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## An eye-tracking study of feature-based choice in one-shot games

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# An eye-tracking study of feature-based choice in one-shot games

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**Abstract**

We analyze subjects' eye movements while they make decisions in a series of one-shot games. The majority of them perform a partial and selective analysis of the payoff matrix, often ignoring the payoffs of the opponent and/or paying attention only to specific cells. Our results suggest that subjects apply boundedly rational decision heuristics that involve best responding to a simplification of the decision problem, obtained either by ignoring the other players' motivations or by considering them only for a subset of outcomes. Finally, we find a correlation between types of eye movements observed and choices in the games.

**Keywords:** one-shot games, eye-tracking, similarity, categorization, focal points, individual behavior, experimental economics, behavioral economics

JEL codes: C72, C91, D01, D83

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# 1 Introduction

Most theories of behavior in games are based on the two fundamental assumptions of strategic thinking and optimization (Camerer, Ho, and Chong 2004): the former meaning that players develop beliefs about the likely behavior of other players, the latter implying that subjects best respond to these beliefs. Models that incorporate bounded rationality (however defined) allow beliefs and choices to be both heterogeneous and out of equilibrium, particularly before any learning process takes place: i.e. in games that are played only once or in initial behavior in repeated games. For example, models of limited cognition (Stahl and Wilson 1994, 1995; Nagel 1995; Ho, Camerer, and Weigelt 1998; Costa-Gomes, Crawford, and Broseta 2001; Bosch-Domnech et al. 2002; Crawford 2003; Camerer, Ho, and Chong 2004; Costa-Gomes and Crawford 2006; Crawford and Iriberri 2007a; 2007b) typically assume that players vary in their ability to perform iterated reasoning, and believe that other players are able to perform less steps than themselves (Camerer, Ho, and Chong 2004). However, players are still assumed to form a correct mental representation of the strategic situation at hand (i.e., to put it crudely, it is assumed that players know and understand which game they are playing), and to apply forms of strategic reasoning that allow them to form a model of the other player(s), however imperfect and incorrect it may be.

However, isolated but important recent results seem to question the validity of these fundamental assumptions. Costa-Gomes and Weizsäcker (2008) show that choices are, on average, inconsistent with beliefs and subjects fail to best respond to their own stated beliefs in roughly half the games being tested. Devetag and Warglien (2008) show that subjects' mental models are systematically (and mistakenly) simplified, so as to reduce the game payoff structure from a mixed motive to a pure motive one. In a series of dominance solvable guessing games, Rydval, Ortmann, and Ostatnicky (2009) show that nearly two thirds of experimental subjects show reasoning inconsistent with dominance, although a quarter of them actually do choose dominant strategies. Using the eye-tracking, Arieli, Ben-Ami, and Rubinstein (2011) show that subjects facing two lotteries often compare prizes and probabilities separately, rather than extensively analyzing the whole structure of each lottery, as suggested by expected utility theory. In Weizsäcker (2003), subjects behave as if they underestimate their opponents' rationality or ignore other players' choices when making their own decisions

The evidence cited above points at two strictly intertwined phenomena; first, some players ignore other players' motivations and incentives, possibly to simplify a choice problem that is perceived as cognitively demanding. Second, players apply decision heuristics that do not involve orthodox strategic reasoning and that are not based on a mental model that corresponds to the true game being played.

Here, we hypothesize that in one-shot games subjects best respond to a simplification of the original decision problem, obtained either by ignoring the other players motivations or by taking them into account only for a subset of all possible game outcomes. Di Guida and Devetag (2012) show that it is possible to induce systematic and predictable changes in players' behavior by manipulating a game set of descriptive features (i.e., features that can be changed without altering the game equilibrium properties). They suggest that descriptive features provide attractive solutions to subjects using boundedly rational heuristics. Only when these features are removed, subjects exert more effort into thinking strategically, and in some cases, choose Nash equilibrium strategies.

A recent approach to the study of gaming behavior aimed to shed light on players' strategic reasoning includes the use of process data. The analysis of information search patterns, together with a classical analysis of subjects' actual choices, allows investigating the subconscious mechanisms at the basis of strategizing. Techniques like mouse-tracking (Costa Gomes, Crawford, and Broseta 2001; Johnson et al. 2002; Brocas et al. 2013), eye-tracking (Arieli, Ben-Ami, and Rubinstein 2011; Chen, Huang, and Wang 2009; Knoepe, Wang, and Camerer 2009; Wang, Spezio, and Camerer 2010), and fMRI (Bhatt and Camerer 2005) allow researchers to catch a glimpse of the cognitive mechanisms driving human strategic behavior while keeping them subconscious, and therefore avoiding the noise produced in the phase of "elicitation" (i.e. when subjects are asked to explain verbally why did they act in a particular way).

In this paper, we analyze subjects' eye movements (or "lookup patterns") when playing the games presented in Di Guida and Devetag (2012) to test whether the information search patterns the subjects exhibit are more compatible with "boundedly rational heuristics" or with the "best responding to beliefs" hypothesis. Our data substantially confirm Di Guida and Devetag (2012) results. Analysis of lookup patterns shows that subjects perform a partial and selective analysis of the game, often ignoring the payoffs of the opponent and/or paying attention only to specific cells of the matrix. The two most frequent eye-movements are those connecting one's own payoffs associated with a specific strategy (i.e., payoffs lying on the same row of the matrix), and those connecting the two players' payoffs within each cell. We also find a correlation between choices and lookup patterns: subjects who choose more often the strategy with the highest average payoff for themselves tend to exhibit the first type of eye-movement, while subjects choosing the strategy leading to an attractor (defined as a focal point with or without the equilibrium property: see Di Guida and Devetag, 2012) more frequently tend to compare payoffs by cell. Finally, subjects who pick the equilibrium strategy exhibit several different types of lookup patterns, revealing a more refined game analysis and the use of sophisticated decision rules that thoroughly take into account moves of the opponent.

Our findings strongly support the hypothesis that subjects in one-shot games in normal form apply boundedly rational heuristics that are based on a simplified model of the true situation.

# 2 Games, Experimental Design, and Behavioral Predictions

## 2.1 The Games

As we are interested in initial behavior only, we implement a random rematching scheme with no feedback (as in Costa-Gomes, Crawford, and Broseta

2001), in order to minimize learning and "repeated game" effects. The payoff matrices used in the experiment are listed in Figure 1.

Table 1 about here

The basic games (see Di Guida and Devetag 2012) are: a game with a strictly dominant strategy for the column player (henceforth, DomCol game); a game without pure strategy Nash Equilibria (noNE), a game with a single pure strategy Nash Equilibrium but not solvable through iterated elimination of dominated strategies (UniqNE), a modified Prisoners' Dilemma (PD), and a Weak Link coordination game (WL).

As in Di Guida and Devetag (2012), we are interested in the effects produced by two descriptive features: the variance of the strategy giving the highest average payoff to the player whose behavior we intend to observe (henceforth HA), and the presence of an attractor (henceforth A). An Attractor is any cell containing Pareto-efficient and symmetric payoffs, located at the center of the matrix[4]. Except in the Weak Link game, our attractors are not equilibria.

To identify both features' separate and joint effects, we created a matrix for every possible combination of features. Six matrices were therefore created for each base game, for a total of 30 matrices: HA with low variance and Attractor, HA with middle variance and Attractor, HA with high variance and Attractor, HA with low variance and without Attractor, HA with middle variance and without Attractor, HA with high variance and without Attractor.

To facilitate our exposition, we refer to each matrix by the acronym identifying the game type, and by two acronyms identifying its features: "A" means a matrix with an attractor, "NA" a matrix without attractor, and "Low", "Medium" and "High" the three levels of variance of the strategy with the highest average payoff.

Since due to matrices' construction constraints we are only interested in row players behavior, all descriptions of features and matrices deal with the row player's perspective, unless otherwise specified.

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[4] In the Weak Link game all symmetric cells were positioned along the main diagonal from the highest to the lowest payoff

Given the structure of the matrices, we assume that agents choosing the row containing the attractor do so because of the attractor itself. Therefore, the row containing the attractor is labeled as “A strategy”. Same holds for the row giving the highest average payoff, labeled as “HA strategy” (see Di Guida and Devetag 2012 for further details of the experimental design)

All versions of each game are created by modifying cells’ content as little as possible and by maintaining unaltered the pure strategy Nash Equilibria. In a few cases, these changes added new Nash equilibria in mixed strategies. In extreme cases, two matrices differed by a single cell. Except in one matrix (WL A Low), the average payoff of the HA strategy remained invariant: only its distribution was modified as to change the value of payoff variance.

In DomCol, noNe, and UniqNe, matrices without attractor are obtained by breaking the symmetry of payoffs and by substantially reducing payoffs’ magnitude. For the PD we are obliged by the game structure to eliminate the attractor by breaking payoff symmetry only, without a significant reduction in payoff size. In the Weak Link, given that the attractor is the payoff-dominant equilibrium, we simply move the corresponding cell out of the main diagonal.

We keep our strategies of interest separate whenever possible. For example, in the DomCol game, Row 1 identifies the HA strategy, Row 2 the A strategy, and Row 3 the pure strategy Nash Equilibrium strategy (henceforth EQ). In the PD, however, EQ and HA necessarily coincide. To avoid spurious effects due to the position of the strategies in the matrix, we always keep the position of every strategy fixed in the different versions of the same game, the only exception being the WL game[5].

## 2.2 Experimental design and implementation

The experiment was conducted at the EPL lab (Experimental Psychology Laboratory) of the University of Trento. Because of the peculiar characteristics of

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[5] Results in Di Guida and Devetag (2012) suggest that the position of a strategy does not affect its frequency.

eye-tracking experiments (and, for that matter, of fMRI experiments as well) non-standard experimental procedures were employed. Knoepfle, Wang, Camerer. (2009) conducted experiments with sessions of 6 subjects, only one (or two) of which were monitored with the eye-tracker. In Kuo et al. (2009) the subject participating in the fMRI session was paired with another subject drawn randomly from a pool of possible opponents who had previously participated in a separate session. In both experiments, monitored subjects did not see the other participants.

We adopted a design similar to Kuo et al. (2009). As we are only interested in the row players' behavior, we collected eye-tracking data for row players only, and matched each row player with a column player drawn at random from the pool of subjects participating in the experiment in Di Guida and Devetag (2012). The pairings differed across games.

A total of 43 subjects were eye-tracked, all playing as row player. Before the experiment started, a printed copy of the instructions was given to the subject and read aloud by the experimenter. Control questions were administered to assure that the mechanism of the experiment was understood[6].

Subjects were explicitly told that they would play in the role of row player, and that their choices would be matched with those of other subjects that had played before. It was specified that the payment would be calculated based on the outcomes of 3 randomly selected games. The mechanism of random selection was made explicit.

For the eye-track record, a head mounted, video-based eye tracker, model "EyeLink", version 1.11 was used. The software for the decision tasks was written in Matlab, using the Psychophysical Toolbox version 2.5.4 and the Eye-Link Toolbox version 1.4.4 to interface it with the eye-tracker hardware.

During the calibration procedure, subjects were asked to fix nine points located in different parts of the screen, to allow the experimenter to record current eye and head position. The calibration was followed by a validation phase, identical to

[6]A translated copy of the instructions and control questions are reported in Appendix A and B.

the calibration one, aimed to verify whether the recorded positions were sufficiently accurate. If necessary, both calibration and validation were repeated.

Before the beginning of each trial a drift correction was performed. To begin the trial, a fixation point coincident with the last point of the drift correction had to be fixed for 300 ms (last point of the validation phase for the first trial of each block).

The fixation point was located at the bottom of the screen, outside the area covered by the matrix, to minimize biases related to the starting fixation point. Most of the subjects moved directly from the fixation point to the top left corner of the matrix, showing a natural tendency to process images with eye movements going from left to right and from top to bottom. This is a well-known bias associated with western writing conventions (Abed 1991; Chua, Boland, Nisbett 2005; Ishii et al. 2011).

After the cameras were calibrated, subjects played four practice games. The games were then presented in three blocks of ten games each, to allow subjects to take a short break and to re-calibrate cameras if necessary. The order in which the 30 matrices were displayed was random and differed across subject. Once the experiment was concluded, subjects had to complete a series of questionnaires aimed at measuring cognitive abilities, personality traits, and degree of risk aversion.

After completing the questionnaire, subjects were presented two urns: the first containing 30 tags, each corresponding to one of the matrices played, the second containing 20 tags, one for each possible opponent. They were then asked to draw 3 tags from each urn, to select both the games and the opponents that would determine their earnings.

The experiment lasted on average one hour, and average payment was 10 Euros (the average payment was calibrated according to the EPL lab guidelines).

As said, participants always played in the role of row players. In each round, they had to select their preferred strategy by pressing the keys “1”, “2”, or “3”, on the keyboard. Their hand was positioned on the keys before calibrating the cameras and they had the chance to practice before the experiment started. Each key corresponded to one row of the matrix.

No feedback was given to subjects until the end of the experiment. In order not to increase pupil dilatation during the experiment, the matrix was designed with white lines on a black background. To minimize noise, information displayed on the monitor was limited to payoffs only. Strategy labels were eliminated, as it was straightforward for subjects to remember (once explained) that players' actions were labeled according to the order in which they appeared, from top to bottom and from left to right. In addition, payoffs were positioned as far as possible from each other, with row and column player payoffs at different latitudes. This made the classification of eye movements easier and less ambiguous. To further avoid confusion, the two players' payoffs were presented in different colors. Finally, no time constraints were imposed on subjects to choose their strategies.

## 2.3 Eye-tracking data

At each round, subjects are presented with a 3x3 payoff matrix. For each matrix, 18 areas of interest (AOIs) are defined, one for each of the 18 payoffs. Figure 1 shows the areas of interest, where the small numbers in italic report the labels used to identify each of them. Each cell contains two areas of interest, centered on the row and column players' payoff. The AOIs of the row player are numbered from 1 to 9, whereas those of the column player from 10 to 18.

