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Lucky Numbers in Simple Games[§]

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Abstract:

Simple game structures such as coordination, discoordination, hide-and seek, and Colonel-Blotto games have been used to model a wide range of economically relevant situations. Yet, Nash-equilibrium, and alternative theories that have been proposed in the literature, notoriously fail to explain observed behavior in these games. This paper proposes a bounded-rationality approach in which players lexicographically employ team reasoning, choose 'lucky numbers' (the choice they would pick in a lottery), and randomise uniformly. This three-step procedure is able to organise the data across many different frames for coordination, discoordination, and hide-and-seek games. Moreover, it predicts three general regularities that bear out on the existing data and additional data from a Colonel-Blotto game and a Rock-Paper-Scissors-type of game.

Keywords: Bounded Rationality, Level-k, Salience, Heuristic, Hide & Seek, Discoordination, Rock-Paper-Scissors, Colonel Blotto, Representativeness.
JEL: C72, C90, D83.

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1 Introduction

Alternatives in real-life situations are hardly ever non-descript, but usually have non-neutral labels attached to them and often have a spatial ordering. When driving from one city to another, we may choose between "the long but pretty route" and "the short but boring route" or between the "northern" and the "southern route", but we rarely choose between "option 1" and "option 2". This paper starts from the observation that such non-neutral decision frames have an influence on behaviour that often seems to be as important as the incentive structure behind these frames. In particular, the paper sets out to understand the strategic behaviour of participants in a variety of games played on such non-neutral frames. Some of these games have been at the heart of game theory for decades, such as (dis-)coordination games and matching-pennies games. In contrast, Schelling's (1960) account of how an action's non-payoff-related characteristics may influence behaviour has re-entered the academic debate only rather recently. I elicit experiment participants' 'lucky numbers'—the options they would pick in a lottery—and feed them into a simplistic strategic-choice heuristic. This heuristic fits the data better than any of the models discussed in the literature, and at least as well as a number of new alternative models that all have higher degrees of freedom. It predicts three general regularities that accurately describe data patterns of existing and new data. As one implication of one of the regularities, the heuristic explains the consistent seeker-advantage in hide-and-seek games (e.g., Rubinstein et al., 1997).

The data I look at comes from the general class of "strategy-isomorphic games" (Hargreaves Heap et al., 2014): in these games, the strategies are indistinguishable once we remove the labels of players' strategies. The games I use all have two players and four actions. All games were played under at least eight different label frames such as ("1", "2", "3", "4"), ("A", "B", "A", "A"), or ("hate", "detest", "love", "dislike"). I look at coordination games, in which the players win a prize if they choose the same action; discoordination games, in which the players win a prize when they choose different actions; and hide-and-seek games (multiple-action matching-pennies games), in which the hiders wins the prize if the seeker chooses a different action and the seeker obtains the prize when choosing the same action as the hider.

These games capture elements of many important situations in every-day life: when a mother and her child lose each other in the middle of a city (an obvious coordination game), when two firms simultaneously decide on market entry in two markets (potentially a discoordination game), or in military, police, and intelligence work (hide-and-seek games), just to name some examples. Understanding how non-payoff-related characteristics of the available options affect behaviour is important, because as I pointed out above, most every-day-life situations carry non-neutral frames: in the example of the mother and her child, “the place where they last talked to each other” may be more salient than “the next street to the right”. Or, in armed conflicts, gaining control over historically important places may be of particular importance to the parties even if it does not help winning the war.

My research strategy has two parts. One is to propose a new desciptive theory—my simple heuristic—and to derive some general implications from the theory that I can use as testable *ex-ante* hypotheses. To do so, I enlarge the set of games by adding a Colonel-Blotto game and a new game I call the ‘to-your-right game’. In the ‘to-your-right game’, a player wins a prize if she chooses the action immediately to the right of her opponent’s choice (in a circular fashion, so that the left-most action wins against the right-most action). The game is not meant to have any direct parallel to every-day life but is similar to the well-known rock-paper-scissors game. In the Colonel-Blotto variant I use, players have to allocate up to 40 troops to the four locations; whoever has more troops on the location wins it, and whoever wins more locations wins the game (with random tie-breaking). *Inter alia*, Blotto games have been used to model allocations of funds towards different voter groups in electoral campaigns.[1]

The other part of my research strategy is to compare the heuristic to sensible benchmark models and to show that the simple heuristic provides at least as much guidance in understanding the data as the alternative models that have more free parameters. Even if we do not like the bounded-rationality idea and disregard the complete heuristic as a behavioural model, this paper strongly shows the explanatory power of ‘lucky numbers’ for behaviour across the games.

[1] *E.g.*, Groseclose and Snyder (1996).

At the same time, I show that we cannot anchor simply any behavioural model in 'lucky numbers' and expect a satisfactory explanation for the data: doing so for a level-k model does not strongly outperform the heuristic on hide-and-seek data and performs clearly worse in coordination and discoordination games.

This paper proposes the following three-step heuristic of strategic behaviour: (i) start by team reasoning (Sugden, 1993, 1995).[2] If team reasoning yields no prescription other than random choice, (ii) choose your 'lucky number' (the choice you would pick in a lottery on the given frame). With a certain probability, reconsider whether this is sensible if others pick 'lucky numbers', too, assuming people's 'lucky numbers' are correlated. If it is not, (iii) make a uniformly-random choice. This heuristic takes as primitives the data from two experimental tasks: a lottery, in which participants select an option and win a prize if nature picks the same option afterwards (the BettingTask), and a salience-rating task (for the team-reasoning part, which is going to be relevant only in the coordination game). For games in which players go beyond the team-reasoning step, the heuristic yields three implications: (i) the qualitative distribution of choices for a given frame should follow the qualitative distribution of 'lucky numbers', irrespective of the game and player role (in hide-and-seek games, this implies the consistent seeker advantage referred to above); (ii) the prevalence of uniform choices should be lower for seekers in the hide-and-seek game than for any of the other player roles, because seekers are the only players for whom it is sensible to choose anything others (i.e., hiders) would choose, too; and (iii) the correlation of 'lucky-number' pattern and choice pattern in a game should increase in the strength of the 'lucky-number' pattern.

These rather strong implications bear out surprisingly well. In contrast, the models discussed in the literature provide little guidance. Running experiments on some of the above games, Rubinstein et al. (1997) show that participants' behaviour deviates systematically from the unique Nash-equilibrium (uniform randomisation).[3] To take a prominent example, in a hide-and-seek game played on ("A", "B", "A", "A"), there is a clear mode on the 'central A' that is even more pro-

[2]Roughly, team-reasoners ask themselves: "what decision rule, when followed by all players, would yield the best outcome," while agents in standard game theory ask: "what is the best I can do, given what everybody else will do (when confronted with the same question)?"

