Rationally Inattentive and Strategically (Un)sophisticated: Theory and Experiment

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November 2022 (Click here for latest draft)

Abstract

In a game with costly information acquisition, the ability of one player to acquire information directly affects her opponent's incentives for gathering information. Rational inattention theory then posits the opponent's information-acquisition strategy is a direct function of these incentives. This paper argues that people are cognitively limited in predicting their opponent's level of information, and hence lack the strategic sophistication that the theory requires. In an experiment involving a real-effort attention task and a simple two-player trading game, I study the ability of subjects to (1) anticipate the information acquisition of opponents in this strategic game, and (2) best respond to this information acquisition when acquiring their own costly information. I study this by exogenously manipulating the difficulty of the attention task for both the player and their opponent. Predictions of behavior are generated by a novel theoretical model in which Level-K agents can acquire information à la rational inattention. I find an out-sized lack of strategic sophistication, driven largely by the cognitive difficulties of predicting opponent information. These results suggest a necessary integration of the theories of rational inattention and costly sophistication in strategic settings.

*New York University: spurlino@nyu.edu. This research has been generously supported by the Center for Experimental Social Science at New York University. I am grateful to Andrew Caplin, David Cesarini, Guillaume Frechette, and Andrew Schotter for their guidance and support. I also thank Srijita Ghosh, Eungik Lee, Daniel Martin, Tianzan Pang, Minu Philip, Anwar Ruff, Isabelle Salcher, Matheus Silva, and seminar participants at the ESA Eurpoean Meeting 2022, NYU CESS Seminar, and NYU Student Micro Theory Lunch for their comments and suggestions.

1 Introduction

Recent advances in behavioral economics have shown that cognition is difficult and that this difficulty can lead to predictable divergences from classic economic behavior. Two areas that have found significant success in modeling such cognitive difficulties are rational inattention and strategic sophistication. Rational inattention proponents (beginning with Sims, 2003) have shown that in decision-making settings, individuals acquire information in a way that maximizes the utility of gaining that information less the mental costs of doing so. In strategic settings, the strategic sophistication literature (beginning with Nagel, 1995) has shown that individuals are limited in their ability to reason contingently and anticipate the actions of others.

The present paper seeks to join these two fields to examine how individuals behave in games with costly information. Recently, many papers have theoretically examined equilibria in such settings—they study how players acquire information optimally in games where one or more players can, at a cost, acquire information about payoff-relevant states of the world. Previous papers examine specific settings such as bargaining games (Ravid, 2020), buyer-seller games (Matějka, 2015; Martin, 2017), global games (Yang, 2015), and Bayesian persuasion games (Gentzkow and Kamenica, 2014; Bloedel, 2019). However, while all of the papers above have allowed for information to be cognitively difficult to acquire, they all assume agents behave in a perfectly strategically sophisticated manner. That is, they assume agents understand the attentional costs of their opponents and correctly predict their opponent's optimal information acquisition in light of these costs. These calculations are likely very cognitively demanding, yet assumed to be easily understood by all players. An open question this paper seeks to answer is then, to what extent are players able to anticipate and best respond to the information acquisition of others?

I study this question using the simplest possible strategic setting. Here, two players must decide whether to accept or reject a deal of unknown value. The expected value of the deal is positive for both agents, but the ex-post realization of this value is positive for one agent and negative for the other. In such a case, the utility of making a "right" or "wrong" decision transparently hinges on the ability of the other player to make a "right" or "wrong" decision themselves. In such a game, each player must (1) predict how often the other player is mistakenly accepting bad deals and rejecting good ones, and (2) optimally choose their own level of accuracy in light of the former. Given the cognitive difficulty of each step, it is vital to test to what degree individuals are capable of such thinking, and in which ways they may systematically deviate. Furthermore, by restricting my focus to the simplest of strategic situations, experimental tests of the model give subjects the "best shot" of behaving in a strategically sophisticated manner, compared to the more complex settings previously discussed in the theoretical literature.

Predictions are generated by combining a leading theory of information acquisition, rational inattention, with a leading theory of strategic sophistication, Level-K theory. The predictions describe how behavior in the game above should react to changes in the ability of the player and their opponent to acquire information about the deal's value. A low-sophistication agent is characterized by having behavior that is independent of their opponent's attentional ability—they do not acquire information as if they are playing another strategic player, but rather treat the game like a single-agent decision problem. Higher levels of sophistication, including Nash predictions, have behavior that is a function of both their own and their opponent's cost of attention. They are aware that facing an opponent with lower costs of attention decreases the potential benefits of accepting a deal, and thus the strategy of a high-sophistication player focuses more on rejecting unfavorable deals than accepting favorable ones.

These predictions are then tested with a laboratory experiment in which I alter the information acquisition costs of each player in a simple two-player game. These costs are altered through the manipulation of a real-effort attentional task with two starkly different levels of difficulty. Subjects play many rounds of this game, under all four possible combinations of their task difficulty level and their opponent's task difficulty level. The main finding is that subjects show an extremely limited ability to conduct contingent reasoning in these games. The vast majority of subjects show no effect of opponent task difficulty on behavior. I argue that the mechanism behind this behavior is beliefs. Specifically, subjects seem to have inaccurate (or possibly uncertain) beliefs about opponent information strategies. Instead of attempting to model and anticipate opponent information (a cognitively demanding task), the subjects ignore the opponent's strategy altogether and simply treat the game as a non-strategic decision problem.

A follow-up treatment tests this mechanism specifically. In this treatment, I remove any possible uncertainty about opponent behavior by having subjects play a computer that plays a predetermined and transparent strategy. For comparability, this strategy exactly mimics the mean behavior of subjects in the main treatment. Subjects in the follow-up treatment significantly adjust their information strategies in response to different computer strategies—they focus their attention on rejecting unfavorable deals when facing a "low cost of attention" computer opponent. This finding supports the hypothesis that beliefs and uncertainty about opponent behavior play a sizeable role in the observed lack of strategic sophistication in behavior.

In studying the above, this paper naturally contributes to two strands of literature: rational inattention and strategic sophistication. The present paper shows how the two can complement each other to provide a more comprehensive model of how individuals interact in strategic settings with information acquisition.

The rational inattention literature, beginning with Sims (2003) and expanded on by Matějka and McKay (2015) and Caplin, Dean, and Leahy (2019) has primarily focused on non-strategic decision-making. However, an emerging sub-field has studied strategic settings in which one or more agents in a game face costs of attention. Theoretical papers studying games with a single rationally inattentive agent include studies on strategic pricing (Martin, 2015), bargaining (Ravid, 2020), and persuasion (Gentzkow and Kamenica, 2014; Bloedel and Segal, 2018; Matyskova, 2018). Papers studying games with multiple rationally inattentive agents have largely focused on coordination games with symmetric attention costs (Yang, 2015; Szkup and Trevino, 2015).

Most recently, Dömötör (2021) studied theoretically a Market for Lemons game with two rationally inattentive players. Dömötör finds that asymmetric costs of attention can result in endogenous asymmetric information, but that these asymmetries do not lead to the same market breakdowns present in Akerlof (1970). My paper also studies how asymmetric costs of attention can result in asymmetric information, however through a simpler model that is more readily testable in the lab, I show how players fail to take into account the asymmetric costs of other players in the game. The game studied in my paper closely resembles that of Carroll (2016). While the simple strategic setting allows Carroll's paper to study welfare implications robust to any possible information structure, I utilize the setting's simplicity to study changes in how one acquires these information structures.

Martin (2016) is the only previous paper to experimentally test the predictions of strategic rational inattention. However, the game studied in that paper only features one rationally inattentive party, whereas the present paper examines a game in which both parties are rationally inattentive. My paper's setting is more well-suited to study strategic sophistication in information acquisition games, which was not the focus of the previous paper. Martin's paper, unlike mine, does find some support for strategic reasoning in such a game. However, his experiment does not manipulate costs of information acquisition, while mine utilizes this manipulation to explicitly show subjects' lack of ability in understanding how such costs translate into behavior. Further discussion of the differences in our results is saved for the paper's conclusion.

This paper also uses ideas and tools developed by the strategic sophistication literature. Specifically, I utilize the Level-K model from Nagel (1995). This model and its close relative, the cognitive hierarchy model (Camerer et al, 2004), have been used in a variety of different settings to explain non-equilibrium behavior in experimental games. Examples include the p-beauty contest (Nagel, 1995), various matrix games (Costa-Gomes et al, 2001), and the 11-20 game (Arad and Rubinstein, 2012). To my knowledge, no paper has studied predictions of Level-K models in a game with costly information acquisition. The present paper is not, however, the first to integrate the two strands of literature. Aloui and Penta (2016) introduce a model of endogenous depth of reasoning, which posits that higher levels of strategic sophistication come at higher cognitive costs, much like how higher degrees of information acquisition come at higher costs in the rational inattention model. Although their paper considers general economic games—and not games with information acquisition—their theory is strongly compatible with the one developed in the present paper. For the sake of exposition, the present theoretical analysis only considers exogenous depth of reasoning (i.e. Level-K theory). However, I believe this is a crucial future direction of the present work, in reflection of the present paper's experimental results which show a substantial lack of strategic reasoning in an environment where such reasoning is likely highly costly to perform.

2 The Model

This section will first present the game that appears in the experimental design. I will then analyze the best responses of each player, conditional on their beliefs of their opponent's behavior. I then discuss a Nash equilibrium in which these beliefs are correct. Lastly, I use Level-K theory to generate predictions on the data for various levels of strategic sophistication.

2.1 The Game

The game consists of two players, which I will call Red and Blue ($i \in \{R, B\}$). The two players must decide whether to accept or reject a deal ($c \in \{a, r\}$). There are two possible states, $\theta \in \{Blue, Red\}$, which dictate the payoffs each player receives if a deal is made. A deal is only made if both players accept the deal. If either or both parties reject the deal, both players receive an identical outside option v_o. If both players accept the deal, their payoffs will be determined by the state of the deal. If the deal is Blue, the Blue player gets v_H and the Red player gets v_L, while if the deal is Red, the Blue player gets v_L and the Red player gets v_H, with $v_L < v_o < v_H$. For ease of explanation, a deal that matches the color of the player will sometimes be referred to as a *favorable* deal, whereas a deal of the opposing color will be referred to as an *unfavorable* deal.

Informationally, I assume that both players have an identical prior over the two states, with $\mu \in (0, 1)$ being the probability of a Red deal. For the remainder of the paper, I will assume that each state is equally likely, $\mu = \frac{1}{2}$, as this will mirror the game present in the experimental design. An additional assumption I will make on the model parameters is that $\frac{v_L+v_H}{2} > v_o$, which means that deals are ex-ante optimal, but ex-post inefficient (as $v_L < v_o < v_H$).

If both players have only the prior, an equilibrium will exist where all players always accept–due to the ex-ante optimality of the deal. If either party instead has perfect information, the only equilibrium will be the one in which no deals are ever made. This is because if one player has perfect information, they will only accept a deal that is favorable to them, and thus unfavorable to their opponent. Thus this player's opponent should never accept a deal, as the only possible deal that could be made would be costly.

What I add to this simple game structure is costly information acquisition, in the style of rational inattention (Sims, 2003). Both players can simultaneously acquire information about the state of the deal. The standard formulation of this is a cost of information that is linear in the expected reduction in Shannon entropy from the prior. Shannon entropy defined over some set of beliefs $P[\theta]$ is simply $-\sum_{\theta} P[\theta] \log P[\theta]$, and can be thought of as how much uncertainty is present in one's beliefs. For example, if one knows the probability of one realization of θ is certain, there is 0 Shannon entropy in beliefs—the minimal possible value. If one has only a uniform prior, Shannon entropy is at its maximal possible value, as there is complete uncertainty about the state. Thus reducing Shannon entropy is equivalent to reducing uncertainty in beliefs, or increasing the informativeness of one's beliefs. As demonstrated in Caplin and Martin (2015), an equivalent formulation is expressed in terms of State Dependent Stochastic Choice data (henceforth *SDSC*), which is given by the probabilities the agent chooses each action in each state. In the present game, because there are only two possible actions—accept or reject—SDSC is fully characterized by $P[a|\theta]$ for $\theta \in \{R, B\}$. Note that it is always at least weakly optimal for a Red player to accept a Red deal and reject a Blue deal, while the reverse is true for a Blue player. So a mistake can either be accepting an unfavorable deal or rejecting a favorable one. Rational inattention theory then says that reducing these mistakes is costly, and the cost of reducing them is convex. Formally, if $P^i[a|\theta]$ is the SDSC of a player, their cost of information is:

$$\lambda^i\left(\sum_{\theta\in\{R,B\}} \frac{1}{2}\left(\sum_{c\in\{a,r\}} P^i[\mathrm{c}|\theta] \ln P^i[c|\theta]\right) - \sum_{c\in\{a,r\}} P^i[c] \ln P^i[c]\right)$$

where $\lambda^i > 0$ parameterizes an individual's difficulty of acquiring information, with a higher value corresponding to higher costs of information. One interpretation of this is that it is more costly to have larger cross-state differences in action probabilities because to do so one needs to be quite good at distinguishing states from one another.

2.2 Solving the Player's Problem

I now solve for the player's optimal strategy. This strategy will be defined in terms of SDSC data. The optimal SDSC maximizes the player's expected utility, less the costs of information as described in the preceding section. Specifically, the expected utility of a given SDSC is given by

$$EU^i[P^i] = \sum_{\theta \in \{R,B\}} \mu(\theta) \sum_{c \in \{a,r\}} P^i[c|\theta] * v^i(c|\theta),$$

where $v^i(c|\theta)$ is the utility of player i choosing action c in state θ.

What adds an extra level of difficulty in strategic settings is that one's $v^i(c|\theta)$ are themselves an expected utility, being a function of the SDSC of their opponent. Due to symmetry, I will limit discussion to that of the Red player[1]. For now, assume that the Red player has some belief about the other player's strategy. Specifically, suppose they think that the Blue player has SDSC of $P^B[a|B]$ and $P^B[a|R]$, i.e. the Red player believes the Blue player will accept a Blue deal with probability $P^B[a|B]$ and a Red deal with probability $P^B[a|R]$. Note that if the Red player chooses to reject, their payoff will be v_o regardless of the state of the deal. If the Red player chooses to accept, however, their payoff depends both on the state of the deal, and the likelihood of the other player choosing to accept in that state. Specifically,

$$v^R(a|R) = P^B[a|R] * v_H + (1 - P^B[a|R]) * v_o$$

$$v^R(a|B) = P^B[a|B] * v_L + (1 - P^B[a|B]) * v_o$$

where $P^B[a|R]$ is the probability that the Blue player accepts an unfavorable deal, and $P^B[a|B]$ is the probability that the Blue player accepts a favorable deal. I can then write:

$$v^R(a|R) = v_o + P^B[a|R](v_H - v_o)$$

$$v^R(a|B) = v_o - P^B[a|B](v_o - v_L)$$

As already established, the state-dependent utilities of rejecting are constant, $v^R(r|R) = v^R(r|B) = v_o$. With these state-dependent action utilities and the cost parameter λ^R, one can fully solve the Red player's optimization problem, conditional on their beliefs about the Blue player's error rates.

To solve for the optimal strategy, I take the approach designed by Caplin, Dean, and Leahy (2019) (henceforth *CDL*) using optimal consideration sets. An action

[1]The Blue player's best response will be identical to that of the Red player's, simply with the labels for each state switched in their SDSC.

(accept or reject) is said to be in the player's consideration set if there is a strictly positive probability of that action being chosen. Thus there are then three cases to consider: indiscriminate acceptance, indiscriminate rejection, and mixing between the two. Naturally, the last case also involves determining with what probabilities each action is chosen in each state.

From CDL Proposition 1, an SDSC is optimal if and only if for all $c \in \{a, r\}$,

$$\sum_{\theta \in \{R,B\}} \frac{e^{v(c|\theta)/\lambda^R}\mu(\theta)}{\sum_{b \in \{a,r\}} P(b)e^{v(b|\theta)/\lambda^R}} \leq 1 \tag{1}$$

with equality if c is chosen with positive probability. I can then use this to develop expressions for when a player best responds by acquiring no information and either indiscriminately accepting or indiscriminately rejecting the deal.

The player will best respond by unconditionally accepting the deal (i.e. $P^R[a] = 1$) when

$$\frac{1}{2}e^{\frac{(v_o - v_L)(P^B[a|B])}{\lambda^R}} + \frac{1}{2}e^{\frac{-(v_H - v_o)P^B[a|R]}{\lambda^R}} < 1$$

Note that a player is more likely to play this strategy if they believe their opponent will be accepting a significant number of unfavorable deals and rejecting a significant number of favorable deals. As λ decreases, these mistakes have to be larger and larger for it to still be optimal to only accept (because attending is becoming much cheaper).

The player will best respond by unconditionally rejecting the deal (i.e. $P^R[a] = 0$) when

$$\frac{1}{2}e^{\frac{-(v_o - v_L)(P^B[a|B])}{\lambda^R}} + \frac{1}{2}e^{\frac{(v_H - v_o)P^B[a|R]}{\lambda^R}} < 1$$

which occurs when the other player is making fewer errors–rejecting a significant number of unfavorable deals and accepting a significant number of favorable deals. As λ decreases, the opponent has to be making very few mistakes for a player to continue unconditionally rejecting.

Finally, I consider the intermediate case in which the player accepts and rejects with positive probability in each state. First, note that this is the only possible case outside of the two described above. A case in which $P[a|B] = 0$ and $P[a|R] > 0$ (or vice versa) would require one to perfectly separate the two possible states. Because the marginal cost of attention is infinitely high at such values, it will never be an optimal solution to the rational inattention problem. Because the two previous conditions are disjoint, and there are only three possible consideration sets, it directly follows that if neither of them is satisfied, the player will have both actions in their consideration set. What remains to be shown is what SDSC a player will optimally best respond with specifically. To find this, I first solve for the unconditional accept probability using the equation (1) for $c = a$, holding at equality since a is present in the consideration set[2]. This yields

$$P^R[a] = \frac{e^{v_o/\lambda^R} - \mu e^{v^R(a|R)/\lambda^R} - (1-\mu)e^{v^R(a|B)/\lambda^R}}{e^{-v_o/\lambda^R}\left(e^{v^R(a|R)/\lambda^R} - e^{v_o/\lambda^R}\right)\left(e^{v^R(a|B)/\lambda^R} - e^{v_o/\lambda^R}\right)}.$$

The conditions on SDSC then are direct functions of the above description, utilizing the conditions found in Matějka Mckay (2015):

$$P^R[a|R] = \frac{P^R[a]e^{v^R[a|R]/\lambda^R}}{P^R[a]e^{v^R[a|R]/\lambda^R} + (1 - P^R[a])e^{v_o/\lambda^R}}$$

$$P^R[a|B] = \frac{P^R[a]e^{v^R[a|B]/\lambda^R}}{P^R[a]e^{v^R[a|B]/\lambda^R} + (1 - P^R[a])e^{v_o/\lambda^R}}.$$

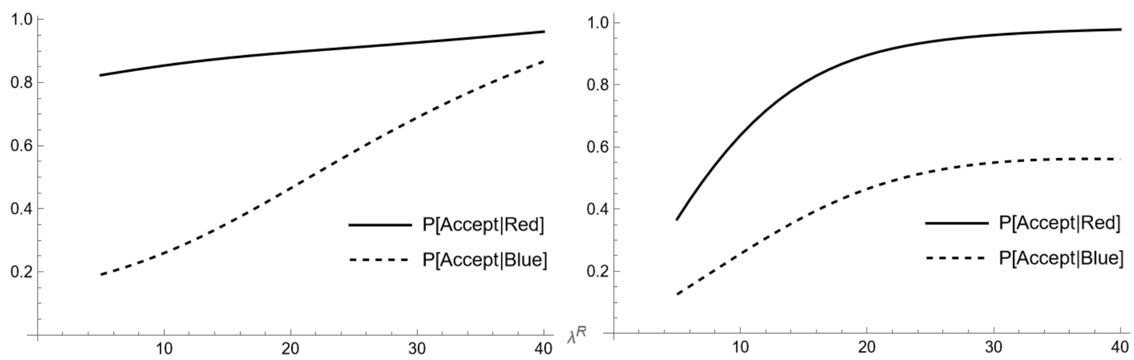
2.3 Nash Predictions

The preceding sections have shown that given an opponent's SDSC, you can generate optimal SDSC as a best response. A Nash equilibrium in this setting is then simply a pair of SDSC $(P^i[a|R], P^i[a|B])$ for each $i \in \{R, B\}$ such that each SDSC is a best response to the other.

Trivially, there is always an equilibrium in which both players never accept any trade. This is because if one player is always rejecting, the other player will always get v_o, regardless of the state or their action. Then, *any* inattentive SDSC (i.e. no information acquired) is a best response, including the one which indiscriminately rejects all deals.

The more interesting case is non-trivial Nash equilibria. It can be shown numerically that there exists a unique non-trivial Nash equilibrium for a wide range of parametric

[2] The same $P^R[a]$ solves the expression for when $c = a$ or $c = r$.