AOIs do not overlap, nor cover the matrix area entirely, but only half of it approximately. In this way, AOIs include only eye-movements whose interpretation is not ambiguous. Although a large part of the matrix is not included in any AOIs, the majority of fixations observed fell inside the AOIs.

For each subject and round, we record four types of variables. The first two are how many times (fixation count) and for how long (fixation time) a subject fixes a point inside (but also outside) an AOI. Since these two variables are usually strongly correlated, we will mostly refer to the first variable (fixation count or simply fixation). The third and fourth variables are the number and type of transitions, i.e. the eye-movements from one AOI to the next.

Figure 1 about here

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, only a subset of these is informative for our purposes.

We consider the following five types of transitions (where AOI R corresponds to the AOIs of row players' payoffs (from 1 to 9), and AOI C to those of column players' payoffs (from 10 to 18)):

- Row Player by row (RPr): eye-movements from one AOI R to another AOI R, in the same row of the payoff matrix (e.g., from 1 to 2, or from 1 to 3). Transitions that remain within the same AOI are excluded. See figure 1: thin continuous line with arrows.
- Column Player by row (CPr): eye-movements from one AOI C to another AOI C, in the same row (e.g., from 16 to 17, or to 18). Transitions that remain within the same AOI are excluded. See figure 1, dashed line with arrows.
- Row Player by column (RPc): eye-movements from one AOI R to another AOI R, in the same column of the payoff matrix (e.g., from 1 to 4, or from 1 to 7). Transitions that remain within the same AOI are excluded. See figure 1, thin continuous line with circles.
- Column Player by column (CPc): eye-movements from one AOI C to another AOI C, in the same column of the payoff matrix (e.g., from 12 to 15, or 18). Transitions that remain within the same AOI are excluded. See figure 1, dashed line with circles.
- Payoffs infracell (INF): eye-movements from an AOI R to an AOI C or vice-versa, within the same cell (e.g., from 5 to 14). See figure 1, thick continuous line.

According to our hypotheses, transitions can be interpreted as information search patterns, and are closely related to the decision rule adopted. Therefore, the analysis of transitions can provide insight about the type of heuristics used by the decision makers. For example, exploring the matrix exclusively or prevailingly through RPr transitions (Row Player by row) indicates a subject ignoring other players' choices. In a case like this, the decision maker may be calculating the average expected value of all strategies available in order to pick the one with the highest value, a process that requires summing up (and therefore observing) payoffs by row. RPc transitions (Row Player by column) are instead compatible with the detection of simple dominance, while CPr (Column Player by row) with the detection of dominant strategies for the column player, i.e., with performing one step of iterated dominance. Finally, INF is compatible with a choice process based on the analysis of matrix cells, induced either by the presence of salient outcomes such as focal points or attractors, or by decision rules that focus on payoffs sums (like the "Altruistic" type, see Stahl and Wilson 1994 and 1995, Costa-Gomes, Crawford, and Broseta 2001), or payoffs differences (fairness, inequality aversion, competitive preferences,… see Bolton & Ockenfels 2000, Fehr and Schmidt 1999, Rabin 1993).

## 2.4 Behavioral Hypotheses

We formulate the following research hypotheses: first, we assume that players are influenced by the presence of "intuitive" and "easy" solutions to a game; therefore, strategy HA when its variance is low, together with strategy A (leading to an attractive outcome) will be chosen more often than the equilibrium strategy, with the share of HA decreasing as its variance increases. Only when these features are absent, more players switch to the equilibrium strategy (Hypothesis 1).

Second (Hypothesis 2), we assume that subjects on average perform a very partial and selective analysis, paying attention only to specific subsets of the matrix elements. The attention depends both on game type and on feature composition, besides presumably varying across players. For example, we expect the "Attractor" cell to attract more attention than the remaining cells, ceteris paribus. Finally (Hypothesis 3), we assume a correlation between choices and lookup patterns. In particular, players who select HA tend to focus on their own payoffs (ignoring the opponents' payoffs) and are more prone to analyze the matrix by row; players who select A are more prone to analyze the game by cell (i.e., they present more infracell saccades) and pay relatively more attention to the attractor cell; players who select EQ perform on average a more complete game analysis (Costa-Gomes, Crawford, and Broseta 2001).

Hypothesis 2 states that subjects' use of decision rules is based on selective information processing, that is, a simplified model of the "true" situation. Hypothesis 3 states that specific choices are the result of specific decision rules, which are based on the aforementioned selective information processing. Both hypotheses are important to discriminate between explanations of behavior based on "best-reply-to-beliefs" and those based on the use of decisional shortcuts that rely on mental simplifications of the real decision problem.

# 3 Results

## 3.1 Behavioral data

Before moving to the lookup pattern analysis, we present an overview of choice data. A total of 43 subjects participated in the experiment. Three eye-tracked observations had to be discarded because of low calibration quality. Therefore the subject pool is composed of 43 subjects in the aggregate analysis and 40 subjects in the lookup pattern analysis.

A data overview is provided in Figure 2. The difference in choice distributions between matrices with and without attractor is evident, as well as the effect due to the increase in the variance of strategy HA. A comparison between choice distributions in the A Low and in the NA High version of each game by a chi-square test reveals that differences are always significant at the 5 per cent level.

Figure 2 about here

In all games except the weak link[7], the frequency of the attractor strategy is higher in matrices with an attractor than in those without it. According to the binomial test, in the games DomCol, noNe, and UniqNe, the difference in choice shares is always significant with p = 0.05 (except in UniqNe Middle where p = 0.1). Figure 3 reports the frequencies of the HA strategy as a function of its

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[7] In the WL NA matrices, the cell containing the attractor is not modified, but rows and columns are shuffled to move the attractor to a less "evident" position. As already shown in Di Guida and Devetag 2012, subjects' behavior indicates that this is not sufficient to reduce a cell attractiveness.

variance level. The expected downward trend is observed, confirming that the increase in variance reduces the appeal of the HA strategy. Overall, our Hypothesis 1 is confirmed, and the results in Di Guida and Devetag (2012) successfully replicated. Our descriptive features create "easy" choices: a safe and attractive strategy, and a strategy leading to a very attractive outcome for both players. The attractor in our game matrices can be labeled as a behavioral "focal point".

Figure 3 about here

## 3.2 Lookup patterns

We only consider fixations longer than 100 milliseconds, which has been proved a sufficient threshold to discriminate between fixations and other ocular activities (Manor and Gordon 2003).

Figure 4 about here

Figure 4 shows the number of fixations by game type and by features combination. It is noteworthy that, moving from left to right, i.e., shifting from matrices with attractor to matrices without, and from low to high levels of variance of HA, the total number of fixations increases, confirming our hypothesis that the absence of attractive features makes a game harder to process.

Notwithstanding this general tendency, however, the distribution of fixations across games appears markedly different. Some games (DomCol, UniqNe, and PD) are particularly sensitive to changes in descriptive features, as shown by their fixations increasing by 50 per cent or more from A Low to NA High games. UniqNe seems less feature-sensitive since only a slight increase in the number of fixations is observed, while the fixations of WL are almost constant across different versions.

Overall attention was very unevenly distributed across the different elements of the game matrix. Fixations devoted to AOIs from 1 to 9 (comprising a subject's own payoffs) amount to 26,118, against the 20,554 fixations dedicated to AOIs from 10 to 18. The two distributions are significantly different at the 5 per cent level by a Wilcoxon signed rank test (p=.039). Hence, on average, subjects devote disproportionately more attention to their own payoffs compared to their opponents' payoffs, in line with what suggested by choice data from previous experiments. For six players out of forty (15 per cent), 95 per cent of fixations were directed at AOIs from 1 to 9 (i.e, to their own payoffs), and 80 per cent of fixations were directed at AOIs 1-9 for the 25 per cent of players (ten out of forty). The most looked at AOI is number 2, which corresponds to the row player's payoff in the cell immediately above the attractor. The second two most looked AOIs are 5 and 14, which correspond to the attractor cell.

Figure 5 (panel A) reports the absolute and relative frequencies of fixations in the matrices with (A) and without (NA) attractor, by cell. It is noteworthy that fixations in matrices with attractor are always less, in absolute terms, than those in matrices without attractor, except, as predicted, for the attractor cell. The two distributions, however, look almost identical (again with the exception of the attractor), suggesting that relative attention was invariant. Panel B shows the absolute and relative frequency of fixations for each of the three variance levels of the HA strategy by cell. The graph shows that each cell is always observed less frequently in matrices with HA low variance than in those with medium and high variance. Distributions are again invariant, suggesting that increasing HA increases the amount of overall gazing time but does not per se change each cell relative importance.

Figure 5 about here

## 3.3 Overview of transitions

Panels C and D report the absolute and relative frequency of transitions by type, distinguishing between matrices with and without attractor (panel C), and between different levels of HA variance (Panel D). The figures show that the most frequent transitions are RPr (Row Player by row) and INF (Payoffs infracell). The third most frequent category is that of CPc transitions. The observation suggests that subjects tend to compare strategies according to their average payoff (RPr and CPc), rather than by looking for dominance relation (RPc and CPr). An equally frequent transition entails comparing payoffs within the same cell. Absolute frequencies of transitions are higher for matrices without attractors, and they increase as the HA variance increases. Nonetheless, their relative frequency seems relatively unaffected by the presence or absence of features. A larger difference is observed when comparing matrices with HA low variance and those with HA high variance. In the first case where HA, besides being attractive, is also a safe strategy RPr transitions are more frequent, and CPc and INF transitions less frequent.

Panel E shows how transitions are distributed across different games and payoff matrices. As the graph shows, there is a clear and stable prevalence of RPr and INF over all typologies of transitions in each of the 30 games, despite substantial variations in absolute levels. Hence, the most frequently observed information processing patterns look roughly similar across all games. However, a careful comparison of relative frequencies of both transitions and fixations reveals that subjects indeed modify their lookup patterns when facing less "intuitive" games. For example, in DomCol A High, RPr transitions are the most frequent, followed by INF and then CPc. It is sufficient to remove the attractor (let's take the case of DomCol NA High) to induce a dramatic change, with CPc becoming the most frequent (almost doubling its share), followed by RPr and INF (with the same share).

## 3.4 Choices and Lookup patterns

This analysis aims to verify whether a correlation may be found between subjects' choices and their lookup patterns. In the experiment, a total of 40 subjects played 30 games each, for a total of 1200 choices. Of these, 40 per cent were HA choices, 16 per cent A, 15 per cent EQ, and 14 per cent EQ/HA[8]. Table 2 shows the correlation results[9]. Shaded coefficients are those that resulted statistically significant at the 5 per cent level.

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[8] The other were: 9 per cent NA, 4 per cent COS, and 2 per cent DOM, see Table 1.

[9] We opted for the Spearman correlation coefficient, as neither normally distributed variables nor a linear correlation among them (which are both necessary assumptions for the use of the Pearson correlation coefficient) can be assumed, and as some of the variables exhibit large variability across subjects (the Pearson correlation coefficient is in fact more sensitive to outliers than the Spearman).

Table 2 about here

Several considerations can be drawn by looking at correlation data: HA choices are positively and significantly correlated with RPr transitions (eye-movements that connect a player's own payoffs by row) and are negatively and significantly correlated with all transitions involving the opponents' payoffs, including INF transitions. Moreover, HA choices are also negatively and significantly correlated with all AOIs from 10 to 18, i.e., all AOIs related to the opponent's payoffs. This evidence strongly confirms our hypothesis that players who choose HA do so by employing a decision heuristic that prescribes to pick the strategy with the highest expected value ignoring the other players' motivations, and implicitly treating the strategic decision problem as an individual decision making problem.

A choices (choices of strategies leading to the attractor), as predicted, are positively and significantly correlated with INF transitions, and with transitions connecting column players' payoffs by row. A choices are also positively and significantly correlated with the attractor cell, (R2, C2) and with a subset of the opponent's AOIs, namely AOIs 10 and 11, and 13 and 14, corresponding to payoffs in the first and second row of the matrix. As assumed, players who pick strategy A do take into account their opponent's payoffs, but only for a subset of possible game outcomes. The heuristic leading to the choice of an attractive outcome for both players (a behavioral, non-equilibrium focal point) is based on an incomplete game analysis and representation, albeit more "strategic" than the one leading to HA choices.

Choices of the equilibrium strategy (EQ) are positively and significantly correlated with the following transitions: CPr, RPc, CPc, and INF. They are positively and significantly correlated with AOIs 3, 6, and 9, i.e., with the player's own payoffs in the third column of the matrix. Moreover, EQ choices are positively and significantly correlated with all AOIs from 10 to 18, that is, AOIs corresponding to all opponent's payoffs. In addition, the correlation with all cells belonging to the third column of the matrix (corresponding to the opponent's choice in equilibrium) is likewise positive and significant. This evidence strongly supports the idea that players who choose the equilibrium strategy are by far the most strategic in the standard game-theoretic meaning, processing the matrix according to eye-movements that suggest the search for dominance (RPc if looking for a dominant strategy for themselves, CPr if looking for a dominant strategy for the opponent), paying attention to the opponents' payoffs for all possible game outcomes, and to cells of the matrix (like the ones on the third column) which other player types typically neglect.

Correlations suggest that our hypotheses 2 and 3 are confirmed; assuming that any information that is not looked at by the decision maker cannot enter the decision maker's decision process, we can conclude that many players in one-shot games apply boundedly rational heuristics that simplify the decision problem either by ignoring the opponents' payoffs, or by considering them only for a subset of all possible outcomes.

## 3.5 Cluster Analysis

To further confirm our correlation results we performed a cluster analysis using the normal distribution of the five transition types classified in section 3.3 (RPr, RPc, CPr, CPc, INF). For this purpose, we use the mixture model presented in Brocas et al. (2013) and proposed by Fraley and Raftery (2002, 2006). Mixture models treat each cluster as a component probability distribution. A bayesian approach is then used to choose among different cluster numbers and statistical methods. As in Brocas et al (2013), we consider a maximum of nine clusters and a total of ten possible models, and we choose the combination that maximizes the Bayesian Information Criterion (BIC). With our data the BIC is maximized at -357 by a "diagonal model, varying volume and shape" yielding 5 clusters.