[3]P. 402; see also Rubinstein and Tversky (1993) and Rubinstein (1999).

nounced for seekers than for hiders. Uniform randomisation is also the quantal-response equilibrium given that strategies are not distinguishable by their payoffs. Finally, level-k or cognitive-hierarchy models yield the same solution if they rely on a uniformly-mixing level-0.

There is only a single model in the literature that accounts for some of Rubinstein et al.'s data. In an important contribution, Crawford and Iriberri (2007) show that a level-k variant based on salience as level-0 can account for hide-and-seek data from a number of frames (notably, "A", "B", "A", "A"). However, Hargreaves Heap et al. (2014) argue that, had Crawford and Iriberri (2007) used all available games for the frames Crawford and Iriberri use, the model's explanatory power would have been small. In Wolff (2016), I use the central frame from Crawford and Iriberri (2007) and elicit salience in nine different ways. The elicited salience patterns all tend to be similar, but they do not allow to account for the data when used as level-0.

Given the existing models explain only a subset of the available data at most, I set up a number of alternative benchmark models. To do so, I use plausible variations of existing models, in addition to the Nash-prediction and a salience-based level-k variant à la Crawford and Iriberri (2007). None of these models outperfoms the heuristic consistently, despite all (but Nash-equilibrium) having a larger number of free parameters.

2 The data

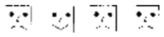
I use data of several papers on behaviour in games where actions are not distinguishable by their payoffs. All of the games are two-player games played on frames that have four locations each. The left-hand column of Table 1 provides an overview of the frames. I use all frames presented by Rubinstein and Tversky (1993) and Rubinstein et al. (1997), plus two obvious complements, BAAA and AAAB, as well as the Ace-2-3-Joker frame introduced by O'Neill (1987) and also referred to in Crawford and Iriberri (2007).

It can be argued that including all of Rubinstein et al.'s frames distorts the analysis because some of these frames use labels with positive or negative connotations. Therefore, choosing the associated actions may increase or decrease utility on top of the utility associated with the resulting monetary outcome. I nevertheless include all of Rubinstein et al.'s frames, for three reasons: (i) in my view, understanding behaviour in non-neutral landscapes extends beyond 'neutral non-neutral' landscapes (and it would be difficult to draw the line if we accept the idea that people tend to have lucky numbers); (ii) at least the heuristic and the LuckyNoEqm Nash-equilibrium variant described below are meant to apply also under 'truly non-neutral' frames (much like the Nash-equilibrium with payoff perturbations considered in Crawford and Iriberri, 2007); and (iii) excluding frames with clearly positive or negative connotations in our sample does not change the results meaningfully but leaves us with less statistical power for the analysis.[4]

Table 1 presents the origin of the data I use in this study, together with the number of observations (in parentheses). The data for the coordination and hide-and-seek games mostly comes from Rubinstein and Tversky's (1993) and Rubinstein et al.'s (1997) studies, only for the abaa frame, I have additional observations from other studies for each game. For the discoordination games, Rubinstein et al. (1997) only have data for six of the frames. I complement this with data on a different subset of six frames collected for two studies run by Dominik Bauer and myself. Finally, I collected the data for the to-your-right and Blotto games specifically for this study, to see whether the predictions and model implications also apply to a new setting. A complete listing of all the data I use—old and new—can be found in Appendix A.

I ran the to-your-right and Blotto games as the first part of (different) sessions comprised of three parts, where I described each part only as it started. Only one part was paid. If the first part was payoff relevant, the roll of a die selected one of the to-your-right games (or Blotto games, in the Blotto sessions) for payment. Participants played under all eleven frames with a randomised order, random rematching, and without feedback between games. I described the to-your-right game as follows:

[4]Appendix C presents the main tables from the data analysis for the reduced sample. Most importantly, the heuristic still has the lowest mean squared error for coordination and discoordination games, and the second-lowest mean squared error in the hide-and-seek games; at the same time, the best-performing model for hide-and-seek games is among the worst-performing models for the other games.

Frame	Coordination	Discoordination	Hiders	Seekers	To-your-right	Blotto
	RTH (50)	RTH (49)	RTH (53)	RTH (62)	new (110)	new (94)
polite-rude-honest--friendly	RTH (50)	RTH (49)	RTH (53)	RTH (62)	new (110)	new (94)
	RTH (50)	RTH (49)	RTH (53)	RTH (62)	new (110)	new (94)
ABAA	RTH+W (122)	RTH+BW+B (442)	RTH+HW+W (339)	RTH+HW+W (281)	new (110)	new (94)
	RTH (50)	RTH (49)	RTH (53)	RTH (62)	new (110)	new (94)
hate-detest-love-dislike	RTH (50)	RTH (49)	RTH (53)	RTH (62)	new (110)	new (94)
1-2-3-4	RT (184)†	BW+B (292)	RT (187)	RT (84)	new (110)	new (94)
AABA	RT (185)†	BW+B (292)	RT (189)	RT (85)	new (110)	new (94)
Ace-2-3-Joker		BW+B (292)			new (110)	new (94)
BAAA		BW+B (292)			new (110)	new (94)
AAAB		BW+B (292)			new (110)	new (94)

†Pooled from the "Chooser" and "Guesser" framings. RTH: Rubinstein et al. (1997). RT: Rubinstein and Tversky (1993). HW: Heinrich and Wolff (2012). B: Bauer (2016). BW: Bauer and Wolff (2016). W: Wolff (2015).

Table 1: Origin of the data I use (numbers of observations in parentheses).

> There are four boxes. You and the other participant choose a box without knowing the decision of the respective other. One of you can obtain a prize of 12 Euros. Who wins depends on the relative position of the two chosen boxes. The participant wins whose box lies to the inmediate right of the box of the other participant. If a participant chooses the right-most box, then the other participant wins if he chooses the left-most box. Who does not win obtains a consolation prize of 4 Euros. Of course, it is possible that neither you nor the other participant wins.[5]

[5]Similarly, the instructions for the Blotto game read: There are four fields. You and the other participant have to assign 40 units to the four fields without knowing the decision of the respec-

Participants had not participated in any other experiments using the same type of non-neutral frames.[6]

To inform my heuristic and some of the other models I use on the game data, I collected data from additional tasks in separate sessions. First, I conducted seven sessions with a total of 140 participants that had a BettingTask as the first of several parts (following the same procedures as with the to-your-right and Blotto games). In the BettingTask, participants faced the following task:

> In each decision situation you have to choose one out of several boxes. Subsequently, one of the boxes will be randomly selected by the cast of a die. In case the randomly-selected box coincides with the box you chose, you receive 12 Euros. If the two boxes do not coincide, you receive 4 Euros.

