices in accordance with the equilibrium predictions by treatment (*AB* and *BA*). The right side of the table shows the Nash equilibria in the belief elicitation task and the average probability of stated beliefs that match the equilibrium predictions by treatment. Note that the data are presented from the perspective of the row players. In games with multiple equilibria (games 15 to 18), the values refer to the Pareto optimal equilibrium. The total average is calculated over the games with unique equilibrium (games 1 to 14).

Game	Equilibrium model					
	Choice task			Belief elicitation task		
	Model predictions *Pareto Eq.*	Treatment AB	Treatment BA	Model predictions *Pareto Eq.*	Treatment AB	Treatment BA
1	T, L	0.26	0.40	L, T	0.45	0.53
2	M, L	0.69	0.40	L, M	0.20	0.17
3	B, R	0.26	0.31	R, B	0.20	0.22
4	M, M	0.20	0.14	M, M	0.19	0.21
5	T, M	0.49	0.49	M, T	0.13	0.15
6	B, M	0.03	0.14	M, B	0.24	0.25
7	M, R	0.31	0.43	R, M	0.44	0.62
8	B, R	0.51	0.49	R, B	0.19	0.30
9	T, R	0.77	0.74	R, T	0.24	0.30
10	B, L	0.26	0.57	L, B	0.60	0.70
11	M, M	0.31	0.51	M, M	0.50	0.59
12	B, L	0.14	0.06	L, B	0.28	0.22
13	T, R	0.40	0.57	R, T	0.31	0.31
14	T, L	0.17	0.20	L, T	0.13	0.11
15	*T, L*	*0.34*	*0.29*	*L, T*	*0.43*	*0.32*
16	*M, M*	*0.49*	*0.31*	*M, M*	*0.47*	*0.28*
17	*B, L*	*0.46*	*0.34*	*L, B*	*0.30*	*0.24*
18	*B, M*	*0.34*	*0.29*	*M, B*	*0.43*	*0.27*
Average		0.34	0.39		0.29	0.33

Table 3
Average proportion of best responses for each game and player's role.

Game ID	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	Average
Row	.44	.50	.44	.78	.61	.83	.53	.50	.47	.50	.42	.61	.47	.47	.72	.78	.69	.81	.59
Column	.56	.32	.74	.41	.65	.65	.44	.59	.41	.50	.41	.47	.50	.76	.79	.82	.74	.74	.58

Next, we test the level of consistency between choices and belief statements at the individual level. To test whether participants in the two treatments best respond to their beliefs more often than they would if choosing randomly, we use Kolmogorov–Smirnov tests to compare the cumulative frequency distribution of treatments *AB* and *BA* with that expected from random choices. We find that both distributions differ significantly (both p-values < 0.001) from what would have been predicted by chance. However, the frequencies of choices that are consistent with the participants' stated beliefs do not differ significantly between the two treatments (two-tailed, two-sample Kolmogorov–Smirnov test; $D = 0.143$, $p = 0.87$).[18] Regardless of the treatment, the average proportion of best responses to the belief statement is equal to 0.59. This proportion varies from a minimum of 0.32 to a maximum of 0.83 depending on the type of game and player's role (Table 3). In particular, the proportion of best responses in games with a unique equilibrium (games 1 to 14) is much lower (rate = 0.54) than that obtained in weak-link games (games 15 to 18, rate = 0.76).

To summarize, we find that players' choices are generally inconsistent with their stated beliefs in games with a unique equilibrium and that the proportion of best responses to belief statements depends on the type of game.[19] Moreover, our results show that participants' choices and stated beliefs are not well explained by Nash equilibrium. However, alternative models may explain the behavior of our participants. In this regard, one possibility is that participants have a bounded depth of reasoning that depends on their cognitive type. Experimental evidence indicates that the general level-k of reasoning achieved by players in strategic interactions is between 1 and 2. Therefore, we test whether *Level-1* or *Level-2* models explain the participants' observed choices and belief statements. The two models are defined as follows: the *Level-1* (*L1*) model assumes that players best respond to the belief that assigns equal probability to all counterpart's actions. The *Level-2* (*L2*) model assumes that players best respond to the belief that the counterpart plays according to the *Level-1* model.

Another possibility is that the behavior of participants is driven by fairness considerations. According to the model of other-regarding preferences proposed by Fehr and Schmidt (1999), some individuals are inequity-averse and are willing to cooperate with their counterpart to achieve more equitable outcomes. According to the Fehr and Schmidt model, in a two player game involving players i and j, player i evaluates her payoff according to the following utility function:

[18] Supplementary Fig. 2, in the online Appendix D, shows the cumulative frequency distribution of the number of best responses to stated beliefs for each of the two treatments.

[19] We find a proportion of best responses to belief statements that is very similar to the one obtained by Costa-Gomes and Weizsäcker (2008).

Table 4
The left side of the table shows the predictions of the four models in the choice task (Top = T, Middle = M, Bottom = B, for the row players and Left = L, Middle = M, Right = R for the column players). The right side of the table shows the proportion of choices predicted by each model reported from the perspective of the row players. Data are pooled across the two treatments.

Games	Choice task							
	Models' prediction				Models' accuracy			
	L2	L1	Inequity aversion	Prosociality	L2	L1	Inequity aversion	Prosociality
1	T, M	M, L	M, L	B, R	0.33	0.40	0.40	0.27
2	T, L	M, M	M, M	B, R	0.29	0.54	0.54	0.17
3	B, M	T, M	T, R	T, M	0.29	0.64	0.64	0.64
4	T, M	T, L	M, L	T, L	0.81	0.81	0.17	0.81
5	T, L	B, L	B, M	B, L	0.49	0.47	0.47	0.47
6	M, M	M, R	B, R	M, R	0.84	0.84	0.09	0.84
7	M, R	B, R	M, R	T, L	0.37	0.30	0.37	0.33
8	B, R	B, L	B, R	M, M	0.50	0.50	0.50	0.33
9	M, R	T, L	T, R	T, R	0.21	0.76	0.76	0.76
10	B, M	T, L	B, L	B, L	0.41	0.36	0.41	0.41
11	M, R	B, M	M, M	M, M	0.41	0.46	0.41	0.41
12	M, M	M, R	M, M	B, L	0.80	0.80	0.80	0.10
13	B, R	T, M	T, R	T, R	0.31	0.49	0.49	0.49
14	M, M	B, M	M, M	T, L	0.41	0.40	0.41	0.19
15	B, R	B, R	B, R	T, L	0.63	0.63	0.63	0.31
16	T, L	T, L	T, L	M, M	0.54	0.54	0.54	0.40
17	M, R	M, R	M, R	B, L	0.59	0.59	0.59	0.40
18	T, R	T, R	T, R	B, M	0.61	0.61	0.61	0.31
Average:					0.49	0.56	0.49	0.43

$U_i(x) = x_i - \alpha_i \max[x_j - x_i, 0] - \beta_i \max[x_i - x_j, 0]$ where $\beta_i \le \alpha_i$ and $0 \le \beta_i < 1$. The parameters α_i and β_i measure the loss from disadvantageous and advantageous inequity, respectively. The model (*Inequity aversion*) assumes that participants have correct beliefs about the distribution of other players' actions. Therefore, to determine the model's predictions, we multiply the observed strategy frequencies with the transformed payoffs to get the expected payoff of each strategy. Experimental evidence suggests that the model achieves a good level of overall fit with parameters $\alpha_i = 2$ and $\beta_i = 0.6$ (Fehr and Schmidt, 2010; Dreber et al., 2014). Therefore, in what follows we test the model using this combination of parameters.[20]

Finally, we test the hypothesis that participants use a simple decision model conceived in terms of cooperation and egalitarianism (Van Lange, 1999, 2000). This model (*Prosociality*) assigns a positive weight to the total payoff of the two players and a negative weight to the inequality in payoffs. In particular, each player changes the payoffs of the game according to the utility function: $U_i(x) = x_i + x_j - |x_i - x_j|$. Then, the model assumes that each player chooses an action that leads to the Pareto superior outcome (in the new game) and believes that the counterpart is doing the same. Empirical support for this assumption comes from Van Lange (1999). The author investigates reciprocity in the context of a single-trial social dilemma in which the participant and the counterpart made their choices simultaneously. The author found that players who are motivated to maximize joint outcomes and equality in outcomes expect their counterpart to reciprocate their behavior 79.6% of the time.

Table 4 shows the proportions of choices that are predicted by the four models mentioned above.[21] The table shows that the model whose action predictions are most consistent with the data is the *Level-1* model (rate = 0.56). To test whether there is a significant difference between the level of accuracy achieved by the *Level-1* model and the model with the second highest level of accuracy (*Level-2* and *Inequity aversion* models achieve the same accuracy rate: 0.49) we compare their hit rate in games where the first- and the second-ranked models make different predictions. We run a permutation test where we randomly assign participants to groups and compare the results from true labels with the distribution generated from the randomly assigned ones. Results show a significant difference between the first- and the second-ranked model (*Level-1 – Level-2*: $n = 70$, $Z = 2.30$, $p = 0.011$, one-tailed permutation test; *Level-1 – Inequity aversion*: $n = 70$, $Z = 2.32$, $p = 0.010$, one-tailed permutation test).

Similarly, looking at the average probability of stated beliefs (Table 5), it is most often predicted that the counterpart would choose according to the *Level-1* model (probability = 0.54). The difference between the *Level-1* model and the second ranked model (*Inequity aversion* model, probability = 0.44) is significant ($n = 70$, $Z = 6.46$, $p < 0.001$, one-tailed permutation test).

These results suggest that participants expect their counterpart to choose the *Level-1* action with high probability. However, they do not best respond to this belief, because their choices are mainly consistent with the *Level-1* model. One

[20] Additional results using different combination of parameters α_i and β_i are reported in the supplementary material (see Supplementary Table 1 and Supplementary Table 2 in online Appendix E).

[21] *Level-1* and *Inequity aversion* models make different prediction only in six games (dominance solvable games and games with unique Nash equilibrium without dominant actions). This is due to the observed distribution of choices used to estimate the *inequity aversion* model.