(a) Changing Own Cost (b) Changing Opponent Cost

Figure 1: Nash Predictions

assumptions, so long as no player has too low of information costs. The problem is fairly simple to solve numerically but does not have a closed-form solution. Thus one must take known parameters (λ^i, v_o, v_H, and v_L) and solve for the non-trivial equilibrium. Figure 1 illustrates an example of such an equilibrium[3]

In a non-trivial equilibrium, numerical solutions demonstrate that as attention costs increase, for either an individual or their opponent, the probability of accepting a deal of either state increases. When costs become sufficiently high, both individuals indiscriminately accept. The intuition of these equilibria is that higher attention costs act as a sort of commitment device, allowing a player to tie their hands and not discriminate much between the two states. As long as the other player does not have such low costs that they can then take advantage of this player, the players can engage in a higher amount of deal acceptance than when costs are low.

2.4 Best Response Dynamics: Level-K Predictions[4]

In addition to examining Nash behavior, I use Level-K theory to generate non-equilibrium predictions for different levels of strategic sophistication. As is standard in Level-K theory, I will assume that a Level-K player plays as if their opponent is of type Level-(K−1). It is also worth noting that the following predictions are simply a

[3]These numerical solutions solve for Nash equilibrium under the parametric setting of the experiment ($v_o = 30$, $v_L = 10$, and $v_H = 90$). Figure 1 illustrates solutions of the Red player, with solutions for the Blue player being identical, with labels switched. In Figure 1a the opponent cost is fixed at $\lambda^B = 20$, while in Figure 1b own cost is fixed at $\lambda^A = 20$.

[4]Additional analyses and derivations for this section can be found in Appendix C.

reasonable way to structure what I mean by strategic sophistication in such a setting. The experiment will be designed to test predictions on behavior given any beliefs, and not just the beliefs as determined in this theory. Discussions are limited to the first 3 levels, Level-0 through Level-2, as predictions for behavior beyond these levels have diminishing intuitive explanations, and because the levels provided are sufficient in explaining any behavior present in the experiment.

2.4.1 Level-0

As with any Level-K analysis, one must first make some assumptions about how a Level-0 player will play. The standard assumption is to assume the Level-0 player plays all actions with equal probability. In this setting, I translate this to mean the player chooses $P[a|\theta] = \frac{1}{2}$ for all θ. However, the only critical assumption is that a Level-0 player has $P[a|B] = P[a|R]$ (i.e. they do not acquire any information). In other words, a Level-0 player in this game is not rationally attentive—they simply indiscriminately accept or reject a deal with some constant probability.

2.4.2 Level-1

A Level-1 player then best responds to a Level-0 player. The essential intuition is that a Level-1 player is *rationally attentive* but does not realize that their opponent is also rationally inattentive. For the following specific predictions, the Level-0 player is assumed to follow the specific $P[a|\theta] = \frac{1}{2}$ strategy, however as noted this is just for clarity of presentation, and any $P[a|\theta] = p$ constant for each θ will suffice. Again, analysis is presented for the Red player, noting that the Blue player will have the same predictions, with the "good" and "bad" states reversed. A Level-1 player then has the state-dependent utilities of accepting,

$$v^R(a|R) = v_o + \frac{v_H - v_o}{2} = \frac{v_H + v_o}{2}$$

$$v^R(a|B) = v_o - \frac{v_o - v_L}{2} = \frac{v_o + v_L}{2}.$$

Using the result from the preceding section, one can then directly map out the SDSC of a Level-1 agent as a function of v_o, v_L, v_H, and λ^i. Crucially, since a Level-1 player assumes they are playing against a Level-0 player, who is not rationally attentive, the SDSC of the Level-1 player does not depend on the attention cost parameter of the

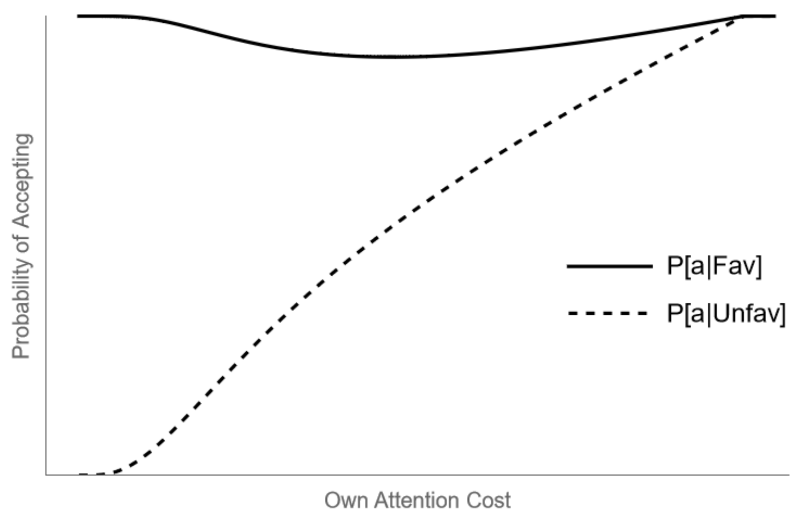


Figure 2: Probability of accepting each color deal as a function of own attentional cost for a Level-1 player

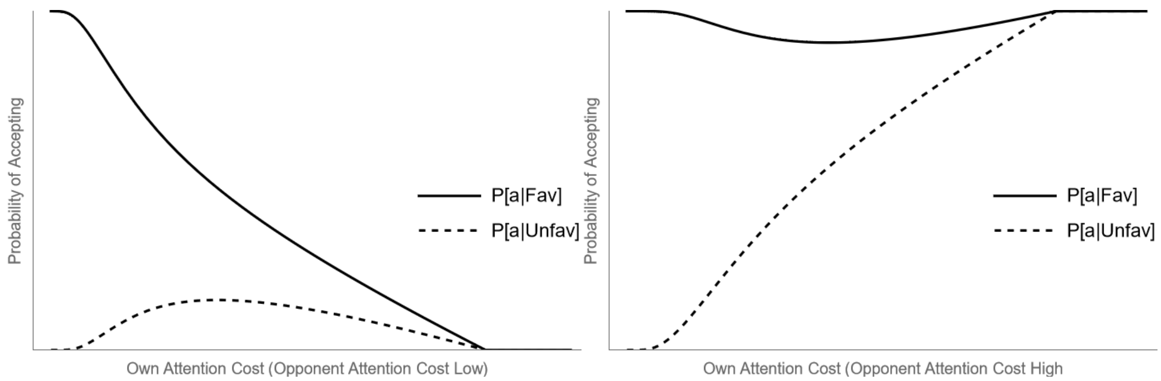
other agent, λ^{-i}.

Figure 2 illustrates the optimal SDSC as a function of the player's own attention cost parameter. Notice that the probability of accidentally accepting an unfavorable deal is strictly increasing in attention costs, while the probability of accepting a favorable deal is non-monotonic. As attention costs go to 0, a player will perfectly distinguish the two states and only accept in the favorable state. As attention costs get sufficiently large, a player will indiscriminately accept, because of the assumption that deal's are ex-ante positive ($\frac{v_L+v_H}{2} > v_o$) and the fact that $P^B[a|R] = P^B[a|B]$.

2.4.3 Level-2

A Level-2 player best responds to the behavior of a Level-1 player. From the previous section, one can derive the SDSC of a Level-1 player as a function of their attention cost parameter. The main takeaway for a Level-2 player is that their SDSC will be a function of not only their own attention cost parameter but also the attention cost parameter of their opponent. That is, a Level-2 player is rationally inattentive, and realizes their opponent is *also* rationally inattentive.

Figure 3 illustrates the optimal SDSC as a function of one's own attention cost parameter, holding the other fixed. One finding of interest is that dynamics concerning one's own costs depend crucially on the cost of one's opponent. Figure 3a shows a



(a) λ^B Low

(b) λ^B High

Figure 3: Probability of accepting each color deal as a function of own attentional cost for a Level-1 player, holding the attention cost of opponent constant at either a high or low level

case in which the opponent has low costs of attention, while Figure 3b shows one in which they have high costs of attention.

If the opponent has low enough costs (underneath some threshold), then as their own costs increase, the probability of accepting favorable deals decreases. If the opponent has higher costs, however, then the probability of accepting unfavorable deals increases. The intuition is that a high-cost Level-1 opponent tends to accept most deals, making the ex-ante benefit from accepting high. A low-cost Level-0 opponent, however, tends to only accept their own favorable deals, making the ex-ante benefit from accepting low. Thus as own costs become sufficiently large, one who faces a low-cost opponent rejects all deals, while one who faces a high-cost opponent accepts all deals.

Figure 4 holds fixed one's own attention cost parameter, and varies that of the opponent. If an opponent has sufficiently low attention costs, a Level-2 player assumes they will do a very good job of discerning the state of the deal, and thus the benefits of paying costly attention are very low. Because of this, with low opponent costs, a Level-2 player will always reject. If the opponent has some sufficiently high costs, the Level-2 player assumes their opponent will accept all deals, and since the deals are ex-ante optimal, there will be a positive rate of acceptance for both favorable and unfavorable deals. Numerical analyses show a continuous mapping bridging these two extremes, with the probability of accepting a favorable deal strictly increasing

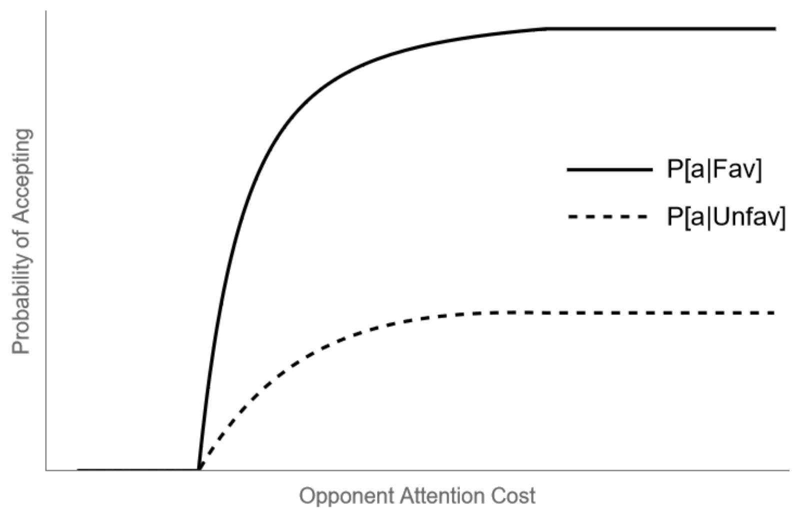


Figure 4: Probability of accepting each color deal as a function of opponent attentional cost for a Level-2 player, holding fixed own attentional cost

with respect to opponent attention cost and, for the parameterizations relevant to the experimental design, the probability of accepting unfavorable deals also increasing in this cost.

3 Experimental Design: Main Treatment

The experiment is designed to test the ability of subjects to both anticipate and best respond to the information acquisition of opponents in the game examined theoretically. In anticipation of heterogeneity in subject behavior, I utilize a within-subject treatment that determines to what extent individuals best respond to the attention costs of themselves and of their opponents. The main experiment consists of four parts–three of them incentivized one of them a non-incentivized survey.

As the predictions in the theory section above rely on expected utility theory and assume I can observe the utilities of certain rewards, I use probability points as my incentivization scheme. That is, the earnings for an individual subject are points, valued from 0 to 100, which indicate their probability of winning a $10 bonus payment, in addition to a $10 completion payment. In my analysis, I can then normalize the utility of the $10 bonus payment to be 100, and the points will then directly correspond to their value in utility. To prevent hedging (especially concerning incentivized belief elicitation), only one randomly selected question from the incentivized portion of the experiment for payment is chosen.

The experiment itself took place online via Prolific and using oTree software (Chen et al 2016). I will save the discussion on the decision to implement this as an online experiment versus an in-person experiment for after a description of the overall design.

3.1 Part One: Decision Making Task

The first part of the experiment serves two purposes: (1) introduce a real-effort attention task to the subjects, which will be used later in the strategic portion of the experiment, and (2) gauge individual level ability in this attention task. The attention task used in this experiment is the "dot task", which has been established as a reliable task that rewards attentional effort with better outcomes (Dean and Neligh 2019). The task consists of a square grid of red and blue dots. With 50% probability, there are more red dots than blue dots (a "red grid"), and with 50% probability, there are more blue dots than red dots (a "blue grid"). The task is then to determine whether the grid is red or blue. Subjects were given a maximum of 30 seconds to determine whether they think the grid is red or blue. A correct classification is rewarded 75 points, while an incorrect classification is awarded 25 points.

Because the strategic portion of the experiment will manipulate the difficulty of the above task for both the subject and their opponent, subjects are introduced to two difficulty levels in this part of the experiment. These difficulty levels are labeled "100-Dot" and "225-Dot". As the names suggest, a 100-Dot grid is a 10-by-10 grid composed of 100 dots, and a 225-Dot grid is a 15-by-15 grid composed of 225 dots. Another difference between the two grid types is the difference in the number of dots between the "majority" and "minority" colors. On the 225-Dot grid, there are either 5 more blue dots (on a blue grid) or 5 more red dots (on a red grid). On the 100-Dot grid, there are 8 more blue dots or 8 more red dots. Piloting designed to elicit the difficulty of various dot tasks (only in decision-making settings) has determined that these two tasks are of consistently different difficulty levels, with the 100-Dot task being much easier than the 225-Dot task. Figure 5 illustrates an example of these two grid types.

To elicit individual SDSC for each task, I utilize repetition. The two classification tasks are repeated 15 times each, for a total of 30 rounds. Because I am eliciting

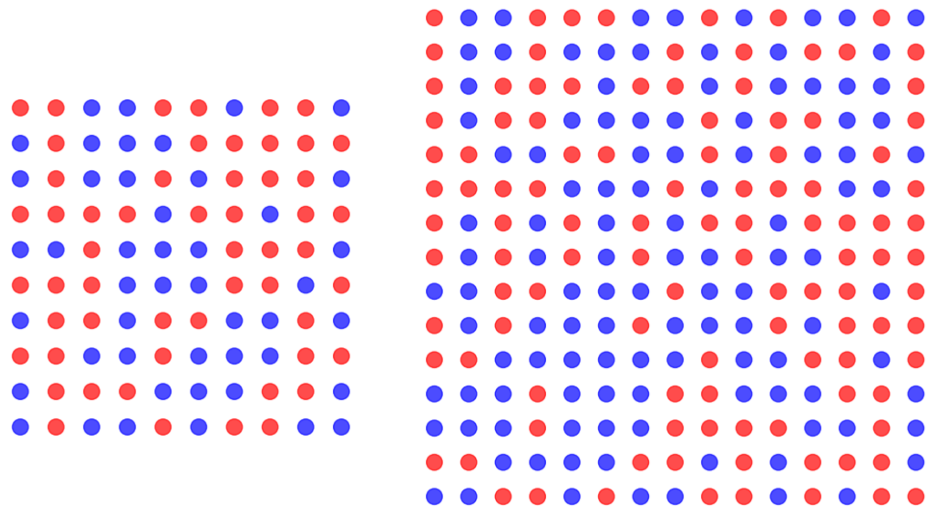


Figure 5: 100-Dot Grid (Left), 225-Dot Grid (Right)

probabilities on the individual level, I did not want subjects to react to feedback, or demonstrate learning over time. Thus, no feedback about whether a subject was right or wrong on any particular round is provided until after the conclusion of the experiment. For ease of instruction, and to familiarize subjects with the structure of the strategic portion of the experiment, these 30 rounds are divided into 6 blocks of 5 rounds each. Within each block, the type of grid (100-Dot or 225-Dot) remains constant. Subjects are reminded of the upcoming grid type and the rules of the decision before each round, with an additional screen indicating any changes before each block.

3.2 Part Two: Strategic Game

Part two is the central part of the experiment. It consists of exactly the game described in Section 3. The values for v_o, v_H, and v_L are set at 30 points, 90 points, and 10 points respectively. These values were chosen to give the data the "best chance" at observing differences in subject errors with respect to opponent task difficulty. First, note that the ex-ante optimality of accepting a deal is very salient. If both agents acquire no information at all and indiscriminately accept the deal, the expected payout is 50 points, versus 30 points for rejecting the deal.

At the start of this part of the experiment, subjects were assigned to one of two roles: Red player and Blue player. To avoid confusion and because the game is essentially symmetric, subjects were assigned to the same role throughout the experiment. Players were then told they would be randomly re-matched with a player of the other role type over 120 rounds. In each round, subjects played the game described in Section 3. Both players knew that a “Red Deal” and a “Blue Deal” were each equally likely. Their choice each round was to accept or reject the deal. A deal was “made” if both players accepted the deal. This would give 90 points to the player whose role color matched that of the deal and 10 points to the other player. If either or both players rejected the deal, they would each receive 30 points.

As in Part One of the experiment, subjects were again shown either 100-Dot or 225-Dot grids. The additional manipulation in this part of the experiment was to also vary their opponent's grid type each round. Like in Part One, this was divided into 8 blocks of 15 questions each. Within each block, the grid type for the subject and their opponent remained constant. Crucially, subjects were repeatedly reminded of their grid type and their opponent's grid type. Thus for each subject, I can elicit their SDSC in all four possible attentional setups. Again to avoid feedback and learning effects in a repeated game environment, no feedback was provided to subjects during this stage of the experiment.

Each subject had a random order of the four task difficulty combinations, and they went through this order twice sequentially to make up the 8 blocks. This structure allows me to elicit beliefs about opponent behavior after only the blocks in the second half of the experiment (to make sure eliciting such beliefs did not change subsequent behavior).

Belief elicitation occurred at the end of blocks 5 through 8. At the beginning of Part 2, subjects were told there would be two additional questions at the end of these blocks but were not told they would be belief elicitation questions specifically. The goal of these questions is to elicit the subject's beliefs of their opponent's SDSC. To do so in a clearly and understandably manner, subjects were asked to estimate the percentage of Red deals, and of Blue deals that their opponents accepted in the last block. Payment would then be made via a quadratic scoring rule[5], where their

[5] Because a quadratic scoring rule with prizes in probability points is equivalent to the binarized

payment would be the maximum of $100 - \frac{\text{Error}^2}{25}$ and 0 points, where the Error is the difference in percentage points between their belief and the actual probability of red or blue deals their opponents accepted in the previous block.

3.3 Part Three: Other Measurements

After the above rounds, a few potential co-variates are elicited. First, subjects play a variation of the 11-20 game proposed by Arad and Rubinstein (2011). Subjects are randomly assigned into pairs and are each told to request a number of points between 51 and 60. Subjects receive the number of points they request, plus an additional 20 points if they request exactly one less point than their opponent. Arad and Rubinstein show that this is an easy-to-explain game that elicits the level of strategic sophistication of an individual. By measuring strategic sophistication through a separate game, I can verify that the subject pool is not unusually sophisticated or unsophisticated in comparison to what is usually found in the literature. It will also allow me to analyze behavior for subsets of the sample who score as more sophisticated in this measure.

Next, subjects are asked the three-question Cognitive Reflection Test (CRT) (Frederick, 2005) as another measurement of cognitive ability. Previous literature has often shown a correlation between this measurement and strategic sophistication, as well as performance in other economic games. This quiz was not incentivized, which is the standard approach in economic experiments involving the CRT. Again, this measure will allow me to assess the cognitive abilities of the subject pool and analyze behavior in the experiment for subsets who score higher on the instrument.

Finally, subjects filled out a brief survey. Aside from basic demographics (gender and education level), subjects were also asked to explain their strategy in part two of the experiment. This is done through a series of questions. First, subjects were asked to what extent they attempted to actually count the dots in each attentional setup of the game. They were then asked how their strategy depended on the task of their opponent for each of their own tasks. Finally, they were asked to give a free-form description of their overall strategy.

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scoring rule (Hossain and Okai, 2013), this scoring rule is incentive compatible regardless of risk preferences. Subjects were also told that it is in their best interest to report true beliefs, as is advised in the literature. The exact payment structure was available via a graph and the actual equation on a separate page that subjects could get to if desired

3.4 Online Implementation of the Experiment

The experiment was conducted online via Prolific, and I will argue that rational inattention experiments (in general), and more importantly *strategic* rational inattention experiments, are particularly well suited for such an environment. Firstly, an online environment allows subjects to go through the experiment at their own pace. In the above experiment, subjects could choose, for example, to inattentively click through each round of decision-making, and finish the experiment extremely early. Likewise, subjects could spend up to 30 seconds on each task, which could end up taking well over an hour. Allowing for both of these, and the spectrum in between, allows subjects to acquire information in a truly flexible and endogenous way—more in line with the spirit of rational inattention. An online environment allows for this kind of flexibility, whereas a traditional classroom lab experiment typically has a structure where participants can not leave the room until all subjects have completed the experiment. This can create unwanted social pressure effects (such as those to finish the experiment quicker than a subject would otherwise prefer) or cause subjects to spend more time than usual (since they would otherwise be sitting in a lab with nothing to do). Both of these issues are difficult to control for and could contaminate any treatment effects the researcher may be interested in.

The above underscores why this is an especially important problem for *strategic* information acquisition experiments. In most classroom labs, it becomes very obvious the average response time of decisions of the other subjects in the lab (via sounds of clicking mice and keyboards or seeing other subjects sitting idly). This has the potential to create large session-level effects and introduces a noisy signal of opponent strategy that is difficult to model or control for.

In an online environment, subjects can play the game at their own pace. Subjects proceed through all stages without waiting for any other player's actions. Because no feedback is provided, this is feasible in the design outlined above. Subjects are told that payments will be calculated once all subjects in the session have completed the experiment, no later than 7 days after that subject has finished. At this time, subjects are given a Qualtrics survey link where they log in with their Prolific credentials and are shown their award in points. These points then translate to their probability in percent of winning a $10 bonus payment. I utilize the lottery mechanism designed by

Caplin et al (2020) to credibly award the bonus with the correct probability. Subjects are shown a timer synced to their computer system clock in milliseconds. They can stop this clock once and only once, and the milliseconds in one's and ten's constitute a random number, where a number less than their point value results in the bonus payment. Subjects have access to a practice version of this task before taking part in the experiment, to credibly signal the randomness of the device.