Figure 6 (Panel A) shows the normalized proportion of different transitions (RPr, RPc, CPr, CPc, INF) with which subjects belonging to different clusters analyze the games. In the first four clusters the predominance of a specific transition type over the others is rather evident; only the last cluster shows a more uniform distribution, as the CPr transition, albeit more frequent than the others, is characterized by a very high variance.

Figure 6 about here

In the first four clusters (grouping 31 out of 40 players) the most observed transition type is a proxy of the most frequent choice. In cluster 1, comparisons are mainly made among the players' own payoffs by row (RPr), hence we can expect a relatively high proportion of HA choices. In cluster 2 a high frequency of INF transitions is observed, which should lead to more A/NA choices. In cluster 3, the most frequent transition is CPc, followed by RPc and CPr; this cluster should therefore include a large proportion of EQ choices. Finally, in cluster 4 the most frequent transition is still CPc, but with smaller differences among the remaining transitions; hence, we can still expect a high proportion of EQ choices, even though lower than that observed in cluster 3.

Panel B reports the average proportions of HA, A/NA, and EQ/QES choices for each cluster. The figure confirms the relationship between transition types and choices: players in cluster 1 analyze their own payoffs by row and select HA with very high frequency (almost 95%). Players in cluster 2 use INF transitions and show the highest frequency of A/NA choices. The distribution of choices in this cluster suggests that players choose A when the attractor is present and switch to HA when it is removed; the high variance is due to the fact that the attractor was present only in half of the matrices. In clusters 3 and 4 players devote the majority of their attention to the column player's payoffs (more than 30% of transitions, but often around the 50%); consistently, these clusters show the highest share of EQ choices. In cluster 5 all transition types (with the exception of CPr) have the same normalized average frequency. Looking at both transitions and choices' distributions, this last cluster suggests that some subjects do not have a specific information pattern in mind when they approach the matrix.

We then performed a temporal analysis of subjects' lookup patterns for each cluster. However, instead of defining fixed temporal windows, we evaluate the proportion of transitions within 9 temporally ordered intervals[10], where each interval is based on a sequence of 4 transitions[11]. Since only some types of transitions are relevant for our purposes, to avoid adding noise, only the five

[10] After the ninth interval the majority of the subjects has already given their responses, therefore we omit to report the successive intervals.

[11] The choice to use sequences of four transitions is arbitrary; however, results do not change using sequences of three, five or six transitions.

classes of transitions above defined were considered. Then, for explanatory purposes, we grouped RPr and RPC transitions as “Own Payoffs Transitions” and CPr and CPc as “Other Payoffs Transitions”. By looking at the frequency of transition types across time we can infer something more about the choice process that the subject employs.

Figure 7 reports the average frequency values for four of the clusters identified. Cluster 5 is not included here due to the high variability of behavior observed for those players.

Figure 7 about here

Players belonging to cluster 1 analyze mainly their own payoffs, and do not change approach throughout the decision making phase. Although the frequency of Own Payoffs transitions slightly decreases toward the end, it still remains by far the preferred transitions type (almost 100% in the first temporal window, and 85% in the last). Subjects from cluster 2 consistently apply Infracell transitions more frequently than any other type. Infracell transitions are constant through time, and fluctuate around 50%. Subjects from cluster 3 begin their analysis by observing the other players payoffs, then switch their attention to their own payoffs, and conclude by using Infracell transitions. Transitions in cluster 4 are more evenly distributed among the three classes, and the observed behavior is somewhat the opposite of what observed in cluster 3. At the beginning, attention is focused on agent’s own payoffs (50%), but it soon switches (at the third temporal window) to the opponent’s payoffs. Other Payoffs transitions will then remain constant until the end (between 40%-50%). Infracell transitions are constant over time (between 20%-30%).

Lastly, we investigate the relationship between eye-movements and attractors. Di Guida and Devetag (2012) made the assumption that attractors act as behavioral focal points, being salient in virtue of payoff symmetry and payoff magnitude, regardless of them being equilibria. If this conjecture holds, then the choice process leading to the selection of the strategy containing the attractor should be similar when the attractor is an equilibrium and when it is not. To test this conjecture, we compare the proportions of Own Payoffs transitions (RpR and RpC), Other Payoffs transitions (CpR and CpC), and Infra-cell transitions in matrices where attractors are not equilibria, with the proportions of the same transitions in matrices where attractors are also the payoff-dominant equilibrium. We consider only those subjects who choose strategy A at least once when the attractor is an equilibrium and once when it is not, for a total of 20 subjects. According to a binomial test, the distributions in the two classes of matrices are statistically undistinguishable[12], bringing further support to the hypothesis that the property of equilibrium is not necessary to render a game outcome a focal point in one-shot games.

Our analysis so far has revealed that a substantial proportion of subjects exhibits information processing patterns that are incompatible with strategic reasoning, at least in its more orthodox, game-theoretic meaning. However, are subjects really non-strategic? Or is their apparently non-strategic behavior the result of an adaptation to the environment they interact with? We attempted to address these questions by checking for correlations between subjects' 'strategic IQ' and their choices/eye movements. Following Bhatt and Camerer (2005), we calculate each subject's 'strategic IQ' simply as his or her expected payoff. As subjects did not receive any feedback until the end of the experiment, we calculate each subject's expected earnings by matching her choice in every matrix with the population average of all the column players. Table 3 reports the correlation coefficients between IQ and choices/eye-movements variables.

Table 3 about here

According to a Spearman correlation test, IQ is positively correlated with EQ choices (0.794), while negatively correlated (-0.366) with HA choices. No significant correlation with A choices is observed. Looking at eye-movements data, it is interesting to notice that IQ is positively correlated both with transitions connecting the opponent's payoffs (CPr = 0.368, CPc = 0.706) and with those connecting one's own payoffs in a 'sophisticated' way (RPc = 0.459). Infracell

[12] For each subject, we calculated the difference between the frequency of each transition type (Own Payoff, Other Payoff, Infracell) observed in matrices in which the attractor is an equilibrium (A=EQ) whit that in matrices in which the attractor is not an equilibrium (A≠EQ). We assigned the value of 1 in all cases in which (A=EQ)>( A≠EQ), 0 otherwise, and tested using a binomial test whether the distribution of 1s is ≠ 0.5. The test does not reject the hypothesis for all types of transitions.

transitions are also positively correlated with IQ (0.432), implying that evaluating each outcome in terms of both players' payoffs (either driven by focality or out of concern for fairness) on average pays off.

## 3.6 The Cognitive Hierarchy Model applied to our data

In the Cognitive Hierarchy model (Camerer, Ho, and Chong 2004), subjects are divided into different strategic categories according to their level of sophistication. Each subject assumes to be more sophisticated than the others, and chooses his strategy as the best response to a distribution of opponents (distributed according to a Poisson) ranging from level 0 to level k-1, where k is the level of sophistication of the subject herself. The model has a single parameter, corresponding to the average reasoning level of the subject sample.

We estimate the parameter for each game by choosing the value that minimizes the mean square deviation (MSD) between observed and estimated frequencies.

As already pointed out in Camerer, Ho, and Chong (2004), different frequency distributions are captured by values of the parameter which may largely differ across games. In our case, calculating the parameter for each matrix separately, it ranges from a minimum of 0.02 (subjects choose their strategy randomly), to a maximum of 2.74 (the average subject performs almost 3 steps of reasoning). Such a large range within the same subject pool suggests that the model might miss some relevant information about the choice process. Although Camerer, Ho, and Chong. admit that the parameter estimation is sensitive to the game structure, they leave the issue of what affects the parameter values to further research. Overall, the cognitive hierarchy model seems to capture the effect of our features only partially.

Table 4 shows the parameters estimated for the matrices grouped together, by game, and by features.

Table 4 about here

Parameters estimated for our games suggest that more intuitive games (like the weak link game, with $\tau = 0.32$) are apparently solved paying less attention to the opponent's options than games in which a preferable choice for the opponent can be more easily and clearly identified (like the Prisoner's Dilemma, $\tau = 0.79$).

Furthermore, the presence of an attractor seems to lower subjects' degree of sophistication, in line with the assumption that a focal point makes choice more intuitive: in fact, parameters in games without attractor are on average larger than those in games with attractor (0.75 against 0.5).

The effect due to HA variance is instead not properly captured by the model. Parameters suggest that players are more sophisticated when variance is low ($\tau$ = 0.94) than when it is high ($\tau$ = 0.42). We claim that this result does not capture the real nature of our data. According to our interpretation, when HA variance is low a large number of subjects will choose that strategy. This behavior is captured by the model since the parameter of 0.94 indicates that the average subject is a level-1 type. Once the variance of HA increases and the strategy becomes riskier, subjects increasingly look for other options, including the equilibrium strategy. The parameter calculated for matrices with HA high variance suggests instead that subjects play almost randomly ($\tau$ = 0.42).

We also calculated the parameter grouping matrices by cluster. Cluster 1 (the one with almost 95% of HA choices) has particularly high parameter values, which never fall below 0.95, consistently with the hypothesis that subjects belonging to this cluster prefer strategy HA. Cluster 2 (the one with the highest number of A choices) shows the largest difference among games with and without attractor (with attractor: $\tau$ = 0.46; without attractor: $\tau$ = 1.28), suggesting that these subjects increase the sophistication of their reasoning considerably when the attractor is removed; this finding further confirms that Infracell transitions are typical of subjects opting for the attractor strategy where available. To support the idea that subjects belonging to these clusters are more sophisticated, clusters 1, 3, and 4 all have an average $\tau$ greater than 1. Lastly, cluster 5 has an average $\tau$ equal to 0.69, the lowest among the five clusters, indicating that subjects in this group are particularly non-strategic.

Summarizing, the Cognitive Hierarchy model does capture some of the effects produced by our feature manipulation (like the presence/absence of an attractor), but misses others (like the variation of the HA strategy variance). This is a limitation common to models based uniquely on choice analysis.

## 3.7 Individual analysis

In this section we report the results of correlation tests (Spearman) among variables related to strategic behavior (choices and eye-movements) and a series of variables that should capture cognitive and personality traits likely to be relevant in the strategic task at hand. After the experiment, subjects were asked to complete a questionnaire analyzing cognitive abilities, personality traits, and risk aversion. In particular, subjects had to complete: an immediate free recall working memory test (Unsworth and Engle 2007), a Wechsler Digit Span test for short memory (Walsh and Betz 1990), the Cognitive Reflection Test (Frederick 2005), the Holt and Laury Risk Aversion test (Holt and Laury 2002), a test of Theory of Mind (Baron-Cohen 2004), and some cognitive and personality questionnaires (Rydval, Ortmann, and Ostatnicky 2009). For a detailed explanation of the tests, see Appendix C.

Table 3 reports the correlation coefficients. As before, correlation coefficients in the shaded cells are significant at the 5 per cent level.

Several interesting findings emerge. First, risk aversion (as measured by the H&L lottery test, where a higher score indicates higher risk aversion) is positively and significantly correlated with transitions of the RPr type ($r = 0.365$), which connect the row players payoffs by row. Hence, players who are more risk averse tend to process their own payoffs by row, a behavior compatible with the choice of HA. The lack of a significant correlation between risk aversion and number of HA choices is most likely due to the fact that players, being risk averse, end up not selecting HA when its variance is high or medium. Hence, this finding strongly confirms the relevance of the risk factor in inducing a choice based on a strategy average payoff. Risk aversion is negatively correlated with equilibrium choices ($r = -0.436$), and positively correlated with the Math Anxiety test ($r = 0.346$), showing that subjects who are risk averse also feel more uncomfortable handling mathematical problems (a higher score in this test indicates a higher sense of uneasiness with mathematical problems). Other interesting findings emerge from looking at correlations between the score in the Wechsler Digit Span test and several measures of cognition and behavior. The Wechsler Digit Span test is one of the most widely diffused tests to measure short term memory capacity (for details see Walsh and Betz 1990), which is considered by many as a reliable proxy for the ability to retain information in memory and to process it efficiently. Devetag and Warglien (2003; 2008) found a correlation between scores in the digit span test and individual capability to perform forms of iterated reasoning common in game theory, such as backward induction, detection of iterated dominance, and recognition of common knowledge. We observe that scores in the digit span test (where a high score indicates high short term memory capacity) are positively correlated with the number of EQ choices (r = 0.377), suggesting that subjects who pick equilibrium strategies are on average more capable of processing information. The score in the digit span test is also positively correlated with several other measures of strategic reasoning: transitions that connect column players' payoffs (CPr r = 0.346; CPc r = 0.526), and transitions that connect row players' payoffs by column (r = 0.541). Besides, there is a positive and significant correlation between individual score in the digit span test and all the AOIs that concern the other players' payoffs, as well as all the AOIs of the row player located in the third column (the column that in 18 out of 30 games corresponds to the equilibrium choice). The Wechsler test is also positively correlated with the Perseverance (r = 0.432) and Cognitive Reflection (r = 0.479) tests. Finally, the test is also positively correlated with a subject's strategic IQ, confirming the importance of short term memory capacity in strategic reasoning and strategic 'performance' (r = 0.460).

Overall, these findings suggest that off-equilibrium choices in a variety of games may be a matter of bounded rationality rather than non-standard preferences or wild beliefs; moreover, short term memory constraints may be able to explain a relevant part of the observed heterogeneity in game playing.

Another interesting finding emerges by considering the positive and significant correlation between strategic IQ and performance in the Frederick test.

