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Planned vs. Actual Attention

Ala Avoyan,[a,*] Mauricio Ribeiro,[b] Andrew Schotter,[b,c] Elizabeth R. Schotter,[d] Mehrdad Vaziri,[e] Minghao Zou[f]

[a] Department of Economics, Indiana University, Bloomington, Indiana 47405; [b] School of Economics, University of Bristol, Bristol BS8 1TU, United Kingdom; [c] Department of Economics, New York University, New York, New York 10003; [d] Department of Psychology, University of South Florida, Tampa, Florida 33620; [e] School of Geosciences, University of South Florida, Tampa, Florida 33620; [f] Department of Economics, Princeton University, Princeton, New Jersey 08540

*Corresponding author

Contact: aavoyan@iu.edu, https://orcid.org/0000-0002-7597-2045 (AA); mauricio.ribeiro@bristol.ac.uk (MR); andrew.schotter@nyu.edu, https://orcid.org/0000-0002-6157-6084 (AS); eschotter@usf.edu (ERS); mehrdadv@mail.usf.edu (MV); mzou@princeton.edu (MZ)

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Abstract. People often need to plan how to allocate their attention across different tasks. In this paper, we run two experiments to study a stylized version of this attention-allocation problem between strategic tasks. More specifically, we present subjects with pairs of 2×2 games, and for each pair, we give them 10 seconds to decide how they would split a fixed time budget between the two games. Then, subjects play both games without time constraints, and we use eye-tracking to estimate the fraction of time they spend on each game. We find that subjects' planned and actual attention allocation differ and identify the determinants of this mismatch. Further, we argue that misallocations can be relevant in games in which a player's strategy choice is sensitive to the time taken to reach a decision.

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1. Introduction

People routinely plan how to split their time—and, hence, attention—between different tasks. This planning can require careful deliberation. However, we are often time-constrained and, hence, have to plan quickly. This ability to plan under time pressure is crucial for many jobs, some of which require allocating attention across tasks with a strategic component. For instance, consider a sales manager who, in a given workday, has to decide the sales plan, motivate a team to implement it, and discuss the plan with other managers. When deciding the sales strategy, the manager has to consider the sales strategies of other companies in the market. When meeting with the team, the manager has to provide the right incentives to motivate them to carry out the sales strategy. When talking with other managers, the manager has to use bargaining skills to get the support needed from the other teams. If the manager's time is constrained, the manager has to decide how much attention to allocate to each of these different tasks. Therefore, failure to correctly allocate time/attention can affect performance on the job because, as noted by Kahneman (2003), Rubinstein (2007, 2016), and others, the amount of time spent making a decision may lead to different choices.

An experienced manager also knows that the manager will face unexpected problems and demands and, hence, that the manager does not have a precise estimate of the amount of time the manager will have to allocate to the different tasks the manager plans to execute. The manager then allocates fractions of the ambiguous time budget to different tasks (e.g., "Most of my time today will go to defining our sales plan"). In fact, there are many jobs in which a person needs to plan a schedule under an unknown time constraint. For instance, think of a physician working at an intensive care unit who has to plan how to allocate time during a shift between several incoming patients.

Whereas there is some consideration of how people plan their time allocation—and, hence, their attention allocation—across nonstrategic tasks (cf. Radner and Rothschild 1975), less attention is paid to how they allocate attention across strategic tasks, particularly when they face a time constraint. We conjecture that people allocate their time based on an (intuitive) assessment of the value and the complexity of the tasks they have to complete.[1] If the assessments are inaccurate, people may allocate too much (or too little) time to a task, which can affect the quality of their decisions.

In this paper, we study a stylized version of this attention-allocation problem, namely, how people allocate attention between 2×2 games.[2] We are interested in three questions:

1. Planned versus actual attention: Are people good at planning their time/attention between games; that is, is the fraction of time they plan to spend in each game similar to the fraction of time they actually spend playing the games?
2. Why do planned and actual attention differ: If planned and actual time/attention allocation differ, what accounts for this difference?
3. Time and choice: Does time affect people's strategy choice in games, and are the effects heterogeneous? Are there games in which choices are more sensitive to the time spent reaching a decision and, for this reason, are more sensitive to time misallocation?

To address these questions, we conduct two experiments. In experiment 1, we present subjects with different pairs of games. In each pair, we give subjects 10 seconds to decide what fraction of a fixed amount of time they want to allocate to each game. When this planning phase is over, subjects play both games in a pair without time constraints. Using eye tracking, we estimate how much time a subject spent paying attention to a game and use this as a proxy of how much time was actually spent thinking about the game. Eye tracking also allows us to identify what features of the game attracted a subject's attention when planning the time allocation and when playing the games. In experiment 2, a different pool of subjects played each game presented to the subjects in experiment 1 for 60 seconds. We use the choice process protocol introduced by Agranov et al. (2015) to track their decisions throughout the 60 seconds.

Experiment 1 addresses questions 1 and 2. We find that people are not good (instinctual) planners; that is, they form inaccurate estimates of the fraction of time they will spend attending to each game in a pair. We argue that this mismatch between planned and actual time allocations is a consequence of the fact that the salient attributes of a game (e.g., its lowest and highest payoffs) can be a poor indicator of its complexity. Because subjects are time-constrained when planning, these salient attributes crucially influence their planned attention allocations. Their actual attention allocations, however, are crucially influenced by the game's strategic complexity.

Experiment 2 addresses question 3. We find that the time subjects spend attending a game affects their strategy choice in most but not all games we consider. In these games, therefore, time misallocation is payoff-relevant.

2. Experimental Design

Experiment 1 (62 subjects) aims to understand the relationship between planned and actual attention and to identify what features of the games influence subjects' planned and actual time allocations. Experiment 2 (40 subjects) is an auxiliary experiment that allows us to assess the time-dependence of choices in the games played in experiment 1. (See the online appendix for the instructions of both experiments.)

The sessions of both experiments were conducted at the experimental laboratory of the Center for Experimental Social Science at New York University during Spring 2018 (experiment 1) and Fall 2019 (experiment 2), using the software z-Tree (Fischbacher 2007) for experiment 1 and the software oTree (Chen et al. 2016) for experiment 2. Subjects were recruited using the ORSEE recruitment program (Greiner 2015) from the general undergraduate population. Eye-tracking data were collected via a Gazepoint 3 (GP3) eye tracker attached to the bottom of the computer screen (see Section 2.1.5 for further details).

Experiment 1 had 31 sessions with two subjects per session. A session lasted about 40 minutes, and subjects earned, on average, a payoff of \$27, which includes a \$10 show-up fee. In this experiment, the payoffs in the games were denominated in points (units) called experimental currency units (ECUs). For payment, ECUs were converted to U.S. dollars at the rate of 1 ECU = \$0.025. The range of payoffs in the games used in this paper is between 0 and 1,000 points, translating to 0 to 25 dollars. Experiment 2 had one session that lasted approximately 50 minutes. Subjects earned, on average, a payoff of \$20, which includes a \$7 show-up fee. The payoffs in the games were also denominated in ECUs. For payment, ECUs were converted to U.S. dollars at the rate of 1 ECU = \$0.01.

2.1. Experiment 1 (Planned vs. Actual Attention)

After providing consent, subjects are given written instructions, which are also read aloud. They are then introduced to the eye-tracking device and instructed to keep their heads as still as possible throughout the experiment, consisting of three parts. (The eye-tracking device, to be described in detail later, is nonintrusive and attached to the bottom of the computer monitor and, hence, does not involve wearing any head apparatus or placing one's head in a device to keep it still.)

2.1.1. Part 1. Part 1 has 12 rounds. In each round, subjects are shown a pair of 2×2 matrix games on the computer screen for 10 seconds. We gave subjects 10 seconds to plan their time allocation to prevent them from solving both games in a pair because, if they did, their time allocation would be irrelevant. Although, ex ante, we did not know that 10 seconds was a suitable amount of time, the average amount of time a subject spends playing a game is (roughly) 8 seconds. Therefore, on average, a subject needs 16 seconds to solve both games in a pair. Hence, the 10-second time constraint is below the average amount of time they need to solve both games, which is consistent with our goal. See Appendix A.1, Table A.2, for the average amount of time spent playing each game. The games used in the experiment represent a broad class of 2×2 games, including prisoners' dilemma, symmetric and asymmetric mixed strategy games, games of chicken, battle of the sexes, and others. The full list of games and game pairs presented to the subjects are in Appendix A.1 (Figure A.1 and Table A.1). For each game pair, the subjects are then given 10 seconds to decide what fraction of an X-second time budget they want to allocate to play each of the two games on the screen: game 1 (on the left) and game 2 (on the right). Because fractions must add up to one, subjects only decide how much to allocate to game 1. Notice that subjects do not play the games in part 1.

Importantly, we do not reveal the value of X to subjects in part 1 because the amount of time that a subject spends playing a game can vary greatly across subjects. Hence, if we revealed the value of X, some subjects could think that they have more time than they need to solve both games, which would lead to a multiplicity of their optimal planned time allocations. For these subjects, a mismatch between planned and actual attention could not be interpreted as an incorrect time allocation, being rather a consequence of their belief that the time constraint they face when playing the games is not binding. On the other hand, other subjects could think that the value X is too low and allocate all their time to one game. For these subjects, a mismatch between planned and actual attention could not be interpreted as an incorrect time allocation, but instead a consequence of their belief that they will not have enough time to solve both games. Similar to the manager in our initial example, we cannot anticipate the unexpected demands that we will face. We then often allocate fractions of our unknown time budget to different tasks.

We denote by α_{ik} the fraction of time allocated by subject i in game pair $k \in \{1, 2, \ldots, 12\}$ to game 1 (i.e., to the game on the left side of the screen). Therefore, $1 - \alpha_{ik}$ denotes the fraction of time allocated by subject i in game pair $k \in \{1, 2, \ldots, 12\}$ to game 2 (i.e., to the game on the right side of the screen).

To ensure that subjects understand how to read a game matrix and to familiarize them with the 10-second time constraint, they play three practice rounds before being presented with the 12 game pairs in which we are interested. In the first practice round, we present subjects with a pair of 2×2 matrix games containing letters in the place of payoffs (the screen is the same as in Figure A.2(a)). In the two remaining practice rounds, we present subjects with a pair of 2×2 matrix games containing three-digit numbers as payoffs (see Figure A.3(a)).

In all practice rounds, subjects have 10 seconds to look at the game pair. After the 10 seconds have passed, we ask, in a new screen, for subjects to state the fraction of X they want to allocate to game 1 by inputting a number from 0 to 100 (see Figure A.2(b)). The remaining fraction is then allocated to game 2. This two-step procedure is repeated in each of the 12 (nonpractice) rounds of part 1.