4 Results

Sessions for the experiment took place in July and August of 2022. In total, 100 subjects completed the experiment online. Subjects were recruited and paid via Prolific and participated in the experiment via oTree on their computer browser[6] Demographically, all subjects were residents of the United States, had at least a high school education, were fluent in English, and were between the ages of 18 and 30. Subjects were also restricted from taking the experiment multiple times, and the subject pool was balanced across sex[7]. The median duration of the experiment was 42.5 minutes, and the mean duration was 50.0 minutes. Average earnings were $15.50, including the $10 participation fee.

4.1 Decision Task: Difficulty Validation

The first priority is to verify that the two tasks were of consistently different difficulty levels. To do this, I examine the accuracy rate of classification during the decision-making rounds. Recall that each participant played 15 rounds of each task type. Figure 6 shows the average accuracy across the two tasks and the average difference between the two, with error bars to indicate one standard error. In the 225-Dot task 61% of grids were correctly classified, while in the 100-Dot task this proportion was 84%.

Table A.1 in Appendix A presents results from a logistic regression and a linear probability model of correctness on round, true color, and task difficulty, with errors clustered at the individual level. Regression analysis confirms that the 225-Dot task is

[6]Subjects recruited through Prolific were explicitly told the experiment could only be performed on a desktop or laptop computer, and not via tablet or mobile phone.

[7]This was to correct for Prolific's recent over-representation of female participants, see https://www.prolific.co/blog/we-recently-went-viral-on-tiktok-heres-what-we-learned

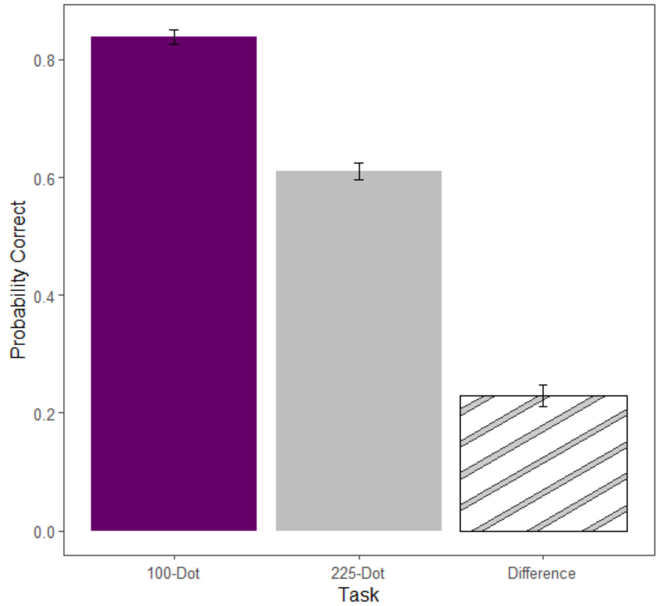


Figure 6: Average accuracy by task (standard errors clustered by subject) and the average difference in Part 1 of the experiment (decision-making task)

significantly more difficult than the 100-Dot task. In addition, there are no aggregate round effects, nor any systematic differences in discerning red or blue images.

It is also of interest to examine any heterogeneity in ability across the two tasks. There is indeed substantial heterogeneity in ability[8]. Figure 7 plots the probability of correct classification in the 100-Dot task on the vertical axis and the probability of correct classification in the 225-Dot task on the horizontal axis, with each point representing an individual subject, along with the 45-degree line. While there is substantial heterogeneity in accuracy across individuals, the vast majority of subjects are more accurate in the 100-Dot task than in the 225-Dot task. This is evident by the majority of points in Figure 6 lying above the 45-degree line. Just 12 of the 100 subjects did not have higher accuracy in the 100-Dot case (including 4 subjects who had the exact same accuracy in the two tasks). These findings are indicative that the tasks developed are almost universally ordered in terms of difficulty.

In addition, the probability of correct classification in the two tasks is ideally calibrated for this setting. The 225-Dot task is very difficult; however, the average accuracy is 61% which is above what one could get by randomly guessing (i.e. the

[8]I use ability and effort interchangeably to mean "accuracy in classification".

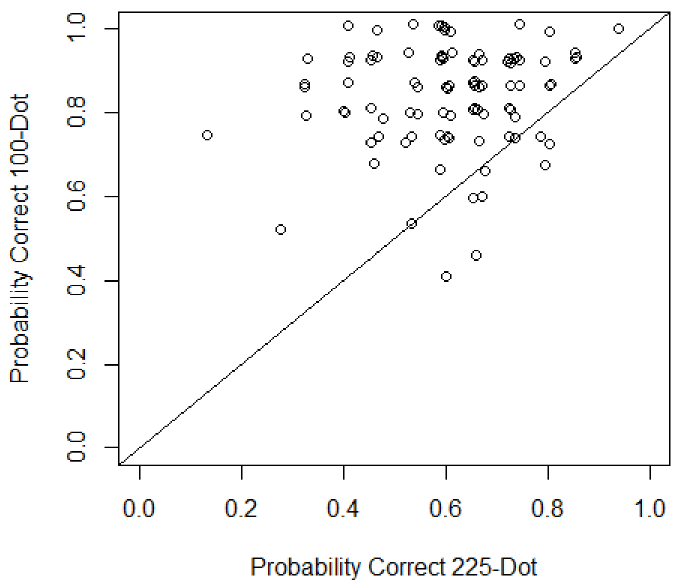


Figure 7: Individual heterogeneity in decision task accuracy

task is *difficult* but not *impossibly* so). The 100-Dot task, on the other hand, has a significantly higher accuracy rate of 84%, which is significantly lower than perfect accuracy (i.e. the task is *easy* but not *trivially* so).

4.2 Strategic Behavior

Having validated the manipulation in task difficulty, I now turn to the subjects' behavior in Part 2 of the experiment. For all results, a state will be referred to as "favorable" if the color of the deal matches the color of the role, with a state being "unfavorable" otherwise.

A basic first test that subjects understand the strategic setting is to verify that $P[a|\text{Favorable}] \geq P[a|\text{Unfavorable}]$. Table 1, Column 2 shows the mean difference in acceptance probability between favorable and unfavorable deals for that attentional setup. Column 3 reports p-values from a two-tailed, paired t-test between the probability of accepting a favorable and unfavorable deal for each setup. Column 4 reports the percentage of subjects who accept weakly more favorable deals than unfavorable deals for each setup, while Column 5 reports the percentage of subjects who accept strictly more favorable deals than unfavorable deals.

Own Task / Opponent Task	Difference	p-value	Weak %	Strict %
100 / 100	0.500	<0.001	92%	82%
100 / 225	0.495	<0.001	93%	83%
225 / 100	0.168	<0.001	86%	69%
225 / 225	0.137	<0.001	80%	64%

Table 1: Attention checks for strategic rounds, columns 4 and 5 report proportion of subjects with weakly and strictly positive differences between accepting favorable and unfavorable deals

Average differences are highly significant and are non-negative for a large majority of the subjects. Note that 20% of subjects have strictly negative differences in the 225/225 setup. This is largely an artifact of a higher proportion of subjects inattentively guessing in the more difficult settings. Nevertheless, 80% compliance in the worst-case scenario is more than sufficient in such an experiment.

I will next examine the SDSC of subjects across attentional setups. Figure 8 visualizes the average data of all 100 subjects, with standard errors clustered at the level of the subject and difficulty level[9]. There is a significant effect of own-task difficulty on accepting both favorable and unfavorable deals. Table 2 shows the difference in acceptance probability, holding fixed the opponent difficulty and favorability of the deal. Column 2 shows the difference of $P[a|\text{Own 100-Dot}] - P[a|\text{Own 225-Dot}]$, Column 3 shows the p-value of the corresponding paired t-test, and Column 4 shows the percentage of subjects whose individual effect is in the same direction as the group effect. The findings demonstrate that, almost universally, subjects who face the more difficult task accept far fewer favorable deals, and far more unfavorable deals. The average difference between accepting favorable deals and accepting unfavorable deals is roughly 15.2% for those with 225-Dot tasks, while this number is 49.8% for those with 100-Dot tasks.

Despite the above facts, Figure 8 also shows that there is *no* aggregate effect of

[9]Clustering in the strategic setting will be at the subject and own difficulty level because standard errors of residuals are likely to be different for the two tasks.

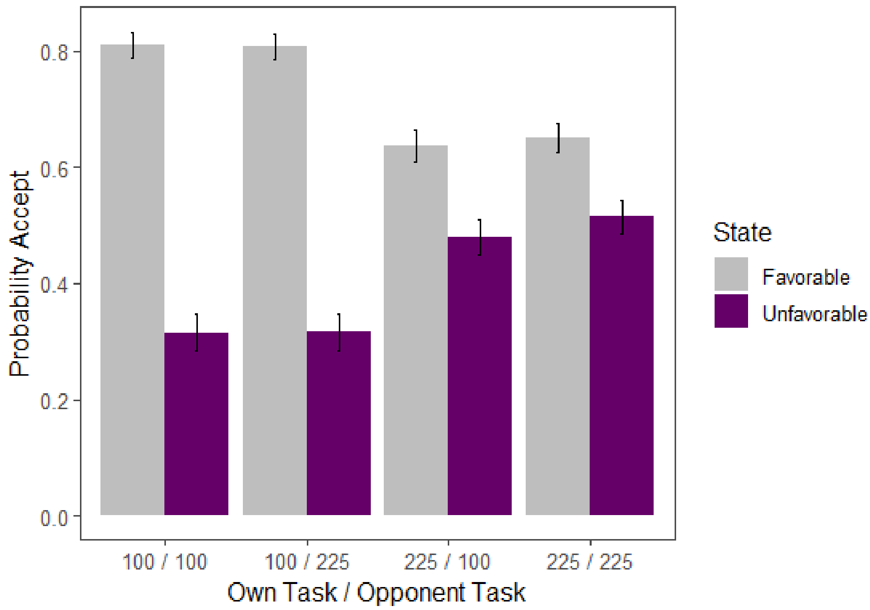


Figure 8: Probability of Accepting Favorable and Unfavorable Deals by Setup

Opponent Task / Favorability	Difference	p-value	Proportion
100 / Favorable	0.172	<0.001	83%
225 / Favorable	0.159	<0.001	80%
100 / Unfavorable	-0.160	<0.001	85%
225 / Unfavorable	-0.200	<0.001	89%

Table 2: Differences in probability of accepting a deal when given a 100-Dot task and a 225-Dot task, holding favorability of deal and opponent task fixed, with column 4 indicating the proportion of subjects with the same sign as the aggregate

opponent difficulty on subject SDSC. There is no significant treatment effect of the opponent's task on the probability of accepting in either a favorable or unfavorable state. Recall from the theory section that insensitivity of behavior to the opponent's task is a defining feature of "Level-1" strategic behavior. Subjects who have a higher level of sophistication should decrease their probability of accepting both favorable and unfavorable deals in light of an easier opponent task. This is because opponents facing an easier task (1) accept more deals that would be favorable to the opponent (and thus unfavorable to the opponent) and (2) reject more deals that would be unfavorable to the opponent (and thus favorable to the subject). This causes the expected value of accepting a favorable or unfavorable deal to decrease, which the theory then claims should lead to a decrease in the probability of accepting either type of deal.

Mirroring Table 2, Table 3 shows the difference in acceptance probability, holding fixed own difficulty and deal favorability. Column 3 shows the p-value of the corresponding paired t-test, while Columns 4-6 show the percentage of subjects where the difference (225-Dot opponent minus 100-Dot opponent) is positive, equal, and negative, respectively. These findings again suggest that there is no aggregate effect of

Own Task / Favorability	Difference	p-value	% Pos	% Equal	% Neg
100 / Favorable	0.004	0.77	40%	21%	39%
225 / Favorable	-0.009	0.67	39%	19%	42%
100 / Unfavorable	-0.001	0.92	41%	18%	41%
225 / Unfavorable	-0.040	0.06	46%	17%	37%

Table 3: Differences in probability of accepting a deal when facing 225-Dot opponent and 100-Dot opponent, holding favorability of deal and own task fixed, with columns 4-6 indicating the proportion of subjects with a difference of each sign

the opponent's task on SDSC. Individual behavior appears to be approximately symmetric around this mean 0 difference, suggesting that deviations from this aggregate value are more likely to be noise than systematic heterogeneity.

To confirm this more rigorously, I run both logistic[10] and linear regressions of:

$$y_{it} = \beta_0 + \beta_1 \text{Own100}_{it} + \beta_2 \text{Opponent100}_{it} + \beta_3 \text{Own100}_{it} * \text{Opponent100}_{it} + \beta_4 t + \epsilon_{it}$$

where y_{it} is an indicator for when subject i accepts a deal in round t. The regression is run twice—once for when the deal is favorable, and once for when it is unfavorable. I do this because the coefficients on the independent variable are likely to be different in each case. "Own100" is an indicator for when a subject faces a 100-Dot task in a given round and "Opponent100" is an indicator for when a subject's opponent faces a 100-Dot task in a given round. In addition, errors are clustered on the subject and own task difficulty levels. The results for these regressions are presented in Table A.2 in Appendix A.

First, note that own task difficulty is highly significant for either acceptance probability. The effect of Own100 is large and positive for the favorable case (i.e. people correctly accept more favorable deals), and large and negative for the unfavorable case (i.e. people correctly reject more unfavorable deals). The opponent task is only significant ($p < 0.10$) in the unfavorable case, suggesting subjects make slightly fewer (roughly 3%) mistakes in accepting unfavorable deals when their opponent has an easy task. However, the opponent's task is not at all significant for the favorable case, and the interaction terms are not significant in either case. Finally, another worry with any experimental study involving many repeated tasks is that performance will change over time due to fatigue or learning. This is especially crucial to check in this setting, as my analysis implicitly assumes that behavior in each game is independent of the other games (this assumption allows one to treat an individual's probabilities of accepting deals in various states as true SDSC in the rational inattention sense). The coefficients on Round support this assumption, which is also supported by previous experimental tests of rational inattention (Dean and Neligh, 2017).

4.2.1 Assessing Possible Heterogeneity

While Table 3 provides suggestive evidence that the aggregate results from the logistic regression are unlikely to be masking meaningful individual-level heterogeneity, I now

[10]The response variable for the logistic equation is $\log y_{it}$.

provide more exhaustive support for this claim.

For each subject i I run the linear probability model of

$$y_{it} = \beta_0^i + \beta_1^i \text{Own100}_{it} + \beta_2^i \text{Opponent100}_{it} + \beta_3^i \text{Own100}_{it} * \text{Opponent100}_{it} + \epsilon_{it}$$

for favorable states and for unfavorable states, where once again y_{it} is a dummy indicator for accepting the deal. Note that by excluding the round variable, the above linear probability regression gives the true marginal probabilities of each of the independent variable dummies. Given the lack of a time trend in the aggregate data, this choice is without much loss.

This results in a collection of β^i coefficient estimates for each individual. Because this is a linear probability model and not a logistic model, these coefficients are directly comparable across individuals. My primary interest lies in the heterogeneity of coefficients on the opponent task's, and the interaction between the opponent's and own task. Thus I create a new set of four coefficient estimates for each individual (opponent and interaction coefficients for favorable and unfavorable regressions).

On this new data set of coefficients, I run the mixture models cluster analysis used by Brocas et al (2014) via the `mclust` package in R (Fraley and Raftery, 2007). This analysis assesses any possible heterogeneity by calculating possible clusters of up to 9 groups using 14 possible models and then choosing the combination with the highest Bayes Information Criterion (BIC). The benefit of this approach is that it assesses *any* possible heterogeneity without assuming the exact nature of this heterogeneity, or the number of possible clusters.

The results of this clustering analysis support the hypothesis that there is very little meaningful heterogeneity in the subjects' sensitivity to their opponent's task. Figure A.1 in Appendix A shows the BIC value for each model and each number of clusters (up to 9). The winning model is that in which the clusters have ellipsoidal shape, equal volume, and equal orientation (EVE) and with 2 clusters. These two clusters consist of 95 subjects and 5 subjects. Table 4 reports the average coefficient values for each cluster.

Figure A.2 in Appendix A shows the scatter plots associated with this classification. The classification again confirms that by and large that the aggregate effects are

Table 4: Mean Parameter Values for Optimal Clusters

	Cluster 1	Cluster 2
β_2^F	0.0108	-0.3760
β_3^F	-0.0065	0.3791
β_2^U	-0.0209	-0.3926
β_3^U	0.0135	0.5007
n	95	5

not hiding meaningful heterogeneity. 95% of subjects fall into a cluster in which the average percentage effect of the opponent having an easy task is between 0% and 2%. Five subjects can be categorized into a cluster where these differences are much larger, indicating an average percentage effect of up to 39%. This suggests that while some subjects appear to have higher levels of strategic sophistication, the vast majority of participants behave extremely similarly to Level-1 types–with behavior invariant to the attentional costs of their opponents. This proportion of Level-1 types is far greater than commonly found in other economic games—an exhaustive study by Georganas et al (2015) finds between 28% and 71% proportion of Level-1 players, depending on the game.

4.3 Beliefs

The preceding section demonstrated a strong effect of own task on behavior, and essentially no effect of the opponent's task on behavior. While this offers strong evidence of an out-sized lack of strategic sophistication, it is yet unclear what *mechanism* is underlying this behavior. There are two clear possibilities: subjects have difficulties in anticipating opponent behavior (i.e. their beliefs are incorrect), or the subjects' information acquisition is not sensitive to incentives (i.e. the subjects are not *rationally inattentive* and ace fixed abilities to discern the two states in each task). The following two sections, alongside a follow-up experiment described thereafter, provide support for the first of these two hypotheses. The current section shows that beliefs are largely incorrect and noisy. The following section shows that subjects largely seem to adjust their attention in response to what they perceive to be the incentives of doing so, which are themselves functions of these incorrect beliefs.

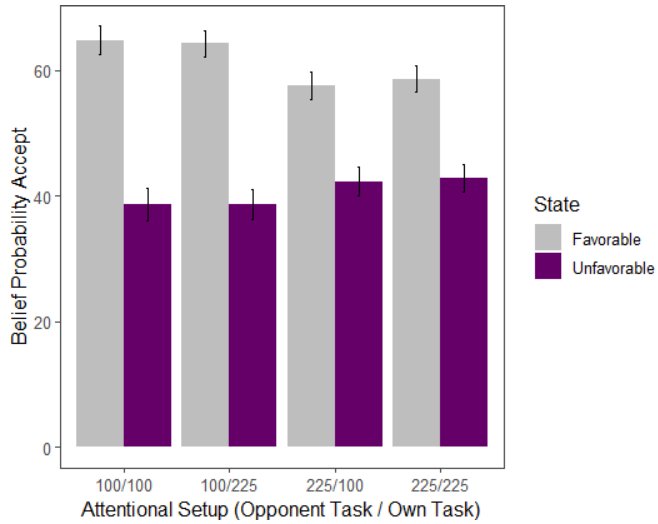


Figure 9: Beliefs of Opponent Behavior by Setup

As a reminder, all subjects are asked to report their beliefs about how frequently their opponents accepted deals of either color in the preceding block (i.e. under the preceding block's attentional setup). That is, I elicit, in an incentive-compatible manner, their beliefs about the SDSC of their opponents. Figure 9 shows the analogous plot of Figure 8, however, this time showing the subjects' mean beliefs of their opponents accepting in the various attentional setups. Note that the figure takes the opponent's perspective in labeling a state as "favorable" or "unfavorable" (so that the figure is exactly comparable to that of Figure 8).

One minimal check to ensure people understood the strategic setup of the game is to see whether they expected their opponents to accept more often in their opponent's favored state. The findings confirm this on the aggregate. Paired t-tests show that subjects believe opponents have a 15.8 and 15.3 percentage point higher acceptance rate in favorable deals over unfavorable deals when the opponent has a 225-Dot task and the subject has a 225-Dot and 100-Dot task, respectively ($p < 0.001$ for both tests). When the opponent has a 100-Dot task, these numbers are 25.6% and 26.2% (again with $p < 0.001$ for each test).

