Finite Foresight in Chomp*

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Abstract

We experimentally study sequential rationality in the Game of Chomp, a two-player win-lose game whose rules are simple but whose subgame-perfect Nash equilibria vary in complexity across initial states. Subjects frequently deviate from SPNE: the probability of making an SPNE-consistent move falls with the distance to the end of the game, and most can correctly implement SPNE only three to five moves ahead. Experience mainly improves play at intermediate distances. We also document a common opening heuristic that, although often theoretically suboptimal, is still associated with higher chances of winning.

JEL classification: C72, C73, C92, D90
Keywords: Chomp; experiment; sequential rationality; limited foresight

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1 Introduction

Finite games of perfect information are among the simplest settings in which game theory delivers sharp predictions. Backward induction is a simple yet powerful solution concept that one might expect subjects to implement, yet real players may be unable to represent even moderately complex games as a tree or to carry out backward induction on large or intricate trees. Limited depth of reasoning, noisy best responses, and mis-learning can all undermine sequential rationality, and their impact is likely to grow with the game's complexity. This paper studies how much of the optimal play predicted by theory survives when players are boundedly rational, and how the ability to play optimally varies across states within the same game.

Understanding dynamic rationality is important: Many economic interactions are dynamic, and standard predictions in these settings rely on players reasoning contingently about how current choices affect later play. If subjects instead have limited foresight, use simplification heuristics, or fail to condition correctly on future paths of play, then equilibrium concepts such as subgame perfect Nash equilibrium (SPNE) may provide a poor description of behavior. This matters for at least three reasons. First, in dynamic mechanism design, the performance of a mechanism depends not only on its formal incentives but also on whether participants can actually carry out the sequential reasoning required to respond optimally. Second, empirical analyses of dynamic strategic settings may draw misleading conclusions if they assume a degree of contingent reasoning that agents do not in fact possess. Third, understanding the limits of dynamic rationality is important for behavioral game theory more broadly, because it can help distinguish between different sources of nonequilibrium behavior, such as limited foresight, decision noise, and the use of heuristics.

Our research asks three related questions. First, how close is behavior to SPNE play, and do subjects get closer with experience? Second, what observable features of a game state are associated with choices that are inconsistent with sequential rationality? Third, when subjects fail to play according to SPNE, do they choose randomly or use structured heuristics?

In this paper, we study behavior in the game of Chomp, a sequential, finite, two-player game of complete and perfect information introduced in Gale (1974). The game is played on an $n \times m$ rectangular grid of boxes. Players select one of the remaining boxes sequentially, and when any box is selected for removal, all those below and to the right of it are also removed. The player forced to remove the top-left box loses the game. Chomp has a first-mover advantage: under sequentially rational play, the first mover should always win.

Although the rules are simple, a game of Chomp can be strategically complex. The number of possible game states grows rapidly with the dimensions of the board (for an $n \times m$ board, it is on the order of $\binom{n+m}{n}$; see Zeilberger (2001)), and optimal play does not, in general, follow a simple pattern. At the same time, some special cases, such as square boards and $N \times 2$ boards, admit relatively simple winning strategies. This combination makes it possible to vary the complexity and length of the game across matches without changing the underlying rules, making Chomp an ideal testing ground for measuring how human subjects deviate from sequential rationality as complexity varies.

An experimental implementation of Chomp is well suited for studying dynamic rationality in games. In field settings, dynamic games are often hard to observe cleanly: the researcher typically does not observe the full game tree, players' beliefs, or even all of the choices that are available at each decision point. Moreover, the characteristics of games often move together: games with longer horizons may also have larger action spaces or richer information structures, making it difficult to isolate which aspect of the environment drives departures from equilibrium play. Chomp, on the other hand, combines strategic richness with unusual transparency. The game tree is finite, payoffs are clearly defined, and key dimensions of complexity, such as board size, board shape, and distance to the end of the game under SPNE, can be varied experimentally without explaining a new set of rules. This allows us to observe not only whether subjects ultimately win, but also where in the game tree they depart from SPNE and how those departures vary with distinct features of the decision problem.

This paper describes an experimental implementation of the Game of Chomp. We randomly match participants into groups of two to play the game. Roles (Player 1 versus Player 2) and initial game state (the dimensions of the grid) are randomized in each match. Participants are told that at the end of the experiment, one match would be chosen at random to be the match that determines payment. The winner of that match receives AUD$65, while the loser receives AUD$15.

Not surprisingly, participants are not perfectly consistent with sequential rationality. Even though the player chosen to move first has the power to win with certainty, they only win the game 51.72% of the time. However, this masks substantial heterogeneity across grids: Some initial game states exhibit Player 1 win rates higher than 60%, while others have Player 1 win rates that are lower than 40%.

We then investigate the determinants of deviations from sequential rationality. We find that a key determinant for whether a player makes a winning move is the distance to the end of the game according to the subgame perfect equilibrium path. This distance to the end of the game interacts with learning in an intuitive way: most learning (the increase in the likelihood of optimal play that is associated with experience) accumulates in game states that are of "intermediate" complexity – those that are 3-5 moves away from the end of the game. Finally, we show that subjects often chose the box $(2, 2)$ as the initial move of the game, despite it being theoretically suboptimal in non-square games. This may be in an effort to simplify the game, as many subjects appear to have learned to play optimally in the resulting "L-shaped" games.

The paper is organized as follows. Section 2 reviews the most relevant literature. Section 3 formally introduces the Game of Chomp, characterizes its subgame perfect Nash equilibria, and outlines our hypotheses. Section 4 details the experimental design. Section 5 presents the main findings on game outcomes and behavior in losing positions, and Section 6 investigates the underlying drivers of these behaviors. Section 7 offers concluding remarks.

2 Related Literature

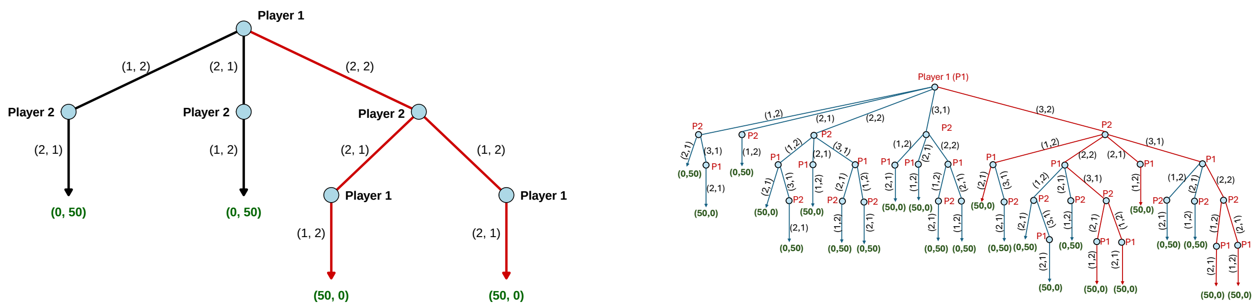
There has been a substantial amount of experimental research into people's decisions in dynamic games with perfect information. Previous research has shown that deviations from the theoretical predictions likely stem from social preferences, limitations in backward induction, and complexity of the games.

Rosenthal (1981) introduced the Centipede Game, a dynamic game with complete and perfect information, where two players take turns choosing to pass or stop at each node of the game. Continuing (usually) increases the total payoff for the group, but stopping gives the active player a higher proportion of the current total payoff. Generally, games are constructed so that in the subgame perfect Nash equilibrium, subjects should choose to stop at the first node of the game. However, results from experimental studies of this game show that this does not match behavior. The Centipede Game was first studied experimentally in McKelvey and Palfrey (1992), which concludes that the failure to adhere to the SPNE is due to a mixture of altruism and decision noise. The existence of "altruists," who always choose "pass" at each node of the game, makes players more likely to continue the game if they believe their opponents are altruists. Fey et al. (1996) study Centipede Games in which the total payoff does *not* increase with each pass, finding that Quantal Response Equilibrium fits behavior the best. Rapoport et al. (2003), in turn, compares Centipede Games under high and low stakes, finding that behavior is closer to SPNE and learning is stronger when stakes are high. Palacios-Huerta and Volij (2009) show that when professional chess players play Centipede Games against each other, outcomes are much closer to SPNE, whereas Levitt et al. (2011) find that even expert chess players who successfully solve a related "race to 100" game often fail to stop early in Centipede Games. In contrast to Centipede Games, a fully rational player acting as the first mover in the Game of Chomp does not need to form beliefs about the other player, because the game is zero-sum and has a binary outcome. Thus, any deviations from the SPNE can be attributed purely to the player's own ability to engage in backward induction.

Another strand of the experimental literature uses the "Race Game," which is a finite sequential zero-sum game of complete and perfect information, to study how cognitive limitations and learning affect the implementation of backward induction. The game's rules can be described as follows: The state of the game at any point is represented as an integer m. Players take turns selecting a number $k \in \{1, \ldots, \bar{k}\}$, which is subtracted from the current state. The player who brings the state to zero wins the game. The Race Game has a simple winning strategy, and if the current state is a winning position, the player whose turn it is can guarantee victory regardless of the opponent's play (Dufwenberg et al., 2010; Gneezy et al., 2010). This strategy involves a relatively simple rule, depending only on m and $\bar{k}$. Both Dufwenberg et al. (2010) and Gneezy et al. (2010) focus on how learning this rule can transfer between different parameterizations (and perhaps subgames) of the game. Rampal (2025) uses the Race Game to compare behavioral game-theoretic models, finding that the level-k model is the best fit for behavior in "short" games while the Limited Foresight Equilibrium of Rampal (2022) is better at explaining behavior in "longer" games. In contrast to the Race Game, the Game of Chomp does not *in general* admit a simple rule governing equilibrium play, so there is less reason to expect a single moment of "epiphany" after which subjects play optimally.

The game of Nim, introduced in Bouton (1901), is a finite sequential zero-sum game of complete and perfect information in which players alternately remove objects from a set of piles and the player who takes the last object wins. Bouton (1901) provides a complete solution, showing that every position can be classified as winning or losing, and provides a constructive procedure for optimal play. McKinney Jr and Van Huyck (2007) use Nim to show how increasing game complexity (measured by rank and related tree-based measures) reduces effective play: most subjects perform well only up to about rank 6, though a few can solve games up to rank 17. In follow-up work, McKinney Jr and Van Huyck (2013) find that learning mainly takes the form of "eureka" discovery of narrow heuristics, such as move-copying in two-row games, with little evidence that subjects acquire the full Bouton algorithm or more complex heuristics. In contrast to Nim, general Chomp positions do not admit a comparably simple global solution or a single dominant heuristic, so a Chomp experiment can shed light on how boundedly rational players search, form and transfer local heuristics in a structurally rich class of games.

Traditional game-theoretic models typically assume that players can carry out backward induction regardless of a game's complexity. Experimental work, however, shows that complexity matters: subjects perform better in simpler versions of the same strategic environment. Recent research has studied different facets of complexity. Oprea (2020) and Banovetz and Oprea (2023) show that subjects both find complex, multistep, and mentally implemented rules harder to follow and systematically choose simpler procedures because they are averse to implementing complex ones. Pycia and Troyan (2023) formalize complexity in terms of foresight, distinguishing between agents by how far they can plan into the future. Nagel and Saitto (2023) propose a measure of strategic complexity for mechanisms based on how many alternative actions or plans a player must compare in order to recognize a dominant strategy. The Game of Chomp provides a convenient testbed for these ideas: it has simple rules and direct winning strategies for square and $N \times 2$ grids, while variation in grid size and position allows us to vary both the number of available moves and the distance to the end of the game.



(a) (2×2) Game (b) (3×2) Game

Figure 1: Extensive form of the Game of Chomp, with its Subgame Perfect Equilibrium highlighted.

3 Theoretical Background

3.1 The Game of Chomp

The Game of Chomp, introduced by Gale (1974), is a dynamic game of complete and perfect information. The game's initial state is an $n \times m$ grid of boxes.[1] Two players take turns choosing from the remaining set of boxes. When a box is chosen, all boxes below and to the right of the chosen box are removed from the grid. Both players can always see the remaining boxes when they make their move. The player who is forced to remove the final (top-left) box is the loser.

Because Chomp is a finite game, it can be represented in extensive form. Figure 1 shows the game trees for grid sizes 2×2 and 3×2. The 2×2 game has only four terminal nodes. The extensive form of the 3×2 appears substantially more complex, with 24 terminal nodes. This complexity of the extensive form grows quickly with the dimensions of the game.