Table 5
Beliefs about the model of choice of the counterpart. The left side of the table shows the models' predictions (Left = L, Middle = M, Right = R, for the row players and Top = T, Middle = M, Bottom = B for the column players). The right side of the tables shows the stated beliefs (average probabilities on model predictions) about the model of choice of the counterpart. Data are reported from the perspective of the row players.

Games	Belief elicitation task (beliefs about the model of choice of the counterpart)							
	Models' prediction				Accuracy on model prediction			
	L2	L1	Inequity aversion	Prosociality	L2	L1	Inequity aversion	Prosociality
1	M, T	L, M	L, M	R, B	0.33	0.49	0.49	0.18
2	L, T	M, M	M, M	R, B	0.18	0.49	0.49	0.33
3	M, B	M, T	R, T	M, T	0.71	0.71	0.21	0.71
4	M, T	L, T	L, M	L, T	0.20	0.62	0.62	0.62
5	L, T	L, B	M, B	L, B	0.74	0.74	0.14	0.74
6	M, M	R, M	R, B	R, M	0.24	0.48	0.48	0.48
7	R, M	R, B	R, M	L, T	0.53	0.53	0.53	0.24
8	R, B	L, B	R, B	M, M	0.24	0.35	0.24	0.40
9	R, M	L, T	R, T	R, T	0.27	0.52	0.27	0.27
10	M, B	L, T	L, B	L, B	0.28	0.65	0.65	0.65
11	R, M	M, B	M, M	M, M	0.21	0.55	0.55	0.55
12	M, M	R, M	M, M	L, B	0.26	0.49	0.26	0.25
13	R, B	M, T	R, T	R, T	0.31	0.45	0.31	0.31
14	M, M	M, B	M, M	L, T	0.59	0.59	0.59	0.12
15	R, B	R, B	R, B	L, T	0.45	0.45	0.45	0.38
16	L, T	L, T	L, T	M, M	0.50	0.50	0.50	0.38
17	R, M	R, M	R, M	L, B	0.54	0.54	0.54	0.27
18	R, T	R, T	R, T	M, B	0.50	0.50	0.50	0.35
Average:					0.39	0.54	0.44	0.40

possibility that can account for these findings is that the behavior of the decision makers is heterogeneous. In the next section, we first provide a detailed analysis of the lookup patterns of the participants at the aggregate level. Then, we group participants according to the patterns of visual analysis they used in the choice and belief elicitation tasks, under the assumption that the lookup patterns they employ to acquire information about the payoff structure of the game disclose their decision strategy and the one attributed to the counterpart. If this is the case, we might be able to provide a clear description of the behavior of our participants. Finally, we test whether the level of consistency between choices and beliefs depends on the coherence between the model of choice used in the choice task and the one attributed to the counterpart in the belief elicitation task.

6. Eye-tracking data

6.1. Fixation analysis

In order to analyze the eye movement data, we define 18 areas of interest (AOIs), centered on the payoffs. All the AOIs have a circular shape with a size of 36000 pixels (Fig. 2). The AOIs cover only 23% of the game matrix area and never overlap. All the fixations that are not located inside the AOIs are discarded. Although a large part of the matrix is not included in any AOI, the vast majority of fixations (92%) fall inside the AOIs.

Three types of variable are recorded by the eye-tracker in each round for each participant: 1) the number of times a participant looks inside an AOI (fixation count); 2) the time a participant spends looking within an AOI (fixation time); and 3) the number and type of transitions (defined as the eye movements from one AOI to the next). Since the first two variables (fixation count and fixation time) are strongly correlated, in our analysis we mostly refer to the first variable (fixation count). However, our results are the same when using fixation time.

We use the Wilcoxon rank-sum test to evaluate possible effects of the two treatments (*AB, BA*) on the proportion of fixations on players' own payoffs (fixation within AOIs from 1 to 9 for a row player participant and from 10 to 18 for a column player participant, see Fig. 2) during the choice task. The level of attention given to own payoffs does not differ between the two treatments (Wilcoxon rank-sum test, $W = 483$, $p = 0.129$). Next, we use the Wilcoxon rank-sum test to evaluate possible effects of the treatments on the level of attention given to own payoffs in the belief elicitation task. Once again, the proportion of own-payoff fixations between the two treatments does not differ significantly (Wilcoxon rank-sum test, $W = 565$, $p = 0.576$).

According to level-k and cognitive hierarchy models, when players state their beliefs, they should attribute a lower level of sophistication to their counterpart than their own level. At the process level, this should be reflected in differences in the allocation of visual attention in the two tasks. For example, in the choice task, *Level-2* players need to take into account both the payoffs of their counterpart (to identify the action with the highest average payoff) and their own payoffs (to best respond to this action). In the belief elicitation task, it is sufficient for them to focus on the payoffs of the counterpart. Therefore, we might expect that the proportion of fixations made by *Level-2* players on their counterpart's payoffs in the belief elicitation task would be higher than the proportion of fixations made on their own payoffs in the choice task.

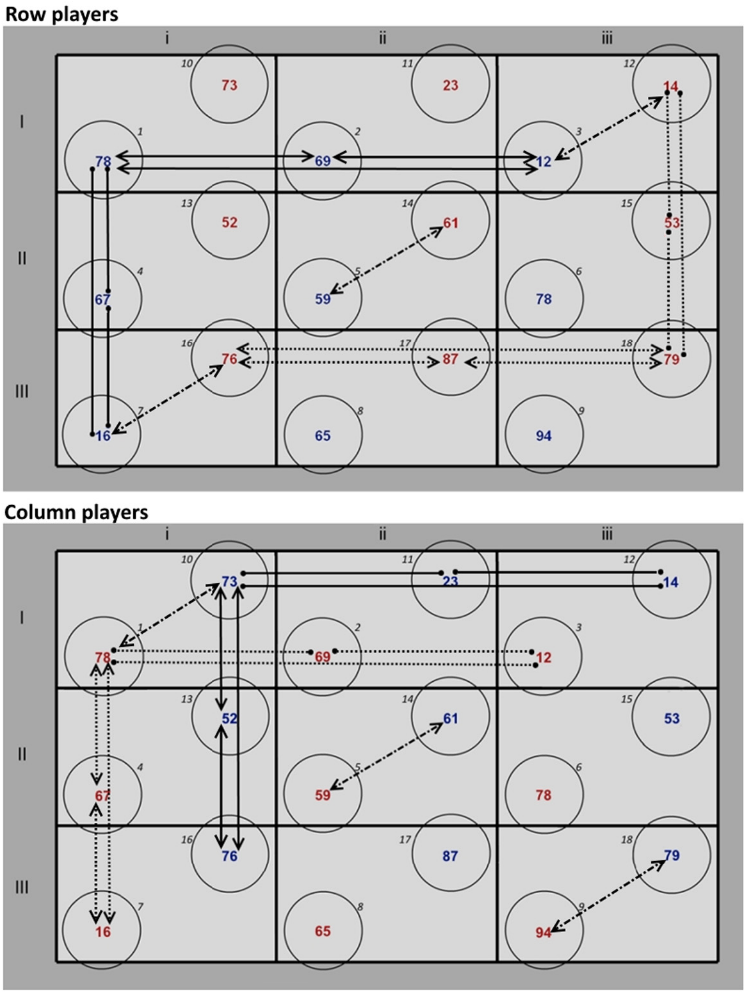

Fig. 2. The screenshot shows how the matrix is presented to row (upper panel) and column (lower panel) players and the summary of the relevant transitions (described in detail in Section 6.2); the numbers from 1 to 18 in italics represent the labels of the different Areas Of Interest (AOIs, not shown to the participants). Examples of the 5 types of relevant transitions are represented as follows: *Own within* transitions: solid line arrows. *Own between* transitions: solid line circles. *Other within transitions*: dotted line circles. *Other between* transitions: dotted line arrows. *Intracell* transitions: dashed line arrows.

However, this prediction does not hold for *Level-1* players, since they should focus their attention on their own payoffs when choosing their action and ignore the incentives of both players when stating their beliefs.[22]

To test whether participants change how they allocate their attention in the two tasks, we compare the average proportion of fixations on players' own payoffs (fixation within AOIs from 1 to 9 for a row player participant and from 10 to 18 for a column player participant) when they choose their actions with the average proportion of fixations on other player's payoffs (fixation within AOIs from 10 to 18 for a row player participant and from 1 to 9 for a column player participant) when they state their beliefs in the two treatments (for each participant the average is taken over all the games). We find a significant difference (Wilcoxon matched-pairs signed-rank test, $N = 70$, $W = 1220$, $p < 0.001$). Results show that participants fixate more on the other player's payoffs when stating their beliefs than they do on their own payoffs when choosing their action. In Fig. 3, we report the proportion of fixations on the 18 AOIs for the two treatments during the choice (Fig. 3, upper panel) and the belief elicitation (Fig. 3, lower panel) tasks. The figure shows that players allocate almost the same amount of attention to their own and their counterpart's payoffs when choosing their actions. Conversely, they are much more focused on the other player's payoffs when stating their beliefs.[23] These results support the hypothesis that the behavior of some participants might be explained by the *Level-2* model.

[22] *Level-1* model assumes that the counterpart is choosing randomly.

[23] In Supplementary Fig. 3 (online Appendix D), we show that using the proportion of fixation time, instead of the proportion of fixations, leads to very similar results.