Both the Working Memory and the Theory of Mind tests are not correlated with any of the variables of interest, while the Cognitive Reflection test almost perfectly overlaps the results obtained with the Wechsler Digit Span test. Of the various tests presented in Rydval, Ortmann, and Ostatnicky (2009), an interesting finding regards the Math Anxiety test (a small score indicates a relaxed feeling towards math), which is positively correlated with A choices (r = 0.393) and negatively correlated with EQ choices (r = -0.336). This suggests that subjects who are able to locate and choose the equilibrium strategy believe to have a higher-than-average mathematical ability, while those who choose A are less confident in their logical and mathematical capabilities. The Sensation Seeking test (where a small score indicates a risk seeking attitude) is negatively correlated with A choices. This indicates that subjects who choose the strategy leading to the attractor are aware of the risk involved, but are willing to bear the consequences of their choices.

All the above findings altogether converge to the conclusion that the ability to reason strategically and to correctly incorporate the other players' incentives and motivations into one's decision making process is strongly correlated with measures of individual capacity to process information as well as with some personality traits; for this reason it is unreasonable to expect them to be identical across individuals.

## 4 Discussion and Conclusion

In this paper we replicated the results in Di Guida and Devetag (2012) in a different experimental setting and extend that research showing that agents' information search process can be used as a proxy of their own strategic behavior.

As in Di Guida and Devetag (2012), here we show that subjects' choices in one-shot games are susceptible to the influence of equilibrium-irrelevant features in systematic and predictable ways. We posit that this effect can be adequately explained by assuming that players use decision heuristics that are based on a simplification of the decision problem, which may or may not involve neglecting the other player's incentives. More specifically, we assume that the presence of an attractor (defined as a symmetric and salient outcome) and the presence of a strategy with an attractive risk-return profile offer easy and convenient "solutions" to the game being played. Only in the absence of such features may subjects engage in a more complete game analysis and employ more strategic decision criteria, including selecting the equilibrium strategy. Our hypotheses concern modal behavior only; hence, we expect heterogeneity in choices, which we assume to be correlated with heterogeneity in patterns of information analysis.

We show that perceived risk matters in determining the frequency with which behavior compatible with level-1 (Camerer, Ho, and Chong 2004; Stahl and Wilson 1994, 1995) occurs. While level-1 agents choose according to the "take the strategy with the highest average payoff" heuristic, we show that this holds only when the variance of the payoffs is low: in other words, when the option is perceived as not so risky. The heuristic "choose the strategy leading to an outcome with uniquely high and equal payoffs" (which in Di Guida and Devetag (2012) was considered akin to the process of selecting a focal point in a coordination game) is not part of any recognized behavioral strategy in type-based models[13], but is one of the preferred options in our subject pool.

In order to find further support for our conjectures, we analyze subjects' eye movements during the experiment to infer some characteristics of the decision rule employed. We find out that most subjects analyze the game only partially, paying disproportionately more attention to their own payoffs as opposed to the other player's payoffs, and to some of the matrix cells (e.g., the cell containing the "attractor") as opposed to other cells. A non-negligible proportion of subjects never look at the opponent's payoff, implicitly transforming the game into an individual decision making problem.

Our analyses of transitions (i.e. eye-movements from one element of the matrix to another) reveal that lookup patterns are relatively game-invariant, involving mostly transitions connecting the player's own payoffs associated with the same strategy (as when calculating payoff averages associated with the various strategies), and transitions confronting the two players' payoffs within the same

[13] The type closest to it is the "altruistic" type who always selects the strategy leading to the cell with the highest payoff sum. In Di Guida and Devetag (2012) however, we show that this type is well represented in our data only when such outcome has symmetric and significantly high payoffs, i.e., only when it is focal according to our definition. In games where this is not the case, the altruistic type does not perform well. Similar considerations apply for the performance of the choice criterion based on team reasoning (Bacharach 1999; Bacharach and Bernasconi 1997; Mehta, Starmer, and Sugden 1994a, 1994b; Sugden 1993, 1995)

cell (as when looking for a focal point able to coordinate players' actions and expectations, or when choosing motivated by social preferences).

As predicted, we find correlations between choices and lookup patterns: subjects who choose the strategy with the highest average payoff for themselves tend to exhibit lookup patterns of the first type mentioned above, whereas subjects who choose the strategy leading to the attractor tend to use patterns of the second type. Finally, subjects who pick the equilibrium strategy, on average, perform a more complete game analysis, and in particular pay attention to the other player's payoffs, in line with a truly strategic approach to the game.

A cluster analysis based on eye movements confirms the correlation sketched above and allows one to predict modal choices from the modal type of eye-movements observed.

A comparison of transition distributions between games where the attractor is an equilibrium with those in games in which it is not highlights no significant differences, and provides support to the idea that focal points need not be equilibria to act as such.

The cognitive hierarchy model (Camerer, Ho, and Chong 2004) applied to our data is able to capture heuristic-based behavior only partially. The difference in the values of the parameter $\tau$ between games with attractor and games without attractor is in line with our data on eye-movements, and supports the intuition that the attractor reduces the need for analytical reasoning and triggers more "intuitive" choices. The variation of $\tau$ in response to the change in variance of the HA strategy, on the other hand, does not capture the effect of perceived risk. These findings, together with the results in Di Guida and Devetag (2012) on the application of the model in Costa-Gomes, Crawfor, and Broseta (2001), suggest that an extension of CH and type-based models including the effect of perceived risk (defined as payoff variance) and focality (triggered by a symmetric and high payoff) might improve their predictive power.

Finally, part of the heterogeneity observed can be explained by differences in risk attitudes and in short term memory capacity, in line with several previous results on game playing (Devetag and Warglien 2008; Rydval, Ortmann, and Ostatnicky 2009).

It is important to stress that the heuristics driving our subjects' choices are presumably not the only boundedly rational heuristics at work in one-shot games. In fact, more than pinning down the specific choice criteria employed, our study (as Di Guida and Devetag 2012) aims to show that players may apply decision rules which 1) are based on an incomplete/imperfect model of the strategic situation at hand, and 2) are context-dependent; more specifically, they are sensitive to features of the game other than its equilibrium properties. Both these aspects are not adequately captured by current models of one-shot game behavior, which in a sense assume too much rationality on the part of players, and always postulate consistency between choices and beliefs.

Moreover, we believe heuristic-based behavior extends well beyond the games presented here and that deciding on the basis of a risk-return calculation is common in many games. Attractors, as defined here, can be present in many games: for example, both the payoff-dominant equilibrium in the stag hunt game and the mutual cooperation outcome in the Prisoner's Dilemma are attractors; players may then choose them on the basis of a heuristic. Likewise, players may pick dominant strategies in dominant-solvable games not because they recognize the dominance relation (in fact, eye-movements compatible with the mental operation of checking dominance relations are rarely observed in our database), but because by definition these strategies have the highest average payoff.

Further research should look more closely into lookup patterns associated with different types of more standard, symmetric games, to detect the extent to which choices are based on incomplete information processing patterns. A correlated study should investigate eye-movements involved in pure coordination games with equilibrium focal points and compare them with those involved in non-equilibrium focal points like our attractors, to test whether the choice process is indeed the same. These extensions could then be incorporated in a redefinition of types, in type-based models, whose distribution within the population might also be predicted partially on the basis of cognitive and personality traits.

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# Tables

**HA low var**

| Game | Attractor | | C1 | C2 | C3 | Freq. | |
|---|---|---|---|---|---|---|---|
| DomCol | A | R1 | 35,20 | 35,25 | 35,30 | 51% | HA |
| | | R2 | 5,55 | 80,80 | 5,85 | 37% | A |
| | | R3 | 10,20 | 10,15 | 40,25* | 12% | EQ |
| | | | | A | EQ/HA | | |
| | NA | R1 | 35,20 | 35,25 | 35,30 | 65% | HA |
| | | R2 | 5,55 | 50,25 | 5,85 | 5% | NA |
| | | R3 | 10,20 | 10,15 | 40,25* | 30% | EQ |
| | | | | NA | EQ/HA | | |
| noNe | A | R1 | 35,15 | 35,20 | 35,30 | 56% | HA |
| | | R2 | 5,45 | 75,75 | 10,80 | 40% | A |
| | | R3 | 15,35 | 5,25 | 40,20 | 5% | QES |
| | | | | A | QES/HA | | |
| | NA | R1 | 35,15 | 35,20 | 35,30 | 60% | HA |
| | | R2 | 5,45 | 50,25 | 10,80 | 16% | NA |
| | | R3 | 15,35 | 5,25 | 40,20 | 23% | QES |
| | | | | NA | QES/HA | | |
| UniqNe | A | R1 | 35,10 | 35,15 | 35,10 | 37% | HA |
| | | R2 | 10,50 | 70,70 | 5,75 | 49% | A |
| | | R3 | 5,10 | 10,5 | 40,15* | 14% | EQ |
| | | | | A | EQ/HA | | |
| | NA | R1 | 35,10 | 35,15 | 35,10 | 51% | HA |
| | | R2 | 10,50 | 50,25 | 5,75 | 23% | NA |
| | | R3 | 5,10 | 10,5 | 40,15* | 26% | EQ |
| | | | | NA | EQ/HA | | |
| PD | A | R1 | 35,10 | 35,5 | 35,35* | 79% | EQ/HA |
| | | R2 | 10,35 | 35,35* | 5,35 | 19% | A |
| | | R3 | 15,15 | 35,10 | 10,35 | 2% | DOM |
| | | | | A | EQ/HA | | |
| | NA | R1 | 35,10 | 35,5 | 35,35* | 84% | EQ/HA |
| | | R2 | 10,35 | 35,25 | 5,35 | 9% | NA |
| | | R3 | 15,15 | 35,10 | 10,35 | 7% | DOM |
| | | | | NA | EQ/HA | | |
| WL | A | R1 | 60,60* | 35,45 | 5,35 | 33% | A |
| | | R2 | 45,35 | 45,45* | 35,35 | 63% | HA |
| | | R3 | 35,5 | 35,35 | 35,35* | 5% | COS |
| | | | A | HA | COS | | |
| | NA | R1 | 35,35 | 45,45* | 45,35 | 51% | HA |
| | | R2 | 5,35 | 35,45 | 60,60* | 44% | NA |
| | | R3 | 35,35* | 35,35 | 35,5 | 5% | COS |
| | | | COS | HA | NA | | |

**HA middle var**

| Game | Attractor | | C1 | C2 | C3 | Freq. | |
|---|---|---|---|---|---|---|---|
| DomCol | A | R1 | 60,20 | 20,25 | 25,30 | 35% | HA |
| | | R2 | 5,55 | 80,80 | 5,85 | 42% | A |
| | | R3 | 10,20 | 10,15 | 40,25* | 23% | EQ |
| | | | | A | EQ/HA | | |
| | NA | R1 | 60,20 | 20,25 | 25,30 | 60% | HA |
| | | R2 | 5,55 | 50,25 | 5,85 | 7% | NA |
| | | R3 | 10,20 | 10,15 | 40,25* | 33% | EQ |
| | | | | NA | EQ/HA | | |
| noNe | A | R1 | 55,15 | 25,20 | 25,30 | 53% | HA |
| | | R2 | 5,45 | 75,75 | 10,80 | 35% | A |
| | | R3 | 15,35 | 5,25 | 40,20 | 12% | QES |
| | | | | A | QES/HA | | |
| | NA | R1 | 55,15 | 25,20 | 25,30 | 58% | HA |
| | | R2 | 5,45 | 50,25 | 10,80 | 12% | NA |
| | | R3 | 15,35 | 5,25 | 40,20 | 30% | QES |
| | | | | NA | QES/HA | | |
| UniqNe | A | R1 | 55,10 | 25,15 | 25,10 | 53% | HA |
| | | R2 | 10,50 | 70,70 | 5,75 | 30% | A |
| | | R3 | 5,10 | 10,5 | 40,15* | 16% | EQ |
| | | | | A | EQ/HA | | |
| | NA | R1 | 55,10 | 25,15 | 25,10 | 60% | HA |
| | | R2 | 10,50 | 50,25 | 5,75 | 14% | NA |
| | | R3 | 5,10 | 10,5 | 40,15* | 26% | EQ |
| | | | | NA | EQ/HA | | |
| PD | A | R1 | 25,10 | 60,5 | 20,20* | 63% | EQ/HA |
| | | R2 | 10,35 | 35,35 | 5,60 | 30% | A |
| | | R3 | 15,15 | 35,10 | 10,25 | 7% | DOM |
| | | | | A | EQ/HA | | |
| | NA | R1 | 25,10 | 60,5 | 20,20* | 63% | EQ/HA |
| | | R2 | 10,35 | 35,25 | 5,60 | 26% | NA |
| | | R3 | 15,15 | 35,10 | 10,25 | 12% | DOM |
| | | | | NA | EQ/HA | | |
| WL | A | R1 | 60,60* | 35,45 | 5,35 | 37% | A |
| | | R2 | 50,35 | 50,50* | 20,35 | 44% | HA |
| | | R3 | 35,5 | 35,35 | 35,35* | 19% | COS |
| | | | A | HA | COS | | |
| | NA | R2 | 20,35 | 50,50* | 50,35 | 47% | HA |
| | | R2 | 5,35 | 35,45 | 60,60* | 30% | NA |
| | | R3 | 35,35* | 35,35 | 35,5 | 23% | COS |
| | | | COS | HA | NA | | |