3.2 Winning Strategy for the First Player

Gale (1974) showed that the Game of Chomp is a first-mover advantage game: Player 1 can always guarantee a win with optimal play. Gale provides a non-constructive proof: Suppose Player 1 loses in the SPNE by choosing the initial move at the bottom right (n, m). Since choosing (n, m) leads to a loss, Player 2 has a best response, (a, b), that puts Player 1 into a losing position. However, Player 1 could have initially chosen (a, b), thus forcing Player 2 into a losing position. This is called "strategy stealing" (Berlekamp et al., 2004). Therefore, Player 1 can always win if he plays optimally. While there can be more than one optimal initial move in the Game of Chomp, the smallest grid size with more than one optimal initial move is 8×10 (Gale, 1974).

A standard method for identifying a winning strategy in an extensive-form game such as Chomp is to determine the SPNE through backward induction. This involves analyzing the final player's

[1]Throughout the paper, we adopt the conventions that (1) an $n \times m$ game has n rows and m columns, (2) the first-mover is referred to as Player 1, and (3) the game is over when only a single box remains.

move: assuming sequential rationality, the player selects the action that maximizes their payoff if the game reaches that point. Given this choice, the preceding player then optimally responds, and so on. In Chomp, this process classifies every possible game state as either a winning or a losing position: a state is winning if at least one available move leads to a losing position, and losing if all moves lead to winning positions. Starting from the terminal 1×1 position, which is losing, each other state can be classified recursively in this way. However, because the number of possible states in a game of size $n \times m$ is $\binom{n+m}{n}$ (Zeilberger, 2001), the strategy space grows combinatorially, conceivably making it difficult for decision-makers to identify winning strategies in larger Chomp games.

While it is difficult in general to compute Chomp's SPNE, there are simple and straightforward winning strategies for square games and $n \times 2$ games, both of which are described in Gale (1974).

Square Games: For a square grid of $n \times n$, Player 1's optimal strategy is to initially choose the box at position (2,2). This results in an L-shaped game state with an equal number of boxes in each arm. Then, Player 1 mirrors all of Player 2's choices until the end of the game. For instance, on their next turn, Player 1 selects (1,a) or (a,1) if Player 2 selects (a,1) or (1,a), respectively. Player 1 repeats this process until she wins the game.

$\mathbf{n} \times \mathbf{2}$ Games: For grids that have either two columns or two rows, Player 1 wins by making the initial move at the bottom right box, which is $(n, 2)$ or $(2, m)$. This initial move results in an imbalanced game state, where the first column or row has one more box than the second. Regardless of Player 2's choices, Player 1 responds by selecting a box that maintains this imbalance. This guarantees a sure win for Player 1.

4 The Experiment

4.1 Experiment procedures

The experiment was conducted with two treatments: *Mixed Shapes* (MS) and *Rectangle Only* (RO). The MS treatment consisted of four sessions completed in August 2024, while the RO treatment consisted of two sessions completed in May 2025. All sessions took place in-person at the University of Queensland's Centre for Unified Behavioural and Economic Sciences Laboratory. The experiment was coded using oTree (Chen et al., 2016). Each session lasted 90 minutes, and no participant took part in more than one session.

In the experiment, subjects were provided with the game's instructions orally, on paper, and on their computer screen.[2] The instructions page provided an example grid size of 10×10 and explained how their choices changed the state of the game. Subjects could examine this by clicking on any box. Subjects were randomly rematched each round and continued playing new games of Chomp until the 65-minute session limit was reached, with the first match to finish after this cutoff serving as the final match of the experiment.[3] Roles (Player 1 or Player 2, with Player 1 moving first) were randomly assigned in each round. The dimensions of the grid were also randomly selected for each group and each round, and the set from which they were selected differed according to the treatments that are discussed below. After the games were completed, subjects were asked to complete a short survey that included demographic questions, a cognitive reflection test (Frederick, 2005), and space to provide feedback on the experiment and their behavior.

Each Chomp game began with a grid of boxes. The top-left box was yellow, and the others were white. The two players took turns selecting a box. Each time a box was selected, all the boxes below and to the right of it turned green. After the player clicked the "Submit" button, these boxes were removed from the grid. Each player had 30 seconds to make their selection. They could change their choice as many times as they wanted within the given time. After making their final decision, they had to click the "Submit" button to proceed to the next round.[4] Figure 2 shows an example of the choice page for Player 2 in a game on a 6×4 grid after Player 1 chose (4,3) in the first round. In each match, the winning player received AUD$65, while the losing player received AUD$15. At the end of this part, the computer randomly selected one match to count for the final payoff. Thus, the average payoff was AUD$40 for the 90-minute experiment.

Our experiment used a between-subjects design that varied the grid sizes subjects faced. In the *MS* ("mixed-shape") treatment, grids were randomly drawn from 2×2, 3×2, 4×2, 4×3, 5×3, 8×3, 4×4, 6×4, 6×5, and 6×6; among these, 2×2, 4×4, and 6×6 are square, while the rest are rectangular.[5] In the *RO* ("rectangular-only") treatment, grids were randomly drawn from 3×2, 4×2, 6×2, 4×3, 5×3, 6×3, 8×3, 5×4, 6×4, and 6×5.[6]

As the grid size increases, the complexity of SPNE and backward induction may also increase.

[2]Screenshots of all parts of the experiment can be found in Appendix C.

[3]We allowed for flexibility in the number of games to be completed because of the potential for high variance in how long each game took. In practice there was not substantial variance: in the four sessions of the MS treatment, subjects completed 20, 22, 18 and 21 games, while in the two sessions of the RO treatment subjects completed 21 and 23 games.

[4]If a player did not click "Submit" before time ran out, the computer randomly selected a box from all remaining boxes in the grid with equal chance. In our experiment, the timeout occurred in 351 out of 7425 turns. In order to avoid selection effects, our data analysis treats the random computer-generated choices as if they were made by the participant. Appendix Figure 9 shows how the proportion of turns that ended with a timeout is related to the number of available boxes.

[5]Here and throughout the remainder of the paper, we use the term "rectangular" to refer to games that are *not* square.

[6]As we discuss in Section 6.3, the most common initial move in the MS treatment is $(2, 2)$. Because this is the SPNE move in the square games in our design, we conjectured that subjects were learning that $(2, 2)$ works well on square boards and then misapplying this heuristic to rectangular boards. The *RO* treatment was therefore designed to eliminate all cases in which $(2, 2)$ is optimal. Nonetheless, $(2, 2)$ remained a common initial choice in the *RO* treatment.

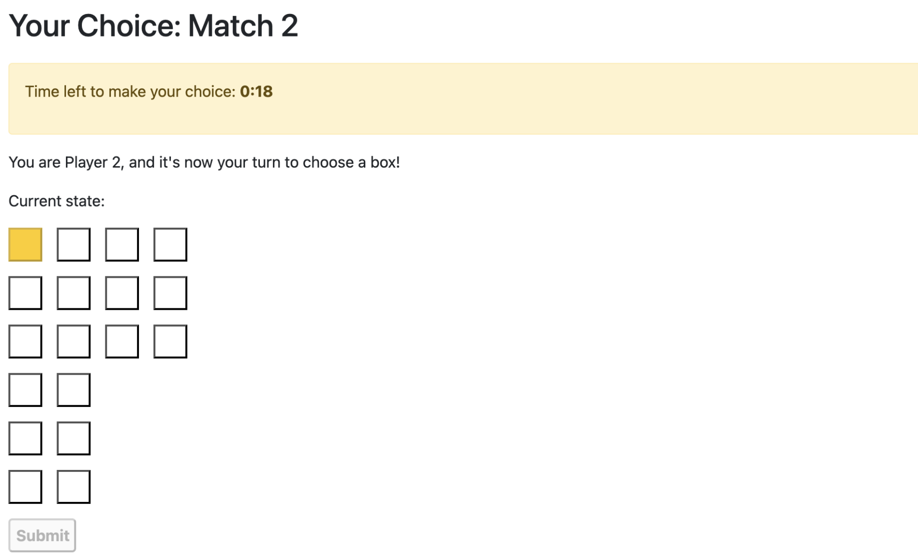


Figure 2: Choice page of Player 2

The simplest versions of square games and $n \times 2$ games are 2×2 and 3×2, respectively. Grid sizes of 4×4 and 6×6 are examples of large dimensions for square games, while 4×2 and 6×2 are examples of $n \times 2$ games. The winning strategies in these games follow a simple rule, while optimal strategies in the rest of the rectangular games vary based on the dimensions of the grids. Also, all the grid sizes used in the experiment are smaller than 8×10. Therefore, each grid size has a unique optimal initial move.

4.2 Hypotheses

This subsection outlines the main hypotheses we test in our experimental framework. The rational benchmark delivers stark predictions in this setting: regardless of the current state of the game, players should always choose actions consistent with the SPNE, which in winning positions typically restricts play to a small subset of the many available options. Prior experimental work suggests that such behavior is rare. We therefore base our hypotheses on a combination of theoretical intuition and existing empirical findings, rather than on the SPNE benchmark alone.

For our first hypothesis, we consider how the game's initial state affects the likelihood that Player 1 will win the game. Under SPNE, the first mover should *always* win. However, this prediction relies on the prediction that Player 1 plays optimally even when not near the end of the game. A single error along the equilibrium path would put Player 2 into a winning position. For this reason, we expect that Player 1 is more likely to be able to win when the game is smaller and when the SPNE strategy is simpler.

Hypothesis 1. *"Player 1" is more likely to win "smaller" games, square games, and* $N \times 2$ *games.*

Our next hypothesis considers how players should choose when they are in a *losing* position. In these cases, SPNE gives no predictions, because all moves are expected to lead to a loss. However, Hypothesis 1 in combination with a recognition that players will make errors naturally leads to an intuitive strategy in these cases: a player in a losing position should remove fewer boxes in order to maintain the game's complexity and leave more chances for the other player to make a mistake.

Hypothesis 2. *Players tend to remove fewer boxes when they are in a losing position than in a winning position.*

Our next hypothesis considers how players' ability to implement SPNE varies with the state of the game. Generally, we expect that in more complex states subjects will be less able to play according to SPNE. We focus on two dimensions of complexity. First, a simple measure is the number of options available to the decision-maker. Second, implementing SPNE can require looking many moves ahead and evaluating multiple contingencies, so depth of reasoning may also be a constraint. When a subject is near the end of the game, fewer contingencies need to be considered and SPNE may be easier to implement. This is consistent with previous research, which finds that subjects are more likely to choose "take" near the end of the Centipede Game and to choose optimally near the end of the Race Game (McKelvey and Palfrey, 1992; Gneezy et al., 2010)

Hypothesis 3. *Players' moves are more likely to coincide with SPNE when there are fewer options available and when there are fewer steps remaining on the equilibrium path.*

Our final hypothesis is related to how behavior changes with experience. Previous work has tended to find that players' behavior becomes closer to SPNE as they gain experience (Dufwenberg et al., 2010; McKinney Jr and Van Huyck, 2013; Rampal, 2025). We expect similar results to hold for the Game of Chomp.

Hypothesis 4. *Players' moves are more likely to coincide with SPNE as they gain experience.*

5 Results

There were a total of 124 participants across the two treatments: 80 subjects completed 796 games across four sessions of *MS* and 44 subjects completed 486 games across two sessions of *RO*. Generally, our results are not substantially different between treatments. Subjects made choices 7425 times across 1282 games in the experiment, implying that the average number of turns per game was about 5.8. We report summary statistics for our demographic variables in Appendix Table 5. Because most of our results are consistent across treatments, we focus on pooled results in the main body of the paper and report the disaggregated results in Appendix B.

5.1 Winner of the Game

This section considers the outcome of the game: who won, and under what conditions.

Result 1. Player 1 won roughly half of the time, and was more likely to win in "smaller" games and in square games. Player 1 did not win more often in $N \times 2$ games.

Result 1 shows that we partially reject Hypothesis 1. The evidence for Result 1 can be found in Figure 3, which shows a histogram of win rates for subjects in the role of Player 1, Figure 4, which shows rates of winning and perfect play according to the initial game state and Appendix Table 6, which reports regressions of Player 1 winning on a game's initial characteristics.