Comparing the above numbers to the actual SDSC of the subjects, however, reveals that subjects hold largely incorrect beliefs about opponent behavior and information acquisition. Table 5 is analogous to Table 1, however, it now shows the differences between reported beliefs that an opponent accepted their favorable deal versus their unfavorable deal. Note that Table 1 shows that the average difference in accepting

Own Task / Opponent Task	Difference	p-value	Weak %	Strict %
100 / 100	0.262	<0.001	93%	66%
100 / 225	0.153	<0.001	90%	54%
225 / 100	0.256	<0.001	91%	63%
225 / 225	0.158	<0.001	91%	57%

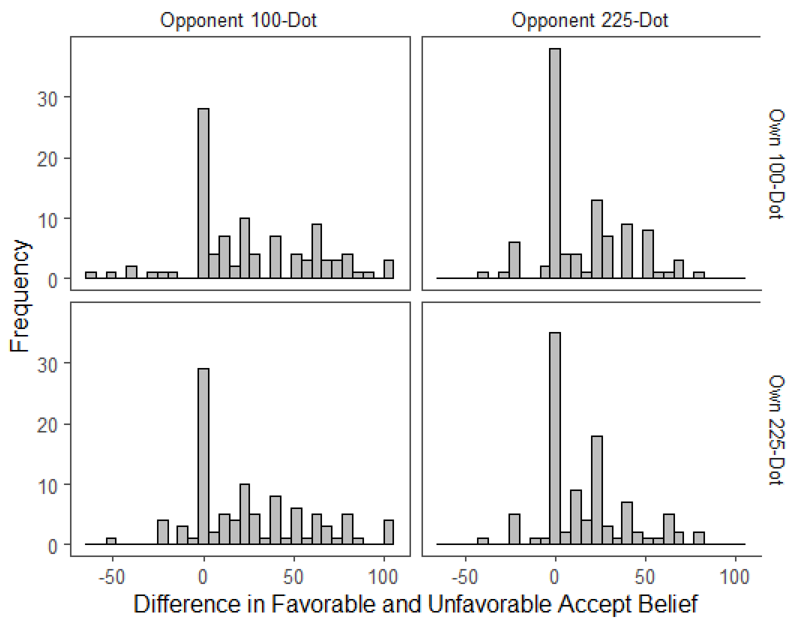
Table 5: Differences between reported beliefs that opponent accepted their favorable versus unfavorable deal, columns 4 and 5 report proportion of subjects with weakly and strictly positive differences in beliefs

favorable and unfavorable deals is nearly 50% for subjects, while the analogous difference in beliefs is only 26%. The gap between differences in Table 1 for the 100-Dot task and the 225-Dot task is approximately 35%, while this gap is only 10% for beliefs. However, Table 5 also shows that people clearly understood the basic strategic setup—columns (4) and (5) show that a vast majority of subjects understood their opponent would be selecting more deals of the subject's unfavorable color than that of the subject's favorable color. However, a very high percentage of subjects, believe these two probabilities to be equal, as demonstrated by the large differences between columns (4) and (5).

To further examine these findings, Figure 10 displays histograms for the differences in Favorable/Unfavorable acceptance beliefs under each attentional setup. This figure, along with Table 5, indicates that a large number of subjects with what are essentially Level-1 beliefs–i.e. they roughly believe $P[a|R] = P[a|B]$. While very few subjects report an incorrect sign (negative) for this statistic, the main takeaway of the figure is the sharp concentration of subjects with reported beliefs of opponent favorable and unfavorable acceptance probabilities which are extremely close to one another.

The above could represent two possible mechanisms. Subjects either truly believe their opponents are acquiring very little information, or they have a large degree of cognitive uncertainty about their opponent's information acquisition, and so for all intents and purposes, they behave *as if* their opponent is acquiring very little information. While the present experiment cannot distinguish these two specific mechanisms, the second seems more plausible and will be discussed further in the paper's

Figure 10: Histogram of difference in favorable and unfavorable accept belief, by attentional setup



conclusion.

Finally, Figure 9 also clearly shows that there is no significant effect of own task on beliefs about opponent behavior. This suggests that the players' beliefs are consistent with no larger than two levels of strategic sophistication, and also indicates that the discrepancies found are an effect of their opponents' task only, and not a reflection of the subjects' own immediate experience.

4.4 Beliefs as the Mechanism for Strategic Unsophistication

Whatever the mechanism behind subjects' largely incorrect beliefs about opponent SDSC, it is clear that even under incentivization they are largely unable to correctly anticipate opponent behavior. The next step is to see whether the subjects themselves acquired information as if their opponents were playing according to these incorrect beliefs.

To do this, I run the same linear regression as presented in Table A.2 but instead substitute two belief variables—"BA" and "BD"—along with their interaction terms with the dummy indicating a 100-Dot task for the subject, in place of of dummies for the opponent task. Here, "BA" refers to the unconditional belief that their opponent chose to accept, calculated by taking the average of the two belief elicitations for that round's attentional setup. "BD" refers to the difference in beliefs of the opponent accepting deals in their favorable state and their unfavorable state for the relevant attentional setup, i.e. the values illustrated in Figure 9. These two transformations of the subjects' elicited beliefs were chosen instead of the two raw beliefs because of the high correlation between a high belief of acceptance of a favorable deal with that of an unfavorable deal. Thus coefficients on either of these values alone are difficult to interpret independently of the other coefficient. The interpretation of the coefficient on "BA" then is how sensitive a subject's behavior is to the unconditional likelihood of their opponent accepting, while the coefficient of "BD" is the causal impact of one's beliefs about the extent of their opponent's information acquisition on their behavior. The dummy for the opponent task was excluded from these regressions as it is highly correlated with beliefs (as seen in Table 5), leading to multicollinearity concerns. Once again, I run this regression twice, for favorable and unfavorable deals, and errors are clustered on the combination of own task difficulty and subject. The coefficients on the relevant interaction terms then indicate how these effects change when the subject is shown a 100-Dot task.

Table 6 presents the results of this regression, while table A.3 in Appendix A shows the analogous logistic regression. Columns (1) and (3) regress on the entire sample, while Columns (2) and (4) regress on only the subset with non-negative values for all four "BD" measurements (76 out of 100 subjects).

In summation, the above analysis suggests that (1) subjects' reported beliefs have significant predictive power on their choice behavior, and (2) the signs on these reported beliefs mostly align with what rational inattention theory predicts. However, due to the caveats explained above, caution must be used when interpreting these results with respect to the reliability of elicited beliefs and whether these beliefs are merely a reflection of own behavior. For these reasons, I conduct a follow-up treatment, to be described in Sections 6 and 7.

Table 6: Linear Probability Regression of Accept, by Favorability

	Dependent variable:			
	Accept (Favorable)		Accept (Unfavorable)	
	(1)	(2)	(3)	(4)
Constant	26.722***	23.519***	2.576	−1.013
	(2.628)	(2.997)	(2.536)	(2.787)
Own100	32.339***	29.962***	−19.498***	−23.020***
	(3.325)	(3.905)	(3.061)	(3.342)
BD	−0.127***	−0.139***	−0.234***	−0.236***
	(0.031)	(0.037)	(0.031)	(0.035)
BA	0.795***	0.842***	0.996***	1.045***
	(0.035)	(0.036)	(0.033)	(0.032)
Own100*BA	−0.403***	−0.347***	0.074	0.133***
	(0.050)	(0.053)	(0.046)	(0.044)
Own100*BD	0.234***	0.291***	−0.103***	−0.065
	(0.038)	(0.045)	(0.039)	(0.045)
Round	−0.004	−0.007	0.013	0.004
	(0.016)	(0.018)	(0.016)	(0.018)

Note: *p<0.1; **p<0.05; ***p<0.01

4.5 Response Times as Attentional Input in Games

The previous literature has shown that response times are an important input in the information acquisition process and that there exists correlations with both mental effort and choice accuracy within a given task (Caplin et al, 2020). Thus, an additional avenue of analysis is to analyze these response times in the two parts of the experiment and under different attentional setups. While the previous literature has shown that these comparisons may not be entirely useful between tasks, they can demonstrate whether people are paying more or less attention within a task, for example in response to incentives. One reason they are not especially useful across tasks is that the "production function" of attention may look very different in different tasks. In the present experiment, for example, counting a large proportion of dots is a viable strategy in the 100-Dot case, whereas it is not in the 225-Dot task[11]. Observing reaction times within opponent tasks then shows whether subjects altered this critical attentional input as a response, even if their ultimate behavior showed little if any response.

Table A.4 in Appendix A shows linear regression under each task, with columns (2) and (4) also including belief data as independent variables. There is a slightly significant negative effect of the opponent having a 100-Dot task on response time under the specification including beliefs where the subject faces 225-Dot tasks, but the response time analysis is largely reflective of the behavioral analysis—there is little to no effect of opponent task on how much time subjects spent on a given task. There is also a strong significant positive effect of the level of attentiveness one believes their opponent has, "BD", on response times–indicating that subjects spend more time examining a 225-Dot grid when they believe their opponent to be separating their stochastic choice more effectively. One interpretation of this could be that subjects spend more time when motivated to avoid "being taken advantage of" and accepting unfavorable deals. In Appendix B, Tables B.8 - B.11, I run equivalent regressions as those shown in Table A.2 and Table 6, except the samples are restricted to those who spent an average length of time on each decision task above various thresholds. As this threshold is increased, the effect of the opponent's task on accepting becomes more significantly negative in the unfavorable case. This suggests that those who are

[11]This observation was present in many open-ended survey responses asking about player strategy, as well as questions about how often they counted dots across tasks.

already spending a larger amount of time on the task do indeed slightly adjust their rate of "mistaken accept" to the task of their opponent. Regressions on beliefs report the same effects as those found in Table 6.

4.6 Survey Data and Correlates with Other Measurements

4.6.1 Survey Explanations of Strategy

In addition to looking strictly at the behavior of subjects to see how they respond to opponent incentives, one can also look at subjects' direct verbal explanations of their strategy in the experiment. At the end of the experiment, subjects are asked to explain, via a text box, three questions to this extent. These questions ask: (1) the subject's general strategy in the strategic rounds of the experiment, (2) how their strategy depended on the task of the other player when the subject had a 100-Dot task, and (3) how their strategy depended on the other's task when the subject had a 225-Dot task[12].

In these open-ended responses, the overwhelming number of subjects admitted that their strategy did not depend on the task of their opponent. Out of 100 subjects, only 30 referred to the opponent's task affecting their strategy in response to any of the three questions above. This is despite subjects being fully aware of the game's strategic setup (subjects were forced to answer all comprehension questions successfully, also viewable in Appendix D). This supports the conclusions made by the behavioral data and elicited belief data—subjects simply did not behave as if their opponents were rationally inattentive.

4.6.2 11-20 Game and Cognitive Reflection Test

While the above shows that subjects had a large lack of strategic sophistication in this setting, it is still necessary to show that this lack of strategic sophistication is *out-sized*, in that it is larger than is typically found in experimental settings. Almost no subjects exhibit a level of sophistication past "Level-1", whereas typically Level-2's are quite common in the data. To ensure the large proportion of lower levels is not simply due to a lower level of sophistication present in online subjects from Prolific, one can examine the behavior in the 11-20 game which was given to subjects at the

[12]Exact wording available in Appendix D

end of the experiment, before the survey and payment screens.

As a reminder, in this game subjects were matched into pairs and asked to request a number of points from 51 to 60. They received the amount they requested but would receive a 20 point bonus if they requested exactly 1 less point than their opponent. Note that this is the same game as in Arad and Rubinstein (2011), but with a flat rate of 50 points added to all payments. Arad and Rubinstein show that there exists a clear mapping from requests to levels of strategic sophistication. A request of 60 would represent the request of a "Level-0" player, making 59 the request of a "Level-1" player, and so on.

Figure A.3 in Appendix A shows a histogram of requests by all 100 subjects in the experiment. The most frequent request by far is 58 points, which corresponds to Level-2 behavior. Only 11 subjects requested amounts consistent with Level-0 or Level-1 behavior. Overall, the distribution is not significantly different from that found in Arad and Rubinstein (2011), and if anything shows a higher degree of sophistication than in their experiments.

Likewise, examining scores on the Cognitive Reflection Test shows an average score of 1.86 out of 3, which is comparable to that found in many university subject pools (Frederick, 2005). So, the lack of strategic sophistication found in the main experiment is not a product of simply a lower sophistication subject pool.

The above CRT and 11-20 game measurements can also be used as a way to restrict the sample and see if those who score as "more sophisticated" in these measurements behave on average in a more sophisticated way in the experimental game. Table 7 shows results from the linear[13] regression of accepting a (favorable or unfavorable) deal on own difficult, opponent difficult, their cross-product, and the round, with errors again clustered on an individual and difficulty level pair. Columns (1) and (4) report results for the sub-sample that requested less than 59 in the 11-20 game. Columns (2) and (5) use the sub-sample that received a score higher than 1 on the CRT, while (3) and (6) restrict the sample to those who scored a perfect score on the CRT.

While there are no opponent effects when restricting the sample to those who behaved

[13]Logistic regression equivalent can be found in Table A.5 in Appendix A

Table 7: Linear regression of Accept, Columns (1) and (4) restricted on sample that requested less than 59 in the 11-20 game, Columns (2) and (5) restricted on sample that received a score higher than 1 on the CRT, Columns (3) and (6) restricted on sample that received a score higher than 2 on the CRT.

	Dependent variable:					
	Accept (Favorable)			Accept (Unfavorable)		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	64.264***	67.482***	66.185***	48.770***	50.139***	48.848***
	(1.706)	(1.956)	(2.481)	(1.805)	(2.122)	(2.632)
Own100	14.768***	18.743***	22.187***	−18.505***	−20.461***	−22.308***
	(1.718)	(1.890)	(2.420)	(1.869)	(2.151)	(2.661)
Opp100	−0.803	−4.096*	−8.083***	−1.785	−3.718*	−6.288**
	(1.861)	(2.161)	(2.801)	(1.931)	(2.242)	(2.824)
Own100*Opp100	1.673	1.691	7.145**	0.983	2.734	4.880
	(2.425)	(2.721)	(3.470)	(2.639)	(3.035)	(3.735)
Round	0.002	−0.023	−0.054**	0.022	−0.001	−0.031
	(0.018)	(0.020)	(0.025)	(0.019)	(0.022)	(0.027)
Note:						*p<0.1; **p<0.05; ***p<0.01

in a sophisticated manner in the 11-20 game, there is an increasingly significant effect when the sample is restricted to those who score highly on the cognitive reflection test. Furthermore, the effect has a negative sign as predicted by the theory when the opponent's cost of attention decreases. As the opponent has easier access to information, these subjects show a slight adjustment towards reducing the error of accepting bad deals in favor of reducing the error of rejecting good deals. This further supports the theory that a key mechanism behind the lack of strategic sophistication in behavior is related to the cognitive difficulty inherent in the task of anticipating and modeling an opponent's information acquisition.

5 Discussion of Main Experiment Results

There are two major conclusions from the results of the preceding experiment. First, there is an out-sized lack of strategic sophistication in this extremely simple economic game environment. Second, the mechanism behind this behavior seems to be inaccurate and perhaps uncertain beliefs. In each of the four attentional setups, the plurality of subjects report beliefs that the probabilities an opponent accepts a favorable and an unfavorable deal are essentially the same. These correspond to the beliefs held by "Level-1" agents in the theoretical framework. Whether through simply incorrect beliefs or through cognitive difficulty in anticipating opponent behavior, these mistaken beliefs seem to drive the "Level-1" behavior of agents.

Recall from the theoretical discussion that when facing an opponent with low attention costs (or one who has an easier task), the benefits of discerning a good and a bad deal decrease. This is because accepting a favorable deal is likely to yield little in the way of positive utility (since the opponent is likely to reject it), and accepting an unfavorable deal is likely to be quite costly (since the opponent is like to accept it). These features make accepting the deal much less attractive when compared to the safe outside option acquired by rejecting it. Subjects do not respond in this way, even though they themselves perform much differently when facing the two tasks. Furthermore, they spend the same amount of time deciding on whether or not to accept a deal regardless of the task of their opponent, again suggestive that players are not adjusting their attention strategy in a way a strategic agent should. While this attention does seem to respond to beliefs, a follow-up experiment seeks to verify that this is the case by removing the uncertainty about opponent behavior entirely.

6 Follow-Up Experiment Design

To further test whether the mechanism behind the results of the previous experiment was indeed cognitive limitations of strategic thinking and forming correct beliefs, I conducted a follow-up experiment. This follow-up experiment followed the exact design of the main experiment, however instead of playing other subjects, subjects played against computer players who followed a pre-specified strategy.

Specifically, instead of being matched with either "225-Dot" or "100-Dot" human subjects, subjects are now matched with either "30:80 Computer" or "50:65 Computer". A 30:80 Computer accepts a deal of the subject's color 30% of the time, and a deal of the opposing color 80% of the time, with the 50:65 Computer being analogous. These numbers were specifically chosen to mirror the average behavior seen by participants in the main experiment. The subjects were told the meaning behind these labels on multiple occasions during the instructions and constantly reminded throughout the experiment. In addition, subjects were quizzed for their comprehension of the computer behavior and had to correctly answer the quiz to proceed with Part 2 of the experiment.

Just as in the main experiment, subjects played 120 rounds of these games, spread across 8 equally sized blocks. There were 2 blocks for each combination of own-grid task and opponent Computer type. Crucially, this is all entirely identical to the main experiment, with the only difference being the removal of all uncertainty about their opponent's strategy. For the belief elicitation questions that appear at the end of blocks five through eight, the subjects were asked to report their beliefs about how often a randomly selected subject of the other role type behaved when they faced the same block setup (own task and computer opponent) as the subject did.

7 Experiment Two Results

The experiment took place again virtually via Prolific, with subjects filtered to be American residents between the ages of 18 and 30 with at least a high school education, and again the subject pool was balanced across sex. Importantly, any subjects

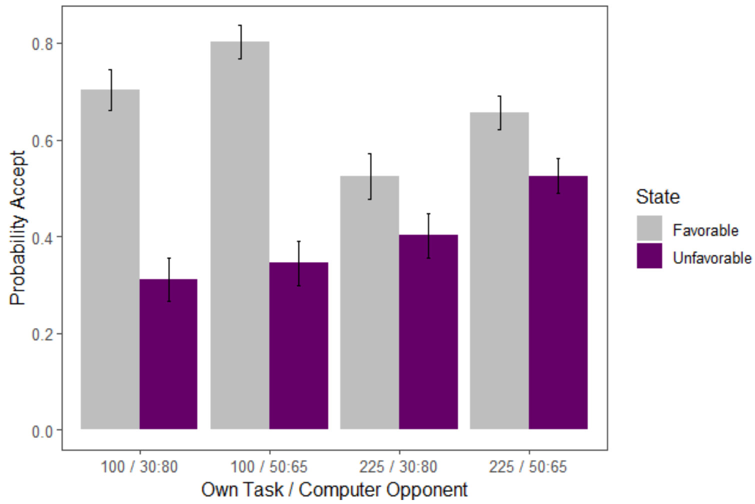


Figure 11: Probability of Accepting Favorable and Unfavorable Deal by Setup, computer Treatment

who may have taken part in Experiment 1 were excluded. Experiment Two was conducted on 40 subjects in September 2022.

First, I recreate the main analyses from the main experiment in the new treatment. Now, instead of referring to opponent tasks, I instead refer to computer players. Recall playing a "30:80" computer is equivalent in behavior to playing the average 100-Dot opponent, while a "50:65" computer is equivalent in behavior to playing the average 225-Dot opponent. Figure 11 shows the probability of accepting a deal in favorable and unfavorable states, for each attentional setup. Contrary to the main experiment, there is a strong significant effect of computers opponent on subjects' SDSC. When subjects face a 30:80 computer (the payoff equivalent of facing a 100-Dot opponent in the main experiment), they rationally shade their SDSC towards rejection–favoring the reduction of accepting unfavorable deals over the reduction of rejecting favorable deals. When subjects face a 50:65 opponent, they prioritize reducing errors in rejecting favorable deals over reducing errors in accepting unfavorable deals.

Table 8 shows the average differences in accept probability when the own task is 100-Dot vs 225-Dot, holding computer opponent and favorability of the deal fixed. Note that Column 2 shows the average difference, Column 3 shows the p-value from the associated paired t-test, and Column 4 shows the percentage of subjects whose data has the same sign as the average. Once again the vast majority of subjects make fewer errors when given a 100-Dot task.

Computer Opponent / Favorability	Difference	p-value	Proportion
30:80 / Favorable	0.196	<0.001	80%
50:65 / Favorable	0.133	0.001	83%
30:80 / Unfavorable	-0.099	0.213	75%
50:65 / Unfavorable	-0.176	<0.002	80%

Table 8: Differences in probability of accepting a deal when given a 100-Dot task and a 225-Dot task, holding favorability of deal and computer opponent fixed, with column 4 indicating the proportion of subjects with the same sign as the aggregate

Table 9, however, shows the average differences in accept probability when the computer is 50:65 versus 30:80, holding the subjects' task difficulty and favorability fixed. Note that Column 2 shows the average difference, Column 3 shows the associate p-value, and Columns 4-6 show the percentage of subjects whose difference is positive, equal, and negative.

Own Task / Favorability	Difference	p-value	% Pos	% Equal	% Neg
100 / Favorable	0.081	0.048	62.5%	15.0%	22.5%
225 / Favorable	0.144	0.002	70.0%	5.0%	25.0%
100 / Unfavorable	0.030	0.224	47.5%	17.5%	35.0%
225 / Unfavorable	0.114	0.007	57.5%	7.5%	35.0%

Table 9: Differences in probability of accepting a deal when facing 50:65 computer and 30:80 computer, holding favorability of deal and own task fixed, with columns 4-6 indicating the proportion of subjects with a difference of each sign

In sharp contrast to the analogous Table 3, there is a strong positive effect of a 50:65 computer on the probability of accepting a deal for all cases except for when subjects have a 100-Dot task and face an unfavorable deal (although at 40 subjects, this experiment does have lower power than the main experiment). While Table 4 showed roughly equal amounts of subjects had a positive and negative sign for this difference, now in all four cases significantly more subjects had a positive sign than a negative sign. This again supports the argument that subjects were largely sensitive to computer opponent accuracy in a way that they were not towards human opponent accuracy.