**HA high var**

| Game | Attractor | | C1 | C2 | C3 | Freq. | |
|---|---|---|---|---|---|---|---|
| DomCol | A | R1 | 80,20 | 10,25 | 15,30 | 37% | HA |
| | | R2 | 5,55 | 80,80 | 5,85 | 30% | A |
| | | R3 | 10,20 | 10,15 | 40,25* | 33% | EQ |
| | | | | A | EQ/HA | | |
| | NA | R1 | 80,20 | 10,25 | 15,30 | 44% | HA |
| | | R2 | 5,55 | 50,25 | 5,85 | 12% | NA |
| | | R3 | 10,20 | 10,15 | 40,25* | 44% | EQ |
| | | | | NA | EQ/HA | | |
| noNe | A | R1 | 75,15 | 15,20 | 15,30 | 35% | HA |
| | | R2 | 5,45 | 75,75 | 10,80 | 42% | A |
| | | R3 | 15,35 | 5,25 | 40,20 | 23% | QES |
| | | | | A | QES/HA | | |
| | NA | R1 | 75,15 | 15,20 | 15,30 | 47% | HA |
| | | R2 | 5,45 | 50,25 | 10,80 | 14% | NA |
| | | R3 | 15,35 | 5,25 | 40,20 | 40% | QES |
| | | | | NA | QES/HA | | |
| UniqNe | A | R1 | 70,10 | 20,15 | 15,10 | 40% | HA |
| | | R2 | 10,50 | 70,70 | 5,75 | 49% | A |
| | | R3 | 5,10 | 10,5 | 40,15* | 12% | EQ |
| | | | | A | EQ/HA | | |
| | NA | R1 | 70,10 | 20,15 | 15,10 | 44% | HA |
| | | R2 | 10,50 | 50,25 | 5,75 | 23% | NA |
| | | R3 | 5,10 | 10,5 | 40,15* | 33% | EQ |
| | | | | NA | EQ/HA | | |
| PD | A | R1 | 15,10 | 80,5 | 10,10* | 49% | EQ/HA |
| | | R2 | 10,35 | 35,35 | 5,80 | 37% | A |
| | | R3 | 15,15* | 35,10 | 10,15* | 14% | DOM |
| | | | | A | EQ/HA | | |
| | NA | R1 | 15,10 | 80,5 | 10,10* | 67% | EQ/HA |
| | | R2 | 10,35 | 35,25 | 5,80 | 14% | NA |
| | | R3 | 15,15* | 35,10 | 10,15* | 19% | DOM |
| | | | | NA | EQ/HA | | |
| WL | A | R1 | 60,60* | 35,45 | 5,35 | 14% | A |
| | | R2 | 60,35 | 60,60* | 5,35 | 53% | HA |
| | | R3 | 35,5 | 35,35 | 35,35* | 33% | COS |
| | | | A | HA | COS | | |
| | NA | R2 | 5,35 | 60,60* | 60,35 | 49% | HA |
| | | R2 | 5,35 | 35,45 | 60,60* | 23% | NA |
| | | R3 | 35,35* | 35,35 | 35,5 | 28% | COS |
| | | | COS | HA | NA | | |

Table 1: The normal form games used in the experiment, grouped by type of game, level of HA variance (low, medium, high), and presence of attractor (A, NA). The (*) symbol indicates a Nash Equilibrium in pure strategies. The rightmost column of each matrix reports the observed frequency of choice for each of the three strategies.

| | EQ choices | A choices | HA choices | RPr | CPr | RPc | CPc | INF | (R1,C1) Cell | (R1,C2) Cell | (R1,C3) Cell | (R2,C1) Cell | (R2,C2) Cell | (R2,C3) Cell | (R3,C1) Cell | (R3,C2) Cell | (R3,C3) Cell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EQ choices | | 0.002 | -0.555 | -0.175 | 0.330 | 0.332 | 0.674 | 0.440 | 0.215 | 0.168 | 0.524 | 0.362 | 0.242 | 0.575 | 0.357 | 0.220 | 0.682 |
| A choices | 0.002 | | -0.727 | -0.154 | 0.473 | -0.080 | 0.194 | 0.387 | 0.254 | 0.163 | 0.059 | 0.307 | 0.363 | 0.269 | -0.003 | 0.028 | 0.072 |
| HA choices | -0.555 | -0.727 | | 0.420 | -0.492 | -0.057 | -0.482 | -0.448 | -0.169 | -0.050 | -0.205 | -0.295 | -0.250 | -0.414 | -0.027 | 0.087 | -0.288 |
| RPr | -0.175 | -0.154 | 0.420 | | 0.211 | 0.544 | 0.081 | 0.070 | 0.548 | 0.696 | 0.397 | 0.469 | 0.533 | 0.294 | 0.618 | 0.714 | 0.245 |
| CPr | 0.330 | 0.473 | -0.492 | 0.211 | | 0.427 | 0.731 | 0.790 | 0.744 | 0.728 | 0.751 | 0.838 | 0.779 | 0.836 | 0.650 | 0.606 | 0.713 |
| RPc | 0.332 | -0.080 | -0.057 | 0.544 | 0.427 | | 0.576 | 0.236 | 0.457 | 0.601 | 0.588 | 0.521 | 0.628 | 0.595 | 0.586 | 0.590 | 0.555 |
| CPc | 0.674 | 0.194 | -0.482 | 0.081 | 0.731 | 0.576 | | 0.624 | 0.540 | 0.575 | 0.806 | 0.684 | 0.632 | 0.838 | 0.566 | 0.463 | 0.822 |
| INF | 0.440 | 0.387 | -0.448 | 0.070 | 0.790 | 0.236 | 0.624 | | 0.761 | 0.640 | 0.779 | 0.794 | 0.751 | 0.836 | 0.647 | 0.556 | 0.777 |
| (R1,C1) Cell | 0.215 | 0.254 | -0.169 | 0.548 | 0.744 | 0.457 | 0.540 | 0.761 | | 0.920 | 0.810 | 0.919 | 0.850 | 0.793 | 0.870 | 0.768 | 0.693 |
| (R1,C2) Cell | 0.168 | 0.163 | -0.050 | 0.696 | 0.728 | 0.601 | 0.575 | 0.640 | 0.920 | | 0.856 | 0.885 | 0.895 | 0.795 | 0.849 | 0.810 | 0.691 |
| (R1,C3) Cell | 0.524 | 0.059 | -0.205 | 0.397 | 0.751 | 0.588 | 0.806 | 0.779 | 0.810 | 0.856 | | 0.857 | 0.823 | 0.938 | 0.800 | 0.731 | 0.902 |
| (R2,C1) Cell | 0.362 | 0.307 | -0.295 | 0.469 | 0.838 | 0.521 | 0.684 | 0.794 | 0.919 | 0.885 | 0.857 | | 0.892 | 0.901 | 0.854 | 0.779 | 0.782 |
| (R2,C2) Cell | 0.242 | 0.363 | -0.250 | 0.533 | 0.779 | 0.628 | 0.632 | 0.751 | 0.850 | 0.895 | 0.823 | 0.892 | | 0.865 | 0.784 | 0.799 | 0.739 |
| (R2,C3) Cell | 0.575 | 0.269 | -0.414 | 0.294 | 0.836 | 0.595 | 0.838 | 0.836 | 0.793 | 0.795 | 0.938 | 0.901 | 0.865 | | 0.751 | 0.695 | 0.898 |
| (R3,C1) Cell | 0.357 | -0.003 | -0.027 | 0.618 | 0.650 | 0.586 | 0.566 | 0.647 | 0.870 | 0.849 | 0.800 | 0.854 | 0.784 | 0.751 | | 0.895 | 0.763 |
| (R3,C2) Cell | 0.220 | 0.028 | 0.087 | 0.714 | 0.606 | 0.590 | 0.463 | 0.556 | 0.768 | 0.810 | 0.731 | 0.779 | 0.799 | 0.695 | 0.895 | | 0.735 |
| (R3,C3) Cell | 0.682 | 0.072 | -0.288 | 0.245 | 0.713 | 0.555 | 0.822 | 0.777 | 0.693 | 0.691 | 0.902 | 0.782 | 0.739 | 0.898 | 0.763 | 0.735 | |
| AOI 1 | 0.002 | 0.108 | 0.099 | 0.766 | 0.483 | 0.455 | 0.276 | 0.499 | 0.890 | 0.839 | 0.644 | 0.772 | 0.721 | 0.598 | 0.763 | 0.713 | 0.479 |
| AOI 2 | -0.075 | 0.011 | 0.252 | 0.873 | 0.439 | 0.571 | 0.297 | 0.367 | 0.765 | 0.899 | 0.664 | 0.688 | 0.763 | 0.564 | 0.695 | 0.745 | 0.462 |
| AOI 3 | 0.342 | -0.024 | 0.021 | 0.615 | 0.613 | 0.606 | 0.639 | 0.654 | 0.824 | 0.902 | 0.937 | 0.825 | 0.828 | 0.855 | 0.801 | 0.768 | 0.795 |
| AOI 4 | 0.027 | 0.115 | 0.102 | 0.713 | 0.492 | 0.387 | 0.263 | 0.538 | 0.844 | 0.815 | 0.622 | 0.823 | 0.739 | 0.597 | 0.819 | 0.753 | 0.505 |
| AOI 5 | -0.079 | 0.221 | 0.095 | 0.793 | 0.481 | 0.550 | 0.235 | 0.431 | 0.730 | 0.815 | 0.575 | 0.708 | 0.850 | 0.579 | 0.701 | 0.816 | 0.474 |
| AOI 6 | 0.461 | 0.165 | -0.209 | 0.533 | 0.693 | 0.650 | 0.651 | 0.744 | 0.823 | 0.845 | 0.903 | 0.891 | 0.888 | 0.925 | 0.827 | 0.800 | 0.827 |
| AOI 7 | 0.071 | -0.161 | 0.281 | 0.782 | 0.326 | 0.456 | 0.170 | 0.364 | 0.710 | 0.675 | 0.526 | 0.630 | 0.565 | 0.445 | 0.848 | 0.816 | 0.472 |
| AOI 8 | -0.065 | -0.084 | 0.339 | 0.894 | 0.292 | 0.558 | 0.115 | 0.222 | 0.605 | 0.672 | 0.451 | 0.548 | 0.610 | 0.406 | 0.732 | 0.874 | 0.409 |
| AOI 9 | 0.480 | 0.013 | -0.068 | 0.511 | 0.543 | 0.622 | 0.573 | 0.579 | 0.672 | 0.695 | 0.787 | 0.701 | 0.734 | 0.756 | 0.772 | 0.831 | 0.880 |
| AOI 10 | 0.461 | 0.347 | -0.441 | 0.210 | 0.869 | 0.381 | 0.734 | 0.916 | 0.892 | 0.787 | 0.844 | 0.896 | 0.814 | 0.875 | 0.787 | 0.664 | 0.811 |
| AOI 11 | 0.479 | 0.322 | -0.414 | 0.255 | 0.917 | 0.454 | 0.820 | 0.868 | 0.836 | 0.823 | 0.892 | 0.887 | 0.838 | 0.908 | 0.779 | 0.697 | 0.853 |
| AOI 12 | 0.643 | 0.194 | -0.444 | 0.084 | 0.822 | 0.456 | 0.897 | 0.834 | 0.714 | 0.692 | 0.908 | 0.786 | 0.721 | 0.909 | 0.685 | 0.591 | 0.906 |
| AOI 13 | 0.470 | 0.345 | -0.427 | 0.261 | 0.899 | 0.485 | 0.805 | 0.851 | 0.841 | 0.787 | 0.871 | 0.947 | 0.849 | 0.942 | 0.747 | 0.678 | 0.830 |
| AOI 14 | 0.470 | 0.389 | -0.481 | 0.208 | 0.885 | 0.533 | 0.840 | 0.852 | 0.763 | 0.767 | 0.873 | 0.855 | 0.889 | 0.937 | 0.664 | 0.637 | 0.834 |
| AOI 15 | 0.600 | 0.263 | -0.478 | 0.123 | 0.833 | 0.509 | 0.888 | 0.828 | 0.719 | 0.707 | 0.903 | 0.836 | 0.775 | 0.965 | 0.644 | 0.568 | 0.867 |
| AOI 16 | 0.581 | 0.197 | -0.365 | 0.209 | 0.857 | 0.419 | 0.802 | 0.856 | 0.789 | 0.721 | 0.853 | 0.856 | 0.746 | 0.876 | 0.833 | 0.727 | 0.896 |
| AOI 17 | 0.546 | 0.249 | -0.377 | 0.235 | 0.875 | 0.444 | 0.807 | 0.847 | 0.758 | 0.732 | 0.855 | 0.840 | 0.799 | 0.890 | 0.794 | 0.769 | 0.902 |
| AOI 18 | 0.677 | 0.190 | -0.443 | 0.052 | 0.798 | 0.438 | 0.896 | 0.834 | 0.663 | 0.642 | 0.879 | 0.762 | 0.704 | 0.901 | 0.657 | 0.586 | 0.936 |

Table 2: Correlation between choices (only the main categories were considered), transitions, and number of fixations (by cell and by AOI). Shaded coefficients are statistically significant at the 5 per cent level.