Next, I conducted three sessions with a total of 58 participants of a HiderBettingTask. This task differs from the BettingTask only in that participants receive the bigger prize if their choice does not coincide with the randomly-selected box. Finally, I asked 96 participants to rate the options' optic salience (SalienceRating) and 102 participants to rate how well each of the boxes within a frame represented all four boxes within that frame (RepresentRating).[7] In both tasks, participants saw the boxes in the same horizontal line-up as in the other tasks. Below each box, they would have a slider (empty at the outset) to indicate the level of optical salience (between "extremely conspicuous", top, and "extremely nondescript", bottom) or representativeness (between "totally representative", top, and "not representative at all", bottom).

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tive other. One of you can obtain a prize of 12 Euros. Who wins depends on how many fields you can win. The participant who has placed more units on a field wins the field. The participant who wins most fields overall wins the prize of 12 Euros. The other participant obtains a consolation prize of 4 Euros. If both participants win the same number of fields, chance determines who obtains which prize.

[6]I used z-Tree (Fischbacher, 2007) and ORSEE (Greiner, 2015).

[7]The rating tasks were included in BettingTask and HiderBettingTask sessions. One could argue that this procedure could bias the rating-task data. However, in particular the SalienceRating data has so little variance and corresponds so well with intuition, that I see little value in repeating the task in separate sessions. The RepresentRating data has more variance, but I do not use it to inform any of the models in Section 3.

3 The heuristic, implications, and the alternatives

This section presents the models I use in the paper. Because there are no 'standard' alternatives available that would come close to explaining the data, I construct two 'sensible' level-k alternatives to compare to. I also include the salience-based level-k of Crawford and Iriberri (2007), with an empirically-defined level-0. Finally, I include an equilibrium with payoff-perturbations that are informed by the BettingTask choices.

TeamLuckyUniform. The three-step procedure I propose in this paper, by which players use the following algorithm to arrive at their decision:

1. start by team reasoning: what decision rule, when followed by all players, would yield the best outcome? If you find such a rule (other than 'pick randomly'), choose the according action and end here. If not,
2. choose your 'lucky number'. This is the choice you would pick in a lottery. With a certain probability p, end here. With the complementary probability, reconsider whether this is a best-response if others pick 'lucky numbers', too, assuming that 'lucky numbers' are correlated between players. If so, stick to your choice and end here. If not,
3. fall back on step 1 and make a uniformly-random choice.

This heuristic is an abbreviation of the following train of thought that players approaching a new situation may be following: "is there any obvious best option for me (step 0a, left out above; it would mean checking for obvious dominance)? If not, is it clear what the other player will do (step 0b, also left out above; checks for obvious dominance for the other player)? If so, react correspondingly, if not, do we both want the same? If so, what do we have to do to make the best out of it (step 1)? If not, that is, if I still don't know what to do, I'll just pick what sounds best to me from among the options I have (step 2). Ah, wait, maybe I shouldn't do that if the other player does the same, should I (step 2b)? In that case, I'll just choose anything (else)." In the formulation of the heuristic, I am leaving out steps 0a and 0b because dominance is ruled out in the class of games I look at.

Step 1 simply follows team reasoning. I refer the interested reader to Sugden (1995) for a formal treatment and treat this step only in passing, because the main focus of the paper are those games in which team reasoning does not have any prescription to offer other than to pick a random decision rule. Team reasoning requires a choice between decision rules. In the model of Sugden (1995), these decision rules are constructed in a hypothetical state before the labels are assigned to strategies. Decision rules could be "choose the smallest number", "choose your favourite colour", "choose the item standing out the most", or "choose the most representative item". The predicted decision rule should then be unique in being collectively optimal. Empirical studies like Mehta et al. (1994) and Bardsley et al. (2010) have shown that in coordination games as the ones employed here, label salience generally seems to be the principle participants rely on.[8] Therefore, for the frames I use, I predict that participants will always coordinate on the most salient option. Because I do not want to rely on intuition on what is the most salient label in a frame, I use the SalienceRating data as input into the model. The TeamLuckyUniform prediction for Rubinstein et al.'s coordination-game data is therefore equal to the fraction of participants who rate the corresponding label highest in terms of salience.[9]

In the train of thought I described, the final step is either to "choose anything" or to "choose anything else" if choosing your lucky number is suboptimal when the other player chooses the same number. These two variants are different in whether they exclude the lucky number. However, the two formulations are equivalent because they will merely imply a different probability p. I chose to use randomisation over all actions in the heuristic because as game-theorists, we are used to thinking of uninformed choice as of uniform randomisation over all actions.

As I stated above, the heuristic predicts coordinators to choose by what they

[8]Important note: I do not intend to say that the above studies find that "participants choose according to salience". The studies only suggest that *for frames like the ones I use*, "choose the item standing out the most" happens to be the decision rule that most participants see as being unique in being collectively optimal.

[9]Sugden (1995) shows that the optimal decision rule maximises variance in choice probabilities. This empirically corresponds to the fact that the SalienceRating data has a very high variance (is very concentrated on single items), which in all but one case is higher than the variance of the alternatives considered in this paper (RepresentRating and 'lucky numbers').

see as the most salient label. Discoordinators will not find a better decision rule than to pick randomly. Therefore, they proceed to step 2, and, with probability p, also to step 3, because discoordinators do not want to choose the same items and 'lucky numbers' will be correlated. Hence, they will choose 'lucky numbers' with probability $(1 - p)$, and uniformly-random with probability p. The same prediction applies to hiders and to players in the 'to your right' game. To test the heuristic against data from the Colonel-Blotto game, we have to adapt its lucky-number step slightly as meaning that people deploy their resources according to the 'lucky-numberedness' of the options.[10] Again, a fraction p of Blotto players will conclude that playing 'lucky numbers' is not a best-response to others playing lucky numbers, and proceed to uniform randomisation. Only seekers should stop after step 2: a seeker is happy to stick to her choice when thinking that the hider is likely to choose the same. These predictions mean that for games that are not 'team-reasoning solvable', the TEAMLUCKYUNIFORM heuristic has two general implications:

invariance the qualitative distribution of choices for a given frame follow the qualitative distribution of 'lucky numbers', irrespective of the game; here, the "qualitative distribution" refers to which items are chosen the most often, the second-most often, *etc.*; and

U-differential the prevalence of uniform choices is lowest for seekers in the hide-and-seek game. Hiders, discoordinators, and 'to-your-righters' rely on 'lucky numbers' to the same degree.