Overall, Player 1 won in 663 out of 1282 games (a winning rate of 51.7%). Figure 3 shows that the winning rate varied widely by subject. Two subjects had winning rates that were above 0.9, and two *never* won when playing as Player 1. The histogram is left-skewed, with a peak winning proportion that falls between 0.6 and 0.65.[7]

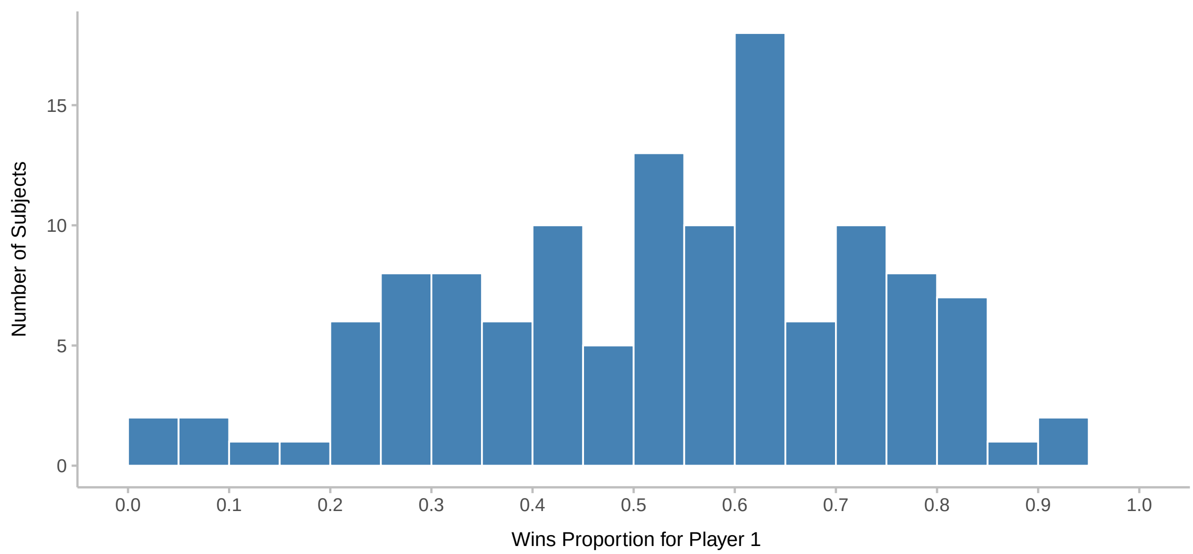


Figure 3: Histogram of proportion of winning as Player 1

We further analyze the winning proportions for Player 1 on different grid sizes and shapes. The left panel of Figure 4 shows the proportion of wins and perfect play by Player 1 for different grid sizes, pooling observations from both treatments. Overall, subjects won more often with square games than with rectangular ones (roughly 70% vs below 50%) and less often with $N \times 2$ grids as compared to other shapes (around 49% vs above 52%). All square grid sizes have a winning

[7]Appendix Figure 10 shows the CDF for subject win rates split between the MS and RO treatments. The CDFs are almost identical. Appendix Figure 11 shows the same figure, but considering only the first 18 games from each session so that all sessions have the same number of games. The results are not substantially different.

proportion above 0.5, with the highest winning rate of approximately 0.9 for grid size 2×2, whereas the figure for the majority of rectangular grid sizes is less than 0.5. The figure also shows that Player 1's rate of perfect play exceeded 50% only in 2×2 and 3×2 games, and was generally low in games that were either non-square or had more than 12 initial blocks.

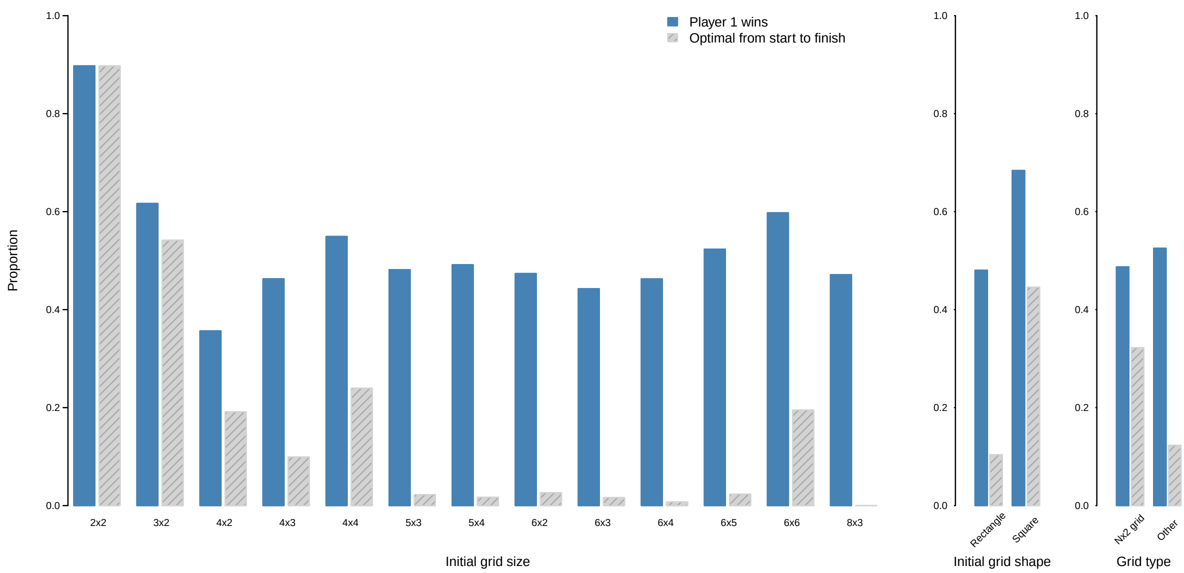


Figure 4: Winning proportion and perfect play of Player 1 by grid size and shape. Blue bars report the proportion of games that Player 1 won while striped grey bars report the proportion of games in which Player 1 *always* made moves that were consistent with SPNE.

Column (1) of Appendix Table 6 reports a regression in which the dependent variable is an indicator for Player 1 winning the game and the independent variables are characteristics of the initial game state. The estimates show that Player 1 wins square games roughly 20 percentage points more often than rectangular games. By contrast, Player 1's probability of winning is not significantly associated with whether the game is played on an $N \times 2$ grid, the number of available boxes at the start of the game, or the length of the game under SPNE. Column (2) then investigates the channel through which square games improve Player 1's chances by adding a control for whether Player 1 chose the SPNE-consistent move on the first turn. Since our interpretation is that square games are easier for subjects to solve, we would expect the coefficient on Square Game to attenuate once first-move correctness is held fixed. This is exactly what we find: the coefficient on Square Game falls to near zero, while the coefficient on $N \times 2$ becomes negative and significant. Thus, the apparent advantage of square boards appears to operate primarily through their effect on the likelihood that Player 1 identifies the SPNE-consistent opening move. Conditional on that opening choice and the other controls, however, grids with two columns appear less favorable to Player 1 than other shapes.

Column (3) provides a sharper measure of subjects' ability to solve the initial board by using an indicator for Player 1 playing according to SPNE throughout the game as the dependent variable. The estimates show that subjects are more likely to implement SPNE throughout the game in both square and $N \times 2$ boards, but are less likely to do so in games with more boxes or a longer SPNE path.

The evidence based on win rates in Figure 4 and Columns (1) and (2) of Appendix Table 6 is therefore suggestive, but it should not be interpreted as definitive evidence on subjects' ability to solve a given initial board. A player need not solve the game perfectly in order to win, so winning is a coarse outcome that can reflect several channels, including whether Player 1 identifies the SPNE-consistent opening move, how well Player 1 continues to play in later turns, and whether Player 2 makes mistakes along the realized path. For that reason, Column (3), which focuses on perfect play from the initial state, provides a cleaner measure of subjects' ability to solve the game. At the same time, the attenuation of the coefficient on Square Game after controlling for First Move SPNE in Column (2) is informative about mechanism, and suggests that the apparent advantage of square boards operates primarily through their effect on the likelihood that Player 1 identifies the correct opening move.

5.2 Moves Made from a Losing Position

All game states in Chomp can be classified as either winning or losing. In a winning state, a player who follows an SPNE strategy at the current and all future nodes is guaranteed to win. Because only a small subset of moves is optimal, SPNE provides sharp predictions for behavior in winning positions. By contrast, in a losing state SPNE implies that every available move ultimately leads to a loss and therefore does not distinguish among actions at that state—it does not make *any* prediction about what players will do. In this section, we study how players actually behave in these losing positions.

To test Hypothesis 2, which states that players in a losing position will remove fewer boxes, we need to account for several other features of the game's state. In particular, there are characteristics of the current position that are correlated with whether it is winning or losing and are also likely to affect how many boxes are removed. These include the current number of boxes in the grid, how close the player is to the end of the game under rational play, and how many boxes *should* be removed in the corresponding winning position according to SPNE.[8]

Result 2. Players remove slightly fewer boxes from losing positions than from comparable winning positions on average, but this difference is small, weakens with experience, and eventually reverses.

[8] In cases where there are multiple SPNE moves, we define this variable as the maximum number of boxes that can be removed while remaining consistent with SPNE.

Table 1 presents the evidence for Result 2 and offers little support for Hypothesis 2. The regressions relate the number of boxes removed to characteristics of the current game state, controlling for "Match Number" (a proxy for experience), the current number of available boxes, and the number of moves left according to SPNE (discussed further in Section 6.1).

Dependent variable: Number of Boxes Removed			
	FE (1)	FE (2)	FE (3)
Winning Position	0.1007**	0.1041	0.5088***
	(0.0397)	(0.1006)	(0.1311)
Winning Position x Match Number			−0.0343***
			(0.0071)
Winning Position x SPNE Boxes Removed		−0.0032	−0.0032
		(0.0880)	(0.0881)
Num. Available Boxes	0.6526***	0.6556***	0.6552***
	(0.0271)	(0.0844)	(0.0846)
Match Number	−0.0421***	−0.0421***	−0.0159***
	(0.0056)	(0.0056)	(0.0038)
SPNE Moves Left	−0.4217***	−0.4252***	−0.4244***
	(0.0348)	(0.0888)	(0.0890)
Observations	7,425	7,425	7,425
Adjusted R^2	0.7001	0.7001	0.7005

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 1: Regression on number of boxes removed

Column (1) of Table 1 shows that, controlling for other characteristics of the game state, players in winning positions remove about 0.1 more boxes than players in a losing position, on average. This difference is statistically significant but very small in magnitude: players must remove at least one box, and the average number of boxes removed is 2.88. When we additionally control for the number of boxes that *should* be removed in the corresponding winning position according to SPNE, the difference between winning and losing positions is no longer statistically significant. The coefficients on the other covariates are informative: subjects remove more boxes when more boxes are available, remove fewer boxes as they gain more experience (as measured by the number of matches they have completed), and remove fewer boxes when they are farther from the end of the game (as measured by the number of remaining moves along the SPNE path).

Column (3) of Table 1 includes an interaction of Match Number and Winning Position, showing how the association between experience and the number of boxes removed depends on whether the player is in a winning position. The negative relationship between experience and the number of boxes removed is *stronger* in winning positions than in losing positions. Thus, rather than moving toward the prediction of Hypothesis 2 that fewer boxes should be removed from losing positions, experience pushes behavior in the opposite direction. The coefficients imply that at the beginning of the experiment, subjects remove about one half of a box more, on average, from winning positions than from losing positions. By about match 15 this gap closes, and by match 20 the estimated relationship has reversed. Overall, we do not find strong evidence in favor of Hypothesis 2.

6 Patterns and Determinants of Play

The results in Section 5 show that while subjects in our experiment do not behave exactly as theory predicts, there are clear patterns in how they choose, and these patterns depend on the state of the game that they face. In this section, we explore the drivers of behavior in the Game of Chomp.

6.1 Complexity and Limited Backward Induction

Most game-theoretic solution concepts, including SPNE, implicitly assume that decision makers face no constraints on their ability to compute equilibria. In practice, however, even computers cannot fully solve complex games such as chess or Go (Simon, 1955). Experimental evidence in McKinney Jr and Van Huyck (2007, 2013) similarly shows that game complexity limits subjects' ability to choose according to equilibrium. Thus, the complexity of the game is a natural candidate determinant of how subjects actually play. In this subsection, we investigate which features of the Game of Chomp make it difficult for players to implement backward induction.