| | Wechsler digit span test | H&L | Working memory | Cognitive Reflection Test | Theory of Mind | Premeditation | Sensation Seeking | Need For Cognition | Perseverance | Math Anxiety | Strategic IQ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Average Time | 0.423 | -0.006 | 0.136 | 0.394 | 0.096 | -0.014 | 0.195 | 0.266 | 0.184 | 0.162 | 0.511 |
| Gender | -0.310 | 0.101 | -0.080 | -0.309 | -0.024 | -0.142 | 0.069 | 0.240 | -0.247 | 0.139 | -0.399 |
| Wechsler digit span test | | -0.258 | 0.211 | 0.479 | 0.098 | 0.181 | 0.252 | -0.089 | 0.432 | -0.157 | 0.460 |
| H&L | -0.258 | | -0.107 | -0.039 | -0.133 | -0.059 | -0.145 | 0.161 | -0.053 | 0.346 | -0.140 |
| Working memory | 0.211 | -0.107 | | 0.141 | 0.240 | 0.043 | 0.305 | -0.253 | 0.189 | 0.085 | 0.190 |
| Cognitive Reflection Test | 0.479 | -0.039 | 0.141 | | 0.191 | -0.053 | 0.258 | -0.133 | 0.063 | -0.276 | 0.614 |
| Theory of Mind | 0.098 | -0.133 | 0.240 | 0.191 | | -0.099 | 0.323 | -0.199 | -0.119 | -0.157 | 0.080 |
| Premeditation | 0.181 | -0.059 | 0.043 | -0.053 | -0.099 | | -0.328 | 0.055 | 0.177 | 0.056 | 0.094 |
| Sensation Seeking | 0.252 | -0.145 | 0.305 | 0.258 | 0.323 | -0.328 | | -0.096 | -0.087 | -0.232 | 0.199 |
| Need For Cognition | -0.089 | 0.161 | -0.253 | -0.133 | -0.199 | 0.055 | -0.096 | | 0.264 | 0.524 | -0.091 |
| Perseverance | 0.432 | -0.053 | 0.189 | 0.063 | -0.119 | 0.177 | -0.087 | 0.264 | | 0.358 | 0.190 |
| Math Anxiety | -0.157 | 0.346 | 0.085 | -0.276 | -0.157 | 0.056 | -0.232 | 0.524 | 0.358 | | -0.206 |
| EQ choices | 0.377 | -0.436 | 0.264 | 0.420 | 0.102 | 0.290 | 0.185 | -0.195 | 0.178 | -0.336 | 0.794 |
| A choices | -0.050 | 0.168 | -0.157 | -0.167 | -0.129 | 0.193 | -0.336 | 0.172 | 0.042 | 0.393 | -0.061 |
| HA choices | -0.162 | 0.131 | 0.042 | -0.115 | 0.155 | -0.418 | 0.278 | 0.006 | -0.177 | -0.072 | -0.366 |
| RPr | 0.087 | 0.365 | 0.138 | 0.031 | 0.017 | -0.426 | 0.271 | 0.086 | 0.006 | 0.233 | 0.069 |
| CPr | 0.346 | -0.031 | 0.069 | 0.188 | -0.012 | 0.037 | -0.072 | 0.323 | 0.319 | 0.392 | 0.368 |
| RPc | 0.541 | -0.055 | 0.240 | 0.359 | 0.007 | -0.111 | 0.271 | -0.127 | 0.333 | 0.041 | 0.459 |
| CPc | 0.526 | -0.278 | 0.248 | 0.487 | 0.074 | 0.077 | 0.072 | 0.025 | 0.315 | -0.022 | 0.706 |
| INF | 0.241 | -0.091 | 0.042 | 0.248 | 0.193 | 0.203 | 0.046 | 0.336 | 0.175 | 0.148 | 0.432 |
| (R1,C1) Cell | 0.273 | 0.066 | 0.111 | 0.328 | 0.134 | -0.036 | 0.133 | 0.229 | 0.037 | 0.202 | 0.329 |
| (R1,C2) Cell | 0.342 | 0.108 | 0.187 | 0.313 | 0.114 | -0.166 | 0.199 | 0.237 | 0.142 | 0.238 | 0.393 |
| (R1,C3) Cell | 0.461 | -0.156 | 0.214 | 0.428 | 0.140 | -0.005 | 0.243 | 0.230 | 0.261 | 0.003 | 0.660 |
| (R2,C1) Cell | 0.408 | -0.027 | 0.176 | 0.358 | 0.024 | -0.027 | 0.148 | 0.256 | 0.172 | 0.215 | 0.465 |
| (R2,C2) Cell | 0.437 | 0.083 | 0.143 | 0.248 | 0.078 | -0.017 | 0.202 | 0.181 | 0.239 | 0.220 | 0.389 |
| (R2,C3) Cell | 0.434 | -0.183 | 0.154 | 0.381 | 0.106 | 0.078 | 0.184 | 0.235 | 0.272 | 0.079 | 0.632 |
| (R3,C1) Cell | 0.445 | 0.036 | 0.245 | 0.457 | 0.103 | -0.088 | 0.253 | 0.091 | 0.153 | 0.048 | 0.489 |
| (R3,C2) Cell | 0.417 | 0.111 | 0.157 | 0.240 | 0.140 | -0.175 | 0.286 | 0.106 | 0.207 | 0.112 | 0.363 |
| (R3,C3) Cell | 0.511 | -0.251 | 0.193 | 0.431 | 0.210 | 0.108 | 0.262 | 0.106 | 0.301 | -0.026 | 0.740 |
| AOI 1 | 0.131 | 0.202 | 0.038 | 0.203 | 0.050 | -0.128 | 0.150 | 0.276 | -0.071 | 0.229 | 0.147 |
| AOI 2 | 0.215 | 0.204 | 0.134 | 0.135 | 0.112 | -0.319 | 0.268 | 0.208 | 0.063 | 0.243 | 0.175 |
| AOI 3 | 0.328 | -0.059 | 0.197 | 0.348 | 0.171 | -0.177 | 0.298 | 0.252 | 0.170 | 0.043 | 0.515 |
| AOI 4 | 0.197 | 0.207 | 0.134 | 0.275 | 0.022 | -0.168 | 0.217 | 0.307 | 0.010 | 0.247 | 0.201 |
| AOI 5 | 0.233 | 0.314 | 0.048 | 0.084 | 0.011 | -0.177 | 0.225 | 0.204 | 0.113 | 0.291 | 0.140 |
| AOI 6 | 0.417 | -0.087 | 0.159 | 0.361 | 0.144 | -0.038 | 0.331 | 0.227 | 0.192 | 0.064 | 0.558 |
| AOI 7 | 0.228 | 0.195 | 0.082 | 0.272 | 0.033 | -0.132 | 0.196 | 0.107 | 0.039 | 0.081 | 0.208 |
| AOI 8 | 0.206 | 0.258 | 0.087 | 0.081 | 0.095 | -0.286 | 0.277 | 0.078 | 0.088 | 0.182 | 0.110 |
| AOI 9 | 0.446 | -0.165 | 0.152 | 0.226 | 0.173 | -0.027 | 0.298 | 0.057 | 0.261 | 0.009 | 0.583 |
| AOI 10 | 0.374 | -0.125 | 0.152 | 0.384 | 0.168 | 0.144 | 0.080 | 0.176 | 0.187 | 0.141 | 0.481 |
| AOI 11 | 0.421 | -0.090 | 0.181 | 0.398 | 0.122 | 0.066 | 0.124 | 0.184 | 0.228 | 0.163 | 0.564 |
| AOI 12 | 0.477 | -0.263 | 0.191 | 0.446 | 0.119 | 0.124 | 0.178 | 0.152 | 0.261 | -0.018 | 0.675 |
| AOI 13 | 0.434 | -0.158 | 0.182 | 0.334 | 0.069 | 0.071 | 0.093 | 0.212 | 0.225 | 0.161 | 0.505 |
| AOI 14 | 0.455 | -0.115 | 0.141 | 0.306 | 0.071 | 0.126 | 0.104 | 0.155 | 0.294 | 0.156 | 0.545 |
| AOI 15 | 0.415 | -0.254 | 0.158 | 0.394 | 0.084 | 0.098 | 0.135 | 0.195 | 0.284 | 0.029 | 0.637 |
| AOI 16 | 0.429 | -0.172 | 0.210 | 0.419 | 0.141 | 0.073 | 0.165 | 0.141 | 0.232 | 0.081 | 0.609 |
| AOI 17 | 0.488 | -0.099 | 0.145 | 0.374 | 0.169 | 0.087 | 0.165 | 0.140 | 0.285 | 0.078 | 0.583 |
| AOI 18 | 0.467 | -0.255 | 0.168 | 0.434 | 0.187 | 0.128 | 0.183 | 0.136 | 0.293 | -0.028 | 0.693 |

Table 3: Correlation between choices (only the main categories were considered), transitions, number of fixations (by cell and by AOI) and strategic IQ. Shaded coefficients are statistically significant at the 5 per cent level.

| | Average τ | HA Low | HA Middle | HA High | A | NA | DomCol | noNe | UniqNe | PD | WL |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **All matrices** | 0.63 | 0.94 | 0.51 | 0.42 | 0.50 | 0.75 | 0.72 | 0.56 | 0.75 | 0.79 | 0.32 |
| **cluster 1** | 1.32 | 1.40 | 1.37 | 1.19 | 1.06 | 1.58 | 0.95 | 2.19 | 1.13 | 1.45 | 0.90 |
| **cluster 2** | 0.87 | 0.73 | 0.91 | 0.99 | 0.46 | 1.28 | 0.53 | 1.95 | 1.01 | 0.60 | 0.29 |
| **cluster 3** | 1.18 | 1.86 | 0.68 | 1.00 | 1.02 | 1.33 | 1.50 | 1.70 | 0.52 | 1.54 | 0.64 |
| **cluster 4** | 1.12 | 1.48 | 0.71 | 1.18 | 0.83 | 1.41 | 0.87 | 0.68 | 2.92 | 0.98 | 0.16 |
| **cluster 5** | 0.69 | 1.42 | 0.36 | 0.31 | 0.41 | 0.98 | 0.60 | 0.79 | 1.37 | 0.46 | 0.27 |

Table 4: Cognitive Hierarchy Model: the value of parameter τ calculated for different groupings of matrices

# Figures

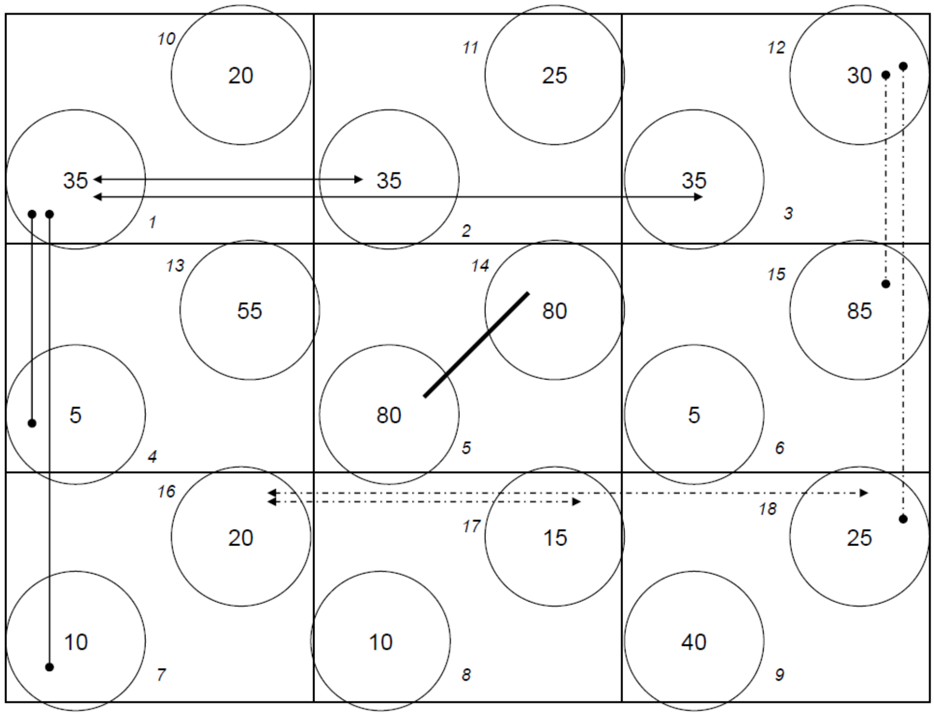
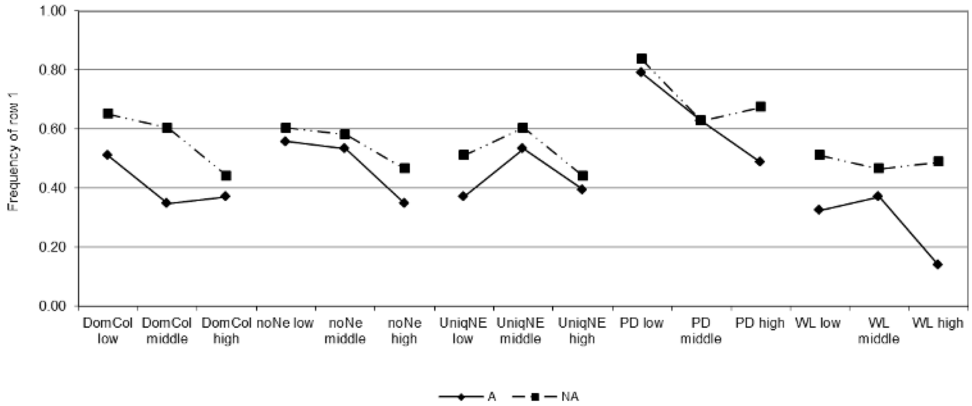
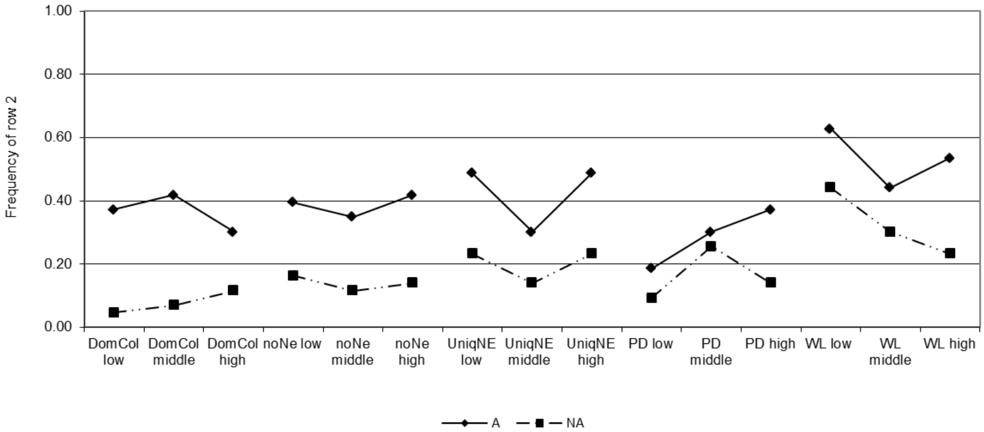



Fig. 1: Summary of the transitions of interest; the numbers in italic represent the labels of the different Areas Of Interest (AOI), from 1 to 18. The transitions are represented as follows: Row Player by row (RPr): thin continuous line with arrows; Column Player by column (CPr): dashed line with arrows; Row Player by Column (RPc): thin continuous line with circles; Column Player by column (CPc): dashed line with circles; Infracell (INF): thick continuous line