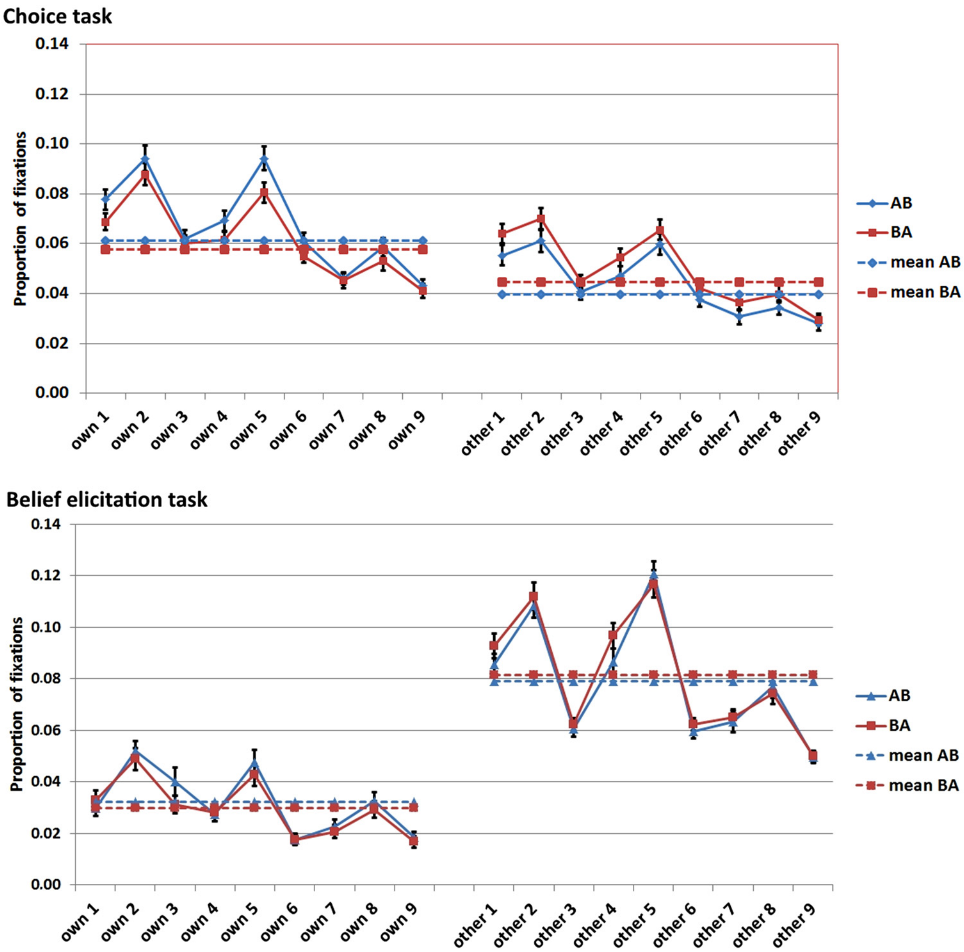

Fig. 3. Proportion of fixations within the 18 AOIs for the choice (upper panel) and the belief elicitation (lower panel) tasks. The dashed lines indicate the average proportion of fixations on one's own and the other player's payoffs for the two treatments.

6.2. Definition of relevant transitions

To extract information about the payoff structure of a game, participants need to move their attention among the 18 AOIs. Following Polonio et al. (2015) and Devetag et al. (2016), we define eye movements from one AOI to the next as transitions. Considering all possible pairs of AOIs and assuming that each pair can be connected by two transitions (one for each direction), the number of transitions that could be potentially observed equals 324, including transitions within the same AOI. However, our main objective, when analyzing the transitions, is to identify the patterns of visual analysis used by participants to acquire information about the payoff structure of the games when facing the 3×3 matrices. Therefore, we consider only transitions useful to capture pieces of information that are necessary to: 1) identify the participant's action with the highest average payoff; 2) identify the presence of dominant actions for the participant or identify the best response to the expected action of the counterpart; 3) identify the counterpart's action with the highest average payoff; 4) identify the presence of dominant actions for the counterpart or identify a counterpart's best response to the expected action of the participant; 5) compare the payoff of the participant with that of the counterpart within the same matrix cell. This information can be captured by considering the following five types of transition where *AOI-own* corresponds to the AOIs of participants' payoffs (AOIs from 1 to 9 for a row player participant and from 10 to 18 for a column player participant), and *AOI-other* to the counterpart's payoffs (AOIs from 10 to 18 for a row player participant and from 1 to 9 for a column player participant):

1. *Own within* transitions: transitions from one *AOI-own* to another *AOI-own* within the same action of the participant (Player's actions: Top, Middle or Bottom for a row player and Left, Middle or Right for a column player; e.g., transitions from 1 to 2 or from 1 to 3 for the action Top of a row player and transitions from 10 to 13 or from 10 to 16 for the action Left of a column player). Examples of these transitions are marked in Fig. 2 with solid lines arrows. Transitions that remain within the same AOI are excluded.

2. *Own between* transitions: transitions from one *AOI-own* to another *AOI-own* between different actions of the participant (e.g., transitions from 1 to 4 or from 1 to 7 for a row player participant and transitions from 10 to 11 or from 10 to 12 for a column player participant). Examples of these transitions are marked in Fig. 2 with solid line circles. Transitions that remain within the same AOI are excluded as well as transitions that are not useful to detect dominance (e.g. transitions from 1 to 5 or from 1 to 9 for a row player participant and transitions from 10 to 14 or from 11 to 18 for a column player participant).
3. *Other within* transitions: transitions from one *AOI-other* to another *AOI-other*, within the same action of the counterpart (Counterpart's actions: Left, Middle or Right for a row player and Top, Middle or Bottom for a column player; e.g., from 12 to 15 or from 12 to 18 for the action Right of the counterpart of a row player participant and from 1 to 2 or from 1 to 3 for the action Top of the counterpart of a column player participant). Examples of these transitions are marked in Fig. 2 with dotted line circles. Transitions that remain within the same AOI are excluded.
4. *Other between* transitions: transitions from one *AOI-other* to another *AOI-other*, between different actions of the counterpart (e.g., from 16 to 18 or from 17 to 18 for a row player participant and from 1 to 4 or from 1 to 7 for a column player participant). Examples of these transitions are marked in Fig. 2 with dotted line arrows. Transitions that remain within the same AOI are excluded, as well as transitions that are not useful to detect dominance (e.g. from 16 to 15 or from 17 to 12).
5. *Intracell* transitions: transitions from an *AOI-own* to an *AOI-other* or vice versa, within the same cell (e.g. from 5 to 14). Examples of these transitions are marked in Fig. 2 with dashed line arrows.

We will refer to these five categories as relevant transitions.

6.3. Cluster analysis based on transitions in the choice and belief elicitation tasks

In this section, we use the information search pattern of the participants in the two tasks to identify their model of choice. To achieve this goal we grouped participants in clusters based on a set of ten variables: the proportion of *own within*, *own between*, *other within*, *other between*, and *intracell* transitions, in the two tasks. To identify the clusters, we use a model-based clustering method proposed by Fraley and Raftery (2002) that has been extensively used in process data studies that involve games (Brocas et al., 2014; Devetag et al., 2016; Polonio et al., 2015). The advantage of using this clustering method is that the number of clusters and the clustering criterion are not determined *a priori*, but are endogenously determined by the method itself. Mixture models treat each cluster like a component probability distribution. A Bayesian statistical approach is used to choose between different numbers of clusters and different statistical methods (Fraley and Raftery, 2002; Fraley et al., 2012). We consider a maximum of nine clusters for up to ten different models, choosing the combination that maximizes the Bayesian Information Criterion (BIC).[24] The BIC is a model selection criterion which adds a penalty to the log-likelihood based on the number of parameters. Using this model-based cluster analysis we obtain six clusters (see Supplementary Fig. 4 and Supplementary Fig. 5 in online Appendix D).[25]

Table 6 shows the proportions of different transitions that participants belonging to different clusters employ to analyze the games in choice and belief elicitation tasks. The information search patterns are markedly different across clusters. Participants in clusters 1 and 2 ($n = 7$ and 17, respectively) devote considerable attention to the other player's payoffs in the choice task. In particular, the pattern of visual analysis of participants in cluster 1 is mainly based on *other within* transitions (rate = 0.48), whereas the lookup pattern of participants in cluster 2 is more heterogeneous and includes all types of relevant transitions (see cluster 2 in Table 6). In the belief elicitation task, participants in clusters 1 and 2 mainly use *other within* transitions (rate = 0.74 and 0.46, respectively).

Participants in clusters 3 and 4 ($n = 7$ and 17, respectively) focus their attention entirely on their own payoffs in the choice task, using almost exclusively *own within* transitions (rate = 0.71 and 0.46, respectively). In the belief elicitation task, they focus their attention on the other player's payoff, using almost exclusively *other within* transitions (rate = 0.72 and 0.49, respectively). Participants in clusters 5 and 6 ($n = 14$ and 8, respectively) mainly use *intracell* transitions in both choice (rate = 0.40 and 0.69, respectively) and belief elicitation tasks (rate = 0.33 and 0.65, respectively), which means that their analysis is focused on comparing their own payoffs with those of the counterpart within the nine cells. In the next section, we test whether the adoption of different patterns of visual analysis is associated with the application of different decision models in the choice and belief elicitation tasks.[26]

[24] Fraley and Raftery (2002) and Fraley et al. (2012) use the following definition of BIC: $BIC_{M,G} = 2l_{M,G}(x|\Psi) - v\log(n)$. Where Ψ includes the parameters of the mixture model. $l_{M,G}(x|\Psi)$ is the log-likelihood at the maximum likelihood estimator Ψ for the model M with G components. v is the number of estimated parameters and n is the sample size. The model M and the number of components G which maximize $BIC_{M,G}$ are selected. See Scrucca et al. (2016) for an exhaustive description of this model-based clustering method.

[25] Supplementary Fig. 4 (online Appendix D) reports a pairs plot of the 10 variables. Supplementary Fig. 5 (online Appendix D) reports the BIC plot for the 10 models.

[26] In Supplementary Fig. 6 (online Appendix D), we test whether the six clusters of participants change their pattern of visual analysis when dealing with games with different strategic structures. We divide the 18 games into four categories: (1) games solvable in two steps of iterated elimination of dominated actions (games 1, 3, 5 and 7 for row players and games 2, 4, 6, and 8 for column players); (2) games solvable in three or four steps of iterated elimination of dominated actions (games 2, 4, 6, 8, 9 and 10 for row players, and games 1, 3, 5, 7, 9 and 10 for column players); (3) games with unique Nash equilibrium without dominant actions (games 11, 12, 13, 14); and (4) coordination (weak-link) games (games 15, 16, 17 and 18). Supplementary Fig. 6 shows that, in

Table 6
Average proportions of relevant transitions in the two tasks (standard deviation in parentheses). Data are calculated from the total number of relevant transitions and reported by cluster and type of transition.