2.1.2. Part 2. Part 2 provides incentives for subjects' time allocation decisions in part 1. In part 1, we tell subjects that, in part 2, they will play both games from one of the game pairs under the time constraints implied by the fraction of time they allocated to each game in the pair. Importantly, we do not yet tell them which game pair will be selected (nor, as mentioned, what the value of X is).

At the beginning of part 2, we reveal the selected game pair, namely, game pair 1, and tell them they have 90 seconds to play both games in the pair. (Game pair 1 is then excluded from part 3 of the experiment.) If (say) a subject allocated 40% of X to game 1 in game pair 1 in the first part of the experiment, the subject would have 36 seconds to play game 1 and 54 seconds to play game 2 in part 2. Time is not transferable in part 2: if a subject has 36 seconds to play game 1 but enters the subject's choice at the 30th second, the 6 remaining seconds are not added to the 54 seconds allocated to game 2.

2.1.3. Part 3. In part 3, the subjects play the remaining 11 pairs ($k \in \{2, 3, \ldots, 12\}$) of games without time constraints. First, they play game pairs 2–4 in random order. Then, they play the remaining game pairs ($k \in \{5, 6, \ldots, 12\}$) in random order. The order in both cases is randomized at the subject level. This (block) randomization scheme allows us to test whether the repetition of some games affects our main results. Notice that a subject plays game pair 1 in part 2 and game pairs 2–4 in part 3; they have not played any game twice. Hence, if the repetition of a game affects our results, it will not affect the results for game pairs 2–4.

In part 3, the games in a game pair are displayed on the screen in the same order they appear in part 1; that is, if a game in a game pair is displayed on the left in part 1, it is also displayed on the left in part 3.[3] Moreover, subjects are no longer time-constrained: they can take as much time as they want to examine the games and make their strategy choices. Once they are done attending to the two games, they hit a button that brings them to a new screen. On this new screen, they enter their strategy choices by clicking the corresponding A or B buttons in each game of the game pair (see Figure A.3(b) for a sample screen).

2.1.4. Payments. The subjects' payoffs in experiment 1 are determined by their strategy choices in two randomly drawn games, one from game pair 1 played in part 2 and the other from a game pair played in part 3. A critical feature of the payment scheme we use is that subjects in experiment 1 are told that they are not playing these games against other subjects in the current experiment. Instead, they are playing against a "previous opponent" who played the game without any time constraints in an auxiliary experiment. In this auxiliary experiment, we had students in an undergraduate class at New York University choose a strategy in each of the games without any time constraint (these subjects played these games against each other, and they were assigned to be either row or column choosers). For each game, we randomly picked a subject that played as a column player in the game in this auxiliary experiment, and the player's choice was assigned as the column player choice in experiment 1. Therefore, a subject's payoff in experiment 1 is determined by the subject's strategy choice and the strategy choice of one of these column players. We introduce this previous opponent because we do not want our subjects to try to predict their opponent's time allocation and consequently best respond to it, engaging in a complicated time-allocation game.[4] Therefore, we attempt to preempt this possibility by using the choices of an outside opponent that is not time-constrained.

This payment scheme can, however, lead to a different problem. A subject's choice can be biased if the subject knows that the choice does not influence the payoff of any other subject in the same session. For example, a prosocial subject might choose a non-prosocial strategy because the subject knows that no one is affected by the subject's actions. To avoid such effects, we randomly divide the subjects in a session into two groups: groups 1 and 2. Each subject in group 1 is matched with a subject in group 2. The payoffs of a subject in group 1 is determined by the subject's choices and the outside opponents' choice. The subject in group 2 with which the subject is matched then receives the payoff of the outside opponent. This procedure ensures that, although subjects play against an outside opponent whose payment they cannot affect, their choice influences the payoffs of a subject in the same session.

2.1.5. Eye-Tracking Procedure and Data in Experiment 1.

We use the GP3 eye tracker, along with corresponding software Gazepoint Control and Gazepoint Analysis, to calibrate subjects and collect eye-tracking data. GP3 specifications include 0.5°–1° of visual angle accuracy, a 60-Hz update rate, 25 × 11 cm (horizontal × vertical) movement, and a ±15 cm range of depth movement.

During the experiment, subjects sit in front of a computer with a 19-inch screen placed directly in front of them with the eye tracker mounted below the monitor. They are told that the eye tracker will track their eyes and they should keep their head as still as possible during the experiment. Other than that, the eye tracker is unobtrusive, and the subjects are not fixed in any way (e.g., we did not use a chin rest).

The camera inside the GP3 turns on as soon as we start Gazepoint Control to perform a subject's calibration. We calibrated the subjects once before the experiment started. During the experiment, a research assistant tracked the subject's eyes on a separate laptop. If there were any issues with eye tracking, the research assistant would recalibrate the subject.[5]

For each game pair, we first define two areas of interest (AOIs). We partitioned the entire screen into two AOIs. One of these covers the entire game on the left, and the other covers the entire game on the right. In addition, we defined 16 AOIs centered over the 16 payoffs of the games in the pair (Figure A.4(a)). Therefore, each cell in the game matrix contains two areas of interest centered on the row and column players' payoff. AOIs around the payoff do not overlap and do not cover the entire matrix area. To answer our research questions, we record each subject's dwell time in an AOI, that is, the total amount of time the subject spent looking at the AOI.

As mentioned, we use eye tracking in experiment 1 to (i) estimate the amount of time that people spend playing a game in part 3 and (ii) keep track of what features of the game attract the subject's attention in parts 1 and 3. Eye-tracking data can be used for (i) and (ii) provided we assume that the time spent looking at a (feature of the) game is an adequate proxy for the amount of attention allocated to that (feature of the) game.[6] The main objection to this assumption is that subjects can engage in parallel processing; that is, they can stare at an AOI while thinking about something else. Although we cannot present hard evidence against parallel processing, we believe it is implausible in our setup because subjects would need to memorize the payoff matrix of a game to parallel process it. That is, subjects would need to memorize not only the eight payoffs, but also their position in the matrix, a cognitively demanding and unnecessary task given that the payoff matrices are readily available on the screen.

2.2. Experiment 2 (Time Dependence of Choice)

After providing consent, subjects are given written instructions, which are also read aloud. Subjects are then presented with the 19 games used in experiment 1. Each game is displayed separately on a computer screen for one minute. To keep track of the strategy choices of our subjects as they think about a game, we employ the choice process (CP) protocol introduced in Agranov et al. (2015) (see Caplin and Dean 2011, Caplin et al. 2011 for the theoretical work related to the CP protocol).

In the CP protocol, subjects can select a strategy in the game—here, strategies A and B—by clicking a button with that label (see Figure A.4(b)). The key feature of the protocol is that subjects can change their selection at any point during the 60 seconds. On the screen, there is a timeline that depicts their choice history.

To incentivize a subject to select the subject's optimal strategy at each point in time, the CP protocol randomly picks a point in time and uses the subject's strategy choice at that point in the game to determine the payoff. If no choice had been made in the selected second, then the subject's payoff in the game is zero. If a choice had been made, we use the strategy choice of an outside opponent, who played these games in a previous experiment without time constraints, to determine the subject's payoff. Subjects' earnings in the experiment are then given by the sum of their payoffs in four randomly drawn games.

2.3. Comparison with Avoyan and Schotter (2020)

This paper is related to Avoyan and Schotter (2020) (henceforth, AS2020). AS2020 argue that the attention a person spends on a problem depends on to what other problems the person is attending. In particular, the more attention one pays to a game, the less attention is left to the other games. Consequently, if a person is playing different games, the choice that the person makes in a game depends on the other games the person is playing because these games are connected via the attention constraint. AS2020 then investigate what payoff features of the games determine the person's attention allocation across these games. In doing so, they introduce an elicitation method for planned attention, which we use in this paper.

Our research questions are, however, different from AS2020. We are interested in whether people, in fact, implement their planned attention allocation, that is, whether their actual attention allocation coincides with their planned attention allocation. Although we use eye tracking primarily to infer people's actual attention allocation, it also allows us to observe to what features of the game people pay attention.

Given that they address different questions, AS2020 and our paper use different criteria to select the set of games that are studied. Whereas AS2020 require a large number of games and controlled pairwise comparisons between the games to identify the features of the games that influence a subject's planned attention allocation, we study a wider variety of games precisely to avoid that subjects play the same game repeatedly, which can bias our estimate of the subject's actual attention in the game. We chose to study games from some canonical game classes (such as prisoner's dilemma and the battle of the sexes games) because they are routinely faced by people and have been thoroughly studied, both theoretically and experimentally.

Importantly, AS2020 and our paper share four game pairs. In two of these game pairs, the games are displayed in the same order on the screen. In the two other game pairs, the games are displayed in reverse order on the screen. When we examine the planned attention allocation in these pairs, we find that subjects' behavior in these pairs is statistically indistinguishable across the two papers, which suggests that the use of eye tracking and the position of the games on the screen do not influence subjects' planned attention allocations.

3. Results

Using eye-tracking data from part 3 of experiment 1, we calculate, for each subject i and every game pair k, the fraction of time subject i spent looking at game 1 in game pair k, which we denote by β_{ik}. Therefore, β_{ik} measures subject i's actual attention on game 1 in game pair k. Recall that α_{ik} measures subject i's planned attention on game 1 in game pair k. Therefore, we can study the (mis)-alignment between planned and actual attention by comparing α_{ik} and β_{ik}.