Because 'lucky numbers' will not be the same for everybody, sampling participants into the experiment will introduce randomness in the aggregate data. This may change the qualitative choice pattern when the 'lucky-number' pattern is weak, but it should rarely do so when the pattern is strong. Hence, we obtain a third implication:

[10] It is unclear whether the 'lucky-numberedness' of an option can be measured by the fraction of people choosing it as their most lucky number. In principle, it seems more sensible to elicit participants' individual lucky-number orderings over all locations (e.g., in a conditional betting task, in which participants have to specify what they bet on if their most-preferred option is not available) and then define the lucky-numberedness of the options by the resulting distribution of lucky-number orderings. Given we do not have this data, the best we can do is to assume both orderings will be correlated and to use the data we have.

predict-differential the TeamLuckyUniform heuristic accounts for the qualitative data pattern the better, the stronger the 'lucky-number' pattern is.

Salience-Lk. Crawford and Iriberri's (2007) level-k model in which level-0 follows salience, and level-k players with $k > 0$ play a best-response to level-$(k-1)$ players. Rather than making assumptions about what is salient, I use data from the SalienceRating task as the level-0 to base the model on.[11] For example, consider a discoordination game played on abaa. The first a is held to be the most salient location by 2% of all SalienceRating participants, b by 91%, and the two other as by 4% each. Therefore, we would expect level-0 to choose with probabilities $(0.02, 0.91, 0.04, 0.04)$, uneven levels to choose the first a, and even levels to randomise between the other three locations.

Betting-Lk. This level-k model uses as level-0 the data from the BettingTask. In level-k theories, level-0 is supposed to be people's intuitive reaction to the game, which may well coincide with the choice they make in a lottery. In the abaa-discoordination-game example, betting proportions—and hence, level-0 choices—are 13%, 33%, 41%, and 13%, uneven levels randomise between the end as and even levels between the two locations in the middle.

Bounded Lk. This model differs from standard level-k with a uniformly randomising level-0 only in terms of level-1. It incorporates that level-1 players may respond to uniform randomisation by non-uniform randomisation (or by not randomising at all). The BettingTask and HiderBettingTask elicit what participants do when facing uniform randomisation. Level-1 coordinators and level-1 seekers will act like participants in the BettingTask, whereas level-1 discoordinators and level-1 hiders will act like participants in the HiderBettingTask. For abaa, the HiderBettingTask choice frequencies are 9%, 53%, 21%, and 17%. Therefore, in our discoordination-game example, level-0 would randomise uniformly, level-1 would choose with probabilities $(0.09, 0.53, 0.21, 0.17)$, even

[11] I use the distribution of locations that participants ranked as most salient, to obtain a metric that is comparable to the data from the BettingTask. Using the average salience rating for each location does not change the results in any significant way.

levels would choose the first A, and uneven levels of level-3 or higher would randomise uniformly among all locations but the first A.

NashEqm. The unique symmetric mixed-strategy equilibrium that has both players randomise uniformly over all locations.

LuckyNoEqm. A Nash-equilibrium variant in which participants derive extra utility from choosing certain locations (cf. Crawford and Iriberri, 2007). For this model, I interpret the BettingTask data as a measure of participants' inherent preferences for the different locations.[12] I compute utility values from the BettingTask data and re-define the game in terms of these utility values: A multinomial-logit utility model estimated by maximum likelihood yields utility values that I transform in an affine-linear way (to obtain positive utility values). Then, I calculate the mixed-strategy equilibria for the games that result when the non-zero entries in the standard game matrix are replaced by the transformed utility values. Finally, I use another layer of maximum-likelihood estimation to obtain the transformation of utility values and probability of trembles by players that yield the best-possible fit to the data. Note that the transformation of utility values does not affect BettingTask choice under the multinomial-logit model, but it does affect the calculated mixed-strategy equilibria. For our ABAA example, (absolute) choice frequencies in the BettingTask were 18, 46, 58, and 18. If these frequencies are the result of a multinomial-logit choice process, the maximum-likelihood estimates for utilities are -0.52, 0.42, 0.65, and -0.52. I recalibrate those utilities to 0.65, 1.27, 1.43, and 0.65 (which are still in accordance with the BettingTask choice frequencies) and use the recalibrated values as the corresponding entries in the normal form game: when a participant chooses one of the end-As and her opponent chooses another location, the participant's utility will be 0.65. Likewise, when she successfully discoordinates by choosing B, her utility will be 1.27. Using the resulting normal-form game, the unique symmetric equilibrium (mixed) strategy would be (0, 0.47, 0.53, 0). As I point out above, I allow for errors and allow the maximum-likelihood procedure to optimise over

[12] Of course, this assumes that people are homogeneous in what utilities they derive from the different locations. This is a strong assumption, but it is the best approximation that I have.

another layer of utility-recalibration for the model comparison in part 4.1.

4 Results

4.1 Accounting for behaviour

The coordination-game data is explained best by participants choosing what they see as the most salient option. The top part of Table 2 shows that this is in accordance with the TeamLuckyUniform and Salience-Lk models but not with Betting-Lk or Bounded-Lk (I omit the Nash-equilibrium and the LuckyNoEqm models here as they do not make a unique prediction). Having said this, I focus on the games that are not 'team-reasoning-solvable' (*i.e.*, where team reasoning only predicts uniform randomisation) for the remainder of this paper.

Result 1. The simplistic TeamLuckyUniform heuristic fits the data at least as well as any of the other models, with fewer parameters than the level-k and LuckyNoEqm alternatives.

Looking at the middle part of Table 2, the TeamLuckyUniform model exhibits the largest log-likelihood of the models when fitted on discoordination-game data.[13] It is outperformed in terms of the mean squared error (MSE) by Salience-Lk and LuckyNoEqm, and in terms of both the MSE and the number of choice-distribution modes correctly fitted by Bounded Lk. However, each of these four models performs clearly worse than TeamLuckyUniform when fitted on hide-and-seek data, as the lower part of Table 2 shows. Here, Betting-Lk—which TeamLuckyUniform outperformed clearly in the upper half of Table 2—takes on the role of the main contender, with higher log-likelihood, lower MSE but less correctly-fitted modes. So, while TeamLuckyUniform does not dominate any of the other models, it always performs best on at least one criterion, and it does so using only one free parameter as opposed to three (for the discoordination data) or five (for the hide-and-seek data) as in the level-k models.