Cluster	Number of participants	Choice task					Belief elicitation task				
		Own within	Own between	Other within	Other between	Intracell	Own within	Own between	Other within	Other between	Intracell
1	7	0.16 (0.09)	0.16 (0.04)	0.48 (0.07)	0.12 (0.02)	0.08 (0.03)	0.00 (0.00)	0.01 (0.01)	0.74 (0.04)	0.23 (0.05)	0.02 (0.01)
2	17	0.24 (0.07)	0.14 (0.04)	0.27 (0.06)	0.15 (0.04)	0.21 (0.07)	0.11 (0.06)	0.08 (0.04)	0.46 (0.10)	0.19 (0.05)	0.14 (0.05)
3	7	0.71 (0.08)	0.15 (0.06)	0.02 (0.02)	0.05 (0.05)	0.07 (0.05)	0.00 (0.00)	0.00 (0.00)	0.72 (0.05)	0.25 (0.04)	0.03 (0.01)
4	17	0.46 (0.11)	0.24 (0.11)	0.11 (0.07)	0.08 (0.04)	0.11 (0.05)	0.12 (0.10)	0.08 (0.06)	0.49 (0.16)	0.20 (0.08)	0.11 (0.05)
5	14	0.21 (0.08)	0.11 (0.03)	0.16 (0.07)	0.11 (0.02)	0.40 (0.011)	0.13 (0.07)	0.10 (0.04)	0.30 (0.09)	0.14 (0.03)	0.33 (0.08)
6	8	0.10 (0.06)	0.06 (0.03)	0.07 (0.04)	0.08 (0.02)	0.69 (0.011)	0.03 (0.02)	0.07 (0.01)	0.17 (0.06)	0.08 (0.04)	0.65 (0.07)
Average Standard deviation		0.18 (0.12)	0.09 (0.05)	0.11 (0.09)	0.06 (0.03)	0.15 (0.012)	0.05 (0.05)	0.04 (0.03)	0.27 (0.13)	0.11 (0.05)	0.12 (0.11)

6.4. *Analysis of decisions and information search*

In the choice task, to best respond to a *Level-1* player, *Level-2* players need to collect information about the payoffs of the counterpart (Costa-Gomes et al., 2001; Bhatt and Camerer, 2005; Brocas et al., 2014; Polonio et al., 2015; Devetag et al., 2016). In particular, they need to use *other within* transitions to look for the counterpart's action with the highest average payoff, or alternatively, *other between* transitions to look at whether the other player has dominant strategies. Then, before making a decision, they should use *own between* transitions to compare their own possible outcomes and find the best response to the expected action of the counterpart. The lookup patterns of participants in clusters 1 and 2 in the choice task are roughly consistent with that expected for *Level-2* players. To better understand their patterns of visual analysis, we perform an analysis of transitions over time (Fig. 4). We decided not to use a fixed time span for our analysis, but to calibrate it on player behavior. For each trial and for each participant in clusters 1 and 2, we compute the number of transitions needed before making a decision and divide them in ten temporally ordered intervals. We find that at the beginning of their decision process, the visual analysis of players in cluster 1 (left part of Fig. 4) is almost entirely based on *other within* transitions (windows 1 to 8); only at the end of their analysis (windows 9 to 10), do they take their own payoffs into account, increasing the proportion of *own within* and *own between* transitions. The frequency of the other types of relevant transition (*other between* and *intracell* transitions) remains lower throughout the whole decision making process.

Players in cluster 2 start their analysis looking at their own payoffs (right part of Fig. 4), using *own within* transitions (windows 1 to 3) to move from one payoff to the next. Then, they evaluate the payoffs of the counterpart using *other within* transitions (windows 4 to 9). Finally, before making their decision, they look again at their own payoffs using mainly *own within* transitions.[27] The temporal pattern of visual analysis of players in cluster 2 is not as well defined as that of participants in cluster 1, but is very similar to that reported in the literature for *Level-2* players (Polonio et al., 2015).

In general, the two temporal information search patterns are both compatible with what would be expected for *Level-2* players. A critical test would be to demonstrate that the visual pattern of players in clusters 1 and 2 is based on a specific subset of *own between* transitions. This subset should include transitions that are required to identify the best response to the expected action of a *Level-1* counterpart. To test this prediction, we first determine, separately for each game, the expected action of a *Level-1* counterpart, and then test whether the visual analysis of participants in clusters 1 and 2 is focused on the subset of *own between* transitions required to best respond to this action. We compare the number of *own between* transitions in correspondence with expected and non-expected actions of a *Level-1* counterpart (Fig. 5) and find a significant difference, in the expected direction, for both clusters (cluster 1: Wilcoxon matched-pairs signed-rank test, $N = 7$, $W = 27$, $p = 0.031$; cluster 2: Wilcoxon matched-pairs signed-rank test, $N = 17$, $W = 142$, $p = 0.002$).

In the belief elicitation task, the analysis of participants in clusters 1 and 2 is mainly based on *other within* transitions (see Table 6), which indicates that they believe that their counterpart is choosing the *Level-1* action. Overall, our data support the hypothesis that participants in cluster 1 and 2 are *Level-2* players.

each cluster and in both tasks, the distribution of the five types of transitions do not change in games with different strategic structures. These results are in agreement with the hypothesis that participants have a predetermined and stable way of acquiring information, which does not depend on the type of game.

[27] Although they also increase their proportion of *intracell* transitions.

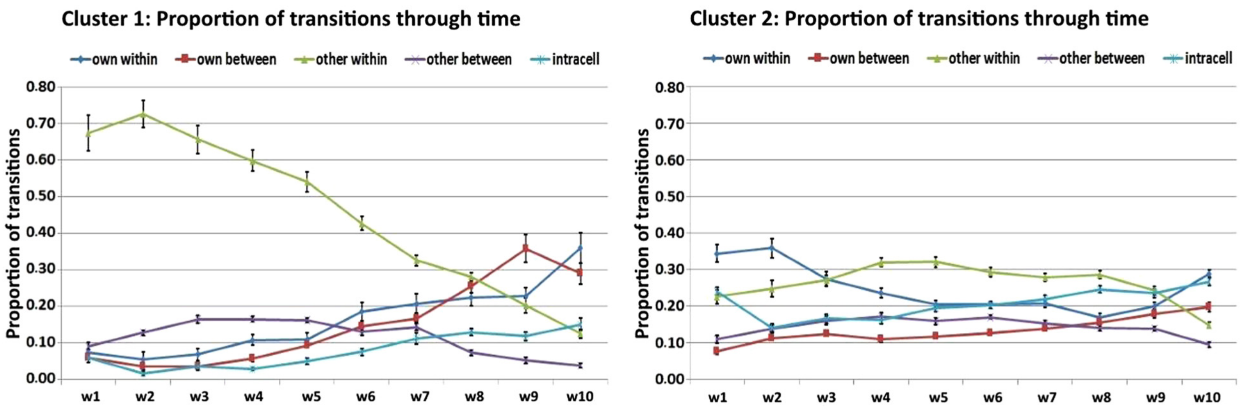

Fig. 4. Analysis of transitions through time of players in clusters 1 (on the left) and 2 (on the right). The proportions of relevant transitions are normalized so that each temporal window (w1, w2, etc...) includes 1/10 of the transitions made in each trial.

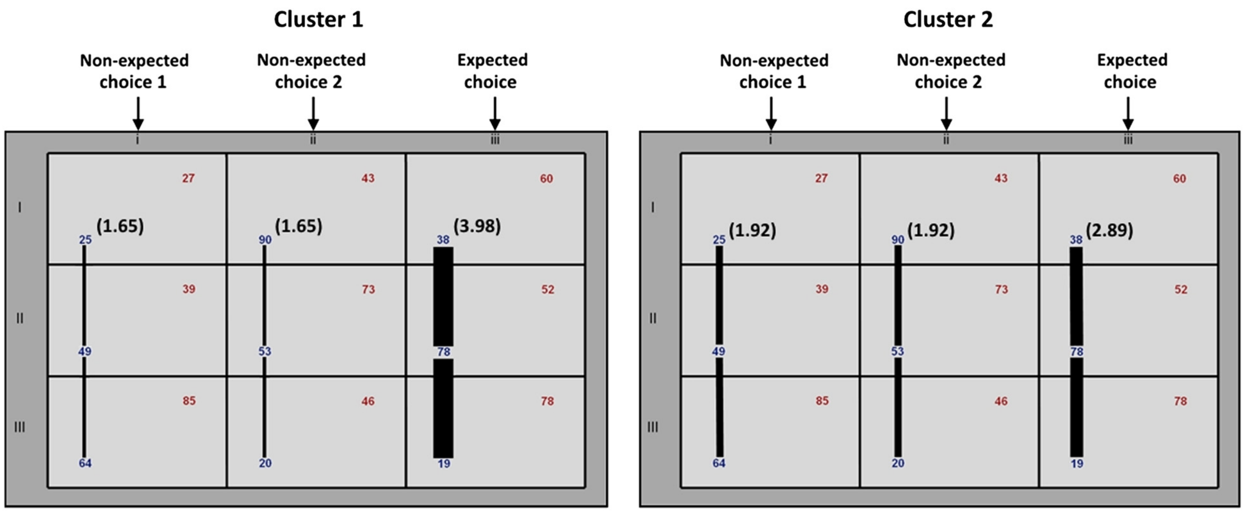

Fig. 5. Average number of *own between* transitions (in parentheses) made by players in clusters 1 (figure on the left) and 2 (figure on the right) in the choice task, for expected and non-expected choices of a *Level-1* counterpart. *Own between* transitions are represented by vertical lines. The size of the lines is proportional to the average number of occurrences among the corresponding payoffs. Data are presented from the perspective of a row player.

Tables 7a and 7b show the average proportion of choices (left side of the tables) and the average probability of stated beliefs (right side of the tables) in accordance with the predictions of the 4 models described above, for players in cluster 1 and 2. We find that, on average, the choices of both clusters are mainly consistent with the prediction of the *Level-2* model (rate $= 0.75$ and 0.58 for participants in cluster 1 and 2, respectively). To test whether there is a significant difference between the level of accuracy achieved by the *Level-2* model and the model with the second highest accuracy (*Level-1* model) we use a one-tailed permutation test. Results show a significant difference for both clusters (cluster 1: $n = 7$, $Z = 2.31$, $p = 0.010$, one-tailed permutation test; cluster 2: $n = 17$, $Z = 2.47$, $p = 0.007$, one-tailed permutation test). The average probability with which participants in cluster 1 and 2 estimate the counterpart to choose the *Level-1* action (probability $= 0.62$ and 0.59, respectively) lends further support to the hypothesis that these participants best respond to the belief that the counterpart is a *Level-1* player. Even in the belief elicitation task, the difference between the *Level-1* model and the second ranked model (*Inequity aversion* model) is significant for both clusters (cluster 1: $n = 7$, $Z = 2.55$, $p = 0.005$, one-tailed permutation test; cluster 2: $n = 17$, $Z = 3.50$, $p < 0.001$, one-tailed permutation test).