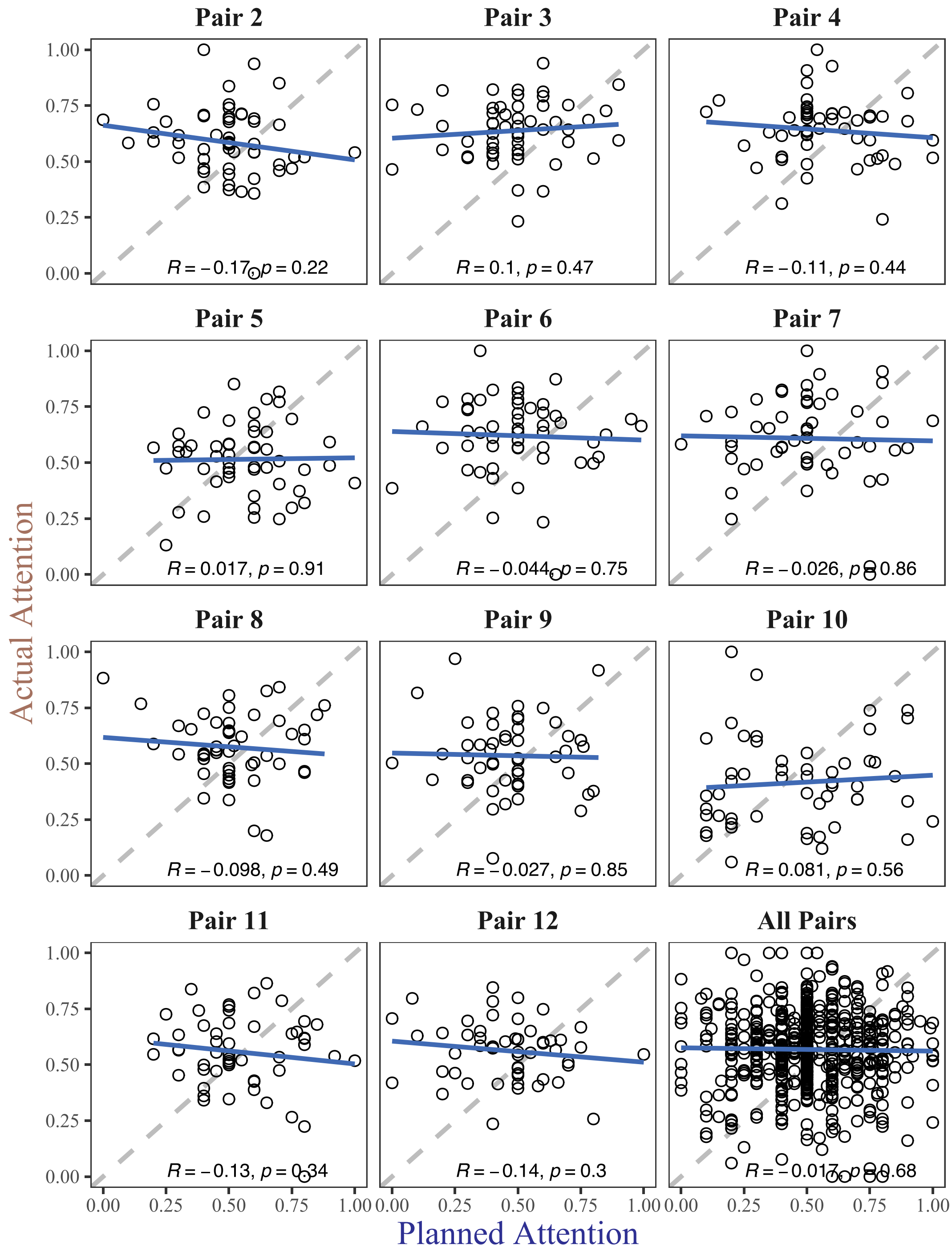
3.1. Planned and Actual Attention: Are Decision Makers Good at Planning Their Attention, That Is, Are α_{ik} and β_{ik} Similar?

Figure 1 presents the scatterplots between α_{ik} and β_{ik} for each game pair separately and for all game pairs pooled together. Regarding the latter (last graph in Figure 1), we see no correlation between planned and actual attention in the aggregate. The correlation between planned and actual attention is also small for each game pair: its absolute value is below 0.2 and is not statistically significant.[7] Therefore, subjects do not accurately anticipate the fraction of time they will spend playing the games in a game pair. In the online appendix, we plot variations on Figure 1 to understand the relationship between (i) actual attention when planning and actual attention when playing and (ii) actual attention when planning and planned attention. The correlation in both cases is low and statistically insignificant in the aggregate and for most of the games.

This mismatch between planned and actual attention is not driven by a few subjects that are particularly bad at anticipating the fraction of time they will spend playing each game in a game pair. In fact, we plot in Figure 2(a) the distribution of subjects' average error magnitude, in which subject i's error magnitude in a game pair is given by $|\alpha_{ik} - \beta_{ik}|$. Subject i's average error magnitude is then obtained by averaging the error magnitude across game pairs. Although Figure 2(a) shows that there is heterogeneity across subjects—indicating that some subjects are better than others in anticipating the amount of time they will need in when playing—even those subjects that are better planners have sizable discrepancies between planned and actual attention.

In Figure 2(b), we plot the fraction of subjects whose average error magnitude is above a given error tolerance threshold for the discrepancy between planned and actual attention allocation. By definition, as the error tolerance threshold increases, the number of subjects whose average error magnitude is above the threshold decreases. Surprisingly, 74% of subjects are above an error tolerance threshold of 10%. Moreover, all subjects have error magnitudes as high as 10% in at least four game pairs. In fact, if we declare that subjects make a mistake in a game pair whenever their error magnitude in the game pair is at least as high as 10%, the mean and median number of mistakes made by subjects is 8 out of 11 (that is, 72%). Therefore, whereas some subjects perform better at anticipating the time they will spend

Figure 1. (Color online) Planned vs. Actual Attention

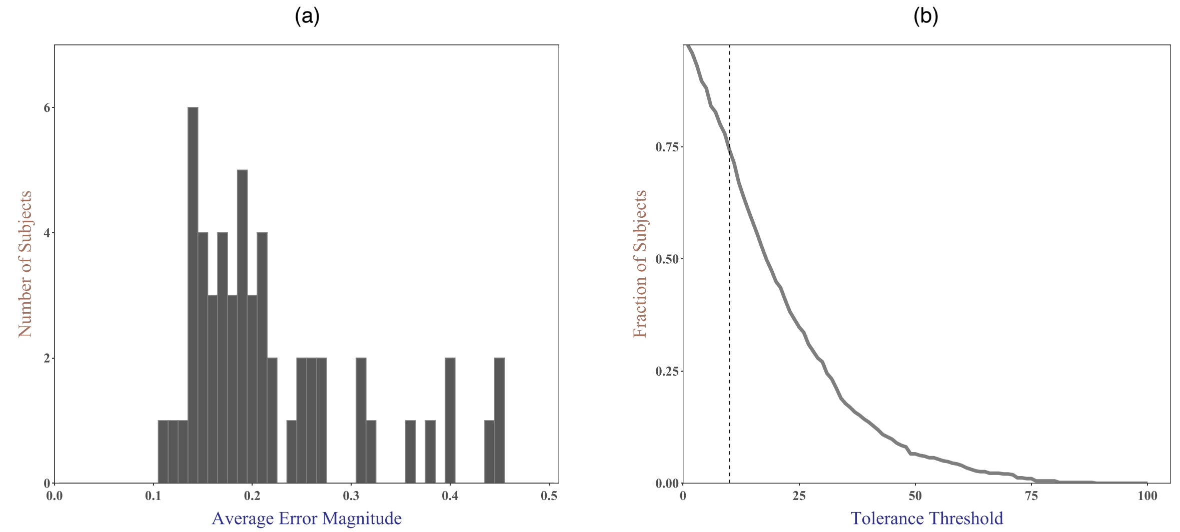


playing each game in a game pair, subjects perform poorly overall. Interestingly, error magnitudes are also heterogeneous across game pairs (see Appendix B, Figure B.1).

3.2. Why Do Planned and Actual Attention Differ?

We conjecture that the mismatch between planned and actual attention follows from the fact that subjects use different features of the games in a pair when planning their attention and when actually allocating attention. When planning, the time constraint forces subjects to focus on salient features of the game, such as maximum or minimum (own) payoffs.[8] They use these salient features to assess the value of the games in the game pair and then allocate a larger fraction of time to the game they deem more valuable. When playing without time constraints, features of a game that are neglected when planning becomes relevant. Among these, strategic

Figure 2. (Color online) Differences Between Planned and Actual Attention



Notes. (a) Average difference. (b) Error tolerance threshold.

considerations are prominent: a strategically simple game with shiny objects (e.g., with large payoffs) might attract a lot of attention in the planning stage but require little attention in the playing stage.

To test our conjecture, we run two regressions: one in which α_{ik} is the dependent variable and the other in which β_{ik} is the dependent variable. As independent variables in both regressions, we include the following features of the game pairs: the difference in maximum payoffs (between the games in the pair), the difference in minimum payoffs, the difference in equity concerns, and the difference in the number of pure rationalizable strategies. With the exception of the last variable, the others were identified to be relevant for planned allocation in AS2020.[9] More precisely, we estimate the following regressions:

$$a_{ik} = \gamma_1^a \Delta\text{Max}_k + \gamma_2^a \Delta\text{Min}_k + \gamma_3^a \Delta\text{Max}_k \cdot \Delta\text{Min}_k + \gamma_4^a \Delta\text{Equity}_k + \delta^a \Delta\text{Strategy}_k + \varepsilon_{ik}, \qquad (1)$$

where $a \in \{\alpha, \beta\}$, ΔMax_k is the difference between the maximum payoffs (in dollars) of games 1 and 2 in game pair k, ΔMin_k is the difference between the minimum payoffs (in dollars) of games 1 and 2 in game pair k, ΔEquity_k is the payoff difference (in dollars) between the average inequity[10] of games 1 and 2 in game pair k, and $\Delta\text{Strategy}_k$ is the difference between the number of rationalizable pure strategies of games 1 and 2 in game pair k. The regression specification also includes the interaction term $\Delta\text{Max} \times \Delta\text{Min}$. AS2020 introduced this interaction to account for the possibility that the effect of an increase in the difference between the maximum of two games in a subject's evaluation of these games can depend on how much safer/riskier one game is with respect to the other. Here, by safer/riskier, we mean that one game has a higher/lower minimum payoff than the other game for the (row) player. The coefficient γ_3^a captures this effect. Table 1 presents the results of these regressions.[11]

Before interpreting Table 1, however, we want to highlight an important aspect of our regressions. To illustrate it, consider the Δ*Max* variable. If Δ*Max* increases by $\$m$, this could have happened in different ways. For instance, the maximum payoff in game 1 can increase by $\$m$, whereas the maximum payoff in game 2 remains the same, or the maximum payoff in game 1 remains the same, whereas the maximum payoff in game 2 decreases by $\$m$. Our regression does not distinguish between these two cases, and hence, it implicitly assumes that they are symmetric.

In the planning stage (first column of Table 1), subjects allocate more time to games with higher maximum and minimum payoffs as the coefficients of Δ*Max* and Δ*Min* are positive and statistically significant. The interaction between these variables, that is, the variable $\Delta\text{Max} \times \Delta\text{Min}$, is also significant, but its magnitude is small. The coefficient of Δ*Equity* is only marginally significant, whereas the coefficient of Δ*Strategy* is not significant even at the 10% significance level, which suggests that subjects overlook strategic considerations when planning.

To calculate the full effect of ΔMax and ΔMin on planned attention, we need to consider their own coefficients and also the coefficient of their interaction term. For instance, the full effect of ΔMax on planned attention is given by

$$\frac{\partial \alpha_{ik}}{\partial \Delta\text{Max}_k} = \gamma_1^\alpha + \gamma_3^\alpha \Delta\text{Min}_k.$$

As this partial derivative is a function of ΔMin_k, we calculate the effect locally at the average of this variable. We then learn that a five-dollar increase in ΔMax_k leads to a

1.8 percentage point increase in α_{ik}. If we repeat the same exercise for ΔMin, we would get that a five-dollar increase in ΔMin_k leads to a 1.6 percentage point increase in α_{ik}.