We focus on two sources of complexity: (i) the number of options available to the player and (ii) how far into the future the player must reason. The first is captured by the number of available boxes, since a player always chooses from the set of boxes that remain (except for the top-left box). To quantify the second, we define the variable "SPNE Moves Left," which measures the number of moves remaining along a particular SPNE path. More specifically, we use backward induction on the game tree, breaking indifference for the player in a losing position by selecting the option that pushes the end of the game furthest into the future, and for the player in a winning position by selecting the option that brings the end of the game closest. Using this rule, "SPNE Moves Left" is defined as the number of turns until the game ends.[9] Table 2 shows the values of these variables for each of the initial game states used in our experiment, and Appendix Figure 12 shows graphically how each measure is related to the likelihood of choosing in a way that is consistent with SPNE.

Grid Size	Moves Left	Available boxes
2x2	3	4
3x2	5	6
4x2	7	8
4x3	7	12
4x4	7	16
5x3	11	15
5x4	11	20
6x2	11	12
6x3	11	18
6x4	11	24
6x5	15	30
6x6	11	36
8x3	15	24

Table 2: Summary of available boxes and moves left for grid size.

Result 3. SPNE-consistent play falls sharply with the steps remaining on the equilibrium path and, conditional on that distance and the shape of the game, is essentially unrelated to the number of available options.

The evidence for Result 3, which partially contradicts Hypothesis 3, can be found in Table 3, which presents fixed-effects regressions where the dependent variable is an indicator for making a winning move.[10] We restrict the sample to choices made from winning positions, so the outcome equals one if the subject selects a move that guarantees they will be in a winning position when they next move and zero otherwise. The independent variables are characteristics of the game state the subject faces. All specifications include Match Number, our proxy for experience.[11] Our main focus in this analysis is on the variables "Num. Available Boxes" and "SPNE Moves Left," which capture different aspects of the complexity of the subject's current state.

[9]By construction, all winning positions have an odd number of moves left, while all losing positions have an even number of moves left.

[10]Implicitly, these regressions use the likelihood of making an SPNE-consistent move as a proxy for complexity. As an alternative proxy, we can consider the time subjects took to make each move, although each turn was capped at 30 seconds. Appendix Figure 13 shows that decision time increases with SPNE moves left and the number of available boxes for low values of these variables, but then levels off at about 20 seconds.

[11]The coefficient on Match Number is positive, indicating the intuitive result that as subjects gain experience they are more likely to make a winning move. We address learning more explicitly in Section 6.2.

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0042***	0.0056***	0.0057***	0.0056***
	(0.0011)	(0.0010)	(0.0010)	(0.0010)
Num. Available Boxes	−0.0373***		0.0054**	0.0028
	(0.0011)		(0.0022)	(0.0019)
SPNE Moves Left		−0.0805***	−0.0898***	−0.0851***
		(0.0012)	(0.0038)	(0.0033)
Square Game State				0.0978***
				(0.0184)
Nx2 Game State				0.0017
				(0.0264)
Observations	5,555	5,555	5,555	5,555
Adjusted R^2	0.3489	0.4580	0.4593	0.4624

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effects of Complexity on SPNE Consistent Move

The negative and statistically significant coefficients for the number of available boxes in model 1 and for moves left in model 2 imply that subjects are less likely to make winning moves when the game is more complex. Model 3 presents a more surprising result: when controlling for the number of moves left to the end of the game, the relationship between the number of available boxes and the likelihood of making a winning move is *positive*, albeit small. However, this relationship disappears when we control for the "shape" of the game, as captured by dummies for the current grid being either a square or having two columns. Thus, in the Game of Chomp, the distance to the end of the game is a more relevant measure of complexity than the number of options available to the decision-maker.

Appendix Table 7 examines whether omitted variables may be biasing our results. Controlling for either the number of moves already made or the fraction of available moves that are consistent with SPNE does not substantially alter the coefficients on Num. Available Boxes or SPNE Moves Left.[12] The table also addresses the selection induced by the game's structure: when a subject in

[12]Recall that in all initial game states used in our experiment, there is exactly one move that is consistent with SPNE. However, in other reachable histories there can be more than one winning move. Of the 5,555 observations with at least one winning move, 5,296 had exactly one winning move available, 226 had two, and 33 had three.

a winning position makes an SPNE-consistent move, their next move will also be from a winning position. To account for this, Table 7 controls for how the subject came to be in a winning position on that turn. These controls are strongly related to the likelihood of making an SPNE-consistent move, but including them leaves unchanged the pattern of negative and statistically significant effects of SPNE Moves Left and near-null effects of Num. Available Boxes.

Appendix Table 8 investigates potential nonlinearities in the effects of our complexity measures. When we flexibly control for the number of available boxes using dummies, the estimated linear effect of SPNE Moves Left remains negative and statistically significant, although smaller than in Table 3. In contrast, when we flexibly control for SPNE Moves Left, the estimated linear effect of Num. Available Boxes is close to zero and statistically insignificant.

The fact that the ability to implement the SPNE strategy depends strongly on the distance to the end of the game and only weakly on the number of available moves speaks directly to the complexity literature discussed in Section 2. In particular, our results speak to the same underlying issue emphasized by Pycia and Troyan (2023): the importance of limited foresight and planning horizons in extensive-form settings. They further reinforce the idea, advanced by Rampal (2022) and Rampal (2025), that limitations to foresight should be explicitly incorporated into behavioral equilibrium concepts.

In order to further explore the prevalence of limited backward induction in our sample, we classify subjects according to the distance to the end of the game at which they are able to implement the SPNE strategy. Specifically, we say that a subject's Foresight Level[13] is k if they choose a winning move (i.e., a move that preserves a win according to SPNE) at least 70% of the time when the end of the game is at most k turns away, and less than 70% of the time when it is further away.[14] Thus, a subject with Foresight Level 1 tends to make a winning move when they can win the game in the current round, but not when they could guarantee themselves a win only by their next move.[15] In all cases, we restrict attention to choices made from winning positions.

Figure 5 shows the distribution of Foresight Levels in our sample.[16] The vast majority of subjects have Foresight Levels of either 3 or 5, suggesting that they can evaluate contingencies a few turns into the future, but not much further. Similar patterns appear in other dynamic games. In Nim, McKinney Jr and Van Huyck (2007) estimate a "rationality bound" and find that the average subject can reason effectively only up to about rank 6, with substantial heterogeneity across subjects. In the Game of 21 and the Race Game, Dufwenberg et al. (2010) and Gneezy et al. (2010) likewise report

[13]We borrow this terminology from Rampal (2022).

[14]The cutoff of 70% was chosen arbitrarily. Appendix Figure 14 shows the classifications for cutoffs of 50% and 80%, respectively.

[15]A Foresight Level of 0 indicates that the subject chooses correctly less than 70% of the time even when they could win in the current round.

[16]Because of the structure of the Game of Chomp, Foresight Levels are necessarily odd: winning moves can only be made in game states that are an odd number of turns away from the end of the game according to SPNE.

that behavior is close to equilibrium only a few moves from the end of the game and deteriorates further away. Our Foresight Levels, which cluster at three to five moves, are thus broadly in line with earlier evidence on finite planning horizons in dynamic games.

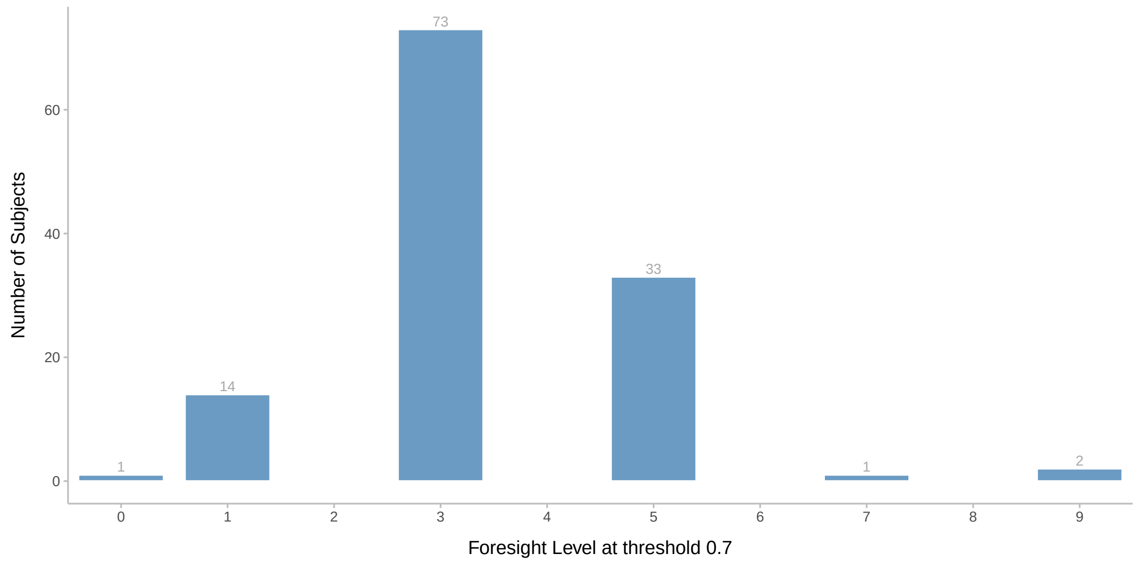


Figure 5: Subjects' Foresight Level at threshold 0.7

Appendix Table 10 explores the correlation between survey responses and optimal behavior in our experiment. The dependent variable in column (1) is a binary indicator for making a choice consistent with SPNE (restricting to observations where the player is in a winning position), while the dependent variable in column (2) is the Foresight Level that we calculate for the subject. We find consistent results in both regressions. Conditional on all the covariates, being male is associated with a 5% increase in the likelihood of making a choice consistent with SPNE and a 0.67 higher Foresight Level. Each additional point on the CRT score is associated with a 5% increase in the likelihood of making a choice consistent with SPNE and a 0.30 higher Foresight Level. No other covariates have statistically significant coefficients.

A natural question is whether standard bounded-rationality models such as level-k, cognitive hierarchy, or quantal response equilibrium (QRE) can account for our findings (Nagel, 1995; Camerer et al., 2004; McKelvey and Palfrey, 1995). In a perfect-information win-lose game like Chomp, canonical level-k and cognitive hierarchy models would predict that any type above level 0 plays very close to SPNE, once she computes a best response, which conflicts with the large, depth-dependent errors we observe. While QRE can generate error rates that depend on the distance to the end of the game, the opening (2,2) heuristic move that we document in Section 6.3 is less naturally explained by QRE and instead is more consistent with subjects using a simplification heuristic in response to limited foresight.

6.2 Learning the Game of Chomp

In this section, we discuss how subjects' behavior changed as they gained more experience. Previous research has shown that, in many repeated games, subjects' play tends to move closer to Nash equilibrium as they gain experience (see, e.g., Van Huyck et al. (1991); Nagel (1995); Camerer and Hua Ho (1999)). Moreover, this learning extends to playing closer to subgame perfection (Gneezy et al., 2010; McKinney Jr and Van Huyck, 2013). The positive coefficient on Match Number in Table 3 is consistent with this: subjects make winning moves more often when they have more experience.

The Game of Chomp provides a unique and rich setting to study how decision-makers learn to play subgame perfect equilibrium. The game involves very simple game states, where the player is only a few moves away from winning, and complex game states for which even experts might have difficulty finding the optimal move.

Result 4. Subjects' consistency with SPNE increases with experience, and this improvement is concentrated in subgames of intermediate complexity.

We measure learning effects by using the indicator dependent variable "SPNE Consistent Move," and then binning game states by SPNE Moves Left, as shown in Table 4. Observations are restricted to moves at winning positions (and, thus, where the number of moves left until the end of the game is odd). The states of the game were categorized as having 3–5, 7–9, or more than 11 moves left to the end node of the game, with the corresponding dummy variables shown in the regression.[17] Interaction terms between the aforementioned dummy variables and the independent variable *Match Number* are also included in column (2). The baseline is when a move that wins the game is available in the current round.

[17] In Appendix Table 9, we reproduce these results using the number of boxes left instead of the number of moves left as the game state. The interpretation is largely the same: learning is concentrated in games of intermediate complexity.