To choose according to the *Level-1* model, it is sufficient for a player to only take her own payoffs into account. The pattern of visual analysis used by participants in clusters 3 and 4 in the choice task is almost entirely based on *own within* transitions (rate $= 0.71$ and 0.46, respectively) and is therefore compatible with the prediction of the *Level-1* model. However, in the belief elicitation task, the visual analysis of these participants is mainly based on *other within* transitions (rate $= 0.72$ and 0.49, respectively). This pattern is consistent with that expected for *Level-2* players who hold the belief that the counterpart is a *Level-1* player. Coherently with the eye-tracking data, results reported in Tables 7c and 7d show that participants in clusters 3 and 4 follow the predictions of the *Level-1* model in the choice task and believe that the counterpart is choosing the *Level-1* action in the belief elicitation task (rate $= 0.86$ and 0.70 in the choice task and probability $=$

Table 7
Consistency between models' predictions and observed behavior in the two tasks by cluster. The left side of each table shows the average proportion of choices that are consistent with the predictions of the five models. The right side of the tables shows the stated beliefs (average probabilities on model predictions) about the model of choice of the counterpart. Data are presented from the perspective of the row players.

(a)

Games	Cluster 1 (7 participants)									
	Choice task					Belief elicitation task				
	Eq. Pareto	L2	L1	Inequity aversion	Pros.	Eq. Pareto	L2	L1	Inequity aversion	Pros.
1	0.86	0.86	0.14	0.14	0.00	0.64	0.33	0.64	0.64	0.04
2	0.00	1,00	0.00	0.00	0.00	0.05	0.05	0.59	0.59	0.36
3	0.71	0.71	0.29	0.29	0.29	0.24	0.66	0.66	0.24	0.66
4	0.14	0.86	0.86	0.14	0.86	0.04	0.04	0.65	0.65	0.65
5	0.86	0.86	0.14	0.14	0.14	0.01	0.96	0.96	0.01	0.96
6	0.00	0.86	0.86	0.00	0.86	0.09	0.09	0.50	0.50	0.50
7	0.86	0.86	0.14	0.86	0.00	0.65	0.65	0.65	0.65	0.03
8	0.71	0.71	0.71	0.71	0.00	0.12	0.12	0.40	0.12	0.48
9	0.57	0.43	0.57	0.57	0.57	0.07	0.07	0.79	0.07	0.07
10	0.43	0.43	0.43	0.43	0.43	0.63	0.34	0.63	0.63	0.63
11	0.43	0.43	0.43	0.43	0.43	0.62	0.04	0.62	0.62	0.62
12	0.14	0.86	0.86	0.86	0.14	0.28	0.16	0.56	0.16	0.28
13	0.29	0.57	0.29	0.29	0.29	0.19	0.19	0.46	0.19	0.19
14	0.00	0.71	0.29	0.71	0.00	0.03	0.61	0.61	0.61	0.03
15	0.14	0.86	0.86	0.86	0.14	0.21	0.67	0.67	0.67	0.21
16	0.14	0.86	0.86	0.86	0.14	0.20	0.60	0.60	0.60	0.20
17	0.14	0.86	0.86	0.86	0.14	0.23	0.54	0.54	0.54	0.23
18	0.00	0.86	0.86	0.86	0.00	0.28	0.64	0.64	0.64	0.28
Average	0.43	0.75	0.52	0.50	0.25	0.26	0.38	0.62	0.45	0.36

(b)

Games	Cluster 2 (17 participants)									
	Choice task					Belief elicitation task				
	Eq. Pareto	L2	L1	Inequity aversion	Pros.	Eq. Pareto	L2	L1	Inequity aversion	Pros.
1	0.35	0.35	0.24	0.24	0.41	0.50	0.34	0.50	0.50	0.16
2	0,41	0.41	0.41	0.41	0.18	0.09	0.09	0.62	0.62	0.29
3	0.47	0.47	0.41	0.41	0.41	0.27	0.67	0.67	0.27	0.67
4	0.12	0.88	0.88	0.12	0.88	0.18	0.18	0.68	0.68	0.68
5	0.76	0.76	0.24	0.24	0.24	0.10	0.79	0.79	0.10	0.79
6	0.06	0.82	0.82	0.06	0.82	0.28	0.28	0.48	0.48	0.48
7	0.59	0.59	0.06	0.59	0.35	0.66	0.66	0.66	0.66	0.09
8	0.29	0.29	0.29	0.29	0.53	0.19	0.19	0.45	0.19	0.35
9	0.59	0.41	0.59	0.59	0.59	0.20	0.20	0.61	0.20	0.20
10	0.53	0.53	0.18	0.53	0.53	0.65	0.25	0.65	0.65	0.65
11	0.59	0.59	0.35	0.59	0.59	0.61	0.18	0.61	0.61	0.61
12	0.06	0.88	0.88	0.88	0.06	0.23	0.31	0.46	0.31	0.23
13	0.35	0.41	0.35	0.35	0.35	0.30	0.30	0.49	0.30	0.30
14	0.18	0.59	0.24	0.59	0.18	0.12	0.64	0.64	0.64	0.12
15	0.24	0.71	0.71	0.71	0.24	0.39	0.42	0.42	0.42	0.39
16	0.35	0.59	0.59	0.59	0.35	0.31	0.59	0.59	0.59	0.31
17	0.35	0.65	0.65	0.65	0.35	0.22	0.63	0.63	0.63	0.22
18	0.35	0.59	0.59	0.59	0.35	0.30	0.63	0.63	0.63	0.30
Average	0.38	0.58	0.47	0.47	0.41	0.31	0.41	0.59	0.47	0.38

0.64 and 0.54 in the belief elicitation task for participants in cluster 3 and 4, respectively). A one-tailed permutation test shows that the difference between the *Level-1* model and the second ranked model is significant for both clusters in the choice task (clusters 3: $n = 7$, $Z = 2.50$, $p = 0.006$, one-tailed permutation test; cluster 4: $n = 17$, $Z = 3.36$, $p < 0.001$, one-tailed permutation test) and also in the belief elicitation task (clusters 3: $n = 7$, $Z = 2.37$, $p = 0.009$, one-tailed permutation test; clusters 4: $n = 17$, $Z = 3.90$, $p < 0.001$, one-tailed permutation test).

The model of *Inequity aversion* assigns a negative weight to inequality in payoffs. The model of *Prosociality* assigns a negative weight to inequality in payoffs and a positive weight to the total payoff of the two players. Thus, in order to use one of these two decision models it is necessary for a participant to compare her own payoff with that of the counterpart for each possible outcome of the game. Participants in clusters 5 and 6 use a visual pattern of information acquisition that is mainly based on *intracell* transitions (rate = 0.40 and 0.69, respectively) and therefore compatible with the adoption of one of these two models. As shown in Table 7e, the choices of participants in cluster 5 are mainly consistent with the predictions of the model of *Prosociality* (rate = 0.65). The *Equilibrium* model achieves the second highest hit rate. Similarly,

Table 7 (*continued*)

(c)

Games	Cluster 3 (7 participants)									
	Choice task					Belief elicitation task				
	Eq. Pareto	L2	L1	Inequity aversion	Pros.	Eq. Pareto	L2	L1	Inequity aversion	Pros.
1	0.00	0.00	1.00	1,00	0.00	0.56	0,35	0.56	0.56	0.09
2	1.00	0.00	1.00	1.00	0.00	0.11	0,11	0.61	0.61	0,28
3	0.00	0.00	0.86	0.86	0.86	0.25	0.65	0.65	0.25	0.65
4	0.29	0.71	0.71	0.29	0.71	0.19	0.19	0.64	0.64	0.64
5	0.00	0.00	1.00	1.00	1.00	0.13	0.74	0.74	0.13	0.74
6	0.00	0.86	0.86	0.00	0.86	0.16	0.16	0.60	0.60	0.60
7	0.14	0.14	0.71	0.14	0.14	0.66	0.66	0.66	0.66	0.12
8	0.86	0.86	0.86	0.86	0.00	0.14	0.14	0.51	0.14	0.35
9	1.00	0.00	1.00	1.00	1.00	0.11	0.11	0.67	0.11	0.11
10	0.00	0.00	1.00	0.00	0.00	0.66	0.26	0.66	0.66	0.66
11	0.14	0.14	0.57	0.14	0.14	0.49	0.22	0.49	0.49	0.49
12	0.14	0.71	0.71	0.71	0.14	0.21	0.21	0.59	0.21	0.21
13	0.57	0.43	0.57	0.57	0.57	0.22	0.22	0.58	0.22	0.22
14	0.00	0.00	1.00	0.00	0.00	0.09	0,61	0.61	0.61	0.09
15	0.00	0.86	0.86	0.86	0.00	0.13	0.66	0.66	0.66	0.13
16	0.00	0.86	0.86	0.86	0.00	0.08	0.73	0.73	0.73	0.08
17	0.00	0.86	0.86	0.86	0.00	0.09	0.77	0.77	0.77	0.09
18	0.00	1.00	1.00	1.00	0.00	0.11	0.75	0.75	0.75	0.11
Average	0.30	0.41	0.86	0.62	0.30	0.28	0.42	0.64	0.49	0.31

(d)