Panel A




Panel B




Panel C

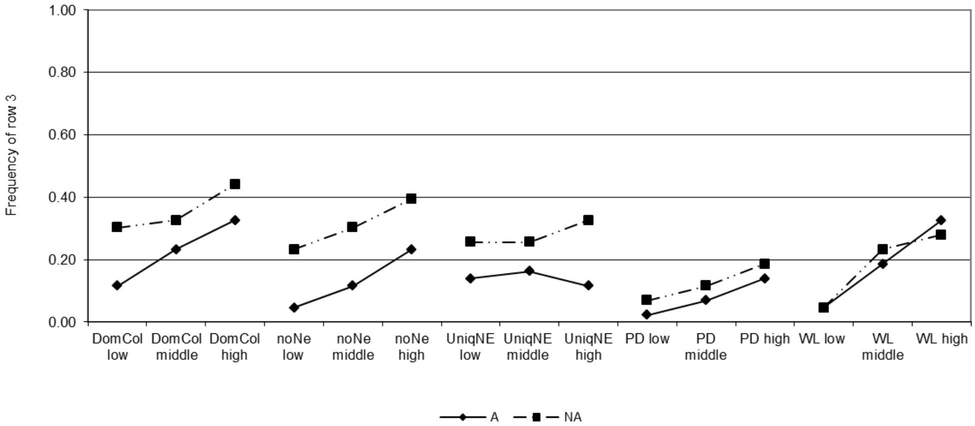



Fig. 2: Panel A: Observed frequencies of row 1 choices. Panel B: Observed frequencies of row 2 choices. Panel C: Observed frequencies of row 3 choices

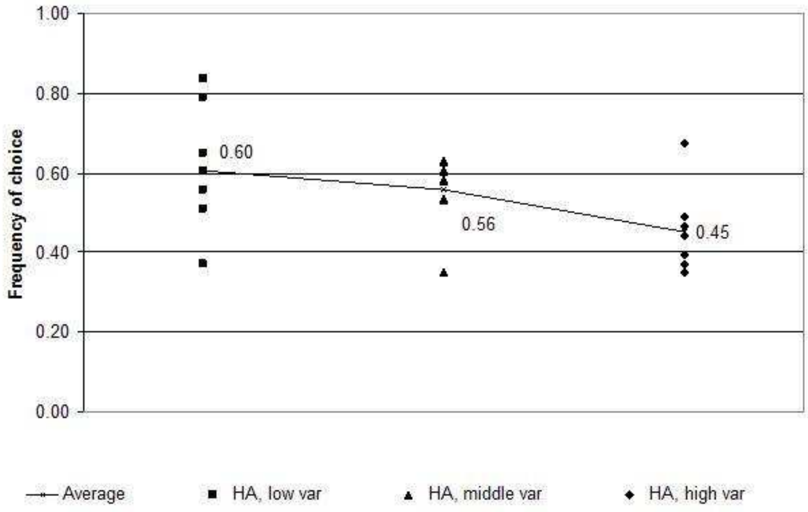



Fig 3: choice frequencies averaged by game and divided by variance of HA

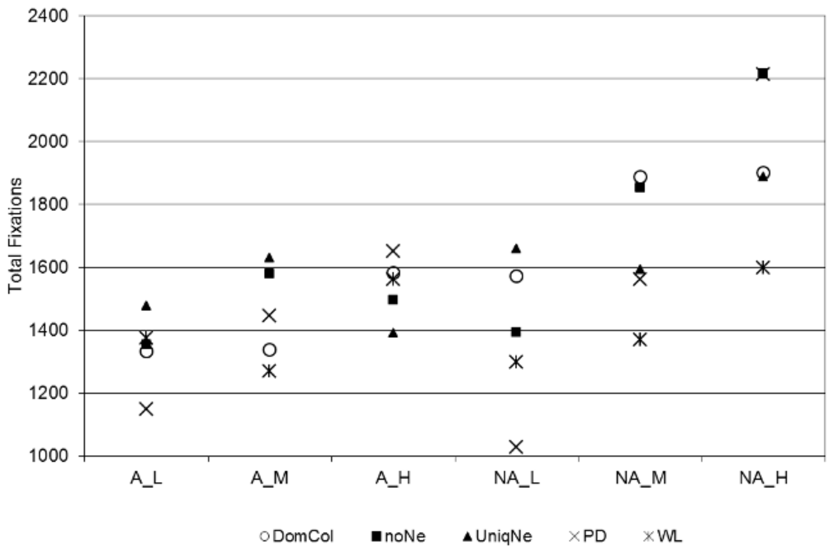



Fig 4: Total fixations divided by game, by presence of Attractor (A/NA), and by HA level

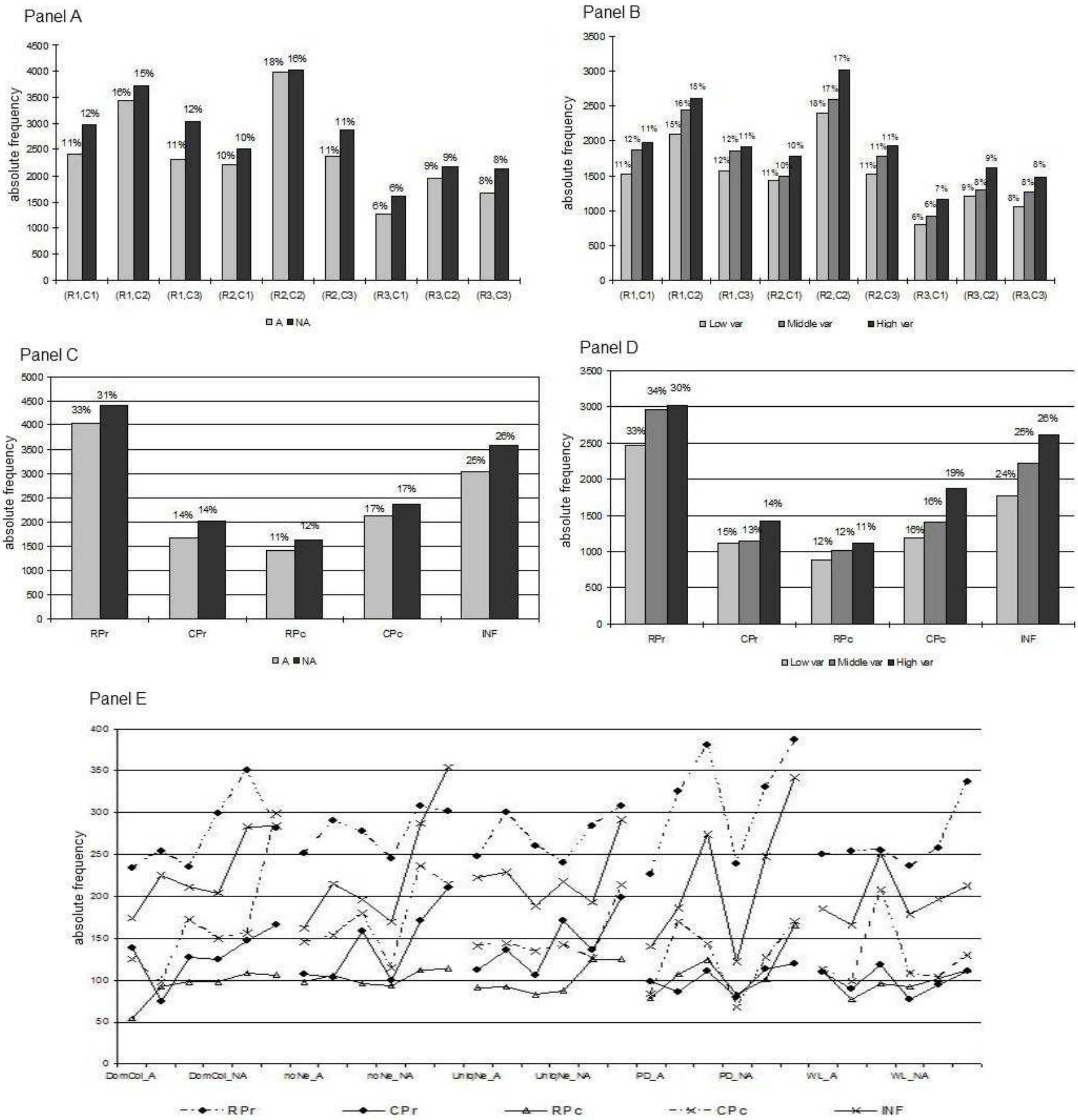



Fig 5: Panel A: Absolute and relative frequency of fixations divided by cell, in matrices with attractor (A) and without attractor (NA). Panel B: Absolute and relative frequency of fixations divided by cell, in matrices with different variances of HA. Panel C: Absolute and relative frequency of transitions, in matrices with attractor (A) and without attractor (NA). Panel D: Absolute and relative frequency of transitions, in matrices with different variances of HA. Panel E: Absolute frequency of transitions, by game

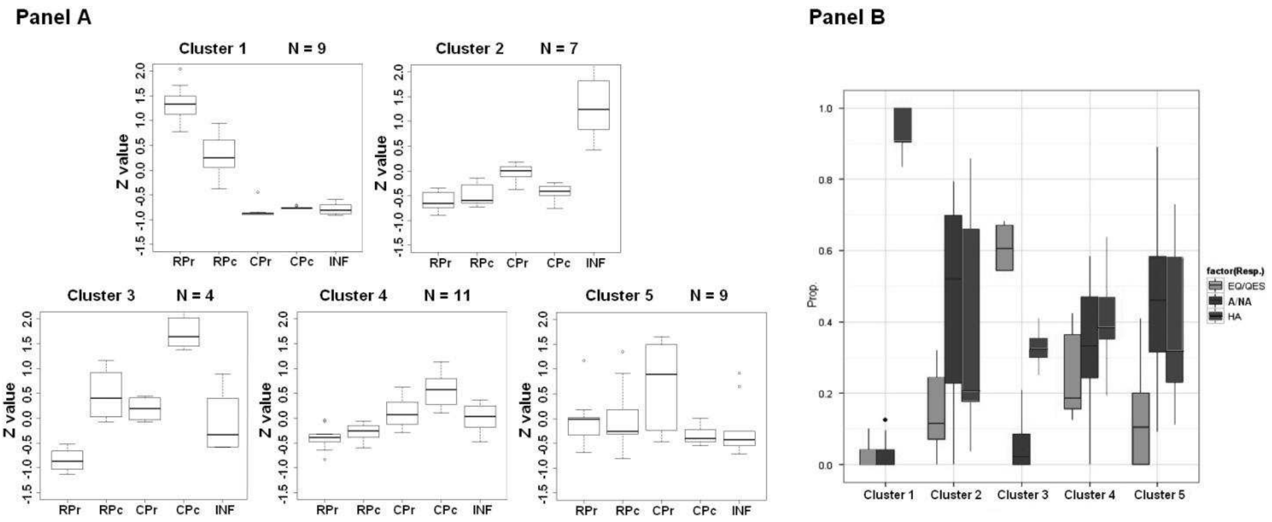



Fig 6: Panel A: Normalized proportion of different transitions, divided by cluster. Panel B: Average proportions of HA, A/NA, and EQ/QES choices for each cluster

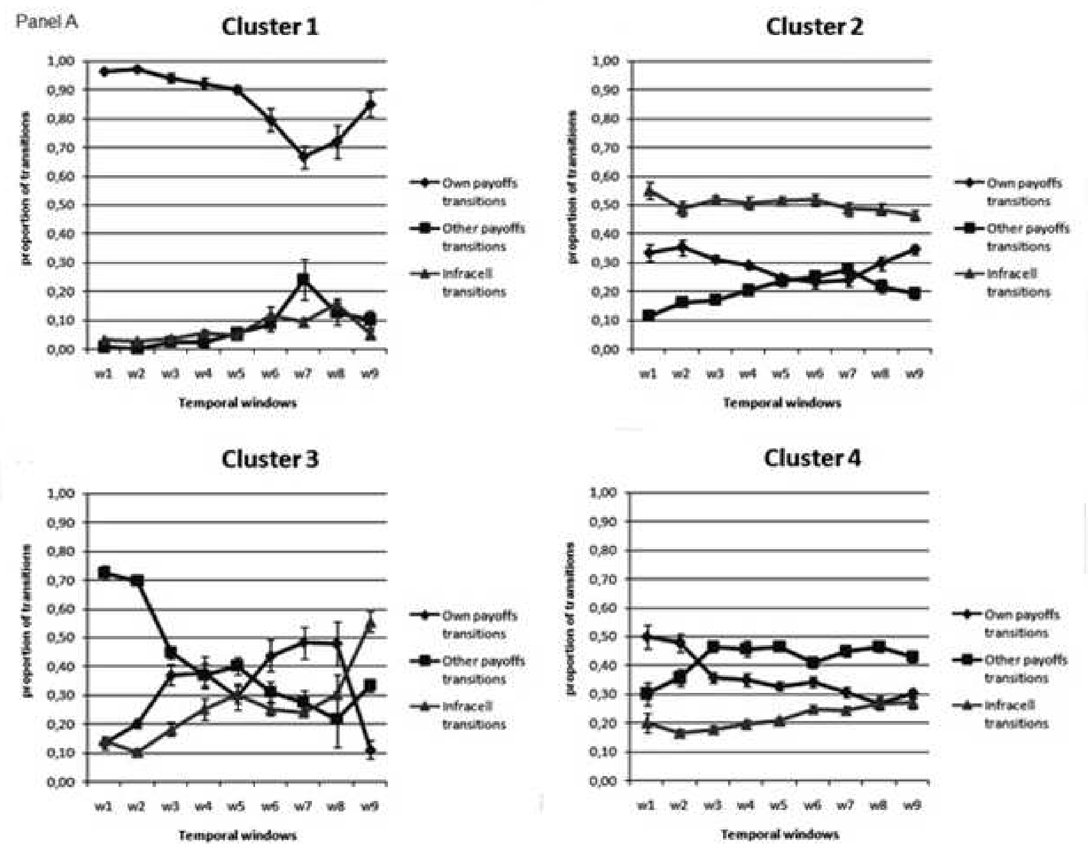



Fig 7:dynamic of transitions through time, grouped by classes (Own Payoffs transitions includes RPr and RPc, Other Payoffs transitions includes CPr and CPc)

## Acknowledgments

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# Appendices

## Appendix A: Experimental Instructions

The following is a translation of the original instructions in Italian. Original instructions are available upon request.