Finally, regression analysis can verify the above results, and findings are reported in Table A.6 in Appendix A. Unlike in the main experiment in which there was little if any effect of the opponent's task on accept probability, there is a strong negative effect of a 30:80 computer on accept probability in either favorability condition. Again this supports the story of the subjects favoring the reduction of erroneously accepting unfavorable deals when facing a more accurate computer opponent.

Following the analysis of response times in the main experiment which showed no aggregate response toward the opponent's task, I run analogous regressions on this treatment. The results of this regression appear in Table A.7 of Appendix A. Unlike the regression in the main treatment, the effect of having a 100-Dot task opponent equivalent has a strong effect on response times, and the direction is negative. When the computer is separating very well, subjects on average spend less time gathering information, and simply reject the deal more often. This is indicative of a rational allocation of mental resources, as the possible benefits of spending longer on the task grow smaller in this case relative to the constant outside option that requires no mental effort. Also of note, the average response times are significantly longer in this treatment than in the main treatment. One possible explanation is that the reduced uncertainty about opponent behavior translated to more explicit incentives for information acquisition and thus more baseline mental effort devoted to doing so.

8 Discussion and Future Directions

In the simplest possible strategic setting where multiple agents face costs of information, I have found that subjects play in a strategically unsophisticated manner. They acquire information about the state of the world, but they do not acquire this information as if they are playing a strategic opponent. Through careful analysis of subjects' elicited beliefs, I find that the mechanism through which this behavior occurs is beliefs—subjects simply do not anticipate the information acquisition of their opponents. In the follow-up experiment, I eliminate the possibility of this mechanism by having subjects play against automated computers with a transparent strategy. Contrary to the results of the main experiment, here subjects significantly adjust their information acquisition strategies in the direction that the theory predicts.

One explanation for why strategic sophistication may be even lower in games with information acquisition than in standard settings may be "cognitive uncertainty". The cognitive uncertainty literature, beginning with Enke and Graeber (2019) suggests that when people are cognitively uncertain, their "decisions are severely attenuated functions of objective problem parameters". In the present setting, this could mean that the cognitively complex task of anticipating opponent information acquisition causes people to systematically act as if playing a "Level-0" opponent (one with no information acquisition at all). The high degree of "Level-1" beliefs and the generally high variation in reported beliefs is suggestive of this explanation.

Yet another explanation lies within the work on costly depth of reasoning by Aloui and Penta (2016). Again coinciding with the above phenomenon, anticipating opponent information–and thus behavior–may be prohibitively costly given the incentives for doing so. Thus while information acquisition responds sharply to the subjects' own task (in experiments 1 and 2), and incentives (in experiment 2), it does not respond to the opponent's task. Attention is costly in this setting, but not prohibitively so. This simply may not be the case with the costs inherent in strategic reasoning.

Both of the above explanations also deliver insights into why the results of the present paper differ qualitatively from those found in Martin (2016). In his paper, the author finds that fully informed sellers in a trading game choose their pricing strategies in a way that suggests they understand the learning behavior of their inattentive buyers. In the present paper, subjects have to (1) anticipate the learning behavior of their opponent, and (2) acquire costly information in light of the former. Thus in this game subjects have to exert cognitive effort in both dimensions, whereas Martin's setting has each agent only exerting cognitive effort in one. In addition, his experiment does not manipulate cognitive costs of information acquisition, making the experiment less well-suited to answer the questions asked in the present paper.

Besides considering settings in which attentional costs are explicitly asymmetric, my paper also yields insights into how uncertainty about opponent information acquisition can lead to deviations from equilibrium play. In all strategic rational inattention papers, an assumption is made that subjects are aware of the attentional costs of their opponents, and can understand how this translates into their opponent's information acquisition and behavior. Even in an extremely simple setting, I have shown that subjects do not behave with this level of sophistication.

A future avenue of work then is to develop a model that integrates the above ideas, and see when—if ever—subjects may respond to strategic incentives. Yielding testable predictions is a central feature of the emerging field of cognitive economics. By synthesizing existing models much in the ways suggested by the endogenous depth of reasoning literature and the cognitive uncertainty literature, steps can be made toward a more unified theory. The present paper demonstrates how using the various cognitive frictions the literature has developed in a vacuum can come at a large cost in predictability.

While the current paper shows how strategic unsophistication can be "fixed" by having subjects play perfectly predictable machines, another future step is to see how more realistic nudges could help alter behavior. For example, how subjects behave in response to feedback or information about past performance could bridge the gap between the main treatment and the computer treatment.

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A Additional Tables

Table A.1: Regression of Correctness in Decision Making Rounds

	Dependent variable:	
	Correct (Logit)	Correct (LPM)
	(1)	(2)
Constant	0.478^{***}	0.616^{***}
	(0.110)	(0.022)
100-Dot	1.200^{***}	0.228^{***}
	(0.105)	(0.018)
Round	0.003	0.001
	(0.005)	(0.001)
Blue-Majority	-0.155	-0.029
	(0.099)	(0.018)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A.2: Regression of Accept in Strategic Rounds

	Dependent variable:			
	Accept (Favorable)		Accept (Unfavorable)	
	Logit	LPM	Logit	LPM
	(1)	(2)	(3)	(4)
Constant	0.638^{***}	0.654^{***}	0.015	0.505^{***}
	(0.130)	(0.028)	(0.129)	(0.032)
Own100	0.822^{***}	0.158^{***}	-0.833^{***}	-0.199^{***}
	(0.183)	(0.034)	(0.192)	(0.044)
Opp100	-0.061	-0.014	-0.144^{*}	-0.036^{*}
	(0.089)	(0.020)	(0.083)	(0.021)
Own100*Opp100	0.075	0.016	0.142	0.036
	(0.129)	(0.025)	(0.114)	(0.027)
Round	-0.0003	-0.00005	0.001	0.0002
	(0.001)	(0.0002)	(0.001)	(0.0002)

Note: *p<0.1; **p<0.05; ***p<0.01

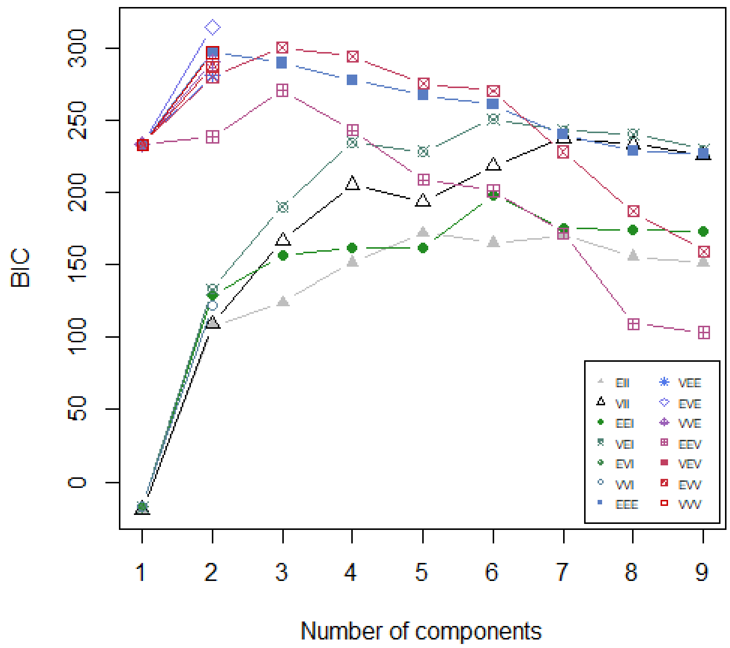


Figure A.1: BIC of Possible Cluster Classifications

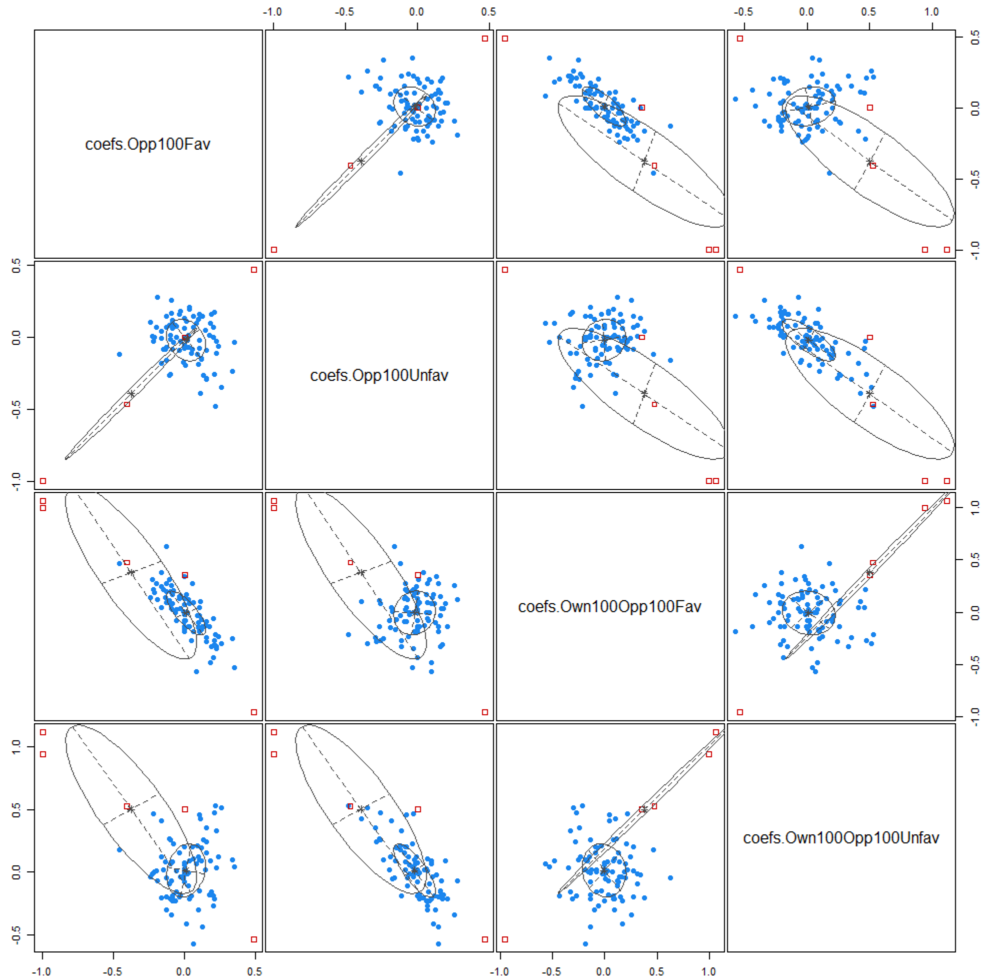


Figure A.2: Classification of Optimal Cluster

Table A.3: Logistic Regression of Accept, by Favorability

	Dependent variable:			
	Accept (Favorable)		Accept (Unfavorable)	
	(1)	(2)	(3)	(4)
Constant	-1.529^{***}	-1.772^{***}	-2.779^{***}	-3.164^{***}
	(0.459)	(0.531)	(0.533)	(0.592)
Own100	1.550^{**}	1.243	-1.174^{*}	-1.709^{**}
	(0.635)	(0.760)	(0.710)	(0.803)
BD	-0.006^{**}	-0.007^{**}	-0.010^{***}	-0.010^{***}
	(0.003)	(0.004)	(0.003)	(0.003)
BA	0.046^{***}	0.052^{***}	0.058^{***}	0.065^{***}
	(0.008)	(0.009)	(0.010)	(0.011)
Own100*BD	0.013^{***}	0.017^{***}	-0.008^{*}	-0.006
	(0.005)	(0.006)	(0.004)	(0.005)
Own100*BA	-0.019	-0.012	0.008	0.016
	(0.012)	(0.014)	(0.013)	(0.014)
Round	-0.0003	-0.001	0.001	0.0002
	(0.001)	(0.002)	(0.001)	(0.001)

Note: *p<0.1; **p<0.05; ***p<0.01

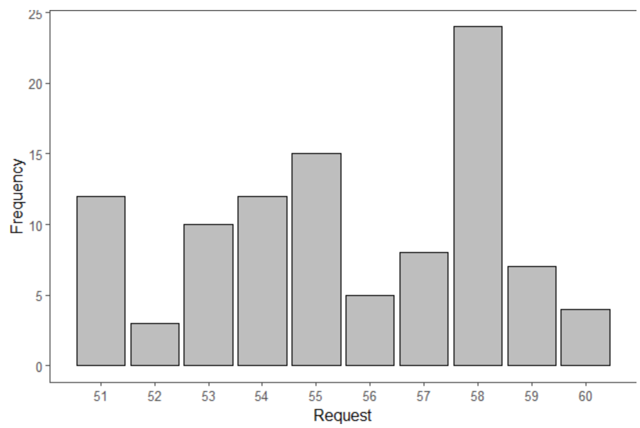


Figure A.3: Requests in the 11-20 Game

Table A.4: Linear Regression of Response Time, by Own Task

	Dependent variable:			
	Own 100-Dot		Own 225-Dot	
	(1)	(2)	(3)	(4)
Opp100	0.121	−0.019	0.017	−0.478*
	(0.154)	(0.224)	(0.159)	(0.290)
Round	−0.025***	−0.025***	−0.014**	−0.015**
	(0.005)	(0.005)	(0.006)	(0.006)
BD		0.014		0.047***
		(0.013)		(0.014)
BA		−0.003		−0.011
		(0.017)		(0.019)
Constant	6.049***	5.932***	6.329***	6.208***
	(0.590)	(0.982)	(0.545)	(1.186)

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.5: Logistic regression of Accept, Columns (1) and (4) restricted on sample that requested less than 59 in the 11-20 game, Columns (2) and (5) restricted on sample that received a score higher than 1 on the CRT, Columns (3) and (6) restricted on sample that received a score higher than 2 on the CRT

	Dependent variable:					
	Accept (Favorable)			Accept (Unfavorable)		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.586***	0.744***	0.708***	−0.053	0.006	−0.034
	(0.080)	(0.097)	(0.120)	(0.075)	(0.088)	(0.113)
Own100	0.742***	1.055***	1.214***	−0.777***	−0.869***	−0.996***
	(0.088)	(0.111)	(0.141)	(0.080)	(0.094)	(0.124)
Opp100	−0.035	−0.179*	−0.340***	−0.072	−0.149*	−0.257**
	(0.081)	(0.094)	(0.117)	(0.077)	(0.090)	(0.115)
Own100*Opp100	0.088	0.004	0.267	0.034	0.101	0.179
	(0.125)	(0.154)	(0.196)	(0.114)	(0.134)	(0.177)
Round	0.0001	−0.001	−0.003**	0.001	−0.0001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.6: Regression of Accept in Strategic Rounds (Computer Experiment)

	Dependent variable:			
	Accept (Favorable)		Accept (Unfavorable)	
	Logit	LPM	Logit	LPM
	(1)	(2)	(3)	(4)
Constant	0.572***	0.641***	0.107	0.527***
	(0.161)	(0.036)	(0.155)	(0.038)
Own100	0.762***	0.147***	−0.749***	−0.182***
	(0.263)	(0.048)	(0.250)	(0.058)
30:80	−0.553***	−0.133***	−0.502***	−0.124***
	(0.187)	(0.045)	(0.164)	(0.040)
Own100*30:80	0.010	0.033	0.343	0.089*
	(0.284)	(0.060)	(0.224)	(0.052)
Round	0.001	0.0003	−0.0001	−0.00002
	(0.002)	(0.0003)	(0.001)	(0.0003)

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.7: Linear Regression of Response Time, by Own Task (Computer Treatment)

	Dependent variable:	
	Own 225-Dot	Own 100-Dot
	(1)	(2)
30:80	-1.017^{***}	-0.519^{*}
	(0.266)	(0.279)
Round	-0.018^{***}	-0.028^{***}
	(0.004)	(0.004)
Constant	7.070^{***}	8.360^{***}
	(0.324)	(0.341)
Note:	*p<0.1; **p<0.05; ***p<0.01	

B Robustness Checks

Table B.8: Linear regression of Accept on opponent task, by favorability, on sub-samples restricted by average time spent on Part 1 decision making tasks

	Dependent variable:			
	Min of 5s Avg On Decision Rounds		Min of 10s Avg On Decision Rounds	
	Accept (Favorable)	Accept (Unfavorable)	Accept (Favorable)	Accept (Unfavorable)
	(1)	(2)	(3)	(4)
Constant	0.666^{***}	0.487^{***}	0.705^{***}	0.497^{***}
	(0.035)	(0.039)	(0.039)	(0.055)
Own100	0.185^{***}	-0.222^{***}	0.192^{***}	-0.196^{**}
	(0.039)	(0.054)	(0.050)	(0.085)
Opp100	-0.034	-0.057^{*}	-0.052	-0.075^{**}
	(0.029)	(0.030)	(0.045)	(0.038)
Own100*Opp100	0.038	0.046	0.063	0.053
	(0.033)	(0.034)	(0.048)	(0.043)
Round	-0.0002	0.00001	-0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0004)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table B.9: Logistic regression of Accept on opponent task, by favorability, on sub-samples restricted by average time spent on Part 1 decision making tasks

	Dependent variable:			
	Min of 5s Avg On Decision Rounds		Min of 10s Avg On Decision Rounds	
	Accept (Favorable)	Accept (Unfavorable)	Accept (Favorable)	Accept (Unfavorable)
	(1)	(2)	(3)	(4)
Constant	0.704***	−0.051	0.899***	−0.017
	(0.165)	(0.159)	(0.194)	(0.222)
Own100	1.022***	−0.969***	1.212***	−0.815**
	(0.229)	(0.250)	(0.334)	(0.372)
Opp100	−0.148	−0.230*	−0.236	−0.300**
	(0.125)	(0.122)	(0.203)	(0.153)
Own100*Opp100	0.180	0.171	0.344	0.198
	(0.177)	(0.149)	(0.264)	(0.179)
Round	−0.001	0.00003	−0.002	0.001
	(0.001)	(0.001)	(0.002)	(0.002)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.10: Linear regression of Accept on beliefs, by favorability, on sub-samples restricted by average time spent on Part 1 decision making tasks, even numbered columns further restricted on sub-sample with non-negative differences in belief opponent accepted favorable and unfavorable deals

	Dependent variable:							
	Minimum of 5 Second Avg On Decision Rounds				Minimum of 10 Second Avg On Decision Rounds			
	Accept (Favorable)		Accept (Unfavorable)		Accept (Favorable)		Accept (Unfavorable)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-1.861^{***}	-1.988^{***}	-3.727^{***}	-3.727^{***}	-1.812^{***}	-1.890^{***}	-4.065^{***}	-4.065^{***}
	(0.083)	(0.098)	(0.065)	(0.065)	(0.082)	(0.098)	(0.084)	(0.084)
Own100	1.714^{***}	1.451^{***}	-0.891^{***}	-0.891^{***}	2.349^{***}	2.974^{***}	-1.004^{***}	-1.004^{***}
	(0.114)	(0.146)	(0.099)	(0.099)	(0.113)	(0.123)	(0.132)	(0.132)
BD	-0.006^{***}	-0.007^{***}	-0.008^{***}	-0.008^{***}	-0.011^{***}	-0.010^{***}	-0.012^{***}	-0.012^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
BA	0.053^{***}	0.056^{***}	0.074^{***}	0.074^{***}	0.057^{***}	0.057^{***}	0.079^{***}	0.079^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Own100*BD	0.010^{***}	0.015^{***}	-0.008^{***}	-0.008^{***}	0.024^{***}	0.019^{***}	-0.013^{***}	-0.013^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Own100*BA	-0.017^{***}	-0.012^{***}	0.0002	0.0002	-0.032^{***}	-0.037^{***}	0.007^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Round	-0.001^{***}	-0.002^{***}	0.0002	0.0002	-0.002^{***}	-0.002^{***}	0.002^{***}	0.002^{***}
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.11: Logistic regression of Accept on beliefs, by favorability, on sub-samples restricted by average time spent on Part 1 decision making tasks, even numbered columns further restricted on sub-sample with non-negative differences in belief opponent accepted favorable and unfavorable deals

	Dependent variable:							
	Minimum of 5 Second Avg On Decision Rounds				Minimum of 10 Second Avg On Decision Rounds			
	Accept (Favorable)		Accept (Unfavorable)		Accept (Favorable)		Accept (Unfavorable)	
Constant	−1.861***	−1.988***	−3.727***	−3.727***	−1.812**	−1.890**	−4.065***	−4.065***
	(0.601)	(0.644)	(0.610)	(0.610)	(0.744)	(0.822)	(0.802)	(0.802)
Own100	1.714**	1.451	−0.891	−0.891	2.349**	2.974***	−1.004	−1.004
	(0.840)	(1.024)	(0.938)	(0.938)	(0.984)	(1.091)	(1.136)	(1.136)
BD	−0.006*	−0.007	−0.008***	−0.008***	−0.011**	−0.010*	−0.012***	−0.012***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
BA	0.053***	0.056***	0.074***	0.074***	0.057***	0.057***	0.079***	0.079***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.013)	(0.013)	(0.015)	(0.015)
Own100*BD	0.010**	0.015**	−0.008	−0.008	0.024***	0.019***	−0.013	−0.013
	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)	(0.007)	(0.008)	(0.008)
Own100*BA	−0.017	−0.012	0.0002	0.0002	−0.032*	−0.037**	0.007	0.007
	(0.016)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)	(0.021)	(0.021)
Round	−0.001	−0.002	0.0002	0.0002	−0.002	−0.002	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Note:								*p<0.1; **p<0.05; ***p<0.01

C Additional Theory and Proofs: Level-K Predictions

For all analyses present in this section, I will normalize $v_o = 0$. This is without loss of generality, as rational inattention results rely only on the distance between potential utility levels, and not the levels themselves (for example, the solutions to the game with $v_H = 90$, $v_L = 10$, and $v_o = 30$ are identical to that of $v_H = 60$, $v_L = -20$, and $v_o = 0$). Note then that the assumption of ex-ante optimality means $v_H + v_L > 0$, whereas the ex-post sub-optimality assumption means $v_H > 0 > v_L$.