Games	Cluster 4 (17 participants)									
	Choice task					Belief elicitation task				
	Eq. Pareto	L2	L1	Inequity aversion	Pros.	Eq. Pareto	L2	L1	Inequity aversion	Pros.
1	0.18	0.18	0.71	0.71	0.12	0.50	0.36	0.50	0.50	0.14
2	0.76	0.18	0.76	0.76	0.06	0.15	0.15	0.43	0.43	0.42
3	0.18	0.18	0.71	0.71	0.71	0.15	0.78	0.78	0.15	0.78
4	0,12	0.82	0.82	0.12	0.82	0.24	0.24	0.49	0.49	0.49
5	0.29	0.29	0.59	0.59	0.59	0.09	0.81	0.81	0.09	0.81
6	0.06	0.88	0.88	0.06	0.88	0.24	0.24	0.40	0.40	0.40
7	0.06	0.06	0.71	0.06	0.24	0.52	0.52	0.52	0.52	0.29
8	0.76	0.76	0.76	0.76	0.12	0.27	0.27	0.40	0.27	0.33
9	0.76	0.18	0.76	0.76	0.76	0.21	0.21	0.61	0.21	0.21
10	0.12	0.12	0.53	0.12	0.12	0.61	0.29	0.61	0.61	0.61
11	0.24	0.24	0.59	0.24	0.24	0.52	0.29	0.52	0.52	0.52
12	0.00	0.82	0.82	0.82	0.00	0.21	0.21	0.58	0.21	0.21
13	0.53	0.24	0.53	0.53	0.53	0.19	0.19	0.47	0.19	0.19
14	0.06	0.41	0.53	0.41	0.06	0.10	0.54	0.54	0.54	0.10
15	0.18	0.76	0.76	0.76	0.18	0.24	0.54	0.54	0.54	0.24
16	0.29	0.65	0.65	0.65	0.29	0.38	0.47	0.47	0.47	0.38
17	0.29	0.71	0.71	0.71	0.29	0.17	0.54	0.54	0.54	0.17
18	0,24	0.76	0.76	0.76	0.24	0.31	0.54	0.54	0.54	0.31
Average	0.29	0.46	0.70	0.53	0.35	0.29	0.40	0.54	0.40	0.37

(*continued on next page*)

in the belief elicitation task, the model of *Prosociality* is the first ranked model (probability = 0.52) followed by the *Level-1* model.

The difference between the first- and the second-ranked models is significant in both tasks (choice task: $n = 14$, $Z = 2.49$, $p = 0.004$, one-tailed permutation test; belief elicitation task: $n = 14$, $Z = 2.20$, $p = 0.014$, one-tailed permutation test). These results suggest that participants in cluster 5 are prosocial players who believe that their counterpart reciprocates their behavior.

Finally, Table 7f shows that the choices of participants in cluster 6 are mainly consistent with the predictions of the *Level-1* model (rate = 0.57). However, the model of *Inequity aversion* achieves a similar level of consistency (rate = 0.54). A permutation test shows that the proportion of choices predicted by the two models does not differ significantly ($n = 8$, $Z = 0.76$, $p = 0.22$, one-tailed permutation test). Similarly, in the belief elicitation task, we find no difference between the model whose predictions are more consistent with the stated beliefs of the participants (*Level-1* model, probability = 0.52) and the second ranked model (model of *Inequity aversion*, probability = 0.49; $n = 8$, $Z = 1.02$, $p = 0.15$, one-tailed permutation test).

To summarize, participants in clusters 1 and 2 (24 participants in total) follow the predictions of the *Level-2* model in the choice task and expect their counterpart to choose the *Level-1* action in the belief elicitation task. Participants in clusters 3 and 4 (24 participants in total) follow the predictions of the *Level-1* model in the choice task and believe their

Table 7 (*continued*)

(e)

Games	Cluster 5 (14 participants)									
	Choice task					Belief elicitation task				
	Eq. Pareto	L2	L1	Inequity aversion	Pros.	Eq. Pareto	L2	L1	Inequity aversion	Pros.
1	0.29	0.29	0.14	0.14	0.57	0.38	0.23	0.38	0.38	0.39
2	0.50	0.14	0.50	0.50	0.36	0.28	0.28	0.31	0.31	0.41
3	0.29	0.29	0.71	0.71	0.71	0.19	0.74	0.74	0.19	0.74
4	0.29	0.71	0.71	0.29	0.71	0.26	0.26	0.63	0.63	0.63
5	0.57	0.57	0.36	0.36	0.36	0.27	0.60	0.60	0.27	0.60
6	0.14	0.86	0.86	0.14	0.86	0.40	0.40	0.38	0.38	0.38
7	0.21	0.21	0.14	0.21	0.64	0.33	0.33	0.33	0.33	0.49
8	0.21	0.21	0.21	0.21	0.57	0.28	0.28	0.15	0.28	0.57
9	0.86	0.14	0.86	0.86	0.86	0.57	0.57	0.24	0.57	0.57
10	0.71	0.71	0.07	0.71	0.71	0.67	0.29	0.67	0.67	0.67
11	0.57	0.57	0.36	0.57	0.57	0.46	0.30	0.46	0.46	0.46
12	0.21	0.71	0.71	0.71	0.21	0.31	0.36	0.33	0.36	0.31
13	0.64	0.21	0.64	0.64	0.64	0.40	0.40	0.33	0.40	0.40
14	0.43	0.36	0.21	0.36	0.43	0.15	0.56	0.56	0.56	0.15
15	0.86	0.14	0.14	0.14	0.86	0.74	0.14	0.14	0.14	0.74
16	0.93	0,07	0.07	0.07	0.93	0.69	0.21	0.21	0,21	0.69
17	0.93	0.07	0.07	0.07	0.93	0.51	0.27	0.27	0.27	0.51
18	0.71	0.07	0.07	0.07	0.71	0.67	0.16	0.16	0.16	0.67
Average	0.42	0.35	0.38	0.38	0.65	0.35	0.35	0.38	0.36	0.52

(f)

Games	Cluster 6 (8 participants)									
	Choice task					Belief elicitation task				
	Eq. Pareto	L2	L1	Inequity aversion	Pros.	Eq. Pareto	L2	L1	Inequity aversion	Pros.
1	0.50	0.50	0.25	0.25	0.25	0.44	0.41	0.44	0.44	0.15
2	0.50	0.13	0.50	0.50	0.38	0.48	0.48	0.41	0.41	0.11
3	0.00	0.00	1.00	1.00	1.00	0.18	0.68	0.68	0.18	0.68
4	0.13	0.88	0.88	0.13	0.88	0.22	0.22	0.71	0.71	0.71
5	0.25	0.25	0.75	0.75	0.75	0.24	0.52	0.52	0.24	0.52
6	0.25	0.75	0.75	0.25	0.75	0.11	0.11	0.72	0.72	0.72
7	0.63	0.63	0.00	0.63	0.38	0.40	0.40	0.40	0.40	0.34
8	0.38	0.38	0.38	0.38	0.50	0.45	0.45	0.21	0.45	0.35
9	0.88	0.00	0.88	0.88	0.88	0.36	0.36	0.29	0.36	0.36
10	0.63	0.63	0.25	0.63	0.63	0.72	0.25	0.72	0.72	0.72
11	0.38	0.38	0.50	0.38	0.38	0.61	0.07	0.61	0.61	0.61
12	0.13	0.75	0.75	0.75	0.13	0.28	0.26	0.47	0.26	0.28
13	0.50	0.13	0.50	0.50	0.50	0.61	0.61	0.38	0.61	0.61
14	0.38	0.25	0.38	0.25	0.38	0.20	0.60	0.60	0.60	0.20
15	0.25	0.63	0.63	0.63	0.25	0.41	0.52	0.52	0.52	0.41
16	0.38	0.50	0.50	0,50	0.38	0.36	0.59	0.59	0.59	0.36
17	0.38	0.63	0.63	0.63	0.38	0.36	0.61	0.61	0.61	0.36
18	0.25	0.75	0.75	0.75	0.25	0.28	0.44	0.44	0.44	0.28
Average	0.39	0.45	0.57	0.54	0.50	0.38	0.42	0.52	0.49	0.43

counterpart to do the same when stating their beliefs. Choices and belief statements of participants in cluster 5 are mainly consistent with the predictions of the model of *Prosociality* (14 participants). Choices and belief statements of participants in cluster 6 (8 participants) are not well explained by any of the proposed models. In the next section we will test the level of consistency between choices and beliefs for the six clusters.

7. Level of consistency between players' choices and their stated beliefs

In this section, we test whether the cumulative frequency distributions of best responses to stated beliefs differ in the six groups of participants (Fig. 6). We hypothesize that participants in clusters 1 and 2 best respond to their belief statements more often compared to participants in the other clusters. The rationale for this hypothesis lies in the fact that only participants in cluster 1 and 2 attribute a model of choice to their counterpart (*Level-1* model) that is one step less sophisticated than the one they actually use to make their choices (*Level-2* model). However, this prediction is only partially supported: the average proportions of actions that are best responses to stated beliefs in clusters 1, 2, 3, 4, 5 and 6 are equal to 0.79, 0.59, 0.57, 0.53, 0.54 and 0.59, respectively. Differences in the frequency distributions of best responses to stated beliefs are compared using the one-tailed, two-sample Kolmogorov–Smirnov test. We find that participants in cluster 1 best respond to their own stated beliefs more often than participants in clusters 2, 3, 4, 5 and 6 (cluster 1 – cluster 2: $D = 0.59$,

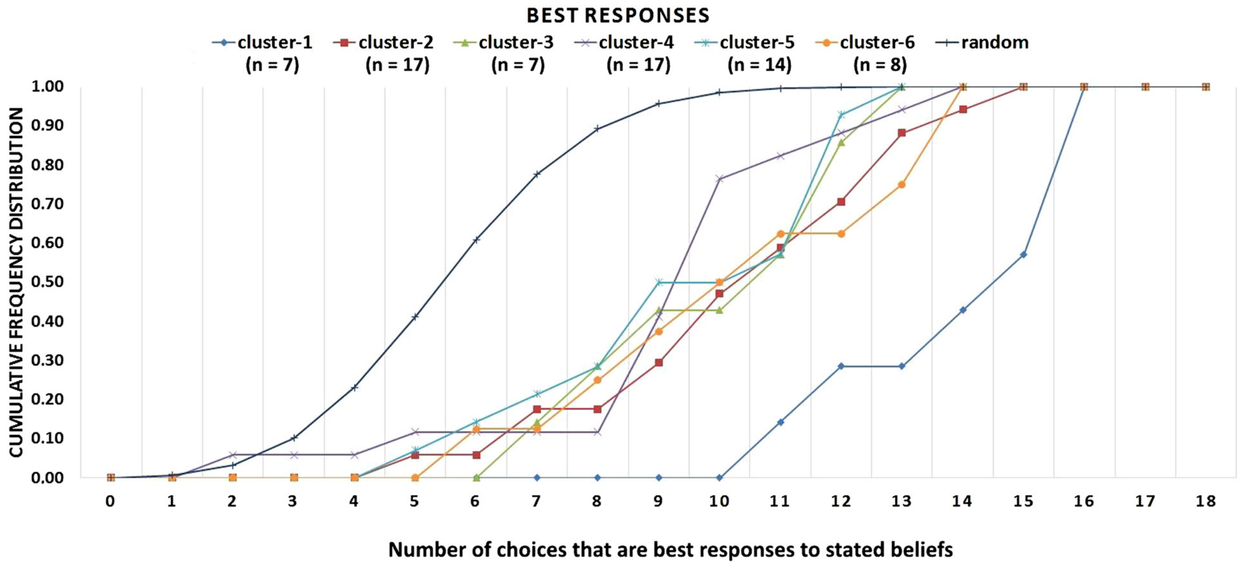

Fig. 6. Cumulative frequency distribution of number of participants with n (ranging from 0 to 18) best responses to their own stated beliefs. All the observed distributions are different from random. Number of participants included in each cluster in parentheses.