### INSTRUCTIONS

Dear student, you are about to participate in an experiment on interactive decision-making. Your privacy is guaranteed: results will be used and published anonymously. All your earnings during the experiment will be expressed in **Experimental Currency Units** (ECUs). Your earnings will depend on your performance in the experiment, according to the rules which we will explain to you shortly. You will be paid privately and in cash at the end of the experimental session. Other participants will not be informed about your earnings. After the experiment you are asked to complete a short questionnaire. The maximum you can earn in the experiment is 14 Euros, the minimum 7.

### THE EXPERIMENTAL STRUCTURE

The experiment consists of 30 rounds; in each round you will face an interactive decision making situation. In each round you will have to choose **one among three options**: the word "interactive" means that the outcome of your decision will be determined by your choice and by the choice of another participant, randomly chosen at the end of the experimental session.

The structure of each interactive decision problem, henceforth GAME, will be represented by a table like the one below:

| | | |
|---|---|---|
| C<br>R | C<br>R | C<br>R |
| C<br>R | C<br>R | C<br>R |
| C<br>R | C<br>R | C<br>R |

where letters will be substituted by numbers, indicating an amount of ECUs. The table has three rows and three columns.

You and the participant with whom you are paired will play the roles, respectively, of ROW PLAYER and COLUMN PLAYER.

The available choices of the ROW PLAYER (for you) are represented by the ROWS of the table (the first row on top, the second row in the middle, the third at the bottom), and the available choices of the COLUMN PLAYER are represented by the COLUMNS of the table (the first column on the left, the second column in the center, the third column on the right).

Each possible combination of choices of row and column player (i.e., each possible combination of rows and columns of the table) identifies one cell in the matrix. Each cell reports two numerical values. These values indicate the earnings (in Experimental Currency Units) of each participant associated with that combination of choices. Conventionally, the number on the bottom of the cell represents the earnings of the ROW PLAYER (your earning), while the number on the top represents the earnings of the COLUMN PLAYER.

For example: in the table below, if YOU choose the top row and the OTHER PLAYER chooses the column in the middle, then your earnings will be those <u>in the cell at the inter- section between the selected row and column</u>.

In this example YOU earn 4 ECUs and the OTHER PLAYER 7 ECU.

| | | |
|---|---|---|
| 4<br>6 | 7<br>4 | 3<br>5 |
| 4<br>3 | 6<br>5 | 5<br>3 |
| 6<br>5 | 4<br>6 | 7<br>4 |

Bear in mind that you cannot directly choose the cell of the table, but only one of the rows (the other participant with whom you are matched will choose one column). Only the combination of both choices will select one and only one cell, corresponding to your earnings and to those of the other participant.

## INFORMATION

In each of the 30 rounds, the screen will show the decisional table for that round, and you will be asked to make a decision knowing your gain will depend only on that choice and the choice of the person matched with you.
Please remember that you cannot choose a single cell, but only the row that you prefer, given your considerations.
To help you with your choice, the ECUs of the row player (yours) are positioned in the bottom-left corner of each cell and will be in yellow, while the ECUs of the column player will be in the top right corner of the cell and will be in red.
To select your choice you will have to press key 1 for row 1 (the row on the top of the matrix), 2 for row 2 (the row in the middle of the matrix), and 3 for row 3 (the row on the bottom of the matrix).

You will face 30 decisional matrices, corresponding to 30 different interactive situations. The matrices are divided in 3 blocks of 10 matrices each. After each block there will be a short procedure to verify the correct focus of the eye-link equipment.

There is no relation among your choices in the different games, each game is independent from the others.

There is no time limit. We only ask you to try, if possible, to take no longer than one minute for each game.

At the end of the 30th round, the first part of the experiment will be completed, and your earnings for this part will be determined.

PAYMENTS

Each matrix is identified by a code. Some tags have been placed in a box, each showing the code of one of the matrices. The experimenter will ask you to pick 3 of these tags from the box. You will be paid according to the earnings obtained in the tables corresponding to the extracted codes. In a second box 20 tags have been placed, corresponding to 20 subjects that have participated in the experiment as column player. You will have to draw 3 tags from this box too.

Your earnings will be determined by your choices and by the choices of the three people selected, in the three matrices you have drawn. Each matrix will be associated with one column player only, to have exactly 3 outcomes.

Since each of the 30 decisional tables of the experiment has a positive probability of being selected for payment, we ask you to devote the same attention to all of them.

Before the experiment starts, we will ask you to answer a simple anonymous questionnaire, in order to test whether instructions have been clearly understood or whether clarifications are needed. If there are incorrect answers, the relevant part of the instructions will be repeated. After the questionnaire phase is completed, the experiment proper will start.

At the end of the experiment, the experimenter will communicate the exchange rate between Euros and ECUs, you will have to complete a questionnaire, and you will be paid privately and in cash.

Thank you for your kind participation!

## Appendix B: Questionnaire

Dear Participant,

the following questionnaire has the sole purpose of verifying your understanding of the rules of this experiment. We ask you to answer the following questions. If you are uncertain about how to respond, please consult the instructions sheet. Your answers to these questions will not affect your earnings in the experiment.

Thank you for your cooperation!

| | | |
|---|---|---|
| 2<br>3 | 4<br>2 | 9<br>1 |
| 6<br>4 | 5<br>4 | 6<br>7 |
| 3<br>2 | 2<br>1 | 8<br>2 |

**Suppose you are assigned the role of ROW PLAYER:**

- If the COLUMN PLAYER chooses the central column and you choose the top row, how many ECUs will you earn? ........... And how many will the other player earn? ...........
- If you choose the central row, and COLUMN PLAYER chooses the column on the right, how many ECUs will that person earn? ........... And how many ECUs will you earn? ...........
- If the other player chooses the column on the left, your earnings will be:
    - If you choose the top row: ...........
    - If you choose the central row: ...........
    - If you choose the bottom row: ...........

**Suppose you are assigned the role of COLUMN PLAYER**

- If the ROW PLAYER chooses the central row and you choose the left column, how many ECUs will you earn? ........... And how many will the other player earn? ...........
- If the other player chooses the top row, your earnings will be:
    - If you choose the column on the left: ...........
    - If you choose the central column: ...........
    - If you choose the column on the right: ...........

- Your role (as ROW or COLUMN PLAYER) in the rounds of the experiment will change:

TRUE or FALSE

- The participant with whom you are paired will be determined randomly in each round, and you will never be matched more than once with the same participant.

TRUE or FALSE

- After you have taken your decision on a table, you will be able to observe the choice of the participant with whom you were paired.

TRUE or FALSE

## Appendix C: Risk attitudes and personality measures

We present here the questionnaires on cognitive abilities and personality traits that have been presented to experimental subjects after the conclusion of the experiment, briefly summarizing the goal of each of these tests. After the experiment, the tests were not presented as a unique questionnaire, since some of them required a direct interaction with the experimenter. Therefore, we prefer to discuss each test separately, rather than report the exact format that was presented to subjects. Besides the tests presented in this appendix, subjects were presented the “Holt and Laury Risk Aversion test”.

### Test of the Theory of Mind

In Psychology, Theory of Mind (TOM) indicates not only the ability to predict and comprehend the mental states of other intelligent beings, but also the ability to understand that others can have state of minds that are different from one’s own.

The term Theory of Mind has been proposed for the first time by Premack and Woodruff (1978) in a study on chimpanzees, and since then this stream of research has received increasing attention, concerning in particular the role of TOM in developmental age (Wimmer and Perner 1983; Fodor 1992) and in individuals with cognitive dysfunctions (like autism, Baron-Cohen 1995).

Tests for TOM are designed to discriminate subjects with normal cognitive capacities from those with cognitive dysfunctions. No tests have been designed to discriminate among different levels of TOM ability in subjects with normal cognitive capacities.

Of the several tests of TOM proposed in the literature, we decided to use the one known as Reading the Mind in the Eyes test (Baron-Cohen et al. 2001; Baron-Cohen 2004). This test is the least trivial for subjects with normal cognitive capacities. The test was aimed to test the existence of correlations between an agents’ TOM ability and her ability to locate equilibria in the game due to an increased capacity to develop correct beliefs on the opponent’s behavior, assuming this latter capacity is correlated with TOM ability.

We used the version presented in Baron-Cohen (2004), translated from English into Italian and validated before publication.
In this test, experimental subjects are presented with 36 pictures of the eye-region of faces of different persons; for each picture, subjects have to select, from a list of four possible states of mind, the one that best describes the state of mind of the person portrayed.

## Working Memory test, Wechsler Digit Span test, and Cognitive Reflection test

In order to test the role of memory capacity and cognitive reflection in strategic behavior, we presented three short tests to our experimental subjects: the Cognitive Reflection test (Frederick 2005), the Wechsler Digit Span test for short memory (Walsh and Betz 1990), and a working memory test (Unsworth and Engle 2007).

The Cognitive Reflection test was proposed by Frederick (2005) and aims to measure a specific type of cognitive ability, i.e. the ability to resist an immediate, intuitive and wrong answer, executed with little deliberation, in favor of the search for the correct answer requiring a more complex reasoning. This is motivated by the distinction of two cognitive systems in the human mind: System 1 gives spontaneous reactions and does not require explicit reasoning (as in recognizing a known face), while System 2 requires effort and concentration (as in solving a complex mathematical equation) (Epstein 1994; Frederick 2005).
The cognitive abilities measured by this test are particularly relevant for the situations faced by subjects in this experiment, as our payoff matrices included both ”intuitive” choice options (like the attractor strategy) and options (such as the equilibrium strategy) requiring sophisticated reasoning to be detected.
The test consists of three simple questions, for each of which an impulsive – and wrong - answer comes naturally to the mind of the reader. The questions are the following (Frederick 2005):

1. A bat and a ball cost 1.10 in total. The bat costs 1.00 more than the ball. How much does the ball cost?

2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

The score of the test corresponds to the number of correct answers given.

The Wechsler Digit Span test is part of a more complex test called Wechsler Memory Scale developed by David Wechsler (1987) to measure human memory capacity.

We focused on the Digit Span, as we were interested only on a test of short-term memory (defined as the ability to store a small amount of information and recall it after a short time). Although the overall reliability of the Wechsler Memory Scale has been more recently reconsidered (Elwood 1991), the reliability of its single components (such as the Digit Span) has been confirmed and has been used in recent economic experiments (Devetag and Warglien 2008; Rydval, Ortmann, and Ostatnicky 2009).

In this test, subjects are asked to repeat a sequence of digits immediately after the experimenter has finished reading it. The first sequence contains three numbers, and successive strings are of increasing length; the test stops when the subject commits an error in recalling a sequence. The whole test is then repeated. The number of digits of the longest string that has been correctly recalled by the subject corresponds to the score obtained in the test.

The strings of numbers were the same for all subjects.

The working-memory test used in this experiment is called Immediate Free Recall and refers to a large literature on working memory that defines it as the ability of temporarily storing and manipulating information. Given the definition of short-term memory that we gave before, working-memory is defined as the ability to manipulate and organize information stored in short-term memory.

Despite the plausibility of this distinction, several scholars do not consider the two processes as distinct, and include short-term memory into working-memory (Unsworth and Engle 2007).

Since the topic is still debated, we decided to administer a test called Immediate Free Recall, one of the few working-memory tests that can be done using paper and pencil.

In the test, the experimenter reads aloud ten words (each every 1 or 2 seconds). Once finished, the subject writes down as many words as she can remember. In this experiment (unlike the Wechsler Digit Span test) the order in which the words are recalled is not relevant.

We selected a list of ten words randomly sampling from the "Toronto Noun Pool" (to be found at http://memory.psych.upenn.edu/WordPools) of the University of Pennsylvania. The list was the same for all experimental subjects.

## Premeditation, Sensation Seeking, Need for Cognition, Perseverance, and Math Anxiety

These five scales aim to measure different personality traits that are relevant from an economic perspective; for example, an individual with low confidence in his mathematical abilities will probably not be able to locate the equilibrium of a game, while an individual prone to sensation seeking will probably be more risk seeking. These tests have already been successfully used in recent economic experiments (e.g., Rydval, Ortmann, and Ostatnicky 2009).

The Premeditation scale measures individuals' propensity to control their impulsive instincts and reason carefully when carrying out a particular task, Need for Cognition measures subjects' intrinsic motivation and level of commitment, while Perseverance measures (as the name suggests) the natural tendency of an individual to persist in a demanding task. We assumed these three scales could be positively correlated with the ability to locate the equilibrium of a game, or negatively correlated with the tendency to look for safe or "obvious" solutions (strategies giving a constant payoff, or attractors). In all scales, a low number indicates a high level of premeditation, commitment, and perseverance.

Sensation Seeking measures the natural tendency of an individual to look for exciting situations and can be considered a measure of risk propensity. In the experiment, sensation seekers might choose the strategy giving the highest possible payoff (maximaxi or Optimistic) regardless of the risk involved in the choice. In this scale, a low score indicates a high level of sensation seeking.

Math Anxiety measures the feelings that an agent has when dealing with mathematical tasks and might be correlated with the ability to locate the equilibrium of the game. A low score indicates a relaxed feeling towards mathematics.

These scales have the common drawback of being self-reports. This implies that there is no control on the attention and effort exerted in answering the questions; in addition, subjects answer according to their own opinion about themselves (which could be an inaccurate evaluation of their capacities or propensities). For example, a person might result as having a high score of Sensation Seeking because she might be overconfident but not really willing to act in accordance with her own self-image.

In the experiment, we presented to the subjects a questionnaire of 55 questions covering all the scales. For each question, subjects had to choose the preferred answer among “True, Quite True, Quite False, False”.