Dependent variable: SPNE Consistent Move		
	LPM (1)	LPM (2)
Intercept	0.9215***	0.9691***
	(0.0122)	(0.0096)
3-5 Moves	-0.2575***	-0.3884***
	(0.0145)	(0.0292)
7-9 Moves	-0.7136***	-0.7473***
	(0.0213)	(0.0385)
More than 11 Moves	-0.9063***	-0.8815***
	(0.0103)	(0.0198)
Match Number	0.0057***	0.0014*
	(0.0010)	(0.0007)
3-5 Moves x Match Number		0.0118***
		(0.0021)
7-9 Moves x Match Number		0.0032
		(0.0027)
More than 11 Moves x Match Number		-0.0018
		(0.0014)
Observations	5555	5555
Adjusted R^2	0.4776	0.4821

Note: Standard errors are clustered at the subject level.
Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Differential effects of experience by SPNE Moves Left

The patterns are intuitive. The coefficients on all distance-to-end dummies are negative and statistically significant at the 1% level, indicating that subjects are less likely to make a winning (SPNE-consistent) move when the game state is farther from the end node. Moreover, these coefficients become more negative for higher distances. Focusing on column (2), the coefficient on Match Number is positive but close to zero and not statistically significant, implying little detectable learning for states that are a single move away from the end of the game.[18] The interaction terms provide more insight into how learning varies across states, and they are generally consistent with Hypothesis 4. Subjects show some improvement in states that are a few moves from the end of the game: the interaction coefficient for states with 3–5 moves remaining is positive and statistically significant at the 1% level. The coefficient implies that the probability of making an optimal choice increases by 20 to 25 percentage points by the end of the experiment. By contrast, learning appears weaker and is statistically insignificant when there are 7–9 moves or more than 11 moves left.

[18]This is not surprising, as the probability of making a winning move is already near one in these states.

6.3 L-shaped Games and the $(2, 2)$ Heuristic

This subsection reports an exploratory analysis of a pattern that emerged clearly in the data but that we did not foresee: the pervasive use of the move (2,2) as an opening and the role of the resulting L-shaped games.

Since all the grid sizes used in the experiment are smaller than 8×10, there is a unique optimal initial choice for each grid size. For instance, the optimal initial choice for a 2×2 grid is $(2, 2)$, and making this move guarantees Player 1 a sure win; for a 3×2 grid, the move $(3, 2)$ is optimal. As noted in Section 3, while $(2, 2)$ is the optimal first move for all square grids, it is *never* the optimal first move for *any* non-square grid.

Figure 6 shows players' first move across all grid sizes. The bottom (striped) portion of each bar represents the proportion of choices that were consistent with SPNE. The SPNE-consistent initial choice was only chosen higher than 50% of the time in 2×2 and 3×2 games. Despite being suboptimal in all non-square games, $(2, 2)$ is the most prevalent choice for all grid sizes other than 3×2, 4×2, and 6×2. For games that are not square, this indicates that subjects started suboptimally and, according to SPNE, lost their initial advantage of being Player 1.

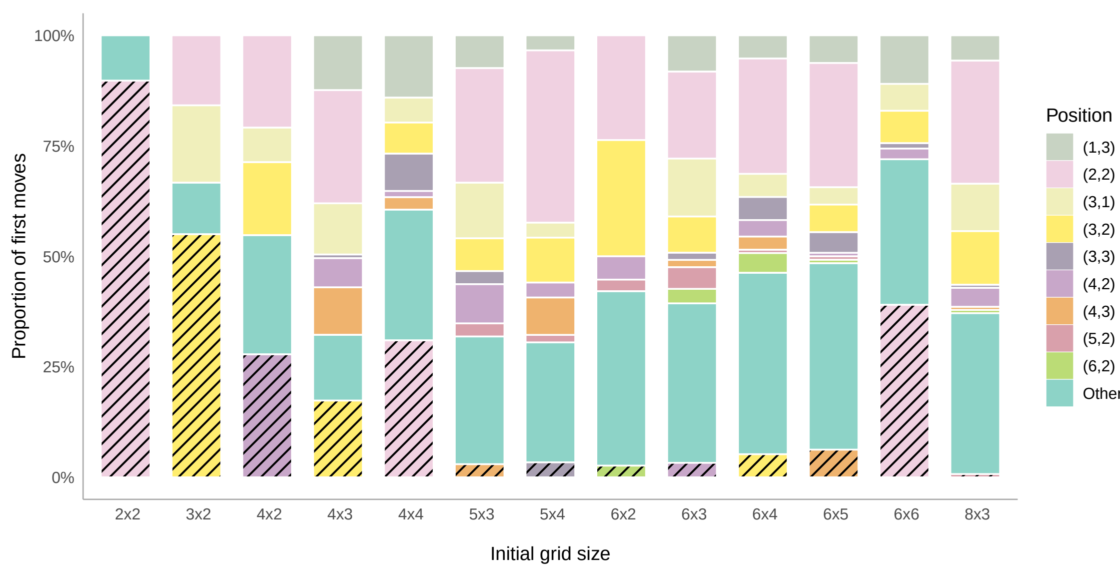


Figure 6: Proportion of initial choice by grid size

A more surprising result is that the rate of Player 1 winning when choosing $(2, 2)$ as initial move is relatively high in both treatments, *even for rectangular games*. These rates are shown in Figure 7. The winning proportion is higher than 0.5 for all square games and for 4×3, 5×4, 6×4, and 6×5 games. In contrast, win rates when choosing the initial choice of $(2, 2)$ were less than 25% in all $N \times 2$ games.

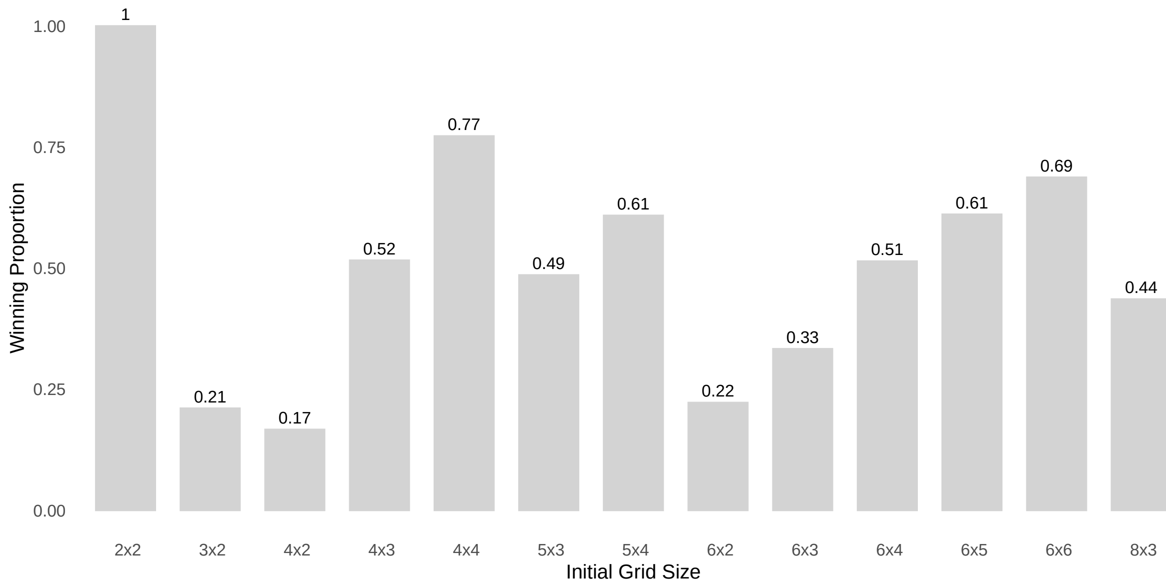


Figure 7: Winning proportion when choosing initial choice $(2, 2)$ by grid sizes

We refer to the game state that results from choosing the box at (2,2) as an L-shaped game. Throughout the experiment, 35% of games eventually reached an L-shaped game. Because L-shaped games are both empirically prevalent and (relatively) strategically straightforward, we further study how subjects learned and performed in them. Figure 8 shows the proportion of winning moves made by 124 subjects in L-shaped games. Six subjects *never* made an optimal choice, while nine played perfectly. Roughly 60% of the subjects have a probability of making a winning move in L-shaped games of more than 0.5. This might explain why the winning proportions while choosing (2,2) as initial move are relatively high. Many subjects learned to play L-shaped games optimally.[19]

[19]Column (3) of Appendix Table 10 reports the results of a linear regression analysis of the probability of making a winning move in L-shaped games, based on the subjects' demographic information. Similar to the relationship between demographics and making optimal moves more generally, both the indicator for being male and the CRT score are positively related to the likelihood of choosing optimally in L-shaped games.

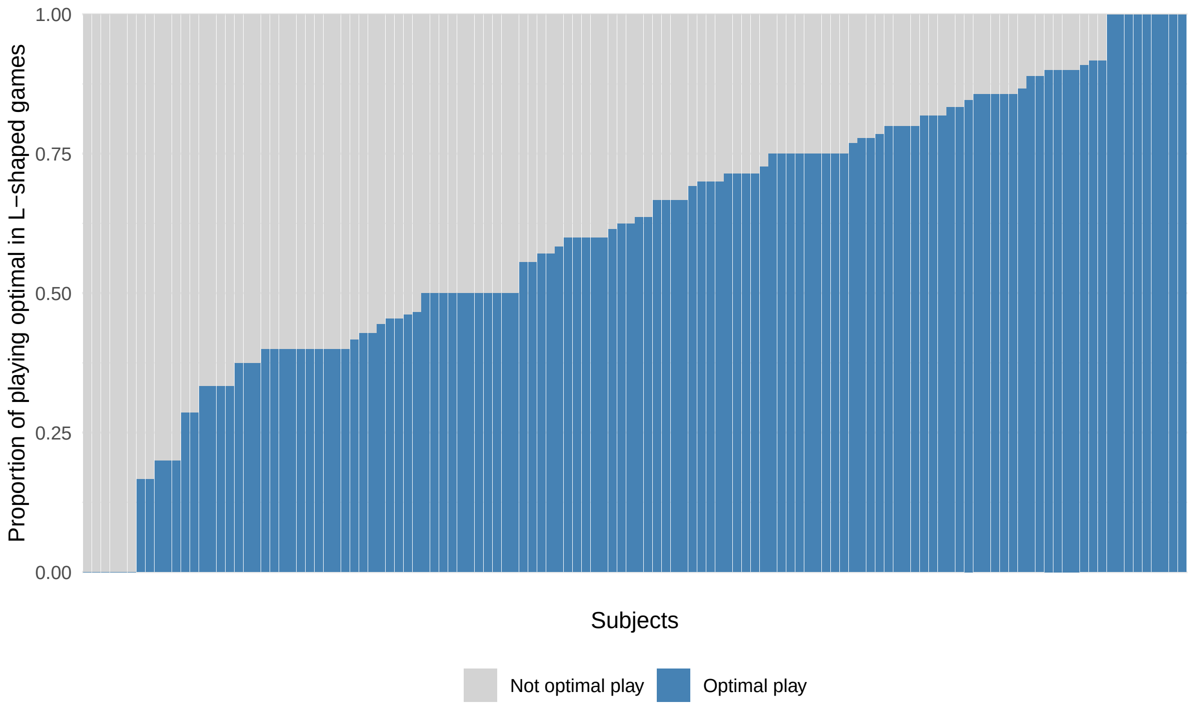


Figure 8: Proportion of winning moves in L-shaped games by subject

Taken together, these findings suggest that many subjects adopt a simple $(2, 2)$ opening heuristic: they frequently choose (2,2) as an initial move, even when it is not SPNE-optimal, in order to transform diverse starting boards into a familiar class of L-shaped games. Because a large share of subjects learn to play these L-shaped subgames close to optimally, this heuristic remains profitable in practice and yields relatively high win rates for Player 1, even on rectangular boards where (2,2) is theoretically suboptimal. This pattern complements our earlier evidence on limited foresight: rather than computing optimal play from each initial state, subjects appear to reshape the game into strategically simpler subgames where they understand how to play optimally.

7 Conclusion

In this paper, we reported the results of an experiment implementing the Game of Chomp. Subjects played repeatedly with random partners and initial game states. They do not play according to SPNE: even when they could guarantee themselves a win, they often fail to choose an optimal move. We explored this behavior further and found that the ability to choose optimally decreases with the number of steps until the end of the game, but that subjects learn to play closer to optimally over the course of the experiment. Finally, we documented a simple heuristic that subjects appear to use to simplify the game, transforming a variety of boards into a familiar class of positions that they can play relatively well.