In the playing stage (second column of Table 1), the coefficient of Δ*Min* remains significant but not the coefficient of Δ*Max*. The coefficient of Δ*Equity* is also statistically significant. To understand how equity concerns might play a role, consider a battle of the sexes game. When subjects are planning under a time constraint, they might not recognize the distributional consequences of their choices. However, when they play, these distributional consequences become important.

As argued, in certain games, strategic complexity might be hard to spot in the planning stage but become relevant in the playing stage.[12] If we use the number of (pure) rationalizable strategies of a game as a proxy for its strategic complexity, this seems to explain why the coefficient of Δ*Strategy* is significant when playing despite not being significant when planning. Moreover, the effect of Δ*Strategy* is sizable. In fact, if game 1 has two (pure) rationalizable strategies, whereas game 2 only has one, our results imply that game 1 receives eight percentage points more time than when both games have the same number of (pure) rationalizable strategies. For the sake of comparison, we would need to increase Δ*Max* by $22 to get an eight percentage point increase in actual attention.

In summary, these regressions support our conjecture that, when planning, subjects are affected by the salient features of the games, and when playing, they focus more on the strategic aspects of the games. Our results, thus, imply that the mismatch between planned and actual attention is a consequence of the fact that salient attributes of a game can be poor indicators of its strategic complexity.[13]

3.3. What (Else) Do We Learn from Eye-Tracking Data?

So far, we used eye tracking to estimate the fraction of time our subjects spend in each game of a game pair. But eye-tracking data sheds further light on the attention pattern of subjects in experiment 1. In this spirit, we examine the time subjects spend on each of the 16 AOIs described in Section 2.1.5 (see Figure A.4(a) in Appendix A.2) to address following questions:

- Are subjects more likely to choose the strategy to which they spend more time attending?
- Do subjects spend more time on their own as opposed to their opponent's payoffs?
- Does the payoff magnitude influence the amount of time spent looking at it?
- Are subjects' attention drawn to "shiny" or "scary" things, such as maximum and minimum payoffs in a game?

To address the first question, we run a regression in which a subject's strategy choice in a game is the dependent variable and the total time the subject spent looking at the strategy's payoffs is the explanatory variable. We code strategy A as one and strategy B as zero. We display the results of the regression in Appendix B.2, Table B.1. Consistent with other papers that use eye tracking to study decision making, we find that a subject's likelihood of choosing a strategy is increasing in the amount of time spent looking at the payoffs associated with that strategy.[14] This suggests that the time a subject spends looking at payoffs correlates with behavior. A natural follow-up question is then what are the features of a payoff that capture the attention of our subjects? Our three remaining questions are particular instances of this broad question. (Unlike the analysis of Table 1, here we are interested in absolute, not relative, time.)

We run two regressions: one to account for the time spent looking at an AOI when planning and the other for the time spent looking at an AOI when playing. As explanatory variables in these regressions, we include the magnitude of the payoff in the AOI, an indicator for whether the payoff in the AOI is a subject's own payoff, indicators for whether the payoff is a maximum or a minimum of the game, and an indicator for whether the payoff in the AOI is zero. More precisely, we estimate the following regressions:

$$\text{Time}_{ij}^k = \nu_1^k\ \text{Payoff}_j + \nu_2^k\ \text{Own}_j + \nu_3^k\ \text{Max}_j + \nu_4^k\ \text{Min}_j + \nu_5^k\ \text{Zero}_j + \varepsilon_{ij}, \tag{2}$$

where Time_{ij}^k is the time (in seconds) that subject i spends on AOI_j, $j \in \{1, 2, \ldots, 16\}$ in part $k \in \{1, 3\}$; $Payoff_j$ is the payoff magnitude in AOI_j; Own_j is a dummy variable that equals one if the payoff in AOI_j is a player's own payoff and zero otherwise; Max_j (Min_j) is a dummy variable that is one if the payoff in AOI_j is the maximum (minimum) of the corresponding game and zero

Table 1. Explaining Discrepancies Between Planned and Actual Attention

	Allocation	
	Planned (α_{ik})	Actual (β_{ik})
ΔMax	0.37***	−0.06
	(0.116)	(0.102)
ΔMin	0.32*	0.62***
	(0.167)	(0.157)
ΔEquity	0.64*	0.54**
	(0.344)	(0.240)
ΔStrategy	−1.55	8.15***
	(2.73)	(2.01)
ΔMax × ΔMin	0.05***	0.05***
	(0.015)	(0.015)

Note. The standard errors are in parentheses, and they are clustered at the subject level.

Significance levels: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 2. Eye-Tracking Data Regression Results

	Dependent variable: *Time*					
	(1) Planned	(2) Actual	(3) Planned	(4) Actual	(5) Planned	(6) Actual
Own indicator	0.135***	0.144***	0.132***	0.129**	0.023	0.132
	(0.051)	(0.051)	(0.050)	(0.052)	(0.051)	(0.084)
Payoff	0.009*	−0.001	0.005*	−0.013***	0.002	−0.007
	(0.005)	(0.003)	(0.003)	(0.005)	(0.002)	(0.006)
Max indicator			0.072	0.109**	−0.017	−0.057
			(0.078)	(0.047)	(0.033)	(0.061)
Min indicator			−0.025*	−0.153***	−0.040	−0.244***
			(0.015)	(0.047)	(0.025)	(0.070)
Zero indicator			−0.024	−0.373***	0.039	−0.240**
			(0.056)	(0.091)	(0.080)	(0.120)
Own indicator × Payoff					0.005	−0.010*
					(0.004)	(0.005)
Own indicator × Max indicator					0.147	0.280***
					(0.128)	(0.101)
Own indicator × Min indicator					0.013	0.134*
					(0.038)	(0.072)
Own indicator × Zero indicator					−0.116	−0.222
					(0.090)	(0.150)

Note. The standard errors are in parentheses, and they are clustered at the subject level.
Significance levels: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

otherwise; $Zero_j$ is a dummy variable that is one if the payoff in AOI_j is zero and zero otherwise.

In one of our regression specifications, we further interact the variable Own_j with the other four variables to account for the possibility that the effect of these four variables can depend on whether the corresponding payoff is the subject's as opposed to the opponent's payoff. We display the regression results in Table 2.

Consistent with other studies that use eye and mouse tracking to understand behavior in games (cf. Polonio et al. 2015, Devetag et al. 2016), subjects spend more time on their own payoffs than that of their opponent when playing (column (1)). Subjects also spend more time on their own payoffs than on that of their opponent when planning.

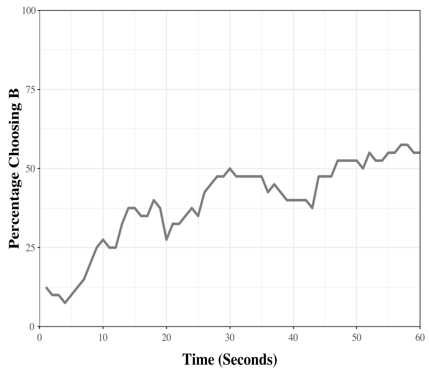
The variable payoff in Table 2 has a positive and significant effect on the time spent looking at a payoff when planning (column (1)). However, the effect of payoff magnitudes in time spent looking at a payoff when playing is either insignificant or negative (columns (2), (4),

Figure 3. Time Profile of Two Selected Games

(a)

Game 11

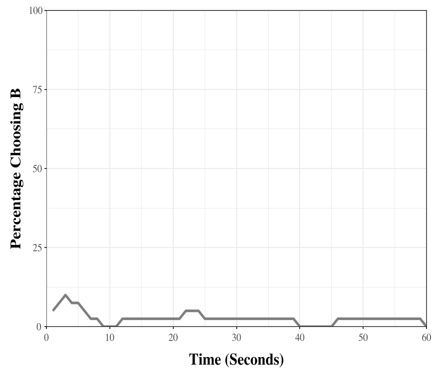
	A	*B*
A	800, 500	0, 0
B	0, 0	500, 800



(b)

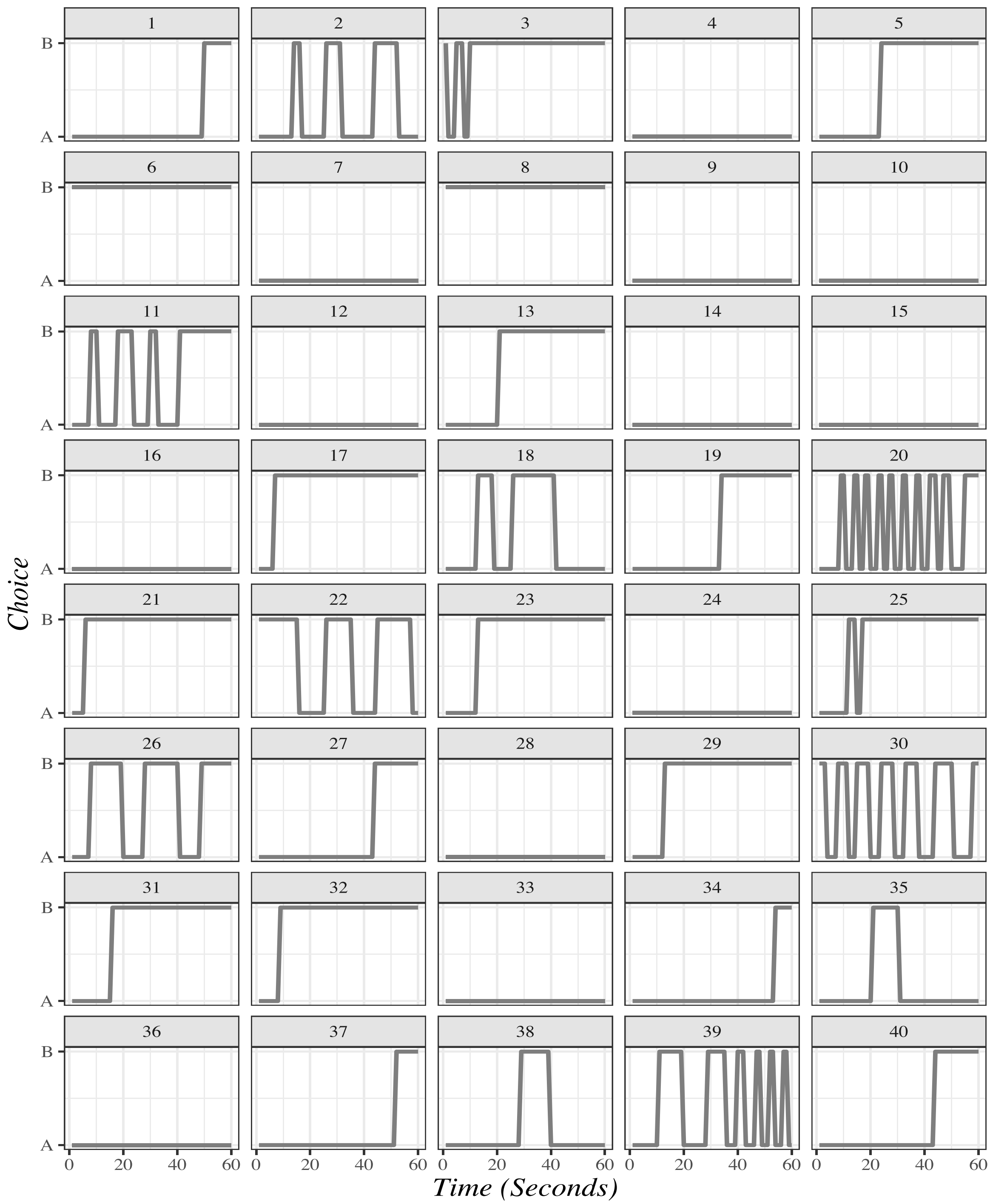
Game 12

	A	*B*
A	800, 800	0, 0
B	0, 0	500, 500



Notes. (a) Battle of the sexes. (b) Pure coordination.