[13]To fit the models, I calculate the predicted marginal probabilities as a function of the model parameters (for level-k models, the level distribution, for TeamLuckyUniform, the 're-thinking probability' p). Using those marginal probabilities, I calculate the likelihood of the observed samples. The maximum-likelihood algorithm then optimises over the parameter values. Unless otherwise indicated, I do not include trembles in the models.

model	fitted on	LogL	MSE	modes predicted	parameters
Betting-Lk	coordination	-951	0.6415	3 out of 8	2
Bounded Lk		-945	0.0635	3 out of 8	3
Salience-Lk		-885	0.0154	8 out of 8	2
TeamLuckyUniform†		-885	0.0154	8 out of 8	0
Betting-Lk	discoordination	-2980	0.0056	5 out of 11	3
NashEqm		-2975	0.0045	2.75‡ out of 11	—
Salience-Lk		-2972	0.0039	6 out of 11	3
Bounded Lk		-2967	0.0034	7 out of 11	3
LuckyNoEqm		-2960	0.0038	6 out of 11	3
TeamLuckyUniform		-2959	0.0039	6 out of 11	1
NashEqm	hide & seek	-2412	0.0160	(2,2)‡ out of (8,8)	—
LuckyNoEqm		-2361	0.0116	(0,8) out of (8,8)	3
Salience-Lk		-2356	0.0126	(2,6) out of (8,8)	5
Bounded Lk		-2340	0.0089	(5,6) out of (8,8)	5
TeamLuckyUniform		-2316	0.0076	(8,8) out of (8,8)	1
Betting-Lk		-2299	0.0066	(8,6) out of (8,8)	5

†Model includes a tremble with 1% probability to take care of zero-probability events. The fit improves further when allowing for more randomisation. ‡Expected number of correctly-predicted modes under uniform randomisation.

Table 2: Performance of the models in terms of data fitting, ordered by log-likelihood.

	Spearman coefficient	$p-$value
hiders	0.63	0.000
seekers	0.60	0.001
discoordinators	0.24	0.122
to-your-right players	0.50	0.001
Blotto players	0.41	0.007

Table 3: Correlations of ranks: game data and BettingTask data.

As further suggestive evidence, the fitted Bounded Lk has virtually only levels 0 (uniform randomisation) and 1 (BettingTask/HiderBettingTask), no matter which game the model is fitted on (a combined 100% if fitted on discoordination, 88% if fitted on hide and seek).

4.2 The *invariance* implication

The TeamLuckyUniform heuristic predicts that the qualitative data pattern in all games will be the same as that of the corresponding BettingTask. Looking at the modes as a first, crude measure, this prediction seems to hold for hiders and seekers (16 out of 16 modes correctly predicted), and to a lesser degree also for to-your-right players (8 out of 11), discoordinators and Blotto players (both times 6 out of 11).[14] While the modes are interesting, the *invariance* implication speaks about the complete distribution. Table 3 presents the Spearman correlations of ranks between the game data and the BettingTask data for each of the player roles.

Result 2. *Invariance* tends to hold: the correlation of ranks between the game data and the BettingTask data is strong and significant for hiders, seekers, to-your-right players, and Blotto players, and still sizable for discoordinators.

As Table 3 shows, the correlation of ranks between the game data and the BettingTask data is 0.63 for hiders, 0.60 for seekers, 0.50 for to-your-right play-

[14]There is nothing systematic to be learnt from the deviations: the frames on which the different games deviate from the prediction overlap only partially, and when they do, the modes coincide in only 2 out of 5 cases.

ers, and 0.41 for Blotto players (all $p < 0.007$). The rank correlation for discoordinators is 0.24 ($p = 0.122$). At the same time, all predictions are clearly better than the predictions made by random choice. To see that, I calculate the mean squared difference in ranks between the game data and the BettingTask data, and compare this difference to the difference to be expected under random choice. To compare the mean squared rank differences to the BettingTask with that to the random-choice benchmark, I draw for each frame 100'000 sets of 110 draws from a uniform distribution over four items and convert the sets to rankings.[15] I then compare the mean squared rank difference between the game data and the BettingTask to the distribution of mean squared rank differences from the simulation, by means of a Kolmogorov-Smirnov test (bootstrapped to correct for the discreteness of the rankings). The corresponding p-values are all $p \leq 0.042$.[16]

4.3 U-differential

The TeamLuckyUniform heuristic predicts that seekers should be relying on 'lucky numbers' the most, and on uniform randomisation the least. The heuristic does not distinguish between the degrees to which hiders, discoordinators, and players of the to-your-right game should rely on 'lucky numbers'. To test the *U-differential* implication, I fit the heuristic separately on hiders, seekers, discoordinators, and to-your-right players, and report the fitted prevalence of uniform randomisation for each of them in Table 4.

Result 3. *U-differential* holds partially: while seekers are clearly the least likely to mix uniformly, there also is a difference among the other player roles.

Table 4 clearly shows that seekers are the least likely to mix uniformly. Whether there is a difference between the other player roles is unclear at first sight: they may all have a propensity to randomise of around 70%, but there also seems to

[15] I chose 110 draws to match the median number of observations in my data set.

[16] Another way of looking at the question is to locate the median mean squared rank difference of a game with the BettingTask data within the simulated distribution of differences to random play. Here, we note that the median mean squared rank difference over all frames is always between 0.7 and 1.3 of a standard deviation (of the simulated random-play distribution) lower than the median of the simulated distribution.

	fitted prob(uniform mixing) in %
seekers	23
hiders	55
discoordinators	70
to-your-right players	85
Blotto players	91

Table 4: Fitted probability of uniform mixing for each player role.

be a clear difference between hiders and to-your-right/Blotto players that the heuristic does not account for. Likelihood-ratio tests reveal that all of the differences reported in Table 4 are significant (with $p \leq 0.021$), except for the difference between to-your-right and Blotto players ($p = 0.485$).[17]

I presented the model as implying that there should not be any difference among the non-seekers. However, there may be a model-inherent reason for a difference between discoordinators and hiders in terms of how much players in these roles should rely on 'lucky numbers'. Discoordinators may spend some time in the team-reasoning step one of the model, trying to figure out a good decision rule. This would imply they are thinking about the other player for some time. From there, it is only a small step to reconsider a second-step lucky-number choice, potentially because the players might have considered picking 'lucky numbers' as a team-reasoning decision rule. Hiders, on the other hand, will go through the team-reasoning stage very quickly, so that their opponent may not be as present in their mind. This, of course, does not explain the even higher prevalence of uniform mixing amongst to-your-right and Blotto players, unless the game description prompts them to think about the other player straight away. In any case, the heuristic offers no obvious reason for discoordinators to use less uniform mixing than to-your-right or Blotto players.

[17]To obtain these p-values, I run maximum likelihood estimates for each role with the probability of uniform mixing being constrained to each of the other estimates. The Likelihood-ratio test then compares the maximum likelihood of the constrained and the unconstrained estimations.

4.4 Predict-differential

In the preceding two sections, I presented evidence that the two implications *invariance* and *U-differential* offer considerable guidance in understanding behaviour. Yet, none of the two implications holds perfectly. As also implied by the heuristic under random sampling of participants, we can use information from the BettingTask data to identify the frames in which the heuristic fits better.

Result 4. There is a positive correlation between the predictive accuracy of the TeamLuckyUniform heuristic and the strength of the 'lucky-number' pattern.