Our results have implications for behavioral and experimental game theory. At a basic level, they suggest that limited foresight is a key feature that should be incorporated into equilibrium concepts for dynamic games, supporting approaches such as that in Rampal (2022). At the same time, these implications should be applied to other game-theoretic settings with caution: Chomp is a deterministic win-lose game of complete and perfect information with a highly structured state space. We do not claim that the specific empirical estimates can be directly applied to other dynamic environments. Instead, we interpret our findings as supporting a broader lesson: performance in dynamic games depends importantly on the depth of reasoning, and when making a complete and contingent plan is difficult, subjects may rely on heuristics that simplify the game. More broadly, systematic deviations from sequential rationality should be taken into account both in dynamic mechanism design and when empirically analyzing dynamic games. Finally, our approach provides a simple tool for evaluating sequential rationality that is easy to implement and explain. We expect this to be useful in future work studying learning and the transfer of behavior across related dynamic environments.

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A Additional Empirical Results

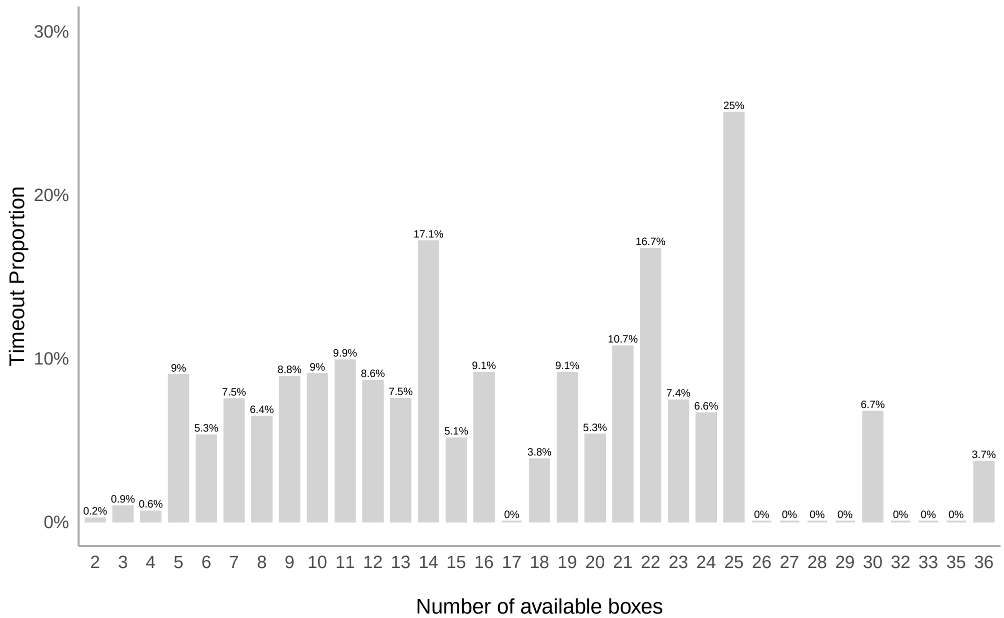


Figure 9: Timeouts by number of available boxes. This figure shows the proportion of timeouts at different number of available boxes. Timeouts are less likely to occur when game states have fewer than four boxes.

	Mean	Std. Dev.
CRT Score	1.40	1.17
Male	0.41	0.49
Age	23.27	4.87
English	0.20	0.40
Economics	0.33	0.47
Subjects	124.00	

Notes: CRT Score is the number of correct answers on a Cognitive Reflection Test, ranging from 0 to 3. Male, English, and Economics are equal to one if the subjects report being male, speaking English as a first language, and majoring in Economics, respectively.

Table 5: Summary statistics

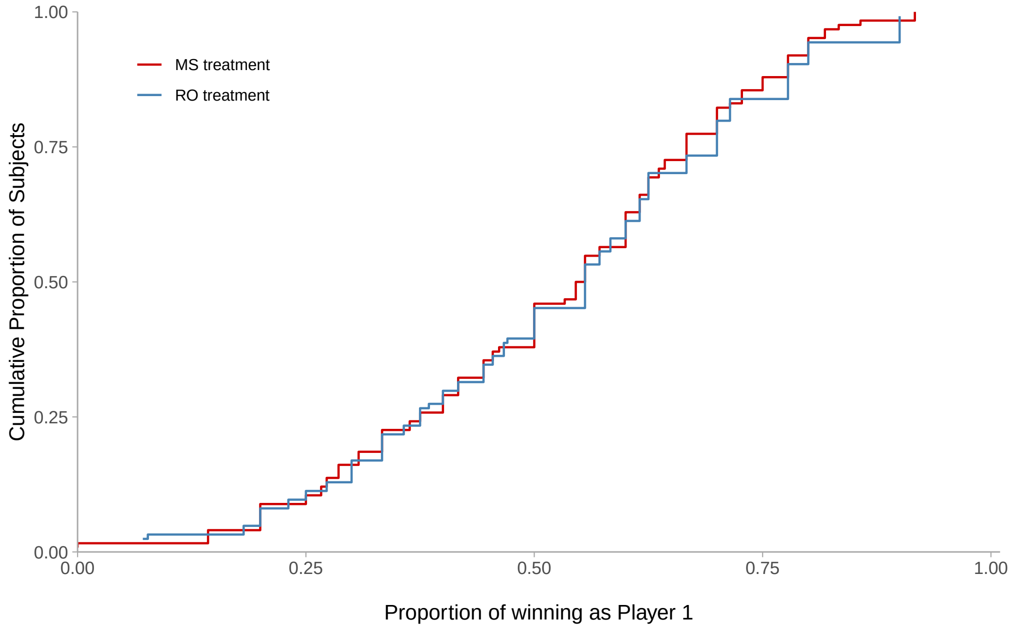


Figure 10: Proportion of winning as Player 1. This figure shows the distribution of subjects' win rates as Player 1 across the two treatments.

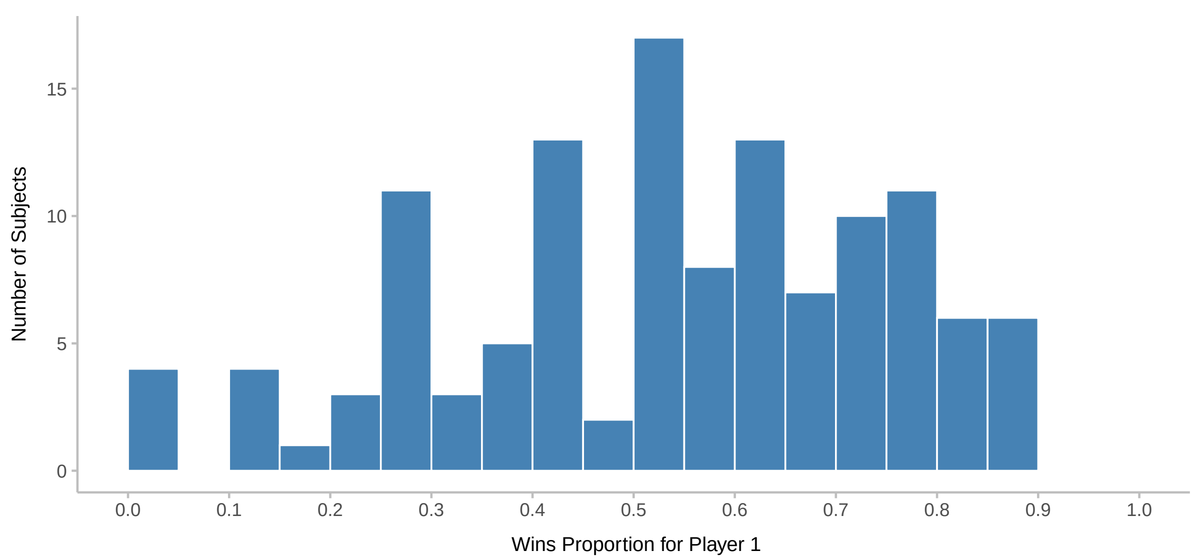
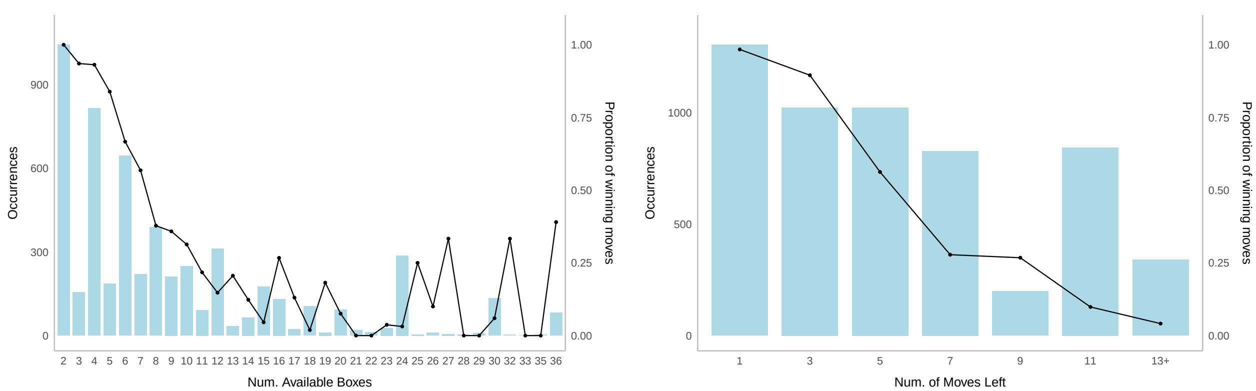


Figure 11: Histogram of proportion of winning as Player 1 in the first 18 round

Dependent variable:	Player 1 Winning		Perfect Play
	LPM (1)	LPM (2)	LPM (3)
Intercept	0.5783***	0.3702***	0.4390***
	(0.0659)	(0.0690)	(0.0488)
Square	0.1912***	0.0593	0.3065***
	(0.0512)	(0.0514)	(0.0460)
Nx2 Grid	-0.0502	-0.1028***	0.0847***
	(0.0406)	(0.0387)	(0.0328)
Num. Available Boxes	-0.0039	-0.0040	-0.0079***
	(0.0033)	(0.0033)	(0.0024)
SPNE Moves Left	-0.0017	0.0142	-0.0210***
	(0.0090)	(0.0091)	(0.0063)
First Move SPNE		0.4300***	
		(0.0419)	
Observations	1282	1282	1282
Adjusted R^2	0.0258	0.1125	0.3131

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

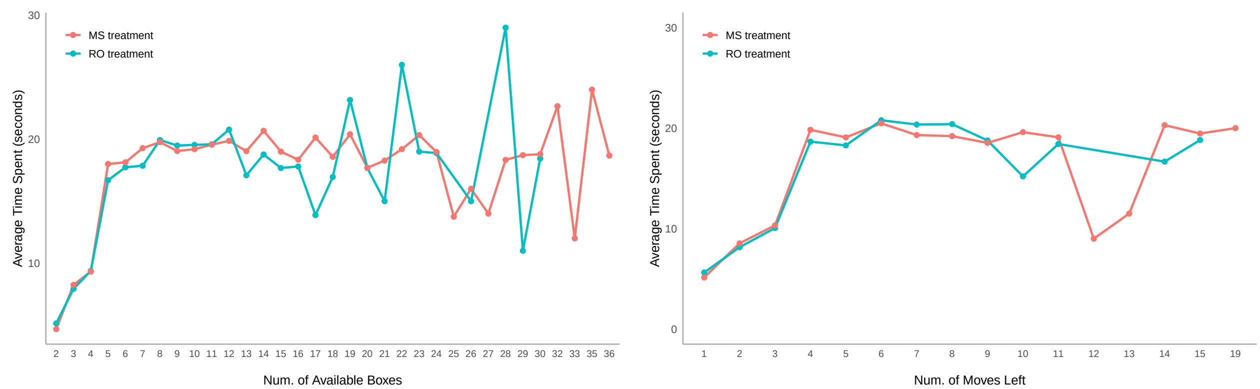
Table 6: Effects of initial game state on winning and playing perfectly



(a) Available Boxes

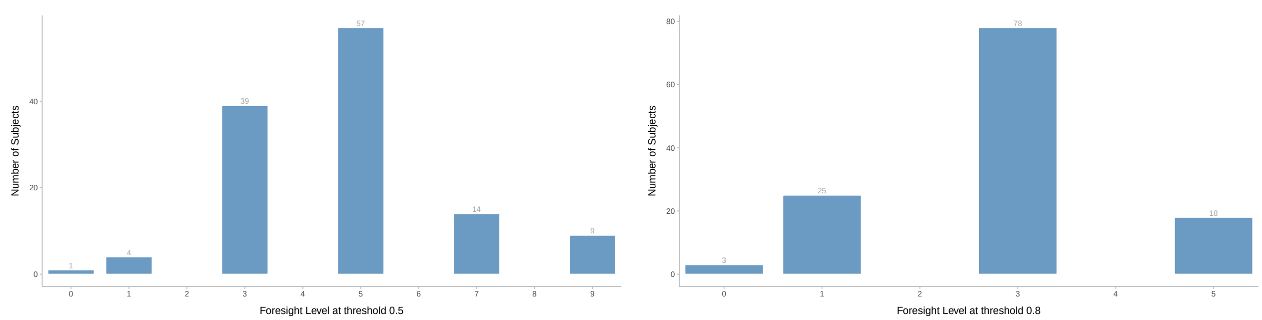
(b) SPNE Moves Left

Figure 12: Relationship between complexity measures and making a winning move. The proportion of moves that are consistent with SPNE is generally decreasing with both complexity measures.