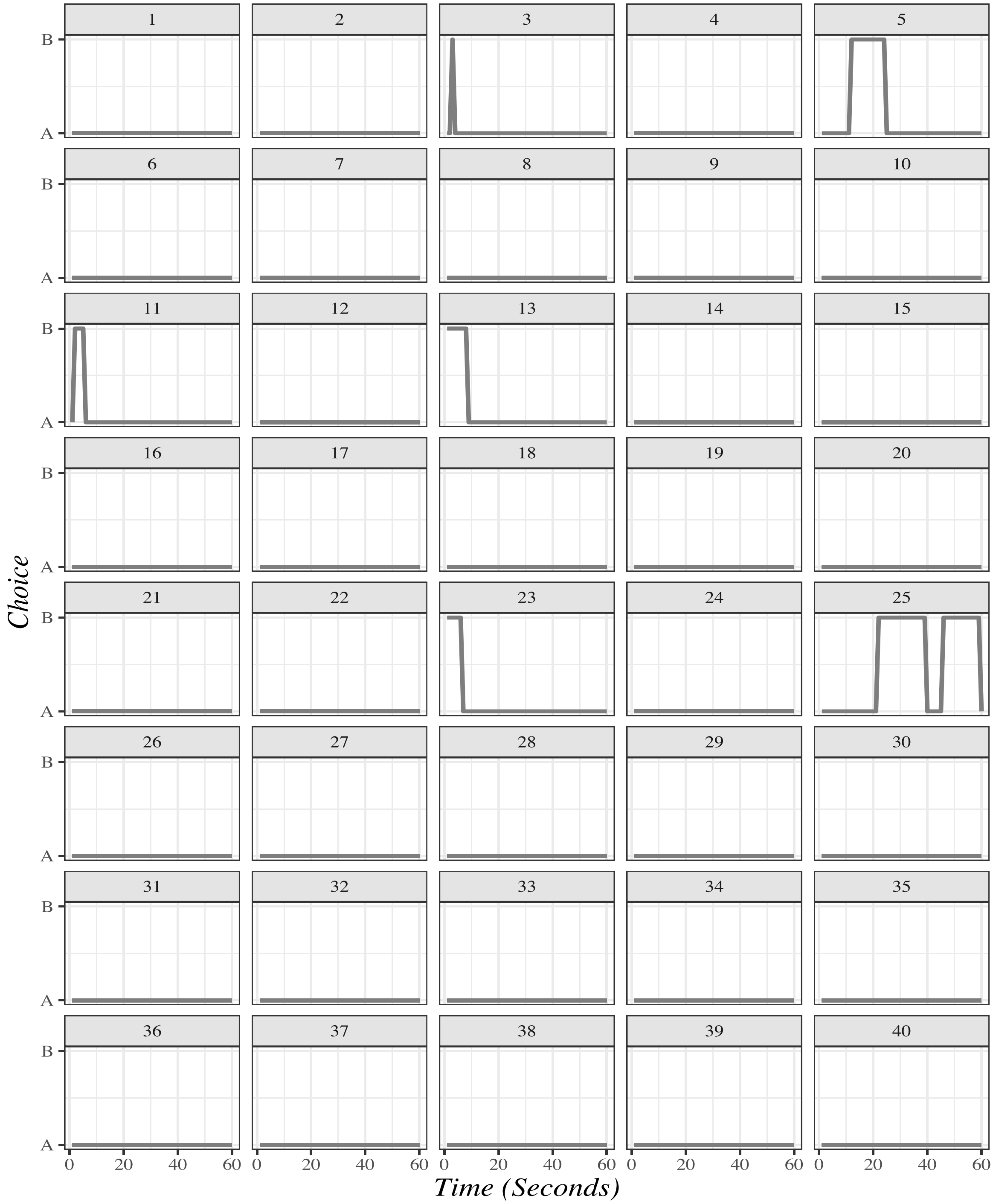
Figure 4. Time Profiles in Game 11 for Each Subject



and (6)). Therefore, the higher the payoff, the more time subjects looked at it when allocating time but not when playing.

To further understand the effect of the payoffs on subjects' attention, consider the three remaining indicators in our regression, that is, the maximum, minimum, and zero. If we control for payoff magnitude (columns (3) and (4) of Table 2), the maximum indicator coefficient has a positive and significant effect on time spent looking at a payoff when playing but not when planning. For instance, if 500 is the maximum payoff of a game, then it receives more attention than if 500 were not the maximum payoff of the game in part 3.[15] The coefficients of the minimum and zero indicators are not significant when planning, but are negative and significant when playing. Therefore, subjects do not look as much at "scary" payoffs when playing the games. Finally, the interactions between indicators reveal that the max and min indicators have a

Figure 5. Time Profiles in Game 12 for Each Subject



larger effect when subjects are looking at their own payoffs as opposed to their opponent's payoffs.

3.4. Time and Choice: Does a Decision Maker's Choice Change over Time?

Now that we know that subjects do not accurately anticipate the fraction of time they will spend playing each game in a pair and have identified (some of) the reasons why, we examine whether time affects strategy choice in games and whether these effects are game-dependent. That is, are there games in which choices are more sensitive to the time spent reaching a decision and, for this reason, are more sensitive to time misallocation?

Certainly, a subject's failure to appropriately anticipate the time spent attending to a game can only have payoff consequences if the subject's choice of strategy in the game depends on the amount of time the subject spends attending to it, that is, if the subject's choices in a game are time-dependent. Put differently, if a decision maker were to make the same strategy choice in a game regardless of the time spent contemplating it, then a failure to accurately allocate time to such a game would be irrelevant for the payoffs. Therefore, it is crucial to identify in which games the subjects' choices are more time-dependent.

To do so, we use the data from experiment 2 to create an aggregate time profile of choices for each of the games considered in this experiment. The aggregate time profile of choices for a game displays what fraction of subjects choose strategy B at each point in time. To illustrate, consider Figure 3(a) and (b). On the x-axis, we have time (from 0 to 60 seconds); on the y-axis, we have the fraction of subjects that choose strategy B at each second (the remaining fraction of subjects at each point in time, thus, choose strategy A). In Appendix B.4, Figure B.2, we plot the time profile of choices for all the remaining games.

The fraction of subjects that choose strategy A in game 11, a battle of the sexes game, (Figure 3(a)) increases with time. The probability that a randomly drawn subject from the population chooses strategy B in the first few seconds is 10%, whereas in the last few seconds, it is 56%. Hence, a subject that anticipates spending less time in game 11 is more likely to choose a different strategy than the one the subject would have chosen if the subject had allocated more time to it. The opposite is true for game 12, a pure coordination game (Figure 3(b)). The likelihood of choosing strategy B is roughly constant throughout the 60 seconds. Therefore, a discrepancy between planned and actual attention in game 12 is inconsequential.

For the mismatch between planned and actual attention to be payoff-relevant for a subject, it must be that the subject switches the choice of strategy at least once.[16] To study whether this is the case, we create individual time profiles of choices. We plot in Figures 4 and 5 how the strategy choice of each subject varies with the time spent contemplating games 11 and 12, respectively. In game 11, 13 subjects do not switch their choices, 15 subjects switch their choices exactly once, and 12 subjects switch their choices at least twice, further confirming that choices vary in this game. In game 12, however, only two subjects change their strategy once, and only four subjects change their choice at least twice, further confirming that the choices of subjects do not vary much in this game. In the online appendix, we plot the individual time profile of choices for all the remaining games.

To shed further light on the time-dependence of the subjects' choices in the games we study, we compare in Table 3 the fraction of B choices made in the first and last seconds of each of these games. We interpret this exercise as comparing subjects' early versus late choices.[17] Looking at Table 3, we see that in a few games, choices in the first and last seconds are not significantly different. Most of these games are strict dominance and pure coordination games with a Pareto-dominant equilibrium.

Table 3. Fraction of B Choices at 1st and 60th Second

Game	Type	1st second	60th second	p-value
Game 1	Pure coordination 1	0.08	0.05	1.00
Game 2	Battle of the sexes 1	0.15	0.45	0.01
Game 3	Prisoners' dilemma 1	0.38	0.70	0.01
Game 4	Mixed strategy 1	0.17	0.45	0.02
Game 5	Mixed strategy 2	0.32	0.57	0.04
Game 6	Strict dominance 1	0.23	0.20	1.00
Game 7	Chicken 1	0.15	0.38	0.04
Game 8	Chicken 2	0.28	0.15	0.27
Game 9	Prisoners' dilemma 2	0.23	0.68	0.00
Game 10	Strict dominance 2	0.23	0.12	0.38
Game 11	Battle of the sexes 2	0.12	0.55	0.00
Game 12	Pure coordination 2	0.05	0.00	0.47
Game 13	Trust/risk 1	0.53	0.60	0.65
Game 14	Strict dominance 3	0.05	0.05	1.00
Game 15	Test/control	0.08	0.15	0.48
Game 17	Mixed strategy 4	0.23	0.60	0.00
Game 18	Equity	0.28	0.57	0.01
Game 19	Trust/risk 2	0.33	0.45	0.36

Note. The p-values are the result of proportion tests.