C.1 Level-1

With the above normalization, a Level-1 player has:

$$v^R(a|R) = \frac{v_H}{2}$$

$$v^R(a|B) = \frac{v_L}{2}$$

with $V^R(r|R) = v^R(r|B) = 0$. From CDL Proposition 1, the Level-1 player will unconditionally accept if

$$\frac{1}{2}e^{\frac{-v_L}{2\lambda^R}} + \frac{1}{2}e^{\frac{-v_H}{2\lambda^R}} < 1.$$

Note that the first term is positive while the second term is negative. As λ^R approaches 0 from the right, the left hand side goes to positive infinity, and as λ^R goes to infinity, the left hand side approaches 1. The function has a derivative with respect to 0 at $\lambda^R = \frac{H-L}{2\ln - \frac{H}{2}}$. Since $H > -L$ and $H > 0 > L$, this value is a positive number. For λ^R prior to this value and after 0, the function is strictly decreasing, and after this value it is strictly increasing. In addition, at this value the function is strictly less than 1, given $H > 0 > L$. These facts combined prove that there exists some $\bar{\lambda^R}$ such that the optimal strategy is to always accept if and only if $\lambda \geq \bar{\lambda^R}$.

The player, however, will never unconditionally reject. This is because in order to unconditionally reject, the player would have to have:

$$\frac{1}{2}e^{\frac{v_L}{2\lambda^R}} + \frac{1}{2}e^{\frac{v_H}{2\lambda^R}} < 1$$

Note that the left hand side is strictly greater than:

$$\frac{1}{2}e^{\frac{-v_H}{2\lambda^R}} + \frac{1}{2}e^{\frac{v_H}{2\lambda^R}}$$

which is always strictly greater than 1.

Again from CDL proposition 1, this means the only possible consideration sets for a Level-1 player are {a}, and {a,r}. With the first being chosen if $\lambda^R > \bar{\lambda^R}$ and the second being chosen if λ^R is below this cut-off.

What remains to be shown is the SDSC strategy for when both actions are in the consideration set. Suppose this is the case, and call $P[a]$ the unconditional probability of accepting a deal. CDL Proposition 1 then says that:

$$\frac{1}{2}\frac{e^{\frac{v_H}{2\lambda^R}}}{P[a]e^{\frac{v_H}{2\lambda^R}} + 1 - P[a]} + \frac{1}{2}\frac{e^{\frac{v_L}{2\lambda^R}}}{P[a]e^{\frac{v_L}{2\lambda^R}} + 1 - P[a]} = 1.$$

I can then solve for $P[a]$ to get:

$$P[a] = \frac{1 - \frac{1}{2}e^{\frac{v_H}{2\lambda^R}} - \frac{1}{2}e^{\frac{v_L}{2\lambda^R}}}{(e^{\frac{v_H}{2\lambda^R}} - 1)(e^{\frac{v_L}{2\lambda^R}} - 1)}$$

which then leads to the SDSC given by the conditions from Matejka and McKay (2015) as:

$$P[a|R] = \frac{P[a]e^{\frac{v_H}{2\lambda^R}}}{P[a]e^{\frac{v_H}{2\lambda^R}} + 1 - P[a]}$$

$$P[a|B] = \frac{P[a]e^{\frac{v_L}{2\lambda^R}}}{P[a]e^{\frac{v_L}{2\lambda^R}} + 1 - P[a]}.$$

First, I will show that the unconditional accept probability is increasing in λ^R. Taking the derivative of $P[a]$ with respect to λ^R yields:

$$-\frac{e^{\frac{v_H}{2\lambda^R}}v_H + e^{\frac{v_H+2v_L}{2\lambda^R}}v_H + e^{\frac{v_L}{2\lambda^R}}v_L + e^{\frac{2v_H+v_L}{2\lambda^R}}v_L - 2e^{\frac{v_H+v_L}{2\lambda^R}}(v_H+v_L)}{4\left(-1+e^{\frac{v_H}{2\lambda^R}}\right)^2\left(-1+e^{\frac{v_L}{2\lambda^R}})^2(\lambda^R)^2\right.}$$

The denominator of the above expression is always strictly positive. Thus what remains to be shown is that the numerator is strictly positive as well. Denote the numerator by $g(\lambda^R)$, note that $g(\lambda^R) > 0$ whenever the below is true:

$$f(\lambda^R) = v_H(2 - e^{\frac{-v_L}{2\lambda^R}} - e^{\frac{v_L}{2\lambda^R}} + v_L(2 - e^{\frac{-v_H}{2\lambda^R}} - e^{\frac{v_H}{2\lambda^R}})$$

because $f(\lambda^R)$ is simply $\frac{g(\lambda^R)}{e^{\frac{H+L}{2\lambda^R}}}$. Deriving the $f(\lambda^R)$ again with respect to λ^R gives:

$$\frac{v_H v_L}{2(\lambda^R)^2}(e^{\frac{H}{2\lambda^R}} - e^{\frac{-H}{2\lambda^R}} - (e^{\frac{-L}{2\lambda^R}} - e^{\frac{L}{2\lambda^R}})).$$

Note that above is strictly negative since $H > 0 > L$ and $H > -L$. Finally, note that $f(\lambda^R)$ goes to 0 as λ^R goes to infinity. Thus, $f(\lambda^R)$ is positive for all $\lambda^R > 0$, making $g(\lambda^R)$ positive for all $\lambda^R > 0$, making $P[a]$ strictly increasing in λ^R for all positive λ^R.

The probability of accepting an unfavorable deal is again

$$P[a|B] = \frac{P[a]e^{\frac{v_L}{2\lambda^R}}}{P[a]e^{\frac{v_L}{2\lambda^R}} + 1 - P[a]},$$

which when derived with respect to λ^R yields

$$\frac{e^{\frac{v_L}{2\lambda^R}}(v_L(P[a]^2 - P[a]) + 2(\lambda^R)^2 P'[a])}{2(\lambda^R)^2(1 + P[a](e^{\frac{v_L}{2\lambda^R}} - 1))^2}$$

where $P'[a]$ is the derivative of $P[a]$ with respect to λ^R, which is strictly positive for positive λ^R. Note that this value is always positive because $0 < P[a] < 1$. So the probability of accepting an unfavorable deal is also strictly increasing in λ^R for all positive λ^R.

The same derivative for $P[a|R]$, the probability of accepting a favorable deal, is:

$$\frac{e^{\frac{v_H}{2\lambda^R}}(v_H(P[a]^2 - P[a]) + 2(\lambda^R)^2 P'[a])}{2(\lambda^R)^2(1 + P[a](e^{\frac{v_H}{2\lambda^R}} - 1))^2}$$

The sign of this derivative can be both positive or negative. Specifically, it is positive whenever:

$$v_H(P[a]^2 - P[a]) + 2(\lambda^R)^2 P'[a] > 0.$$

As λ^R approaches 0, the above does not hold, as $P[a]$ approaches $\frac{1}{2}$, making the first term negative, while the second term is small and positive. As λ^R approaches $\bar{\lambda^R}$, $P[a]$ approaches 1, making the first term go to 0 while the second term stays positive. This gives rise to the dynamics seen in Figure 2.

Also note that since $P[a]$ is strictly increasing in λ^R and $P[a|B]$ is strictly increasing in λ^R, we have that $P'[a|B] > -P'[a|R]$ whenever $P'[a|R]$ is negative, as $P[a] = \frac{P[a|R]+P[a|B]}{2}$. In addition, when both derivatives are positive, the derivative of $P[a|B]$ is greater than that of $P[a|R]$. To see this, one can take the difference of two derivatives as seen above, with $P[a]$ and $P'[a]$ specified as above as well. Dividing this expression by λ^R yields an expression in terms of $\tilde{v_H} = v_H/\lambda^R$ and $\tilde{v_L} = v_L/\lambda^R$. It can be verified that this new expression is positive for all $H > 0 > L$ (the restriction of $H > -L$ is unnecessary here).

C.2 Level-2

With the above normalization, a Level-2 player has:

$$v^R(a|R) = P_1[a|R]v_H$$

$$v^R(a|B) = P_1[a|B]v_L$$

with $V^R(r|R) = v^R(r|B) = 0$, and $P_1[a|\theta]$ equal to the probability that a Level-1 opponent accepts a deal of quality θ.

The ex-ante value of accepting a deal is then

$$E[a] = \frac{P_1[a|B]v_L}{2} + \frac{P_1[a|R]v_H}{2}$$

which is increasing in the opponents cost of attention, because $v_H > -v_L$ and $P_1'[a|B] < P_1'[a|R]$, from the preceding section.

As the opponents cost of attention approaches 0, the ex-ante value of accepting a deal becomes $\frac{v_L}{2} < 0$. As the opponents cost of attention approaches infinity, the ex-ante value of accepting a deal becomes $\frac{v_L+v_H}{2} > 0$.

First note that if $E[a]$ is positive, the analyses is exactly identical to the Level-1 analysis, under new variable $\tilde{v_H} = P_1[a|R]v_H$ and $\tilde{v_L} = P_1[a|B]v_L$, which satisfy the same assumptions that v_H and v_L satisfied. Hence, here behavior will have the same comparative statics as a Level-1 player with respect to own attention costs. If own attention costs are higher than some $\bar{\lambda^R}$, the player will unconditional accept. If else, the player will accept with positive probability. The SDSC of accepting unfavorable deals will be strictly increasing, as will the unconditional probability of accepting deals, with the probability of accepting favorable deals being non-monotonic.

Next, consider the case in which $E[a]$ is negative. I will show that the optimal behavior of the Level-2 agent is exactly opposite of that of the $E[a]$ positive case. That is, if own attention costs are higher than some cutoff, the player will unconditionally reject all deals. If else, the probability a player accepts favorable deals will be strictly decreasing in own costs, as will the unconditional probability of accepting deals. The probability of accepting unfavorable deals will be non-monotonic.

The problem is equivalent to one in which a player receives H for accepting a Red deal and L for accepting a Blue deal, with $H > 0 > L$, but with the added assumption that $-L > H$ (which is the opposite of the usual assumption).

Then the player will unconditionally reject if and only if

$$\frac{1}{2}e^{\frac{L}{\lambda^R}} + \frac{1}{2}e^{\frac{H}{\lambda^R}} < 1.$$

As λ^R approaches 0 from the right, the left hand side goes to positive infinity. As λ^R goes to infinity, the left hand side goes to 1. The function has has a derivative with respect to 0 at $\lambda^R = -\frac{H-L}{\ln -\frac{-H}{L}}$ which is positive because $-L > H$ and $H > 0 > L$. In addition, the value of the left hand side at this value is strictly less than 1, meaning that there exists some $\bar{\lambda^R}$ such that the optimal strategy is to unconditionally accept if and only if $\lambda \geq \bar{\lambda^R}$.

The player will also never unconditionally accept. This is because the expression

$$\frac{1}{2}e^{\frac{L}{\lambda^R}} + \frac{1}{2}e^{\frac{H}{\lambda^R}} < 1$$

is never true, as it is greater than

$$\frac{1}{2}e^{\frac{L}{\lambda^R}}+\frac{1}{2}e^{\frac{-L}{\lambda^R}}>1$$

.

So the only two possible consideration sets in this case are (1) only reject, (2) accept and reject. Thus whenever costs are below the threshold established above, the player will accept and reject with positive probability. In this case, CDL then gives the the unconditional probability of accepting must be equal to

$$P[a]=\frac{1-\frac{1}{2}e^{\frac{H}{\lambda^R}}-\frac{1}{2}e^{\frac{L}{\lambda^R}}}{(e^{\frac{H}{\lambda^R}}-1)(e^{\frac{L}{2\lambda^R}}-1)}$$

The derivative with respect to λ^R is then

$$-\frac{e^{H/\lambda^R}H+e^{\frac{H+2L}{\lambda^R}}H+e^{L/\lambda^R}L+e^{\frac{2H+L}{\lambda^R}}L-2e^{\frac{H+L}{\lambda^R}}(H+L)}{2\left(-1+e^{H/\lambda^R}\right)^2\left(-1+e^{L/\lambda^R}\right)^2(\lambda^R)^2}$$

Here again the sign relies on the sign of the numerator. Taking the numerator, dividing it by $e^{\frac{H+L}{\lambda^R}}$, and taking the derivative with respect to λ^R yields

$$\frac{HL}{(\lambda^R)^2}(e^{H/\lambda^R}-e^{-H/\lambda^R}-(e^{-L/\lambda^R}-e^{L/\lambda^R}))$$

which is negative because $H<-L$.

Finally, note that the probability of accepting a favorable deal is

$$P[a|R]=\frac{P[a]e^{\frac{v_H}{\lambda^R}}}{P[a]e^{\frac{v_H}{\lambda^R}}+1-P[a]}$$

and that the derivative of this with respect to λ^R is

$$\frac{e^{\frac{H}{\lambda^R}}(H(P[a]^2-P[a])+(\lambda^R)^2P'[a])}{(\lambda^R)^2(1+P[a](e^{\frac{H}{\lambda^R}}-1))^2}$$

which is strictly negative because $0<P[a]<1$, and $P^{'}[a]<0$ as shown above. Note that the equivalent derivative for the probability of accepting unfavorable deals is

$$\frac{e^{\frac{L}{\lambda^R}}(L(P[a]^2 - P[a]) + (\lambda^R)^2 P'[a])}{(\lambda^R)^2(1 + P[a](e^{\frac{L}{\lambda^R}} - 1))^2}$$

which has an inconclusive sign, since the first term on the numerator is always positive and the second term is always negative.

Next, I turn to the analysis of holding the Level-2 players own cost fixed, and instead increasing the attention cost of their Level-1 opponent. Algebraically, this problem becomes quickly intractable, so I proceed using numerical methods for this level of analysis. I analyze the exact parameters relevant in the experimental design ($v_H = 90$, $v_L = 10$, $v_o = 30$). Figure C.4 illustrates optimal Level-2 SDSC holding one's own cost fixed at levels of $\lambda = 10, 20, 30, 40, 50$, while varying $\lambda^{-}i$ of the opponent from 0 to 50. Note that as λ of the opponent increases beyond this range, the SDSC remains constant as at values of opponent λ higher than those shown the opponent is unconditionally accepting all deals, and thus the behavior of the Level-2 player remains unchanged.

Generally, the probability of accepting a deal in either state is increasing with respect to opponent attention costs. Note that this is a subtle problem, and there are parameterizations for which the slope (from the left) in the probability of accepting an unfavorable deal is slightly negative at the point at which the opponent begins unconditionally accepting. However, as illustrated in Figure C.4 this is not the case under the experiment's chosen parameters.

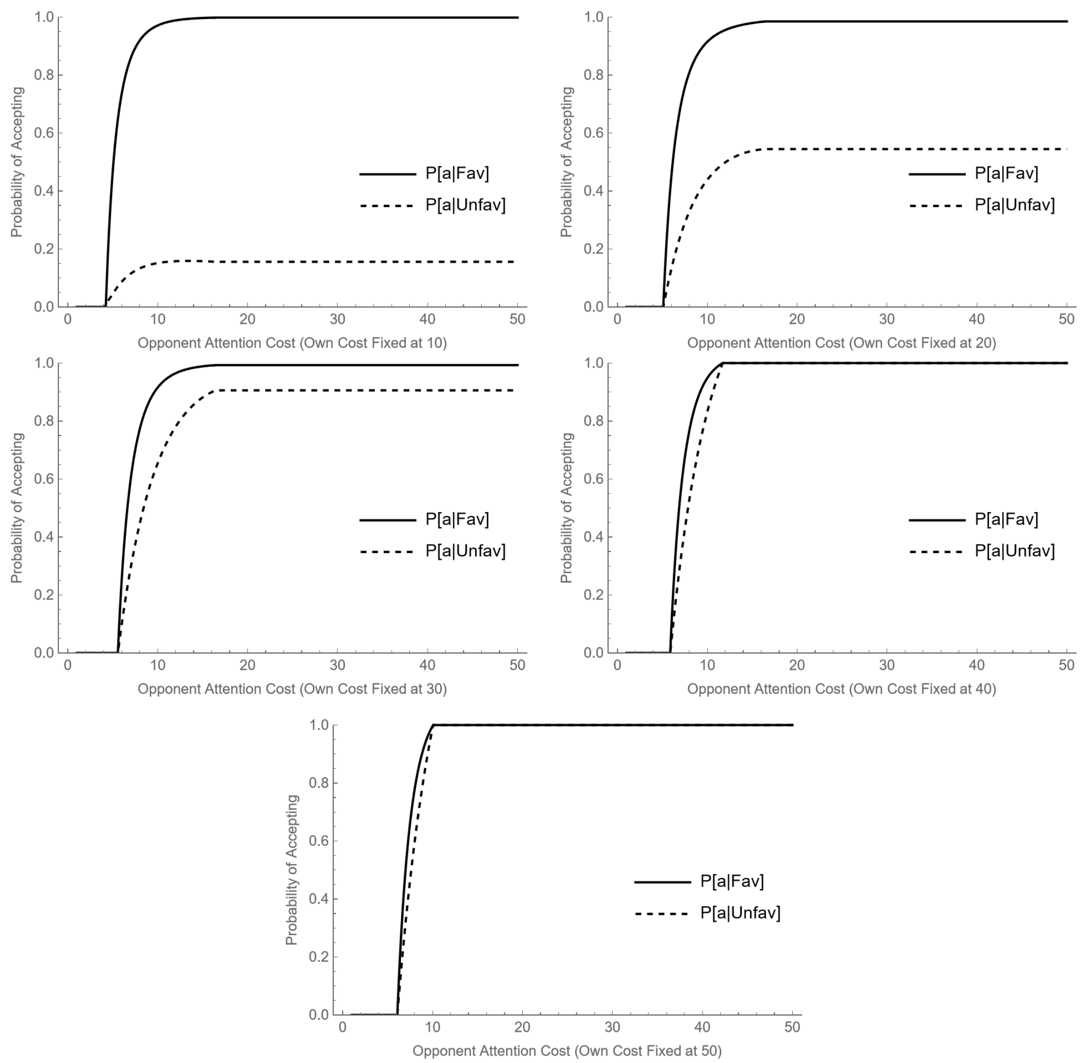


Figure C.4: Numerical derivations of the probability of a Level-2 player accepting deals of either type, holding own attention costs fixed while varying the attention cost of the opponent

D Instructions (Experiment 1)

Part 1 Instructions

Experiment Structure

There will be 4 parts of the experiment. Parts 1 through 3 involve making incentivized economic decisions, either with another random subject, or individually. Part 4 is a short non-incentivized survey.

Bonus Payment

In total, there are 159 incentivized questions in Parts 1-3. At the end of the experiment, one of these 159 questions will be selected at random for payment.

In this question, you will earn some amount of points between 0 and 100. These points will be your percent probability of winning a $10 bonus payment (in addition to your $10 completion payment). For example, if you earn 50 points, you will have a 50% probability of winning a $10 bonus payment.

Because the number of points you earn may depend on decisions made by other subjects, you may not know how many points you have earned until after the experiment is completed by all subjects.

How You'll Receive Your Bonus Payment

You will receive a Prolific message no later than 7 days following your completion of this experiment with a link to a survey. On this survey, you will see your earnings in points.

Then, it will be determined whether you earn the $10 bonus payment. In order to ensure your probability of winning the bonus prize is equal to the number of points earned, we are utilizing a timer device. You will be shown a timer that uses your computer system clock, in milliseconds. You will get one chance to stop this timer. The number of milliseconds in one's and ten's will be a number between 0 and 99. If your earnings in points is strictly greater than this number, you will then earn $10.

Note that it is essentially impossible to stop a clock in milliseconds with any degree of accuracy, so the number generated by the timer game is random for all practical purposes.

To convince yourself of this game's randomness, you can try the timer game multiple times at the link below.

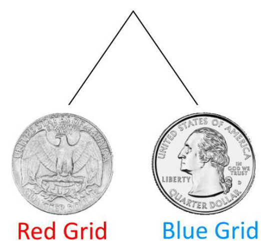
Click here for a demo of the randomized payment device (link opens in new tab)

Part 1 Instructions: Red and Blue Grids

For each of the 30 rounds in Part 1, you will be shown an image of red and blue dots.

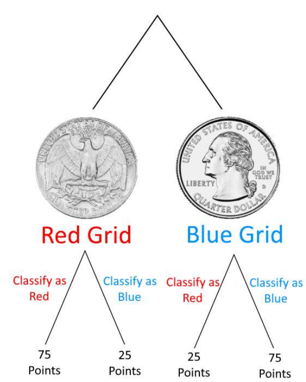
In each round, with 50% probability there will be more red dots than blue dots (call this a Red Grid), and with 50% probability there will be more blue dots than red dots (call this a Blue Grid).

Whether there is a Red Grid or a Blue Grid is determined independently each round. You can think of this as a coin flip that occurs each round, and on heads the grid is Blue and on tails the grid is Red. This means that a grid in one round being one color does not imply anything about future rounds being either Red or Blue.