(a) Available Boxes (b) SPNE Moves Left

Figure 13: Average time spent by game state. This figure summarizes the average time spent at different game states, either by number of boxes (panel (a)) or moves left (panel (b)). Subjects spent less time when there are fewer than 4 boxes left and when there are 3 moves left until the terminal state of the game. On average, subjects spent around 20 seconds making a choice.



(a) Threshold of 0.5 (b) Threshold of 0.8

Figure 14: Foresight Levels under alternative thresholds. Panels (a) and (b) show the distribution of Foresight Levels (see text for definition) using thresholds of 0.5 and 0.8, respectively. With a 0.5 threshold, Foresight Levels range from 0 to 9; with a 0.8 threshold, they range from 1 to 5. One subject has Foresight Level 0 at the 0.5 threshold, meaning she chooses optimally less than 50% of the time even when the game is one move from the terminal state.

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0045***	0.0054***	0.0040***	0.0043***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Num. Available Boxes	0.0035*	0.0009	0.0045**	0.0034*
	(0.0019)	(0.0019)	(0.0020)	(0.0020)
SPNE Moves Left	-0.0801***	-0.0668***	-0.0752***	-0.0641***
	(0.0033)	(0.0040)	(0.0035)	(0.0041)
Square Game State	0.1207***	0.1504***	0.1336***	0.1668***
	(0.0183)	(0.0187)	(0.0188)	(0.0194)
Nx2 Game State	0.0275	0.0302	0.0552**	0.0684**
	(0.0266)	(0.0274)	(0.0269)	(0.0277)
Moves Made	0.0376***			-0.0104*
	(0.0062)			(0.0054)
Fraction of Available Winning Moves		0.2482***		0.1972***
		(0.0292)		(0.0290)
OppMistake1			0.0066	0.0190
			(0.0185)	(0.0183)
WinAgain			0.0535***	0.0816***
			(0.0204)	(0.0218)
StayedWin			0.1909***	0.1747***
			(0.0245)	(0.0270)
RecoveredWin			0.1204***	0.1538***
			(0.0402)	(0.0403)
Observations	5555	5555	5555	5555
Adjusted R^2	0.4672	0.4756	0.4767	0.4830

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Robustness of the effects of complexity. This table extends the results from Table 3 to account for potential omitted variables. "Moves Made" is an integer representing the number of moves that had already been made up to the point of the subject's choice. "Fraction of Available Winning Moves" is the ratio of the number of moves consistent with SPNE to the total number of moves that could be made (Num. Available Boxes minus one). The final four variables of the table are indicators for how the player arrived at a winning position: 1) OppMistake1 equals one when it is Player 2's first move and Player 1's previous move was inconsistent with SPNE; 2) WinAgain equals one when the player was previously in a winning position, deviated from SPNE, and returns to a winning position because the opponent also deviated; 3) StayedWin equals one when the player was previously in a winning position, chose consistently with SPNE, and remains in a winning position; and 4) RecoveredWin equals one when the player was previously in a losing position and reaches a winning position because the opponent deviated from SPNE. The omitted category is thus where the player is in a winning position on their first move of the game.

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0056***	0.0058***	0.0063***	0.0059***
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Num. Available Boxes	0.0028	-0.0724***	0.0003	
	(0.0019)	(0.0068)	(0.0021)	
Num. Available Boxes^2		0.0016***		
		(0.0001)		
SPNE Moves Left	-0.0851***	-0.0637***		-0.0222***
	(0.0033)	(0.0118)		(0.0057)
SPNE Moves Left^2		0.0024***		
		(0.0006)		
Square Game State	0.0978***	0.1337***	0.1069***	0.0589***
	(0.0184)	(0.0171)	(0.0205)	(0.0179)
Nx2 Game State	0.0017	-0.0034	0.1024***	-0.0120
	(0.0263)	(0.0281)	(0.0289)	(0.0322)
SPNE Moves Left FE	No	No	Yes	No
Num. Available Boxes FE	No	No	No	Yes
Observations	5555	5555	5555	5555
Adjusted R^2	0.4624	0.5169	0.5136	0.5287

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Nonlinear complexity effects. This table investigates the potential for nonlinear effects of our two complexity measures. Column (1) reproduces the results from the final column of Table 3. Column (2) reports estimates of the quadratic model with the effect of both complexity measures being negative for small amounts of complexity but having a diminishing marginal effect. Columns (3) and (4) estimate linear effects of Num. Available Boxes and SPNE Moves Left while flexibly controlling for the other using dummy variables. The results show that there is no average effect of Num. Available Boxes when controlling flexibly for SPNE Moves Left, but the effect of SPNE Moves Left remains negative and statistically significant when controlling flexibly for Num. Available Boxes.

Dependent variable: SPNE Consistent Move		
	LPM (1)	LPM (2)
Intercept	0.9098***	0.9342***
	(0.0126)	(0.0118)
5-9 Boxes	-0.4035***	-0.5135***
	(0.0183)	(0.0329)
More than 10 Boxes	-0.8270***	-0.8005***
	(0.0109)	(0.0210)
Match Number	0.0052***	0.0030***
	(0.0010)	(0.0008)
5-9 Boxes x Match Number		0.0097***
		(0.0024)
More than 10 Boxes x Match Number		-0.0022
		(0.0016)
Observations	5555	5555
Adjusted R^2	0.4889	0.4924

Note: Standard errors are clustered at the subject level.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Learning by number of boxes left. This table reproduces the results from Table 4 , using the number of boxes instead of number of moves left as the game's state. The results are consistent with those in the text, with learning concentrated in game states of intermediate complexity.

	(1)	(2)	(3)
Intercept	0.4861***	2.7141***	0.6264***
	(0.0664)	(0.8724)	(0.0882)
Male	0.0516**	0.6703**	0.0828**
	(0.0234)	(0.2700)	(0.0337)
Age	0.0000	0.0056	−0.0022
	(0.0028)	(0.0354)	(0.0039)
English	−0.0460	−0.4549	−0.0256
	(0.0279)	(0.2815)	(0.0433)
Economics	0.0044	−0.1128	0.0326
	(0.0270)	(0.2932)	(0.0387)
CRT Score	0.0453***	0.2989***	0.0670***
	(0.0088)	(0.1088)	(0.0132)
Observations	5555	124	1275
Adjusted R^2	0.0149	0.0913	0.0339

Note: Standard errors are clustered at the subject level.
(1) SPNE Consistent Move, (2) Foresight Level,
(3) SPNE Consistent Move in L-shaped Game.
Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10: Relationship between demographics and consistency with SPNE. Controlling for all covariates, CRT score and being male are both positively and statistically significantly associated with all three consistency measures, while age, speaking English as a first language, and being an economics major are not significantly related to any of them.