On the other hand, games 3 and 9, while possessing strictly dominant strategies, are prisoners' dilemma games, and hence, the dominant strategy B can lead to a socially inefficient outcome. We find that, in these games, subjects initially choose strategy B less often: 38% in game 3 and 23% in game 9. However, most subjects end up choosing strategy B, probably because they realize that it protects them against a possible defection from the column player. Therefore, a subject who allocates less time to these games is more likely to choose strategy A, whereas if the subject had allocated more time to it, the subject would have chosen strategy B.[18]

4. Conclusion

This paper focuses on the relationship between planned and actual attention in strategic decision making. We find that, when presented with games in pairs, subjects fail to (instinctively) anticipate the fraction of time they will spend in each game of the pair; that is, their planned attention allocation differs from their actual attention allocation. Our results suggest that this mismatch between planned and actual attention emerges from a difference in the determinants of attention between planning and playing.

This difference is partly driven by the different goals in each stage and partly by the time constraint in the first stage. When planning their attention under a time constraint, subjects seem to overweight how valuable a game is and underweight its strategic complexity. Consistent with this interpretation, maximum and minimum payoffs play an important role in subjects' planned attention allocation, whereas the game's strategic complexity does not. When playing, however, subjects' actual attention allocation is primarily driven by strategic complexity: more complex games receive more attention in the playing stage. Therefore, our results suggest that the wedge between planned and actual attention is driven by the fact that salient indicators of the value of a game are not good predictors of its strategic complexity.

Finally, we argue that this mismatch between planned and actual attention has payoff consequences in games in which a subject's choice is sensitive to the time the subject spends thinking about the game. Because the sensitivity of choice with respect to time seems to be a common property of many tasks that have a strategic component, the mismatch between planned and actual attention is likely to have significant welfare consequences. The sales manager in our initial example should, thus, be particularly careful when planning attention between tasks in which the final decisions are more sensitive to the time they allocate to them.

A natural next step is to investigate whether our results apply to more realistic settings. If so, understanding the extent to which a person's experience in instinctively allocating attention across tasks can close the gap between planned and actual attention is important, particularly when a person's choices in the tasks are sensitive to the time of deliberation.

Acknowledgments

The authors thank Guillaume Frechette and Andrew Caplin for their helpful feedback and Anwar Ruff for technical and programming assistance.

Appendix A. Further Details on the Experimental Design

A.1. Game Pairs and Games

Table A.1. Game Pairs Used in Experiment 1

Pair 1	Game 1	versus	Game 2
Pair 2	Game 3	versus	Game 4
Pair 3	Game 5	versus	Game 6
Pair 4	Game 7	versus	Game 8
Pair 5	Game 9	versus	Game 4
Pair 6	Game 5	versus	Game 10
Pair 7	Game 11	versus	Game 12
Pair 8	Game 7	versus	Game 10
Pair 9	Game 13	versus	Game 14
Pair 10	Game 15	versus	Game 16
Pair 11	Game 17	versus	Game 16
Pair 12	Game 18	versus	Game 19

Table A.2. Average Number of Seconds Spent on a Game in Part 3

Game	Seconds	Game	Seconds	Game	Seconds
Game 3	12.4	Game 9	9.3	Game 15	4.3
Game 4	9.3	Game 10	4.9	Game 16	8.4
Game 5	10.9	Game 11	7.5	Game 17	9.9
Game 6	5.6	Game 12	3.7	Game 18	8.5
Game 7	11.1	Game 13	7.5	Game 19	7.4
Game 8	5.4	Game 14	5.8		

Figure A.1. List of Games Used in Experiments 1 and 2

Game 1

	A	*B*
A	800, 800	100, 100
B	100, 100	500, 500

Game 2

	A	*B*
A	800, 500	100, 100
B	100, 100	500, 800

Game 3

	A	*B*
A	300, 300	100, 400
B	400, 100	200, 200

Game 4

	A	*B*
A	400, 100	100, 400
B	100, 400	400, 100

Game 5

	A	*B*
A	300, 100	200, 200
B	100, 400	400, 300

Game 6

	A	*B*
A	300, 300	400, 400
B	200, 100	200, 300

Game 7

	A	*B*
A	800, 800	500, 1000
B	1000, 500	400, 400

Game 8

	A	*B*
A	800, 800	500, 1000
B	1000, 500	0, 0

Game 9

	A	*B*
A	800, 800	100, 1000
B	1000, 100	500, 500

Game 10

	A	*B*
A	800, 800	900, 900
B	700, 600	700, 800

Game 11

	A	*B*
A	800, 500	0, 0
B	0, 0	500, 800

Game 12

	A	*B*
A	800, 800	0, 0
B	0, 0	500, 500

Game 13

	A	*B*
A	0, 600	900, 600
B	400, 500	400, 500

Game 14

	A	*B*
A	700, 800	500, 500
B	600, 200	400, 500

Game 15

	A	*B*
A	500, 500	500, 500
B	500, 500	500, 500

Game 16

	A	*B*
A	400, 500	400, 400
B	600, 600	300, 700

Game 17

	A	*B*
A	300, 600	600, 300
B	600, 300	300, 600

Game18

	A	*B*
A	200, 0	200, 0
B	200, 400	199, 900

Game 19

	A	*B*
A	0, 300	600, 300
B	100, 200	100, 200

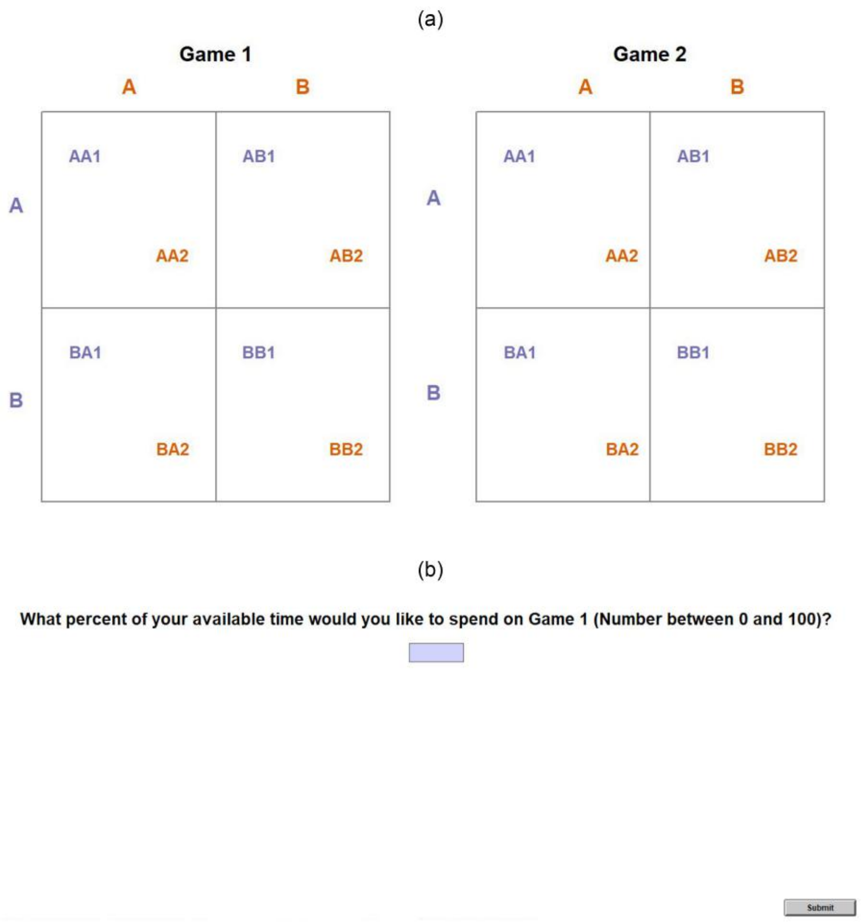
Game 16′

	A	*B*
A	400, 500	400, 400
B	600, 600	500, 500

Note. Because of a programming error in experiment 2, subjects played game 16′ instead of playing game 16.