$p = 0.029$; cluster 1 – cluster 3: $D = 0.71$, $p = 0.028$; cluster 1 – cluster 4: $D = 0.76$, $p = 0.003$; cluster 1 – cluster 5: $D = 0.71$, $p = 0.008$; cluster 1 – cluster 6: $D = 0.57$, $p = 0.087$).[28] No differences are found between cluster 2 and clusters 3, 4, 5 and 6 (cluster 2 – cluster 3: $D = 0.15$, $p = 0.79$; cluster 2 – cluster 4: $D = 0.29$, $p = 0.230$; cluster 2 – cluster 5: $D = 0.22$, $p = 0.467$; cluster 2 – cluster 6: $D = 0.08$, $p = 0.931$). Fig. 6 shows the cumulative frequency distribution of number of participants with n best responses to their own stated beliefs across the six clusters. Our results show that there is only a small fraction of participants (the 7 participants in cluster 1) who best respond to their own stated beliefs most of the time (rate = 0.79). These participants devote most of their attention to the payoffs of the counterpart in the choice task, using *other within* transitions. Conversely, all the other participants (clusters from 2 to 6) best respond to their own stated beliefs approximately half of the time (average rate = 0.56).

Finally, we test whether the number of choices that are best responses to stated beliefs depends on the type of information acquired by the participants. We run two separate mixed-model logistic regressions for the two tasks (choice and belief elicitation tasks) with an indicator variable for best response as the dependent variable and the proportion of the five types of transition (*own-within*, *own between*, *other within*, *other between* and *intracell*) and the type of games as independent variables.[29] Participants are treated as random effect. Table 8 displays the results of the regressions. We find that the probability with which participants best respond to their own stated beliefs increases with the increasing proportion of *other within* transitions ($\beta = 0.508$, $p < .001$) in the choice task. No effect of the type of transition is found in the belief elicitation task. Moreover, we find that, in coordination games, participants' choices and belief statements are more consistent than in the other three types of games (see Table 8).[30]

Overall, we find that the level of consistency between choices and beliefs in games is determined by the amount of attention that participants devoted to the payoffs of their counterpart during the choice task. However, looking at the payoffs of the other player does not guarantee that the participants will provide a best response to their own stated beliefs; they need to use a specific pattern of visual analysis to achieve a high rate of consistency. This pattern is the one expected for *Level-2* players who best respond to the belief that the counterpart is choosing the *Level-1* action, and it requires using *other within* transitions to find the action with the highest average payoff among those of the counterpart. We find that in the choice task, participants with a high proportion of best responses to their own stated beliefs (participants in cluster 1) take their own payoffs into account only at the end of the decision process, to find a best response to the expected action of a *Level-1* counterpart (see the left part of Fig. 4 and Fig. 5).

28 The difference between cluster 1 and 6 is significant at 10 percent level.

29 We divide the 18 games into four categories. *2-rounds*: games solvable in two steps of iterated elimination of dominated actions (games 1, 3, 5 and 7 for row players and games 2, 4, 6, and 8 for column players). *3–4 rounds*: games solvable in three or four steps of iterated elimination of dominated actions (games 2, 4, 6, 8, 9 and 10 for row players, and games 1, 3, 5, 7, 9 and 10 for column players). *Unique-Nash*: games with a unique Nash equilibrium without dominant actions (games 11, 12, 13, 14). *Coordination*: games with multiple equilibria (games 15, 16, 17 and 18).

30 Table 8 shows that there is also a significant difference between games solvable in two steps of iterated elimination of dominated actions and games solvable in three or four steps ($\beta = 0.310$, $p < .053$).

Table 8
Mixed model logistic regressions. The dependent variable is 1 when the choice of the participant is a best response to her own stated beliefs and 0 otherwise. Independent variables are three dummies for the type of game (*game type*) and the five types of relevant transitions. Games solvable in two steps of iterated elimination of dominated actions (2-rounds) are used as a baseline. We ran two separate models, one considering the relative proportions of the five relevant transitions in the choice task (left side of the table) and one considering the same transitions in the belief elicitation task (right side of the table).

Game type	Choice task						Belief elicitation task					
	Coef.	Std. Err.	Z	$P > \|z\|$	95% CI		Coef.	Std. Err.	Z	$P > \|z\|$	95% CI	
3–4 rounds	0.310	0.160	1.93	0.053	−0.004	0.624	0.317	0.159	1.99	0.047	0.004	0.630
Unique Nash	0.046	0.175	0.27	0.790	−0.297	0.390	0.046	0.174	0.27	0.791	−0.295	0.387
Coordination	1.190	0.190	6.24	0.000	0.816	1.564	1.219	0.190	6.40	0.000	0.846	1.593
Own within	0.213	0.126	1.69	0.090	−0.033	0.460	0.059	0.094	0.63	0.530	−0.125	0.243
Own between	0.027	0.083	0.32	0.745	−0.137	0.191	0.037	0.080	0.47	0.639	−0.119	0.195
Other within	0.508	0.111	4.56	0.000	0.290	0.727	0.105	0.135	0.78	0.438	−0.160	0.371
Other between	−0.137	0.073	−1.85	0.064	−0.282	0.007	0.090	0.082	1.10	0.272	−0.071	0.252
Intracell	0.146	0.131	1.11	0.268	−0.112	0.404	0.152	0.133	1.15	0.251	−0.108	0.414
Cons.	−0.014	0.131	0.11	0.912	−0.242	0.272	−0.001	0.136	0.99	0.994	−0.269	−0.267
N. obs.	1260						1260					
N. independent obs.	70						70					
Log L. =	−803						−817					

8. Conclusions

In this study, we report on an experiment in which 70 participants play and state first order beliefs about their counterpart's choices in 18 one-shot matrix games. We record eye movements for all of them. The level of consistency between choices and beliefs is tested by assuming that participants can use one of four different models. The four models include two models of bounded rationality (the *Level-1* and the *Level-2* models), and two models of other-regarding preferences (the Fehr and Schmidt model of *Inequity aversion* and a model of *Prosociality*). We find that participants do not play according to Nash equilibrium, and they do not believe their counterpart to do so. Moreover, when tested on the entire dataset, none of the four models provides a clear explanation of both choices and belief statements of the participants. Therefore, we investigate the hypothesis that participants are heterogeneous with respect to their decision-making behavior. We use a model-based clustering method and classify participants according to the lookup patterns they use when playing the games and when stating their beliefs. The cluster analysis clearly reveals the presence of heterogeneity in the patterns of visual analysis that participants use to acquire information in the two tasks. This heterogeneity in the lookup patterns reflects the adoption of different models of choice. We find six clusters of participants. Players in cluster 1 devote considerable attention to the payoffs of the counterpart in the choice task and focus their attention entirely on these payoffs in the belief elicitation task. Their behavior is consistent with that expected from *Level-2* players. In particular, they state that the counterpart is choosing the *Level-1* action, and best respond to this belief by playing in accordance with the *Level-2* model. Indeed, we find that their choices and stated beliefs are mainly consistent.

Players in cluster 2 equally distribute their attention between their own and their counterpart's payoffs in the choice task and focus on the payoff of the counterpart in the belief elicitation task. Their choices and stated beliefs are also consistent with the predictions of the *Level-2* model, even though they best respond to their own beliefs less often than participants in cluster 1.

Participants in clusters 3 and 4 focus their attention on their own payoffs in the choice task and on the payoffs of their counterpart in the belief elicitation task. We find that they believe their counterpart to choose the *Level-1* action, while in the choice task they follow the predictions of the *Level-1* model. Thus, their choices and beliefs are mainly inconsistent.

Players in clusters 5 and 6 use identical patterns of visual analysis in the choice and belief elicitation tasks. They use *intracell* transitions to compare their own payoffs with those of the counterpart for each possible outcome of the game, as expected for participants having other-regarding preferences. We find that both the choice and the belief statements of participants in cluster 5 are consistent with the prediction of a model of *Prosociality*: a simple model that assigns a positive weight to the total payoff of the two players and a negative weight to the inequality in payoffs. Participants in cluster 5 best respond to their stated beliefs significantly less often than participants in cluster 1. This is due to the fact that they try to achieve mutual cooperation.

Finally, the behavior of participants in cluster 6 is not well explained by any of the proposed models. Similarly to what we find for clusters 2, 3, 4 and 5, the observed level of consistency between choices and beliefs is lower than the one achieved by participants in cluster 1.

Our results suggest that there are two main reasons why participants often do not best respond to their beliefs in one-shot games: the first is that many of them do not take into account the other player's incentives before choosing their actions but consider the incentives of their counterpart only when stating their beliefs. The second is that some participants have other-regarding preferences and attempt to find a cooperative solution of the game.