Part 1 Instructions: Your Choice

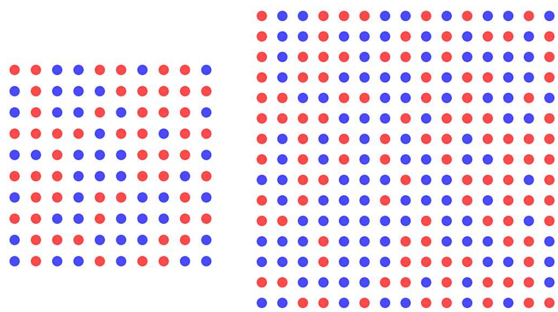
Your task will be to determine whether each grid is Red or Blue. You will have a maximum of thirty seconds to determine this. For each round, you will classify the grid as either "Red" or "Blue". If you are correct, you will earn 75 points, and if you are incorrect you will earn 25 points.



Part 1 Instructions: Types of Grids

You will always try to determine whether a grid is Red or Blue. However, there will be two different types of grids you will see in this part of the experiment, called "100-Dot" and "225-Dot". The 30 rounds in this part will be divided into 6 blocks of 5 rounds each. There will be 3 blocks of 100-Dot grids, and 3 blocks of 225-Dot grids.

- 100-Dot grids will have 100 dots in a 10 by 10 grid. There will be 8 more blue dots than red dots on Blue grids, and 8 more red dots than blue dots on Red grids
- 225-Dot grids will have 225 dots in a 15 by 15 grid. There will be 5 more blue dots than red dots on Blue grids, and 5 more red dots than blue dots on Red grids



100-Dot Grid Example (Left), 225-Dot Grid Example (Right)

Part 1 Instructions: Other Important Notes

After each round, you will not receive any feedback, nor learn whether the grid was truly Red or Blue. Once you have classified a grid as Red or Blue, you are free to proceed to the next question. Once you have proceeded to the next question, you cannot go back to previous questions.

Comprehension Questions

Below are three questions designed to test your comprehension of the instructions.

You must answer each question correctly in order to move on to the next page.

Once you have answer all questions correctly and click on the "Next" button, you will be shown a practice round of the types of questions in Part 1.

If you need to refer back to the instructions for this part of the experiment at any point, you can click on the following link: (Part One Instructions). This link will always be located on the bottom of your screen during Part 1 of the experiment.

If a 225 dot grid is Blue, how many more blue dots will there be than red dots?

If a 100 dot grid is Red, how many more red dots will there be than blue dots?

True or False: Any given grid is equally likely to be Blue or Red.

- True
- False

Next

Practice Question

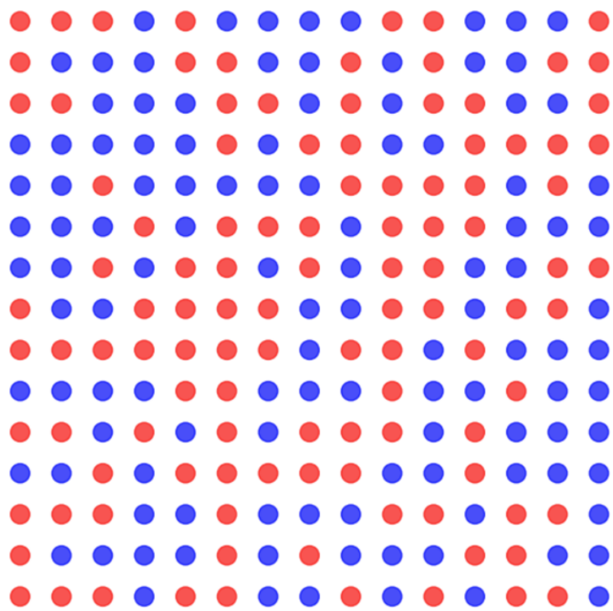
You will now have the chance to complete a practice question. The general format of this question is the same format as all other questions in Part 1 of the experiment, although as stated in the instructions the type of grid will vary from block to block. This Practice Question will not be included in those randomly selected for payment, it is just for practice.

Practice Question

This round, your grid is a **100-Dot** grid.

It is equally likely the grid is Red (8 more red dots than blue dots) or Blue (8 more blue dots than red dots)

The 30 second timer will show here



You will earn 75 points for a correct classification, and 25 points for an incorrect classification.

Your classification:

Red Blue

(Part One Instructions)

Begin Part 1

You will now proceed with Part 1 of the experiment. As a reminder, this part consists of 30 questions, broken into 6 blocks of 5 questions. At the start of each block you will be told the type of grids you will see in that block.

You have up to 30 seconds to make your decision once you have been shown the grid. You cannot go back once you submit your answer. You will not receive any feedback after each round.

Next

New Block: Block 1 of 6: Type 100-Dot Grid

For all five rounds in this block, you will be shown a **100-Dot** grid.

It is equally likely the grid is Red (8 more red dots than blue dots) or Blue (8 more blue dots than red dots)

As in all rounds of Part 1, you will earn 75 points for a correct classification and 25 points for an incorrect classification.

You may now start this block by clicking the "Next" button below.

Next

(Part One Instructions)

Loading Screen
Block 1 of 6: 100-Dot Grid
Question 1 of 5

Recall: Your grid is a **100-Dot** grid.

This means is equally likely the grid is Red (8 more red dots than blue dots) or Blue (8 more blue dots than red dots)

You will earn 75 points for a correct classification, and 25 points for an incorrect classification.

When you click the Next button below, you will be shown the above information, in addition to the dot grid. You will then have up to 30 seconds to make your decision.

Next

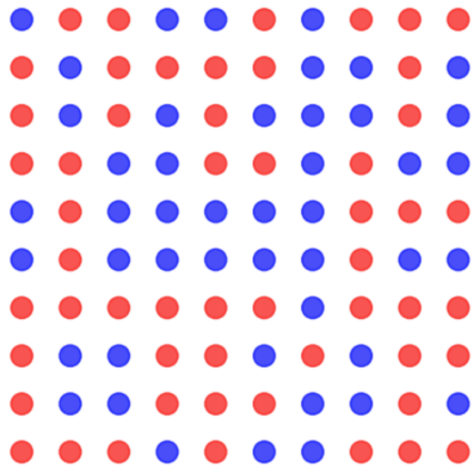
(Part One Instructions)

Block 1 of 6: 100-Dot Grid
Question 1 of 5

Recall: Your grid is a **100-Dot** grid.

This means is equally likely the grid is Red (8 more red dots than blue dots) or Blue (8 more blue dots than red dots)

Time Remaining: 29 seconds



You will earn 75 points for a correct classification, and 25 points for an incorrect classification.

Your classification:

Red Blue

(Part One Instructions)

Part 2 Instructions

Part 2 Instructions

The next few screens will explain the instructions for Part 2 of this experiment.

Part 2 of the experiment will consist of 128 questions. These will be spread out in 8 blocks of 15 questions, with blocks 5-8 having two extra questions at the end of each block (to be explained when you reach those questions).

Part 2 Instructions: The Setup

At the start of Part 2, you will be assigned to one of two roles, called Red Player and Blue Player. Each round, you will be randomly matched with another Prolific user of the other role type. Recall that only Prolific users between the ages of 18-30, residing in the United States, and with at least a high school degree in education are eligible to participate in this experiment.

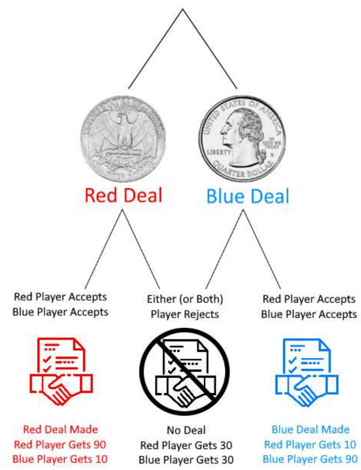
Each round (with the exclusion of the extra questions mentioned, to be described later), you and this other player will be deciding whether to Accept or Reject a deal.

Your payoffs resulting from a deal being made depend on the type of deal. There are two types of deals: Red Deals and Blue Deals, each equally likely (i.e. there is a 50% probability the deal is Red and a 50% probability the deal is Blue). Note that the deal in each round will be the same for each player. For example, if one player is shown a Red deal, the other play is also shown a Red deal. Again, whether the deal is Red or Blue is determined independently each round. You can think of this as a coin flip that occurs each round, and on heads the deal is Blue and on tails the deal is Red.

Part 2 Instructions: Your Actions and Payoffs

As mentioned, both you and the other player are going to decide to Accept or Reject a deal. A deal is only made if both players Accept the deal. If either or both players Reject a deal, it is not made, and both players will receive 30 points (regardless of the color of the deal). If a deal is made, however, the payoffs for each player will depend on the color of the deal:

- If both players Accept a Red Deal, the Red Player receives 90 points and the Blue Player receives 10 points
- If both players Accept a Blue Deal, the Blue Player receives 90 points and the Red Player receives 10 points

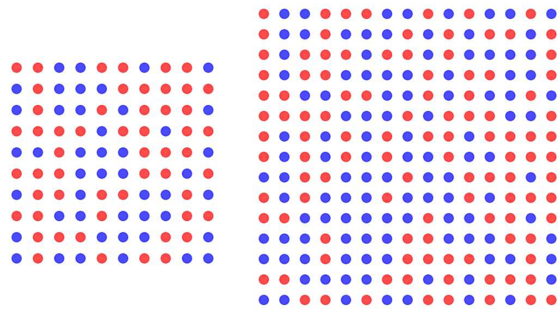


Part 2 Instructions: Determining the Type of Deal

While the above payment scheme is always true, you will have to determine whether you think the deal is Red or Blue by examining a grid of red and blue dots, as in the previous part of the experiment. A Red deal is represented by a Red grid, and a Blue deal is represented by a Blue grid. Recall a Red grid is one with more red dots than blue dots, and a Blue grid is one with more blue dots than red dots.

Like in Part 1, from block to block you will be shown different grid types, either 100-Dot grids or 225-Dot grids. However, in Part 2, the other player will also be shown different grid types from block to block, either 100-Dot grids or 225-Dot grids. At the start of each block, you'll be told the type of grids you will be shown, and the type of grid the other player will be shown. Recall:

- 100-Dot grids will have 100 dots in a 10 by 10 grid. There will be 8 more blue dots than red dots on Blue grids and 8 more red dots than blue dots on Red grids
- 225-Dot grids will have 225 dots in a 15 by 15 grid. There will be 5 more blue dots than red dots on Blue grids, and 5 more red dots than blue dots on Red grids



100-Dot Grid Example (Left), 225-Dot Grid Example (Right)

Part 2 Instructions: Blocks

There are 8 blocks of 15 questions each of the above type. There will be two blocks each of the following setups:

- Red Player and Blue Player both shown 100-Dot grids
- Red Player and Blue Player both shown 225-Dot grids
- Red Player is shown 100-Dot grid, while Blue Player is shown 225-Dot grid
- Red Player is shown 225-Dot grid, while Blue Player is shown 100-Dot grid

These 8 blocks will appear in random order. At the start of each block, you will be given a description of that block.

Part 2 Instructions: Time Limit and Reminders

Like in Part 1, once you are shown your grid you will have up to 30 seconds to decide whether to Accept or Reject the deal. Once you have made your decision, you can proceed to the next round. After proceeding, you cannot go back to previous rounds. You will also receive no feedback after each round.

As a reminder, one of the 159 rounds that make up Parts 1-3 will be randomly selected for payment at the end of the experiment. Should a round from this part be selected for payment, you will receive your payment in points according to the payoffs described above. Recall that these points then correspond to your probability of winning a $10 bonus payment (via the timer mechanism).

Role Assignment

For all Blocks in Part 2 of the experiment, you have been assigned the role of **Red Player**.

On the next screen, you will again be shown a brief comprehension quiz before starting Part 2 of the experiment. Please make sure you understand the instructions before moving on.

Next

Comprehension Quiz

Please answer the below questions to test your understanding of the instructions for Part 2. These questions are solely to check your understanding of the instructions, and have no influence on your payment.

You must answer all questions correctly before moving to the next screen. Once you have answered each question correctly, we will provide an explanation to the answers to each question on the next page.

If you need to refer back to the instructions for this part of the experiment at any point, you can click on the following link: (Part Two Instructions). This link will always be located on the bottom of your screen during Part 2 of the experiment.

For all 120 rounds of Part 2 of the experiment, you have been randomly assigned to the role of **Player Red**.

Please answer the below questions to test your understanding of the instructions for Part 2. These questions are solely to check your understanding of the instructions, and have no influence on your payment. If you have any questions, please raise your hand.

For questions 1-4, suppose you are a Red Player, and the grid on your screen is Red.

1. How many points will you receive if both you and the other player choose Accept?

2. How many points will the other player receive if you and the other player choose Accept?

3. How many points will you receive if you choose Reject?

4. How many points will you receive if the other player chooses Reject?

---

5. True or False: In any given round, you and the other player will have the same color grids

- True
- False

Next

Comprehension Quiz: Answers

For your reference, below are the correct answers for the comprehension quiz, and their explanation.

For questions 1-4, suppose you are a Red Player, and the grid on your screen is Red.

1. How many points will you receive if both you and the other player choose Accept?

   90 points. If both you and the other player Accept, then the deal is made. Since the deal is Red, you will earn 90 points.

2. How many points will the other player receive if you and the other player choose Accept?

   90 points. If both you and the other player Accept, then the deal is made. Since the deal is Red, the Blue Player will receive 10 points.

3. How many points will you receive if you choose Reject?

   30 points. If you choose to Reject the deal--regardless of what the other player chooses--you will receive 30 points. Note that in this case the color of the deal does not matter, a rejected deal will always pay both you and the other player 30 points.

4. How many points will you receive if the other player chooses Reject?

   30 points. If the other player chooses to Reject the deal--regardless of what you choose--the deal will not be made, and you will receive 30 points. Note that in this case the color of the deal does not matter, a rejected deal will always pay both you and the other player 30 points.

---

5. True or False: In any given round, you and the other player in your round always have the same color majority on your grids

   True. You and the other player will always have the same color majority in any specific round.

You can now proceed with the experiment. Recall that you have 30 seconds to complete each round.

Next

(Part Two Instructions)

Begin Part 2

You will now proceed with Part 2 of the experiment. Recall Part 2 consists of 8 blocks of 15 questions each, in addition to two extra questions at the ends of Blocks 5-8.

You have up to 30 seconds to make your decision (Accept or Reject) once you have been shown the grid. Once you have submitted your answer for a particular question, you cannot go back. You will not receive any feedback after each round.

Next

(Part Two Instructions)

New Block: Block 1 of 8

You are now beginning a new block, consisting of 15 questions.

In all 15 questions, you will be presented with a **225-Dot grid** and the other player will be presented with a **225-Dot grid**.

As a reminder:

- A 225-Dot grid consists of 225 dots, with 5 more red dots if the deal is "Red" and 5 more blue dots if the deal is "Blue".

It is equally likely that the deal is Red or Blue. You and the other player will both be seeing the same color deal.

- If either or both party rejects a deal of any color, you will both receive 30 points.
- If you both accept a Red deal, you will get 90 points and the other player will get 10 points.
- If you both accept a Blue deal, you will get 10 points and the other player will get 90 points.

You may now start this block by clicking the "Next" button below.

Next

(Part Two Instructions)

Loading Screen
Block 1 of 8
Question 1 of 15

Your Grid: 225-Dot Grid | Blue Player's Grid: 225-Dot Grid

Reminder: In all rounds of this block:

Your (Player Red's) Image:	225-Dot Grid
Blue Player's Image:	225-Dot Grid

As a reminder:

- A225-Dot grid consists of 225 dots, with 5 more red dots if the deal is "Red" and 5 more blue dots if the deal is "Blue".

Reminder: In all rounds of Part 2:

It is equally likely that the deal is Red or Blue. You and the other player will both be seeing the same color deal.

- If either or both party rejects a deal of any color, you will both receive 30 points.
- If you both accept a Red deal, you will get 90 points and the other player will get 10 points.
- If you both accept a Blue deal, you will get 10 points and the other player will get 90 points.

When you click the Next button below, you will be shown the above information, in addition to the dot grid. You will then have up to 30 seconds to make your decision.

Next

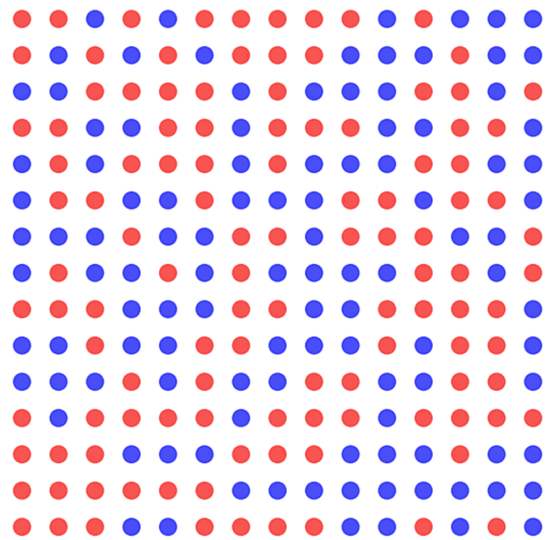
(Part Two Instructions)

Block 1 of 8

Question 1 of 15

Your Grid: 225-Dot Grid | Blue Player's Grid: 225-Dot Grid

Time Remaining: 21 seconds



Accept Reject

Reminder: In all rounds of this block:

Your (Player Red's) Image:	225-Dot Grid
Blue Player's Image:	225-Dot Grid

As a reminder:

- A225-Dot grid consists of 225 dots, with 5 more red dots if the deal is "Red" and 5 more blue dots if the deal is "Blue".

Reminder: In all rounds of Part 2:

It is equally likely that the deal is Red or Blue. You and the other player will both be seeing the same color deal.

- If either or both party rejects a deal of any color, you will both receive 30 points.
- If you both accept a Red deal, you will get 90 points and the other player will get 10 points.
- If you both accept a Blue deal, you will get 10 points and the other player will get 90 points.

(Part Two Instructions)

End of Block 8: Beliefs

Before moving onto the next block, we'd like to ask for your beliefs about how often the other player chose to Accept in the previous block.

Specifically, we're interested in what percent of Red deals and Blue deals you think the other player accepted in the last block.

If either of these questions is selected at random for payment, you will earn more points if the error in your belief (the distance between your reported belief and the actual percentage) is small. If you wish, you can view the specific relationship between your error and your points is demonstrated on a graph by clicking .

this link.

If you are roughly correct, you will earn close to 100 points. As your error becomes larger and larger, your payment will become lower and lower. If your error is more than 50 percentage points, you will receive 0 points.

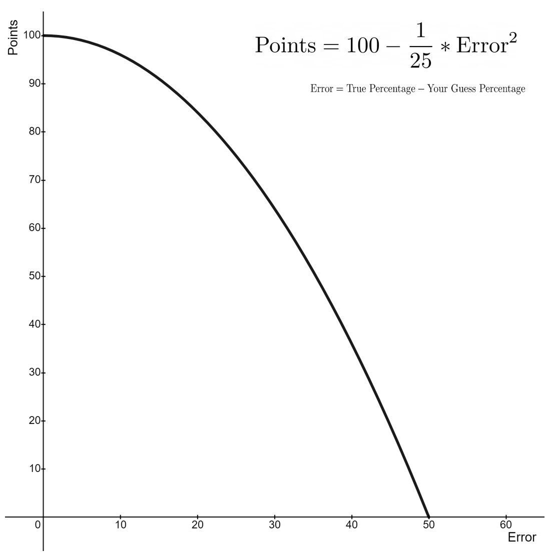
This payment mechanism was designed so that it is financially in your best interest to report your true beliefs. So, **the best thing you can do to maximize your expected earnings is to simply state your true beliefs about what you think the other player will do. Any other guess will decrease the amount you can expect to earn.**

Recall that in the previous block, you had a 225-Dot grid and the other player had a 100-Dot image.

What percent (out of 100) of Red deals do you think the other player accepted in this last block?

What percent (out of 100) of Blue deals do you think the other player accepted in this last block?

Next



Part Three Instructions

Part 3 of the experiment consists of one round. In this round, you will be matched with another Prolific participant. As a reminder, all participants of this experiment are Prolific users between the ages of 18 and 30, located in the United States, with at least a high school education.

You and this other player will play a game in which each player requests an amount of points. This amount must be a whole number between 51 and 60 points. Each player will receive the amount they request. A player will receive an additional amount of 20 points if they ask for exactly one point less than the other player.

As a reminder, one of the 159 questions that make up Parts 1-3 will be randomly selected for payment at the end of the experiment. Should the question from this part be selected for payment, you will receive your payment in points according to the payoffs described above. Recall that these points then correspond to your probability of winning a $10 bonus payment.

Next

Your Request

You and another player are playing a game in which each player requests an amount of points. The amount must be a whole number between 51 and 60 points. Each player will receive the amount they request. A player will receive an additional amount of 20 points if they ask for exactly one point less than the other player.

What amount of ECUs do you request?

Next

Survey Page 1 of 3

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

If it takes 5 machines 5 minutes to make 5 widgets, how long in minutes would it take 100 machines to make 100 widgets?

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 in days would it take for the patch to cover half the lake?

Next

Survey Page 2 of 3

Before calculating your earnings for this experiment, please fill out the following survey. These questions do not have any effect on your payment, but we ask you please complete them to the best of your ability.