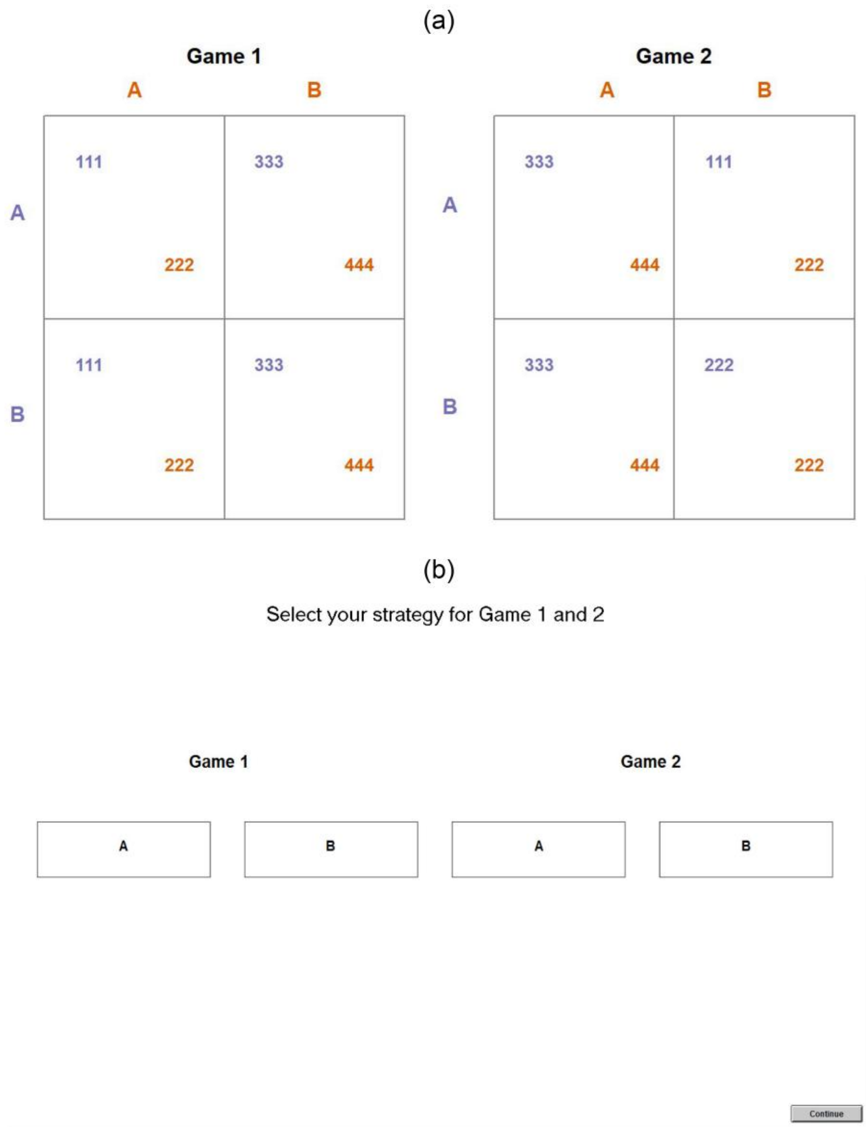
A.2. Screenshots

Figure A.2. (Color online) Sample Screens



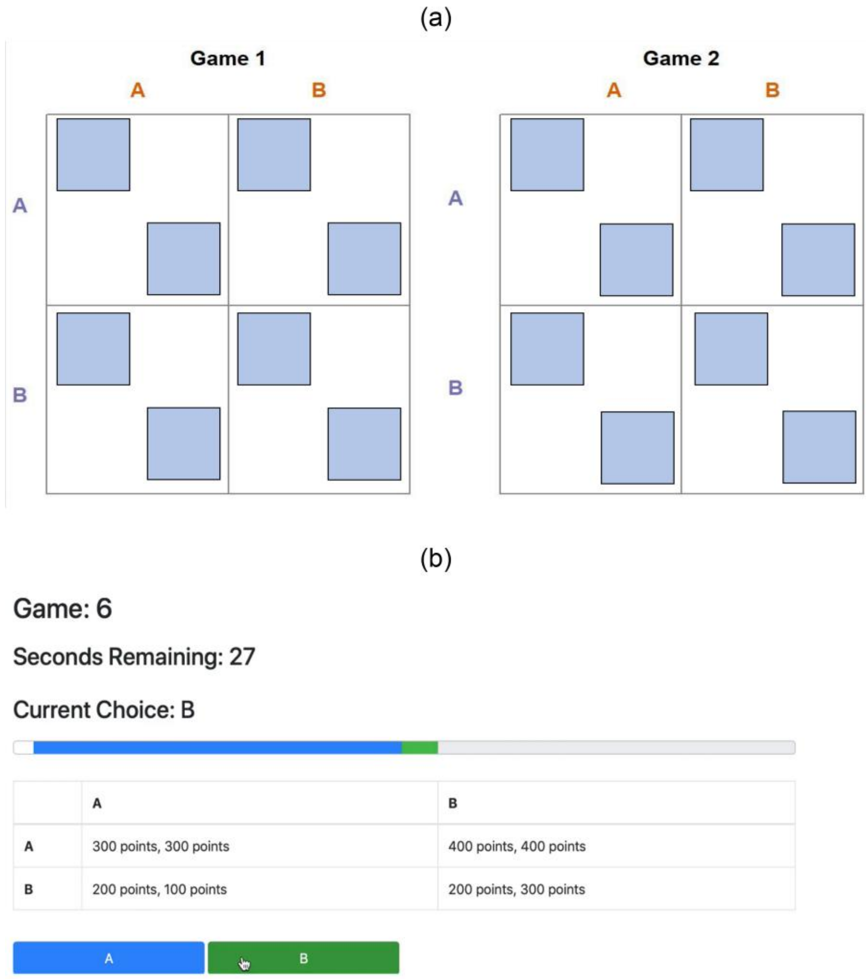
Notes. (a) Practice screen (experiment 1). (b) Submission screen part 1(experiment 1).

Figure A.3. (Color online) Sample Screens Continued



Notes. (a) Sample practice screen (experiment 1). (b) Submission screen part 3 (experiment 1).

Figure A.4. (Color online) Sample Screens Continued

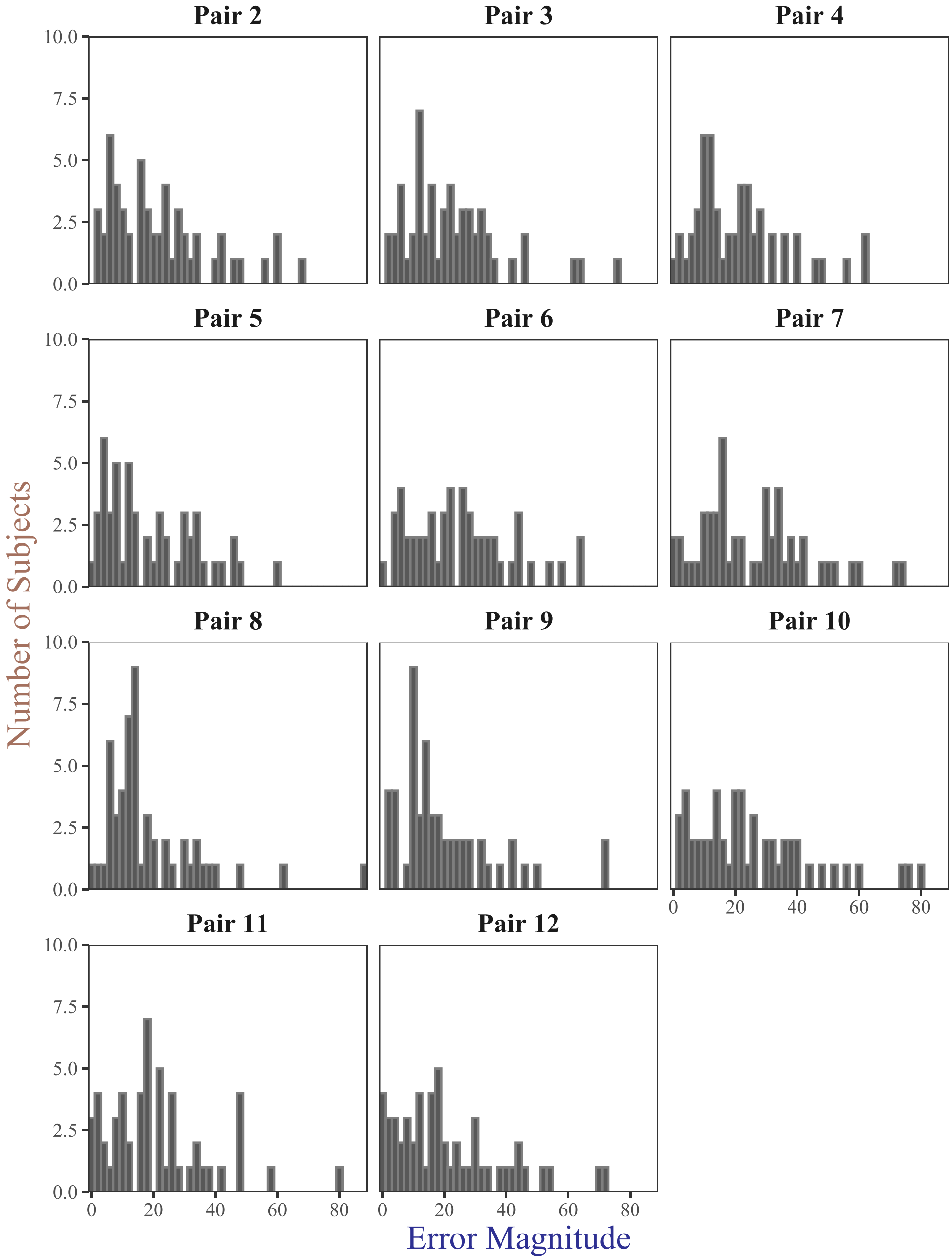


Notes. (a) AOI around the payoffs. (b) Sample screen from experiment 2.

Appendix B. Additional Figures and Tables

B.1. Error Magnitudes by Game Pair

Figure B.1. (Color online) Error Magnitudes by Game Pair



B.2 Time Spent on Strategies and Consequent Choice

Table B.1 presents the results of a regression in which the dependent variable is the choice of a strategy in a game (strategy A is coded as one and strategy B as zero), and the independent variables are the time (in seconds) spent looking at the payoffs associated with strategies A and B in the game.

Table B.1. Time Spent on Strategies and Consequent Choice

	Dependent variable Choice A
Time on A	0.031***
	(0.010)
Time on B	−0.040***
	(0.010)

Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B.3. Alternative Regression Specifications

In Section 3, we examine variables that Avoyan and Schotter (2020) determine to be relevant when people plan their attention allocation. In addition, we included a strategy variable to the regressions to capture strategic considerations. In this section, we evaluate the effects of three alternative payoff-related variables: $\Delta Average$, $\Delta Variance$, and $\Delta ExpectedDifference$. $\Delta Average$ is defined as

$$\Delta \text{Average} = \text{Average}_{Game_1} - \text{Average}_{Game_2},$$

where Average_{Game_1} and Average_{Game_2} are the average own payoffs (in dollars) in games 1 and 2. Similarly, $\Delta Variance$ is defined as

$$\Delta \text{Variance} = \text{Variance}_{Game_1} - \text{Variance}_{Game_2},$$

where Variance_{Game_1} and Variance_{Game_2} are the variance of own payoffs (in dollars) in games 1 and 2. Finally, $\Delta Expected\ Difference$ is defined as

$$\Delta \text{ExpectedDifference} = \text{ExpectedDifference}_{Game_1} - \text{ExpectedDifference}_{Game_2},$$

where $\text{ExpectedDifference}_{Game_1}$ and $\text{ExpectedDifference}_{Game_2}$ are the absolute difference in the expected payoffs (in dollars) from choosing strategy A versus B in games 1 and 2 when we assume that the column player randomizes uniformly over the player's strategies.

Table B.2 presents the results of running similar regressions to the ones in Equation (1), Section 3, but in which we replace the payoff-related variables by each of the three variables just defined.

The coefficient of $\Delta Average$ is positive when planning and negative when playing. However, neither of these coefficients is statistically significant. These results suggest that using the difference in average own payoffs instead of more specific payoff variables, such as differences in maximum and minimum own payoffs, hides too much of the variation of a change in payoffs. The coefficient of $\Delta Variance$ is positive although not statistically significant when planning and negative when playing. Therefore, although differences in own payoff variance between the games do not influence planning, games with higher (own) payoff variance end up receiving less attention when subjects are playing.

The variable $\Delta ExpectedDifference$ is inspired by a recent literature that, in the context of value-based decisions, shows that people spend more time in decisions between alternatives that yield similar payoffs than in decisions between alternatives that yield dissimilar payoffs (cf. Oud et al. 2016). This pattern points to an inefficiency in time allocation because people allocate too much time to decisions in which the payoff difference between a correct and an incorrect choice is small.[19] This literature raises the following question in our setup: if the absolute difference between the expected payoffs of strategies A and B in game 1 is smaller than that of game 2, do subjects spend more time in game 1 when playing? What about when planning?

The coefficient of $\Delta Expected$ difference is positive and marginally significant when planning, whereas it is negative and marginally significant when playing. Therefore, when planning, if the expected payoff difference between strategies A and B is higher in game 1 than in game 2, subjects allocate more time to game 1. When playing, the opposite is true, which is in line with the results of the literature we just discussed. These results highlight yet another difference between planned and actual attention allocations.