Our results have important implications for non-equilibrium models such as level-k (Stahl and Wilson, 1994, 1995; Nagel, 1995; Costa-Gomes et al., 2001; Costa-Gomes and Crawford, 2006) and cognitive hierarchy models (Camerer et al., 2004).

As predicted by the level-k model, we find that participants who make choices consistent with two steps of reasoning (*Level-2* players) state that the counterpart is choosing the *Level-1* action with the highest probability. However, we find that participants whose choices are consistent with the *Level-1* model do not assign equal probability to all counterparts' actions (as expected for *Level-0* players) but state that the *Level-1* action is chosen much more frequently.

More generally, our study supports the hypothesis that players' behavior in one-shot games is driven by two different types of mental processes: motivation and cognition, which determines different decision rules or types that remain invariant over different games. Our classification based on eye-tracking data shows that the level of consistency between choices and belief statements is closely related to how attention is allocated during the decision making process.

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Appendix. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.geb.2018.11.003.

References

Andreoni, J., Miller, J., 2002. Giving according to GARP: an experimental test of the consistency of preferences for altruism. Econometrica, 737–753.
Arieli, A., Ben-Ami, Y., Rubinstein, A., 2011. Tracking decision makers under uncertainty. Am. Econ. J. Microecon. 3 (4), 68–76.
Armantier, O., Treich, N., 2013. Eliciting beliefs: proper scoring rules, incentives, stakes and hedging. Eur. Econ. Rev. 62, 17–40.
Bellemare, C., Sebald, A., Strobel, M., 2011. Measuring the willingness to pay to avoid guilt: estimation using equilibrium and stated belief models. J. Appl. Econom. 26 (3), 437–453.
Bhatt, M., Camerer, C.F., 2005. Self-referential thinking and equilibrium as states of mind in games: fMRI evidence. Games Econ. Behav. 52 (2), 424–459.
Blanco, M., Engelmann, D., Koch, A.K., Normann, H.T., 2010. Belief elicitation in experiments: is there a hedging problem? Exp. Econ. 13 (4), 412–438.
Bolton, G.E., Ockenfels, A., 2000. ERC: a theory of equity, reciprocity, and competition. Am. Econ. Rev., 166–193.
Brocas, I., Carrillo, J.D., Wang, S.W., Camerer, C.F., 2014. Imperfect choice or imperfect attention? Understanding strategic thinking in private information games. Rev. Econ. Stud..
Camerer, C.F., Ho, T.H., Chong, J.K., 2004. A cognitive hierarchy model of games. Q. J. Econ. 119 (3), 861–898.
Charness, G., Rabin, M., 2002. Understanding social preferences with simple tests. Q. J. Econ. 117 (3), 817–869.
Costa-Gomes, M.A., Crawford, V.P., 2006. Cognition and behavior in two-person guessing games: an experimental study. Am. Econ. Rev. 96 (5), 1737–1768.
Costa-Gomes, M.A., Crawford, V.P., Broseta, B., 2001. Cognition and behavior in normal-form games: an experimental study. Econometrica 69 (5), 1193–1235.
Costa-Gomes, M.A., Weizsäcker, G., 2008. Stated beliefs and play in normal-form games. Rev. Econ. Stud. 75 (3), 729–762.
Cox, J.C., Friedman, D., Sadiraj, V., 2008. Revealed altruism. Econometrica 76 (1), 31–69.
Crawford, V.P., Costa-Gomes, M.A., Iriberri, N., 2013. Structural models of nonequilibrium strategic thinking: theory, evidence, and applications. J. Econ. Lit. 51 (1), 5–62.
Croson, R.T., 2000. Thinking like a game theorist: factors affecting the frequency of equilibrium play. J. Econ. Behav. Organ. 41 (3), 299–314.
Danz, D.N., Fehr, D., Kübler, D., 2012. Information and beliefs in a repeated normal-form game. Exp. Econ. 15 (4), 622–640.
Devetag, G., Di Guida, S., Polonio, L., 2016. An eye-tracking study of feature-based choice in one-shot games. Exp. Econ. 19 (1), 177–201.
Dreber, A., Fudenberg, D., Rand, D.G., 2014. Who cooperates in repeated games: the role of altruism, inequity aversion, and demographics. J. Econ. Behav. Organ. 98, 41–55.
Dufwenberg, M., Gächter, S., Hennig-Schmidt, H., 2011. The framing of games and the psychology of play. Games Econ. Behav. 73 (2), 459–478.
Dufwenberg, M., Gneezy, U., 2000. Measuring beliefs in an experimental lost wallet game. Games Econ. Behav. 30 (2), 163–182.
Dufwenberg, M., Kirchsteiger, G., 2004. A theory of sequential reciprocity. Games Econ. Behav. 47 (2), 268–298.
Falk, A., Fischbacher, U., 2006. A theory of reciprocity. Games Econ. Behav. 54 (2), 293–315.
Fehr, E., Gächter, S., Kirchsteiger, G., 1997. Reciprocity as a contract enforcement device: experimental evidence. Econometrica, 833–860.
Fehr, E., Schmidt, K.M., 1999. A theory of fairness, competition, and cooperation. Q. J. Econ. 114 (3), 817–868.
Fehr, E., Schmidt, K.M., 2010. On inequity aversion: a reply to Binmore and Shaked. J. Econ. Behav. Organ. 73 (1), 101–108.
Fisman, R., Kariv, S., Markovits, D., 2007. Individual preferences for giving. Am. Econ. Rev. 97, 1858–1877.
Fraley, C., Raftery, A.E., 2002. Model-based clustering, discriminant analysis, and density estimation. J. Am. Stat. Assoc. 97 (458), 611–631.
Fraley, C., Raftery, A.E., Scrucca, L., 2012. Normal Mixture Modeling for Model-Based Clustering, Classification, and Density Estimation. Technical Report No. 597. Department of Statistics, University of Washington.
Hyndman, K., Ozbay, E.Y., Schotter, A., Ehrblatt, W.Z.E., 2012. Convergence: an experimental study of teaching and learning in repeated games. J. Eur. Econ. Assoc. 10 (3), 573–604.
Iriberri, N., Rey-Biel, P., 2013. Elicited beliefs and social information in modified dictator games: what do dictators believe other dictators do. Quant. Econ. 4 (3), 515–547.
Isaac, R.M., Walker, J.M., 1988. Group size effects in public goods provision: the voluntary contributions mechanism. Q. J. Econ. 103 (1), 179–199.
Johnson, E.J., Camerer, C., Sen, S., Rymon, T., 2002. Detecting failures of backward induction: monitoring information search in sequential bargaining. J. Econ. Theory 104 (1), 16–47.
Krajbich, I., Armel, C., Rangel, A., 2010. Visual fixations and the computation and comparison of value in simple choice. Nat. Neurosci. 13 (10), 1292–1298.
Manski, C.F., 2004. Measuring expectations. Econometrica 72 (5), 1329–1376.
Manski, C.F., Neri, C., 2013. First-and second-order subjective expectations in strategic decision-making: experimental evidence. Games Econ. Behav. 81, 232–254.
Nagel, R., 1995. Unraveling in guessing games: an experimental study. Am. Econ. Rev. 85 (5), 1313–1326.
Neri, C., 2015. Eliciting beliefs in continuous-choice games: a double auction experiment. Exp. Econ. 18 (4), 569–608.
Nyarko, Y., Schotter, A., 2002. An experimental study of belief learning using elicited beliefs. Econometrica 70 (3), 971–1005.
Offerman, T., Sonnemans, J., Schram, A., 1996. Value orientations, expectations and voluntary contributions in public goods. Econ. J., 817–845.

Palfrey, T.R., Wang, S.W., 2009. On eliciting beliefs in strategic games. J. Econ. Behav. Organ. 71 (2), 98–109.
Polonio, L., Di Guida, S., Coricelli, G., 2015. Strategic sophistication and attention in games: an eye-tracking study. Games Econ. Behav. 94, 80–96.
Rabin, M., 1993. Incorporating fairness into game theory and economics. Am. Econ. Rev., 1281–1302.
Reutskaja, E., Nagel, R., Camerer, C.F., Rangel, A., 2011. Search dynamics in consumer choice under time pressure: an eye-tracking study. Am. Econ. Rev. 101 (2), 900–926.
Rey-Biel, P., 2009. Equilibrium play and best response to (stated) beliefs in normal form games. Games Econ. Behav. 65 (2), 572–585.
Rutström, E.E., Wilcox, N.T., 2009. Stated beliefs versus inferred beliefs: a methodological inquiry and experimental test. Games Econ. Behav. 67 (2), 616–632.
Sapienza, P., Toldra-Simats, A., Zingales, L., 2013. Understanding trust. Econ. J. 123 (573), 1313–1332.
Schotter, A., Trevino, I., 2014. Belief elicitation in the laboratory. Annu. Rev. Econ. 6 (1), 103–128.
Scrucca, L., Fop, M., Murphy, T.B., Raftery, A.E., 2016. mclust 5: clustering, classification and density estimation using gaussian finite mixture models. R J. 8 (1), 289.
Stahl, D.O., Wilson, P.W., 1994. Experimental evidence on players' models of other players. J. Econ. Behav. Organ. 25 (3), 309–327.
Stahl, D.O., Wilson, P.W., 1995. On players' models of other players: theory and experimental evidence. Games Econ. Behav. 10 (1), 218–254.
Trautmann, S.T., Kuilen, G., 2015. Belief elicitation: a horse race among truth serums. Econ. J. 125 (589), 2116–2135.
Van Lange, P.A., 1999. The pursuit of joint outcomes and equality in outcomes: an integrative model of social value orientation. J. Pers. Soc. Psychol. 77 (2), 337.
Van Lange, P.A., 2000. Beyond self-interest: a set of propositions relevant to interpersonal orientations. Eur. Rev. Soc. Psychol. 11 (1), 297–331.
Vanberg, C., 2008. Why do people keep their promises? An experimental test of two explanations. Econometrica 76 (6), 1467–1480.
Weizsäcker, G., 2003. Ignoring the rationality of others: evidence from experimental normal-form games. Games Econ. Behav. 44 (1), 145–171.
Ziegelmeyer, A., Koessler, F., Bracht, J., Winter, E., 2010. Fragility of information cascades: an experimental study using elicited beliefs. Exp. Econ. 13 (2), 121–145.