Which best describes the highest level of education you have attained?

With which gender do you identify?

Next

Survey Page 3 of 3

For questions 1-6 below, we describe a type of round you faced in Part Two. Select the option that best describes your typical strategy for that type of question. If you need help recalling the instructions for this part of the experiment, you can click on the following link: (Part Two Instructions)

1. You had a 100 Dot grid and the other player had a 100 Dot grid

----

I did not count any dots on the image
I counted some of the dots on the image
I counted all of the dots on the image

ad a 100 Dot grid

3. You had a 100 Dot grid and the other player had a 225 Dot grid

----

4. You had a 225 Dot grid and the other player had a 225 Dot grid

----

5. When you had the 100 Dot task, how did your strategy depend on the task of the other player?

6. When you had the 225 Dot task, how did your strategy depend on the task of the other player?

7. Please explain as clearly as possible what your strategy was in general in the games in Part Two of this experiment. When did you try harder to avoid making mistakes? What type of mistakes did you try to avoid making (accepting the wrong deals, or rejecting the right deals)?

8. What do you think this experiment was trying to study?

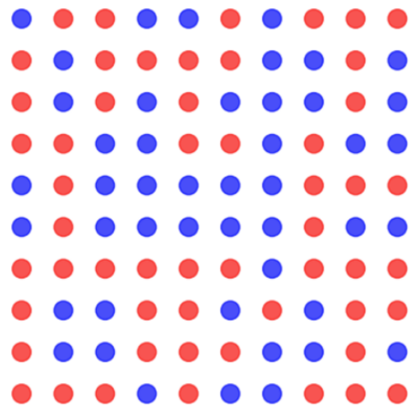
Next

Results

You have reached the end of the experiment. Thank you for your participation.

Out of the 159 questions that make up Parts 1-3 of the experiment, Question 1 of Block 1 of Part 1 was randomly selected for payment.

As a reminder, in this part of the experiment you were playing the single player game. In this specific round, you were shown a 100-Dot grid. Specifically, you were shown the grid below:



You were told you would earn 75 points for correctly guessing whether the grid was Blue or Red, and 25 points for guessing this incorrectly.

The grid in this question, displayed above, was Red. You classified it as Red.

Thus, your payment from this randomly selected question is 75 points.

As described at the beginning of the experiment, you will receive a Prolific message no later than 7 days from now with a Qualtrics link. You will log-in to this Qualtrics survey with your Prolific ID, and there you will see a summary of the above and the points you ended up receiving (if they depend on the choices of other subjects). You will then draw from a random lottery that gives a X percent probability of winning a $10 bonus payment, where X is the number of points you earned. Please be on the lookout for this Prolific message!

Thank you for your participation in this experiment. Please click the completion link below to make sure you get your completion payment.

You may wish to print this screen, or save an image of it for your records.

Click Here To Print Screen!

Important: Click here to complete the study (you must click this in order for Prolific to register you as completed)

E Instructions (Experiment 2)

Note: Part 1 of Experiment 2 is entirely identical to that of Experiment, and are thus excluded below.

Part 2 Instructions

Part 2 of the experiment will consist of 128 questions. These will be spread out in 8 blocks of 15 questions, with blocks 5-8 having two extra questions at the end of each block (to be explained when you reach those questions).

Part 2 Instructions: The Setup

At the start of Part 2, you will be assigned to one of two roles, called Red Player and Blue Player. Each round, you will play a game with a pre-programmed Computer player of the other role type. This Computer player has been programmed to play in a specific way, to be fully detailed later. Importantly, the Computer player's behavior is completely independent of your choices--the Computer player follows a pre-determined strategy that does not depend on your choices.

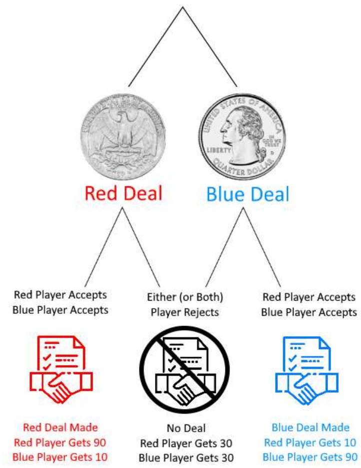
Each round (with the exclusion of the extra questions mentioned, to be described later), you and the Computer will be deciding whether to Accept or Reject a deal.

Your payoffs resulting from a deal being made depend on the type of deal. There are two types of deals: Red Deals and Blue Deals, each equally likely (i.e. there is a 50% probability the deal is Red and a 50% probability the deal is Blue). Note that the deal in each round will be the same for you and the Computer. For example, if the deal is Red for you, the deal is also Red for the Computer. Again, whether the deal is Red or Blue is determined independently each round. You can think of this as a coin flip that occurs each round, and on heads the deal is Blue and on tails the deal is Red.

Part 2 Instructions: Your Actions and Payoffs

As mentioned, both you and the Computer are going to decide to Accept or Reject a deal. A deal is only made if both you and the Computer accept the deal. If either or both you and the Computer reject a deal, it is not made, and you will receive 30 points (regardless of the color of the deal). If a deal is made, however, your payoffs will depend on the color of the deal:

- If both you and the Computer accept a Red Deal, a Red Player would receive 90 points, and a Blue Player would receive 10 points
- If both you and the Computer accept a Blue Deal, a Blue Player would receive 90 points and the Red Player would receive 10 points

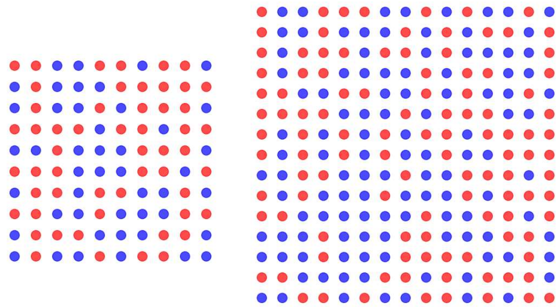


Part 2 Instructions: Determining the Type of Deal

While the above payment scheme is always true, you will have to determine whether you think the deal is Red or Blue by examining a grid of red and blue dots, as in the previous part of the experiment. A Red deal is represented by a Red grid, and a Blue deal is represented by a Blue grid. Recall a Red grid is one with more red dots than blue dots, and a Blue grid is one with more blue dots than red dots.

Like in Part 1, from block to block you will be shown different grid types, either 100-Dot grids or 225-Dot grids. At the start of each block, you'll be told the type of grids you will be shown. Recall:

- 100-Dot grids will have 100 dots in a 10 by 10 grid. There will be 8 more blue dots than red dots on Blue grids and 8 more red dots than blue dots on Red grids
- 225-Dot grids will have 225 dots in a 15 by 15 grid. There will be 5 more blue dots than red dots on Blue grids, and 5 more red dots than blue dots on Red grids



100-Dot Grid Example (Left), 225-Dot Grid Example (Right)

Part 2 Instructions: The Computer Players

We will now describe how Computer players will behave in this experiment. There will be two different types of Computer, we will call them **30:80** and **50:65**. Each type of Computer can be of either role type (if you are a Red player the Computer will always be Blue, and if you are a Blue player the Computer will always be Red).

The computers differ by how often they choose to Accept a deal of their role color, and a deal of your role color.

Computer **30:80** will:

- Accept a deal of *your* role color **30%** of the time
- Accept a deal of *their* role color **80%** of the time

Computer **50:65** will:

- Accept a deal of *your* role color **50%** of the time
- Accept a deal of *their* role color **65%** of the time

To help you remember this, we will color the Computer names appropriately. For example, if you are a Blue Player, the 50:65 Computer will be written as "50:65", as it accepts 50% of Blue deals and 65% of Red deals. If you are a Red Player, the 50:65 computer will instead be written as "50:65", as it accepts 50% of Red Deals and 65% of Blue Deals.

Note that the Computer's strategy is completely independent of the choices you make, in that round or in previous rounds.

Whether you play a Computer 30:80 or Computer 50:65 player will differ from block to block, and you will be told this beforehand.

Part 2 Instructions: Blocks

There are 8 blocks of 15 questions each of the above type. There will be two blocks each of the following setups:

- You have 100-Dot grids, the Computer Player is 30:80
- You have 100-Dot grids, the Computer Player is 50:65
- You have 225-Dot grids, the Computer Player is 30:80
- You have 225-Dot grids, the Computer Player is 50:65

These 8 blocks will appear in random order. At the start of each block, you will be given a description of that block.

Part 2 Instructions: Time Limit and Reminders

Like in Part 1, once you are shown your grid you will have up to 30 seconds to decide whether to Accept or Reject the deal. Once you have made your decision, you can proceed to the next round. After proceeding, you cannot go back to previous rounds. You will also receive no feedback after each round.

As a reminder, one of the 159 rounds that make up Parts 1-3 will be randomly selected for payment at the end of the experiment. Should a round from this part be selected for payment, you will receive your payment in points according to the payoffs described above. Recall that these points then correspond to your probability of winning a $10 bonus payment (via the timer mechanism).

On the next screen you will be shown your random role assignment (Red Player or Blue Player), which will remain the same throughout all blocks of Part 2. After that, you will be asked to complete a brief comprehension quiz.

Role Assignment

For all Blocks in Part 2 of the experiment, you have been assigned the role of **Red Player**.

On the next screen, you will again be shown a brief comprehension quiz before starting Part 2 of the experiment. Please make sure you understand the instructions before moving on.

Next

Comprehension Quiz

Please answer the below questions to test your understanding of the instructions for Part 2. These questions are solely to check your understanding of the instructions, and have no influence on your payment.

You must answer all questions correctly before moving to the next screen. Once you have answered each question correctly, we will provide an explanation to the answers to each question on the next page.

If you need to refer back to the instructions for this part of the experiment at any point, you can click on the following link: (Part Two Instructions). This link will always be located on the bottom of your screen during Part 2 of the experiment.

For all 120 rounds of Part 2 of the experiment, you have been randomly assigned to the role of **Player Red**.

Please answer the below questions to test your understanding of the instructions for Part 2. These questions are solely to check your understanding of the instructions, and have no influence on your payment. If you have any questions, please raise your hand.

For all of the following questions, suppose you are a Red Player.

For Questions 1-3, suppose the grid on your screen is Red.

1. How many points will you receive if both you and the Computer choose Accept?
2. How many points will you receive if you choose Reject?
3. How many points will you receive if the Computer chooses Reject?

---

4. Suppose you are playing a Computer 30:80. What percent of Red deals will the Computer Accept?
5. Suppose you are playing a Computer 30:80. What percent of Blue deals will the Computer Accept?
6. Suppose you are playing a Computer 50:65. What percent of Red deals will the Computer Accept?
7. Suppose you are playing a Computer 50:65. What percent of Blue deals will the Computer Accept?

Next

Comprehension Quiz: Answers

For your reference, below are the correct answers for the comprehension quiz, and their explanation.

For all of the following questions, suppose you are a Red Player.

For Questions 1-3, suppose the grid on your screen is Red.

1. How many points will you receive if both you and the Computer choose Accept?

    90 points. If both you and the Computer Accept, then the deal is made. Since the deal is Red, you will earn 90 points.

2. How many points will you receive if you choose Reject?

    30 points. If you choose to Reject the deal--regardless of what the Computer chooses--you will receive 30 points. Note that in this case the color of the deal does not matter, a rejected deal will always pay you 30 points.

3. How many points will you receive if the Computer chooses Reject?

    30 points. If the Computer chooses to Reject the deal--regardless of what you choose--the deal will not be made, and you will receive 30 points. Note that in this case the color of the deal does not matter, a rejected deal will always pay you 30 points.

---

4. Suppose you are playing a Computer 30:80. What percent of Red deals will the Computer Accept?

    30 percent. Since you are a Red Player, the Computer is a Blue Player. This means it will accept a Red deal (which is not its role color) 30% of the time.

5. Suppose you are playing a Computer 30:80. What percent of Blue deals will the Computer Accept?

    80 percent. Since you are a Red Player, the Computer is a Blue Player. This means it will accept a Blue deal (which is its role color) 80% of the time.

6. Suppose you are playing a Computer 50:65. What percent of Red deals will the Computer Accept?

    50 percent. Since you are a Red Player, the Computer is a Blue Player. This means it will accept a Red deal (which is not its role color) 50% of the time.

7. Suppose you are playing a Computer 50:65. What percent of Blue deals will the Computer Accept?

    65 percent. Since you are a Red Player, the Computer is a Blue Player. This means it will accept a Red deal (which is its role color) 65% of the time.

Next

(Part Two Instructions)

Begin Part 2

You will now proceed with Part 2 of the experiment. Recall Part 2 consists of 8 blocks of 15 questions each, in addition to two extra questions at the ends of Blocks 5-8.

You have up to 30 seconds to make your decision (Accept or Reject) once you have been shown the grid. Once you have submitted your answer for a particular question, you cannot go back. You will not receive any feedback after each round.

Next

(Part Two Instructions)

New Block: Block 1 of 8

You are now beginning a new block, consisting of 15 questions.

In all 15 questions, you will be presented with a **100-Dot grid** and you will play **Computer 50:65**.

As a reminder:

- Computer 50:65 will accept **50%** of Red deals
- Computer 50:65 will accept **65%** of Blue deals
- A 100-Dot grid consists of 100 dots, with 8 more red dots if the deal is "Red" and 8 more blue dots if the deal is "Blue".

It is equally likely that the deal is Red or Blue.

- If either (or both) you or the Computer Player rejects a deal of any color, you will receive 30 points.
- If both you and the Computer Player accept a Red deal, you will get 90 points.
- If both you and the Computer Player accept a Blue deal, you will get 10 points.

You may now start this block by clicking the "Next" button below.

Next

(Part Two Instructions)

Loading Screen
Block 1 of 8
Question 1 of 15

Your Grid: 100-Dot Grid | Computer Player: 50:65

Reminder: In all rounds of this block:

- Computer 50:65 will accept **50%** of Red deals
- Computer 50:65 will accept **65%** of Blue deals
- A 100-Dot grid consists of 100 dots, with 8 more red dots if the deal is "Red" and 8 more blue dots if the deal is "Blue".

Reminder: In all rounds of Part 2:

It is equally likely that the deal is Red or Blue.

- If either (or both) you or the Computer Player rejects a deal of any color, you will receive 30 points.
- If both you and the Computer Player Accept a Red deal, you will get 90 points.
- If both you and the Computer Player Accept a Blue deal, you will get 10 points.

When you click the Next button below, you will be shown the above information, in addition to the dot grid. You will then have up to 30 seconds to make your decision.

Next

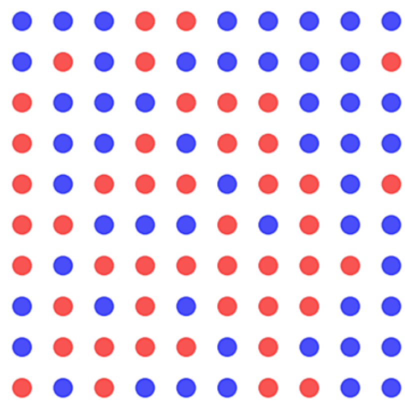
(Part Two Instructions)

Block 1 of 8

Question 1 of 15

Your Grid: 100-Dot Grid | Computer Player: 50:65

Time Remaining: 17 seconds



Accept   Reject

Reminder: In all rounds of this block:

- Computer 50:65 will accept 50 % of Red deals
- Computer 50:65 will accept 65 % of Blue deals

- A 100-Dot grid consists of 100 dots, with 8 more red dots if the deal is "Red" and 8 more blue dots if the deal is "Blue".

Reminder: In all rounds of Part 2:

It is equally likely that the deal is Red or Blue.

- If either (or both) you or the Computer Player rejects a deal of any color, you will receive 30 points.
- If both you and the Computer Player Accept a Red deal, you will get 90 points.
- If both you and the Computer Player Accept a Blue deal, you will get 10 points.

(Part Two Instructions)

End of Block 8: Beliefs

Before moving onto the next block, we'd like to ask for your beliefs about how often a Player of *the other role type* chose to Accept in the previous block (when they had a 100-Dot image and played a Computer 30:80 (note that since this other player was of the other role type, this meant the computer accepted 30% of Red deals and 80% of Blue deals).

Specifically, we're interested in what percent of Red deals and Blue deals you think a randomly selected Blue Player accepted in the last block. This other player is selected at random from other human subjects who completed this same experiment on Prolific. Recall that Blue Players have the exact same setup as you, however they earn 90 points when a Blue deal is made, and 10 points when a Red deal is made.

If either of these questions is selected at random for payment, you will earn more points if the error in your belief (the distance between your reported belief and the actual percentage) is small. If you wish, you can view the specific relationship between your error and your points is demonstrated on a graph by clicking this link.

If you are roughly correct, you will earn close to 100 points. As your error becomes larger and larger, your payment will become lower and lower. If your error is more than 50 percentage points, you will receive 0 points.

This payment mechanism was designed so that it is financially in your best interest to report your true beliefs. So, **the best thing you can do to maximize your expected earnings is to simply state your true beliefs about what you think the other player will do. Any other guess will decrease the amount you can expect to earn.**

Recall that in the previous block, this player had a 100-Dot grid and played against a Computer 30:80.

What percent (out of 100) of Red deals do you think this Blue player accepted in this last block?

What percent (out of 100) of Blue deals do you think this Blue player accepted in this last block?

Next

(Part Two Instructions)

Note: The 11-20 Game, CRT, and Demographic questions are identical to those in Experiment 1, and are thus excluded below.

Survey Page 3 of 3

For questions 1-6 below, we describe a type of round you faced in Part Two. Select the option that best describes your typical strategy for that type of question. If you need help recalling the instructions for this part of the experiment, you can click on the following link: (Part Two Instructions)

1. You had a 100 Dot grid and the computer was Computer 30:80

----

2. You had a 225 Dot grid and the computer was Computer 30:80

----

3. You had a 100 Dot grid and the computer was Computer 50:65

----

4. You had a 225 Dot grid and the computer was Computer 50:65

---

5. When you had the 100 Dot task, how did your strategy depend on which computer you were playing?

6. When you had the 225 Dot task, how did your strategy depend on which computer you were playing?

---

7. Please explain as clearly as possible what your strategy was in general in the games in Part Two of this experiment. When did you try harder to avoid making mistakes? What type of mistakes did you try to avoid making (accepting the wrong deals, or rejecting the right deals)?

8. What do you think this experiment was trying to study?

Next

F Instructions: Timer Payment Mechanism

F.1 Practice

Practice Timer Task

You will see the following instructions before playing the timer task:

On the next screen you will see a clock, like the one below. The time from this clock is in milliseconds and uses your computer's clock. You will have one chance to stop this clock. The right-most two digits are then your random number, between 0 and 99. If this random number is strictly lower than your earnings in points, you will earn a $10 bonus payment.

4409

On the next page, you will be able to practice this task. Recall this is just to show you how the timing mechanism works and will not affect any actual payments.

→

Powered by Qualtrics

Click "Stop" below to stop the timer. Remember you can only click the "Stop" button once. The last two digits will be your random number. If this random number is strictly lower than your earnings in points, you would earn the $10 bonus payment. Once you have stopped the clock, go the next page to read a summary.

16418

Stop

→

Your random number was 16418.

The last two digits were 18. If this number is strictly lower than your earnings in points, you would be awarded the $10 bonus payment. If it is not strictly lower, you would not earn the bonus payment.

You can try this task again as many times you want by going to the next page. Feel free to stop whenever you want. Note that when you do this to determine your bonus, you will not be able to try this task more than once.

→

F.2 Payment

Please log in.

Prolific ID

→

Thank you for completing the experiment!

On the next screen you will be shown a summary of your results, including how many points you earned.

After this, whether or not you win the $10 bonus payment will be randomly determined via the timer mechanism described in the experimental instructions. Recall that your number of points will be equal to your probability, in percent, of winning the bonus payment.

→

Out of all of the questions in parts 1-3 of the experiment, Question 5 of Block of Part 2 was randomly selected for payment.

If desired, instructions for this round can be found here.

In this question, you were shown a grid, and the other player was shown a grid.

You were a Player and you chose to Accept. The grid in this question was actually Red.

Your opponent chose Reject. Your earnings from this question are thus 30 points.

If any of the above is inconsistent with your records, please reach out to the experimenter via Prolific message.

→

On the next screen you will see a clock, like the one below. The time from this clock is in milliseconds and uses your computer's clock. You will have one chance to stop this clock. The right-most two digits are then your random number, between 0 and 99. If this random number is strictly less than your earnings in points (which was 30), you will earn a $10 bonus payment. This bonus payment will be awarded on Prolific within 24 hours.

1874

IMPORTANT: To prevent subjects from retaking the lottery, once you move onto the next screen, you will be unable to restart this survey. Please do not refresh the screen or attempt to restart the survey.

Please re-enter your Prolific ID below if you agree with these conditions.

→

Click "Stop" below to stop the timer. Remember you can only click the "Stop" button once. If you leave this page before clicking stop, the timer will stop at the moment you leave the page.

The last two digits will be your random number. If this random number is strictly lower than your earnings in points (which was 30), you will earn the $10 bonus payment. Once you have stopped the clock, please go the next page to get confirmation on your earnings.

4561

Stop

→

Your random number was 4561.

The last two digits were 61. Recall your earnings were 30 points.

Since your random number was greater than or equal to 30, you have not earned the $10 bonus payment.

Thank you for completing this experiment. On the next page, you can find a summary of your results below for your records, if you so choose.

→