I measure the strength of the 'lucky-number' pattern by the difference between the relative frequencies of the most popular and the least popular choices in the BettingTask. Then, I relate this difference to the mean squared rank difference between game data and TeamLuckyUniform prediction, for each player role. I find that all five correlations are negative (for discoordinators, hiders, seekers, to-your-right and Blotto players). The probability of all five correlations showing as negative if there was no true relationship is $p = (\frac{1}{2})^5 = 0.03125$.

4.5 Relating 'lucky numbers' and other concepts

As a final point, I relate 'lucky numbers' to characteristics of the labels within their frame. As characteristics, I use subjective and relatively objective criteria. As objective criteria, I include relative position (0.5 for the middle, 1 for the rightmost locations) and valence (positive, negative, or neutral). Subjective criteria are salience and representativeness, which I objectivise by measuring students' assessment of them (in SalienceRating and RepresentRating (representativeness is important for choice among evidently equivalent items, cf. Bar-Hillel, 2015). Table 5 reports the corresponding regression.

Observation. Several characteristics interact to make an item a 'lucky number', among them salience, position, and valence.

As we can see from the Table, there seem to be four characteristics that increase the relative frequency of an item being picked in the BettingTask: (i)

	coefficient	s.e.	p-value
(Intercept)	-0.21	(0.14)	0.1461
negative	0.01	(0.12)	0.9425
positive	-0.11	(0.08)	0.1959
SalienceRating	0.43	(0.13)	0.0020
RepresentRating	0.25	(0.13)	0.0693
relative position	0.62	(0.11)	$1 \cdot 10^{-6}$
(relative position)^2	-0.54	(0.10)	$5 \cdot 10^{-6}$
negative·SalienceRating	-0.26	(0.22)	0.2574
positive·SalienceRating	0.33	(0.15)	0.0364
R^2	0.72		
Adj. R^2	0.66		
Num. obs.	44		

Table 5: Regression of relative choice frequencies in the BettingTask on label characteristics.

being rated as more salient, (ii) being positioned in the middle (to see this, combine relative position and its square); (iii) having a positive connotation when the item is salient (in the context of our frames, this essentially means that the positively connoted item is presented along with three negatively connoted items); and potentially, (iv) being rated as being representative. While this analysis has to be taken with caution because the set of frames is rather peculiar, it may serve as a first indication of what may determine 'lucky numbers' in general.

5 The discovery process

Some readers might worry in how far the heuristic has been tailored to the data. To address this issue, I take the unusual step to briefly portray the research process. This project started out as an attempt to adapt the level-k approach to explain the data from coordination, discoordination, and hide-and-seek games by basing it on empirical measures (as in my Betting-Lk or Bounded Lk models). At some point I noted that nothing more than the BettingTask data and uniform randomisation was needed to account for the data remarkably well—and that I was not able to come up with any model that would perform systematically better. Therefore I sat down and thought about which easy-but-plausible psychological train of thought might lead to such behaviour. This was the moment when I came up with the heuristic. But because the heuristic was at that moment tailored to fit the data, I had to find some implications of the model that I could test as new hypotheses. So I drew out the implications and, after having confirmed that they bear out on the old data I conducted the sessions for the to-your-right and Blotto games. So, rather than to think about what observed patterns could be implied by the heuristic, I looked for potential regularities the heuristic would predict and only then tested the predictions against the data.

6 Discussion

In this paper, I have presented a heuristic for strategic choice that seems to capture behaviour in strategy-isomorphic games, in which the payoff matrix provides little guidance for choice. I drew out three crude implications, *invariance* (to the game), *U-differential* (on the prevalence of uniform choices), and *predict-differential* (on explanatory power as a function of the lucky-number pattern) that bear out well also on newly collected data. The three implications are unique to the heuristic. *Predict-differential* makes sense only within the context of the heuristic. None of the alternative models predicts the *U-differential* convincingly.[18] And the only other model that would predict any kind of *ex-ante invariance* (in a trivial sense) is the standard Nash-equilibrium. However, for two distributions sampled under Nash-equilibrium play, we would not expect *invariance* in the rank distributions.

The domain of the proposed heuristic is the set of strategy-isomorphic games, in which the payoff matrix provides little guidance. This class of games is rele-

[18] Deriving the predictions for the three level-k models and calculating the predictions' mean squared deviations from randomness do in fact yield the highest mean squared deviations for seekers; however, the differences in mean squared deviations to the next-closest player role are all negligible (at most 5%, compared to about 66% for the heuristic).

vant and prominent in the literature: coordination, discoordination, hide-and-seek, rock-paper-scissors and Colonel Blotto are all well-studied games. Researchers already have studied coordination, discoordination, and hide-and-seek games using the abstract 'landscapes' we have looked at in this paper, and for rock-paper-scissors and Colonel Blotto, studying them in non-neutral 'landscapes' makes a lot of sense, too. "Rock", "paper", and "scissors", or "Florida" and "Ohio" (when applying Colonel Blotto to electoral campaigns) are all non-neutral descriptions. So the question arises naturally what effect non-neutral descriptions have on how people play the games. The answer is that people's choices are strongly biased towards the descriptions they prefer to bet on in a lottery task. An important question for further research is whether this is still the case if we introduce payoff asymmetries like in the coordination games Crawford et al. (2008) study.

At a first glance, 'lucky numbers' may seem like a weird concept for economic decisions.[19] At a second glance, the concept may make sense when we understand it as a tie-breaking rule: even if we put the heuristic aside, we can see that the lucky numbers tell us a lot about behaviour. This becomes obvious in Result 4: the qualitative pattern of behaviour in games tends to come closer to the lucky-number pattern the more pronounced the lucky-number pattern is. Perhaps the most surprising finding in the paper is that there is so little of a systematic strategic reaction to the attraction to lucky numbers even in games like hide-and-seek: adding several layers of best-responses to a lucky-number-choosing level-0 performs only somewhat better—and only in the hide-and-seek game—than adding a single layer of uniform randomisation under the heuristic.

The way I have been using the concept of 'lucky numbers' in this paper is not fully congruent to the meaning of lucky numbers in everyday language. I do not assume that participants being asked "what is your lucky number in A-B-A-A?" would reply by "central A." Rather, I use 'lucky numbers' as a description for what participants choose in a lottery context. Section 4.5 relates these choices to other concepts like salience, representativeness, and valence. I strongly believe that using individual-level data—measuring 'lucky-numberedness' and behaviour in

[19]In fact, they have been studied only in the context of lottery choices themselves (e.g. Simon, 1998), and in the context of Chinese customer behaviour (e.g. Yang, 2011).

the games within-participant—is infeasible. This belief rests on the intuition that once I have chosen a particular item in an A-A-A-B frame, this will change my reasoning and perception in the next task on the same frame. Because of this, the present paper relies on approximations that are valid only under certain assumptions: the 'lucky-numberedness' as seen by a decision-maker in a specific game is approximated by the lottery-ticket choices of other people in the same frame. This approximation assumes homogeneity of lucky numbers across participants, and abstracts from sampling variation by equating empirical relative frequencies with population probability parameters. However, I prefer this approach over relying on the researcher's intuition for specifying, *e.g.*, level-0, the approach taken in some prominent papers on level-k reasoning.