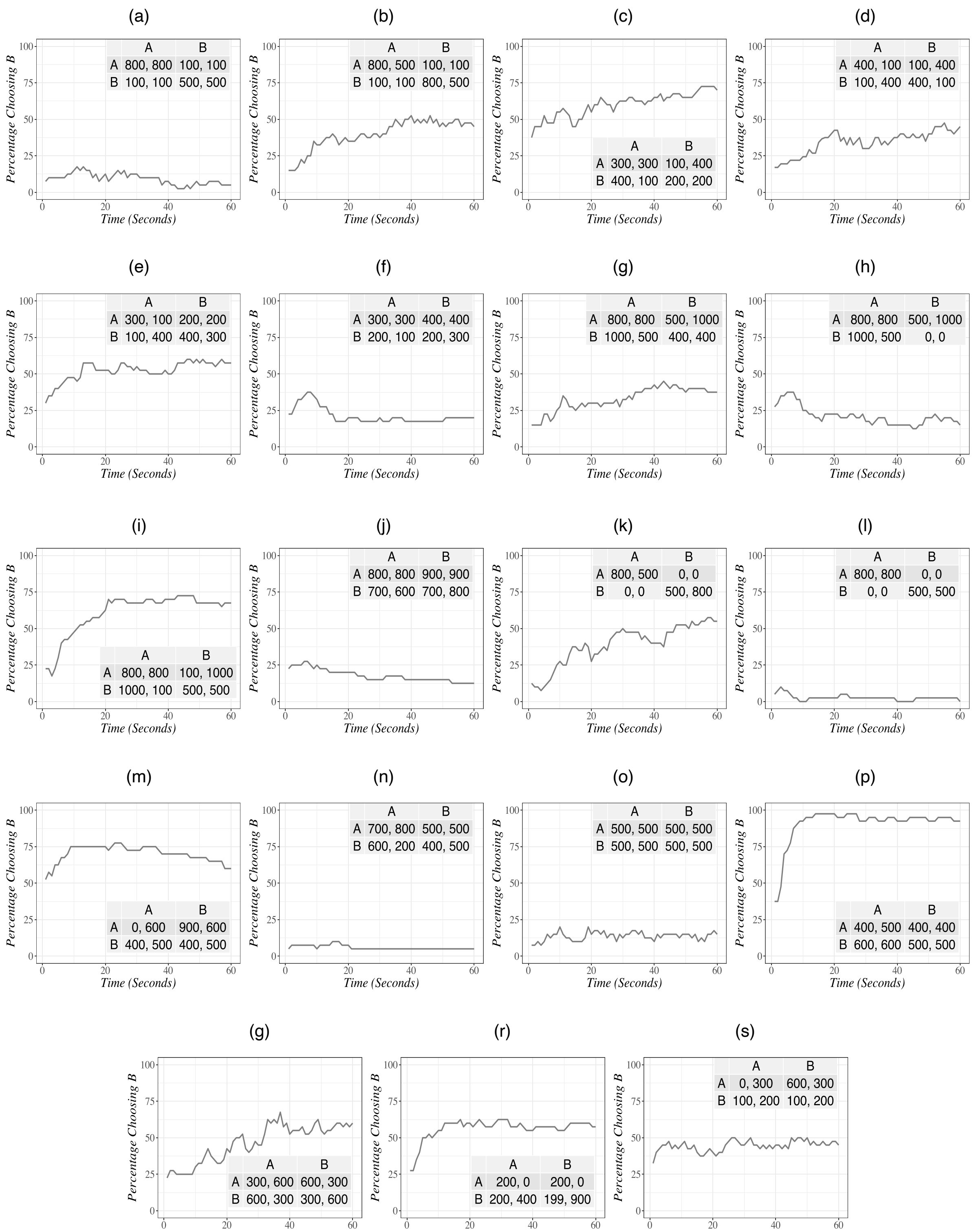
Table B.2. Alternative Regression Specifications

	Dependent variable: *Allocation*					
	(1) Planned	(2) Actual	(3) Planned	(4) Actual	(5) Planned	(6) Actual
$\Delta Strategy$	−0.480	3.500**	−2.400	7.700***	−1.100	4.000**
	(2.600)	(1.700)	(2.600)	(1.600)	(2.500)	(1.700)
$\Delta Average$	0.240	−0.230				
	(0.190)	(0.160)				
$\Delta Variance$			0.013	−0.081***		
			(0.012)	(0.014)		
$\Delta Expected\ Difference$					0.400*	−0.400*
					(0.230)	(0.210)

Significance levels: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B.4. Time Profiles (Experiment 2)

Figure B.2. Time Profile for All Games in Experiment 2



Notes. (a) Game 1. (b) Game 2. (c) Game 3. (d) Game 4. (e) Game 5. (f) Game 6. (g) Game 7. (h) Game 8. (i) Game 9. (j) Game 10. (k) Game 11. (l) Game 12. (m) Game 13. (n) Game 14. (o) Game 15. (p) Game 16′. (q) Game 17. (r) Game 18. (s) Game 19.

Endnotes

[1] The value and complexity of a task both influence how much time one should allocate to it. For instance, suppose that the tasks in question are 2×2 games (as in this paper). If one game is strategically complex but yields tiny payoffs, whereas the other is strategically simple but yields huge payoffs, which of the two games should receive more time? Although we do not study such extreme cases in this paper, they are useful to illustrate the trade-offs one faces when allocating time between strategic tasks.

[2] Avoyan and Schotter (2020) study the attention allocation constraint and its effects on choice in an isolated game. Avoyan et al. (2022) study time allocation between nonstrategic tasks (decision problems). We here focus on time allocation between strategic tasks (2×2 matrix games) and on a person's ability to anticipate the time needed to solve these tasks.

[3] We could have made subjects play each game in a game pair sequentially in part 3 and recorded their response time as their actual time. Further studies could examine what would change in our results under this alternative protocol. Because, however, the primary goal of the experiment is to compare planned allocation in part 1 to actual allocation in part 3, we chose to keep parts 1 and 3 as similar as possible. By doing so, we guarantee that any differences between planned and actual time allocation cannot be attributed to a change in how the game pairs are presented.

[4] Konovalov and Krajbich (2019) and Frydman and Krajbich (2022) argue that response time contains additional information beyond the realized choice. They argue that subjects extract information about the other player's signal strengths depending on the speed of their decision.

[5] A subject's calibration process requires that the subject follow a dot on the screen. We used a nine-point calibration, that is, the dot moves to nine different points on the screen and the subject is asked to follow the dot. We then check the accuracy of the movement before moving to the next steps. We only recalibrated subjects in two sessions.

[6] Eye-tracking data in the study of games has been used increasingly in economics. See, for instance, Knoepfle et al. (2009), Polonio et al. (2015), or Devetag et al. (2016). Meißner and Oll (2019) propose a taxonomy for the use of eye tracking based on a synthesis of the existing eye-tracking literature, which they use to review the papers that study organizational research topics using eye tracking.

[7] We find no difference in the results whether we look at pairs 2–4, which were presented first in part 3, or at pairs 4–12, presented later in part 3.

[8] See Leland and Schneider (2015) for an analysis of salience in the play of 2×2 games.

[9] Because we use a different set of games and comparisons, some of the features studied in AS2020 are not examined here (see Section 2.3).

[10] We measure "equity concerns" in a game through the game's average inequity, in which average inequity is defined as the average absolute difference between a player's own payoffs and the opponent's payoffs (in dollars) for each cell of the game. That is, for each of the four cells in a game, we find the absolute difference between own and opponent's payoffs. The average inequity of the game is then the average of these values.

[11] We consider alternative regression specifications in Appendix B.3. More specifically, we include in the regressions the differences in average payoffs between the games in a pair as well as the difference in the variance of the payoffs in the games. We also study how the expected payoff differences between the strategies of the games in a pair influence actual and planned time allocations. We find that, in all these alternative specifications, the strategy variable remains statistically significant when playing but not when planning.

[12] There is now substantive literature that discusses the relationship between response times and strategic considerations (cf. Gill and Prowse 2017 and references therein). In fact, Gill and Prowse (2017) use the average amount of time people spend thinking about a situation as a measure of the complexity of the situation.

[13] The optimal fraction of time allocated to a game can be a function of X, and X is unknown to the subjects. Therefore, incorrect conjectures about X could lead to the mismatch between planned and actual attention. We propose instead that when subjects do not know the values of X, they allocate fractions of their time to different tasks based on their assessment of the relative importance of these tasks. Because we cannot distinguish between these conjectures with the data we have, we leave it to future work to investigate how people cope with an ambiguous time budget.

[14] See Orquin and Loose's (2013) discussion of what they call the "utility effect" and the references therein.

[15] This result does not contradict our interpretation of the results in Table 1. The fact that subjects spend more time looking at a payoff if it is a maximum payoff when playing does not conflict with the fact that the difference between the maximum payoffs of the games in a game pair does not explain actual attention allocation.

[16] The CP protocol incentivizes subjects to choose an option as soon as they can. This is because the subject receives a zero payoff if the subject had not chosen a strategy in the second that is drawn for payment. Because the strategy at the top of the payoff matrix (i.e., strategy A) is salient, many subjects choose it by default; that is, they display an initial bias toward strategy A. The CP protocol, however, also incentivizes subjects to change their choice of strategy as soon as they realize that the other strategy is better. Therefore, this initial bias toward strategy A can only account for switches in the first few seconds of the game. In particular, if subjects switch between the strategies more than once, then the initial A bias cannot account for these switches. Moreover, suppose subjects stick to strategy A for more than a few seconds. In that case, they must be seriously entertaining the possibility of choosing strategy A.

[17] If we take the fifth second instead of the first second in Table 3, our results remain (roughly) the same. See Figure B.2 in Appendix B.4 for the effect over the 60 seconds.

[18] This pattern of switching to a less cooperative strategy after some contemplation is similar to a result of Rand et al. (2012) for a one-shot public goods game. The pattern is, however, controversial (see Tinghög et al. 2013, Krajbich et al. 2015, Bouwmeester et al. 2017, Kessler et al. 2017, Chen and Krajbich 2018, Recalde et al. 2018, Alós-Ferrer and Garagnani 2020). As shown by Kessler et al. (2017), the magnitude of the payoffs matter. By varying the payoff of a prisoner's dilemma game and using the CP protocol of Agranov et al. (2015) to track a subject's choice path, Kessler et al. (2017) find that, depending on the efficiency of cooperation, people can either switch from the selfish to the cooperative strategy or from the cooperative to the selfish strategy.

[19] See also Krajbich et al. (2014). Additionally, see Konovalov and Krajbich (2019), Frydman and Krajbich (2022), and Hausfeld et al. (2020) for a discussion on how response times can be used to reveal the strength of preferences and Spiliopoulos and Ortmann (2018) for a discussion about the applications of response time in economics.

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