The common models of strategic behaviour probably err on the side of ascribing too much strategic reasoning to the average participant in our experiments. The heuristic I have presented here is likely to err on the other side. And yet, it seems to capture important elements of decision-making. The heuristic should be seen as a thought-provoking impulse to help us finally get to grips with the conundrum we face since the papers by Rubinstein, Heller, and Tversky.

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Appendix A Full data

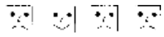
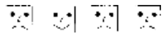
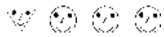
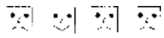
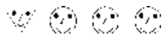
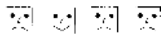
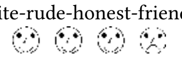
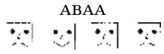
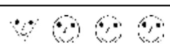
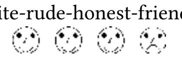
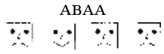
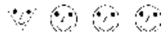
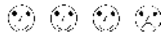
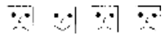
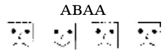
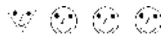
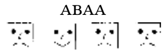
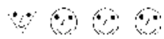
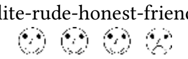
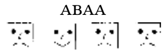
Player role	frame	location 1	location 2	location 3	location 4
coordinators		86	0	10	4
	polite-rude-honest-friendly	6	54	12	28
		6	6	14	74
	ABAA	14	72	13	1
		6	88	6	0
	hate-detest-love-dislike	2	6	88	4
	1-2-3-4	38	17	29	15
	AABA	5	27	54	14
discoordinators		39	14	18	29
	polite-rude-honest-friendly	28	20	32	20
		17	27	23	33
	ABAA	18	21	38	24
		17	40	29	15
	hate-detest-love-dislike	16	29	26	29
	1-2-3-4	21	32	30	17
	AABA	26	24	32	18
	Ace-2-3-Joker	31	17	21	31
	BAAA	34	23	19	23
	AAAB	31	22	18	29
hiders		23	23	43	11
	polite-rude-honest-friendly	15	26	51	8
		21	26	34	19
	ABAA	15	29	33	23
		15	40	34	11
	hate-detest-love-dislike	11	23	38	28
	1-2-3-4	25	22	36	18
	AABA	22	35	19	25
seekers		29	24	42	5
	polite-rude-honest-friendly	8	40	40	11
		7	25	34	34
	ABAA	9	21	53	17
		16	55	21	8
	hate-detest-love-dislike	20	21	55	14
	1-2-3-4	20	18	48	14
	AABA	13	51	21	15
to-your-right players		15	30	32	24
	polite-rude-honest-friendly	22	22	33	24
		18	22	33	27
	ABAA	15	19	34	32
		16	20	33	31
	hate-detest-love-dislike	23	17	30	30
	1-2-3-4	17	21	39	23
	AABA	22	23	29	26
	Ace-2-3-Joker	25	23	31	21
	BAAA	15	26	34	25
	AAAB	24	23	28	25
Colonel-Blotto players		30	26	26	18
	polite-rude-honest-friendly	26	25	26	22
		24	26	28	22
	ABAA	23	29	24	24
		25	26	26	23
	hate-detest-love-dislike	25	23	30	21
	1-2-3-4	24	25	26	25
	AABA	24	25	28	23
	Ace-2-3-Joker	26	26	24	24
	BAAA	29	25	26	20
	AAAB	24	26	25	24

Table A.6: Full data of the games (relative choice frequencies; for Colonel Blotto: average proportion of troops).

Task	frame	location 1	location 2	location 3	location 4
BettingTask		25	29	36	11
	polite-rude-honest-friendly	12	8	53	27
		16	34	35	16
	ABAA	13	33	41	13
		6	58	26	11
	hate-detest-love-dislike	7	12	69	12
	1-2-3-4	18	21	36	25
	AABA	13	36	36	15
	Ace-2-3-Joker	33	14	19	34
	BAAA	27	25	24	24
	AAAB	18	21	34	26
HiderBettingTask		40	19	19	22
	polite-rude-honest-friendly	12	17	50	21
		24	17	28	31
	ABAA	9	53	21	17
		14	59	16	12
	hate-detest-love-dislike	12	14	53	21
	1-2-3-4	19	28	31	22
	AABA	26	19	40	16
	Ace-2-3-Joker	28	14	29	29
	BAAA	31	24	19	26
	AAAB	16	22	22	40
RepresentRating†		10	32	27	31
	polite-rude-honest-friendly	34	7	26	32
		38	32	27	3
	ABAA	38	5	30	28
		29	19	30	21
	hate-detest-love-dislike	34	15	20	30
	1-2-3-4	33	23	16	28
	AABA	34	23	8	35
	Ace-2-3-Joker	39	15	17	29
	BAAA	11	35	25	29
	AAAB	43	25	24	8
SalienceRating†		94	2	4	0
	polite-rude-honest-friendly	14	57	21	8
		5	6	8	81
	ABAA	2	91	4	4
		13	72	11	4
	hate-detest-love-dislike	16	19	62	3
	1-2-3-4	38	21	25	16
	AABA	3	4	93	1
	Ace-2-3-Joker	28	3	3	66
	BAAA	92	3	5	0
	AAAB	5	6	3	86

†In case a participant rated several items as most representative/most salient, her count would be evenly distributed on all corresponding locations.

Table A.7: Full data from the complementary tasks (relative choice frequencies; for the Rating tasks: relative frequencies of location ranked the highest).

Appendix B Full data (absolute numbers)

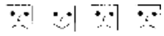
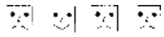
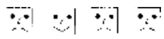
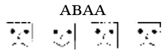
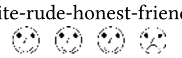
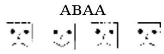
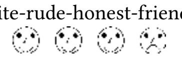
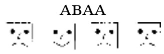
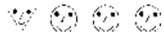
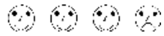
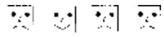
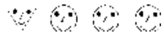
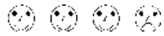
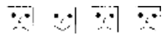
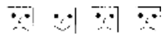
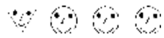
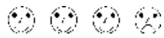
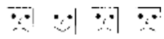
Player role	frame	location 1	location 2	location 3	location 4
coordinators		43	0	5	2
	polite-rude-honest-friendly	3	27	6	14
		3	3	7	37
	ABAA	17	88	16	1
		3	44	3	0
	hate-detest-love-dislike	1	3	44	2
	1-2-3-4	70	32	54	28
	AABA	9	50	100	26
discoordinators		19	7	9	14
	polite-rude-honest-friendly	14	10	16	10
		8	13	11	16
	ABAA	80	92	166	104
		8	19	14	7
	hate-detest-love-dislike	8	14	13	14
	1-2-3-4	61	92	89	50
	AABA	75	71	93	53
	Ace-2-3-Joker	90	49	62	91
	BAAA	100	68	56	68
	AAAB	90	63	54	85
hiders		12	12	23	6
	polite-rude-honest-friendly	8	14	27	4
		11	14	18	10
	ABAA	51	97	113	78
		8	21	18	6
	hate-detest-love-dislike	6	12	20	15
	1-2-3-4	46	41	67	33
	AABA	41	65	36	47
seekers		18	15	26	3
	polite-rude-honest-friendly	5	25	25	7
		4	16	21	21
	ABAA	26	59	149	47
		10	34	13	5
	hate-detest-love-dislike	11	12	31	8
	1-2-3-4	17	15	40	12
	AABA	11	43	18	13
to-your-right players		16	33	35	26
	polite-rude-honest-friendly	24	24	36	26
		20	24	36	30
	ABAA	17	21	37	35
		18	22	36	34
	hate-detest-love-dislike	25	19	33	33
	1-2-3-4	19	23	43	25
	AABA	24	25	32	29
	Ace-2-3-Joker	28	25	34	23
	BAAA	17	29	37	27
	AAAB	26	25	31	28
Colonel-Blotto players		11.87	10.38	10.35	7.31
	polite-rude-honest-friendly	10.28	10.18	10.56	8.87
		9.62	10.40	11.06	8.81
	ABAA	9.16	11.48	9.55	9.65
		10.02	10.33	10.49	9.03
	hate-detest-love-dislike	10.03	9.37	11.86	8.22
	1-2-3-4	9.69	9.89	10.45	9.90
	AABA	9.73	10.14	11.03	9.10
	Ace-2-3-Joker	10.21	10.31	9.66	9.56
	BAAA	11.52	9.98	10.47	8.03
	AAAB	9.68	10.48	10.13	9.57

Table B.8: Full data of the games (for Colonel Blotto: average number of troops).

Task	frame	location 1	location 2	location 3	location 4
BettingTask		35	40	50	15
	polite-rude-honest-friendly	17	11	74	38
		22	47	49	22
	ABAA	18	46	58	18
		8	81	36	15
	hate-detest-love-dislike	10	17	96	17
	1-2-3-4	25	29	51	35
	AABA	16	45	45	18
	Ace-2-3-Joker	46	19	27	48
	BAAA	38	35	34	33
	AAAB	25	30	48	37
HiderBettingTask		23	11	11	13
	polite-rude-honest-friendly	7	10	29	12
		14	10	16	18
	ABAA	5	31	12	10
		8	34	9	7
	hate-detest-love-dislike	7	8	31	12
	1-2-3-4	11	16	18	13
	AABA	15	11	23	9
	Ace-2-3-Joker	16	8	17	17
	BAAA	18	14	11	15
	AAAB	9	13	13	23
RepresentRating†		10.5	32.67	27.17	31.67
	polite-rude-honest-friendly	34.5	7.5	27	33
		38.33	32.83	27.83	3
	ABAA	38.25	4.75	30.75	28.25
		29.83	19.5	30.83	21.83
	hate-detest-love-dislike	34.67	15.5	20.83	31
	1-2-3-4	33.33	23	16.67	29
	AABA	35	23	8.5	35.5
	Ace-2-3-Joker	39.92	15.42	17.58	29.08
	BAAA	11.5	35.5	25.5	29.5
	AAAB	44.17	25.67	24.17	8
SalienceRating†		90	2	4	0
	polite-rude-honest-friendly	13	55	20	8
		5	5.5	7.5	78
	ABAA	2	87	3.5	3.5
		12.5	69	11	3.5
	hate-detest-love-dislike	15	18.5	59.5	3
	1-2-3-4	36.67	20.17	23.67	15.5
	AABA	2	3	74	1
	Ace-2-3-Joker	27	3	3	63
	BAAA	88.5	2.5	5	0
	AAAB	5	5.5	3	82.5

†In case a participant rated several items as most representative/most salient, her count would be evenly distributed on all corresponding locations.

Table B.9: Full data from the complementary tasks.

Appendix C "Neutral non-neutral" frames only

model	fitted on	LogL	MSE	modes predicted	parameters
Betting-Lk	coordination	-627	0.0376	1 out of 3	2
Bounded Lk		-626	0.0389	1 out of 3	3
Salience-Lk		-684	0.0234	3 out of 3	2
TeamLuckyUniform†		-684	0.0225	3 out of 3	0
Betting-Lk	discoordination	-2635	0.0033	3 out of 6	3
NashEqm		-2637	0.0036	1.5‡ out of 6	—
Salience-Lk		-2635	0.0032	3 out of 6	3
Bounded Lk		-2632	0.0032	5 out of 6	3
LuckyNoEqm		-2623	0.0027	2 out of 6	3
TeamLuckyUniform		-2621	0.0026	4 out of 6	1
NashEqm	hide & seek	-1615	0.0135	(.75,.75)‡ out of (3,3)	—
LuckyNoEqm		-1572	0.0094	(0,1) out of (3,3)	3
Salience-Lk		-1604	0.0225	(0,3) out of (3,3)	5
Bounded Lk		-1579	0.0091	(1,3) out of (3,3)	5
TeamLuckyUniform		-1558	0.0071	(3,3) out of (3,3)	1
Betting-Lk		-1540	0.0042	(3,3) out of (3,3)	5

†Model includes a tremble with 1% probability to take care of zero-probability events. The fit improves further when allowing for more randomisation (e.g., 20% randomisation, LogL = -603, MSE = 0.0106). ‡Expected number of correctly-predicted modes under uniform randomisation.

Table C.10: Data-fitting performance of the models, order as in the main text (by LogL of the original estimate).

	Spearman coefficient	$p-$value	No. of frames
hiders	0.47	0.118	3
seekers	0.67	0.025	3
discoordinators	0.28	0.185	6
to-your-right players	0.37	0.078	6
Blotto players	0.30	0.149	6

Table C.11: Correlations of ranks: game data and BettingTask data.

	fitted prob(uniform mixing) in %
seekers	0
hiders	59
discoordinators	65
to-your-right players	79
Blotto players	92

Table C.12: Fitted probability of uniform mixing for each player role.

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