B Results Separated by Treatment

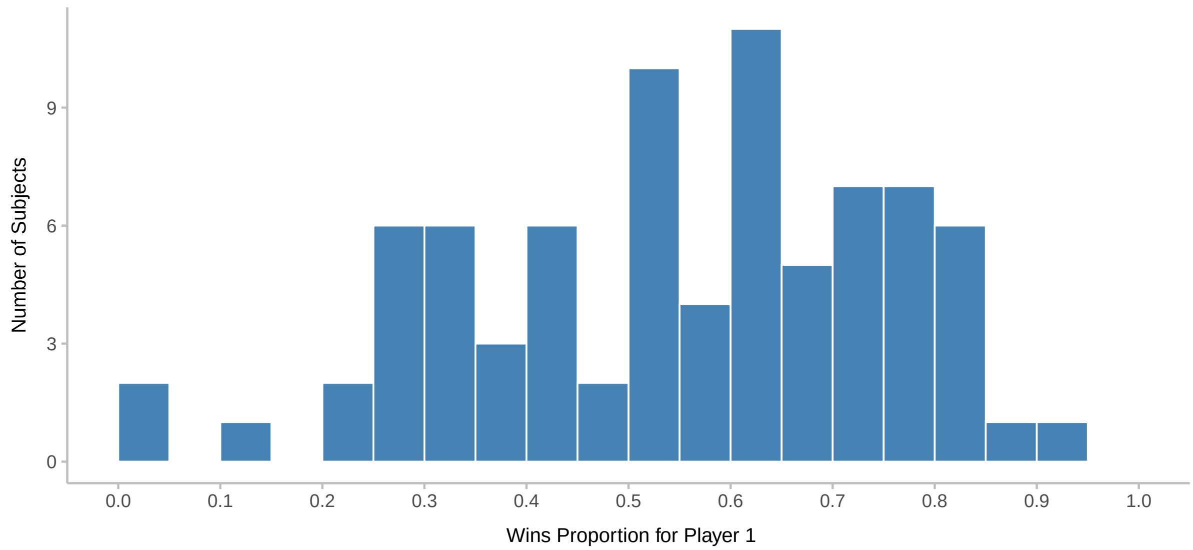


Figure 15: Histogram of proportion of winning as Player 1 in the MS Treatment

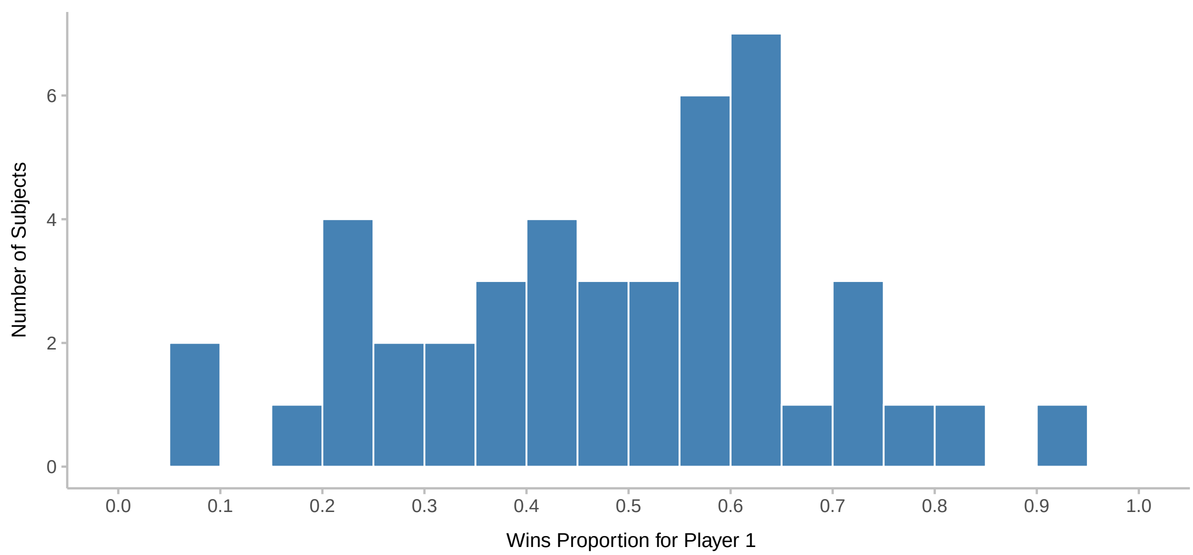


Figure 16: Histogram of proportion of winning as Player 1 in the RO Treatment

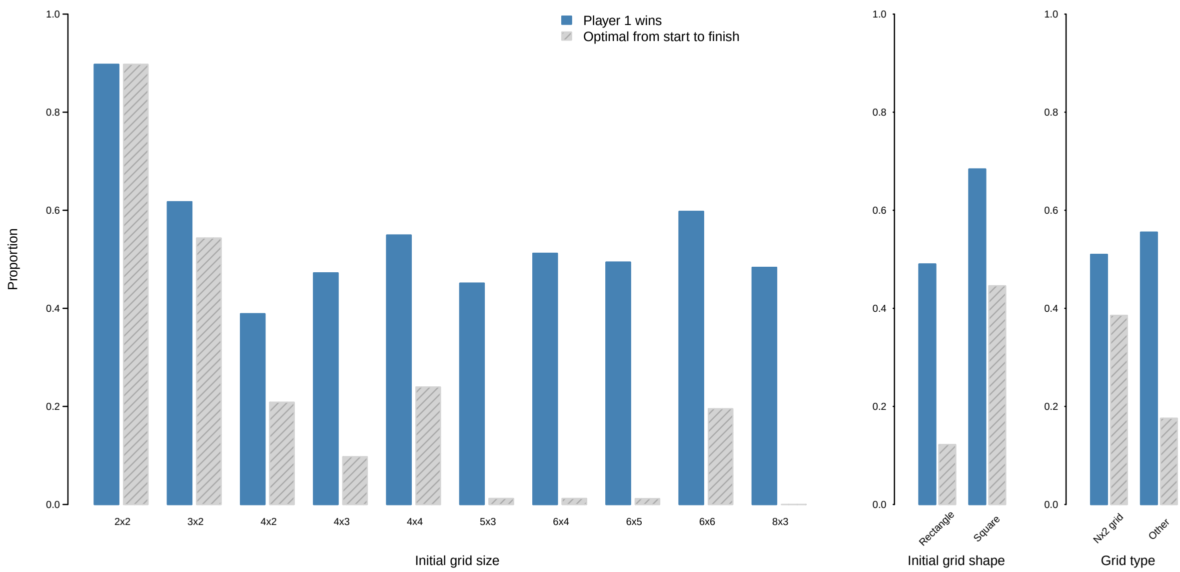


Figure 17: Winning proportion and perfect play of Player 1 by grid size and shape in the MS Treatment. Blue bars report the proportion of games that Player 1 won while striped grey bars report the proportion of games in which Player 1 *always* made moves that were consistent with SPNE.

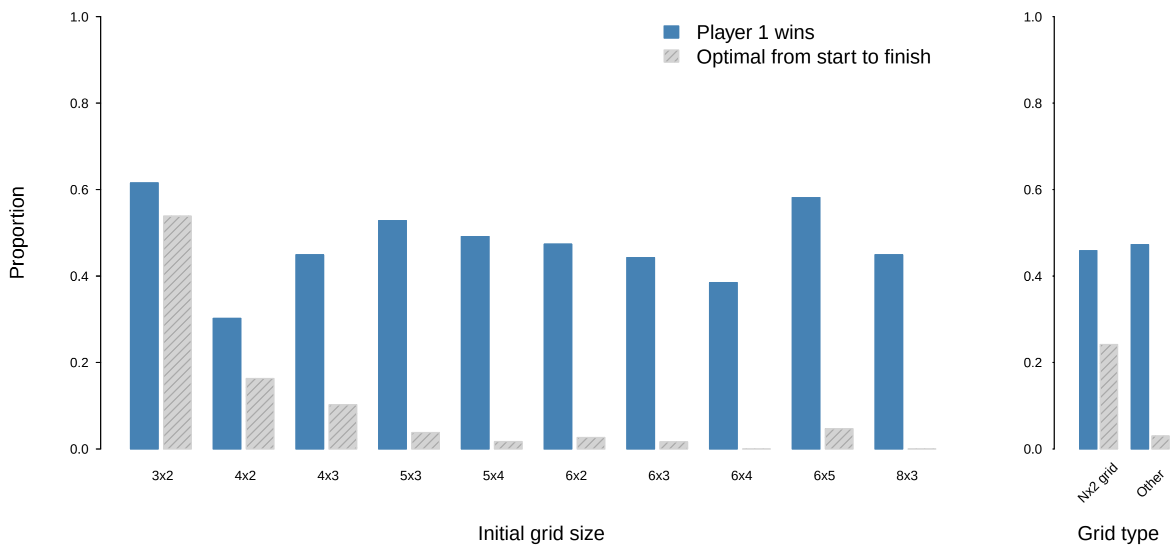


Figure 18: Winning proportion and perfect play of Player 1 by grid size and shape in the RO Treatment. Blue bars report the proportion of games that Player 1 won while striped grey bars report the proportion of games in which Player 1 *always* made moves that were consistent with SPNE.

Dependent variable: Number of Boxes Removed			
	FE (1)	FE (2)	FE (3)
Winning Position	0.0968*	-0.0429	0.3026*
	(0.0504)	(0.0888)	(0.1739)
Winning Position x Match Number			-0.0308**
			(0.0133)
Winning Position x SPNE Boxes Removed		0.1362***	0.1368***
		(0.0407)	(0.0406)
Num. Available Boxes	0.6553***	0.5240***	0.5234***
	(0.0311)	(0.0404)	(0.0404)
Match Number	-0.0367***	-0.0373***	-0.0141
	(0.0071)	(0.0058)	(0.0116)
SPNE Moves Left	-0.4585***	-0.3082***	-0.3073***
	(0.0411)	(0.0486)	(0.0486)
Observations	4661	4661	4661
Adjusted R^2	0.7046	0.7052	0.7055

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Regression on number of boxes removed in the MS Treatment

Dependent variable: Number of Boxes Removed			
	FE (1)	FE (2)	FE (3)
Winning Position	0.0711	0.4432***	1.0337***
	(0.0654)	(0.1141)	(0.2175)
Winning Position x Match Number			-0.0459***
			(0.0144)
Winning Position x SPNE Boxes Removed		-0.3169***	-0.3195***
		(0.0587)	(0.0586)
Num. Available Boxes	0.6668***	0.9214***	0.9227***
	(0.0464)	(0.0503)	(0.0502)
Match Number	-0.0488***	-0.0481***	-0.0121
	(0.0085)	(0.0059)	(0.0127)
SPNE Moves Left	-0.3873***	-0.6643***	-0.6652***
	(0.0488)	(0.0590)	(0.0589)
Observations	2764	2764	2764
Adjusted R^2	0.6955	0.6986	0.6996

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Regression on number of boxes removed in the RO Treatment

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0050***	0.0064***	0.0065***	0.0065***
	(0.0016)	(0.0015)	(0.0015)	(0.0015)
Num. Available Boxes	-0.0335***		0.0051**	0.0019
	(0.0012)		(0.0025)	(0.0022)
SPNE Moves Left		-0.0779***	-0.0869***	-0.0814***
		(0.0015)	(0.0045)	(0.0038)
Square Game State				0.1121***
				(0.0226)
Nx2 Game State				0.0191
				(0.0331)
Observations	3461	3461	3461	3461
Adjusted R^2	0.3170	0.4357	0.4372	0.4420

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Effects of Complexity on SPNE Consistent Move in the MS Treatment

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0030**	0.0044***	0.0045***	0.0044***
	(0.0015)	(0.0014)	(0.0014)	(0.0014)
Num. Available Boxes	-0.0462***		0.0049	0.0028
	(0.0014)		(0.0041)	(0.0040)
SPNE Moves Left		-0.0850***	-0.0929***	-0.0888***
		(0.0018)	(0.0066)	(0.0068)
Square Game State				0.0627**
				(0.0281)
Nx2 Game State				-0.0309
				(0.0438)
Observations	2094	2094	2094	2094
Adjusted R^2	0.4250	0.4968	0.4972	0.4980

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Effects of Complexity on SPNE Consistent Move in the RO Treatment

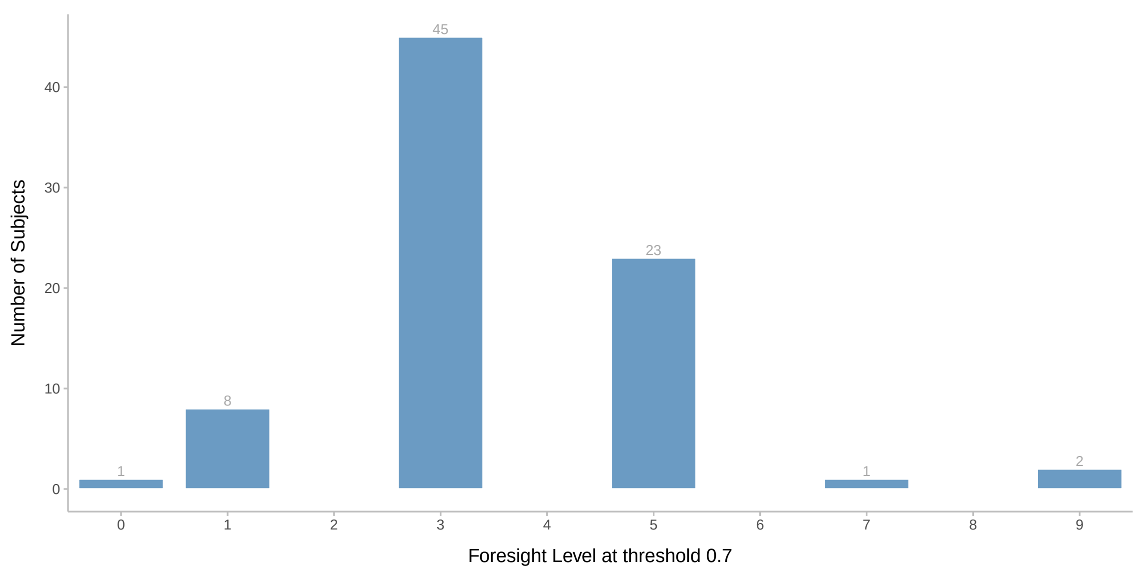


Figure 19: Subjects' Foresight Level at threshold 0.7 in the MS Treatment

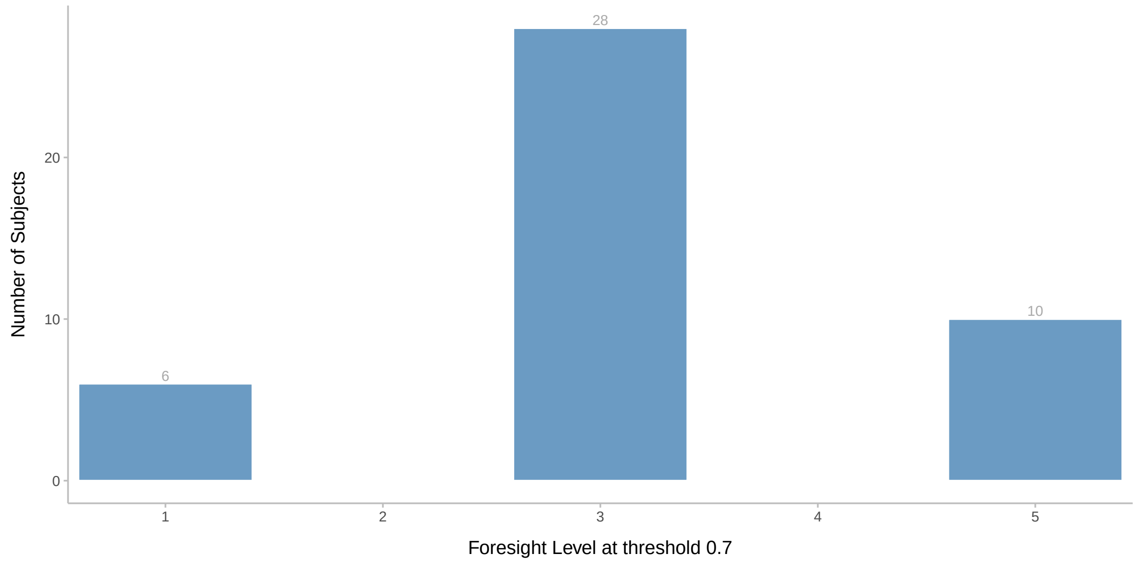


Figure 20: Subjects' Foresight Level at threshold 0.7 in the RO Treatment

Dependent variable: SPNE Consistent Move		
	LPM (1)	LPM (2)
Intercept	0.9099***	0.9716***
	(0.0163)	(0.0117)
3-5 Moves	-0.2497***	-0.4051***
	(0.0184)	(0.0393)
7-9 Moves	-0.7093***	-0.7613***
	(0.0282)	(0.0488)
More than 11 Moves	-0.8779***	-0.8525***
	(0.0140)	(0.0283)
Match Number	0.0070***	0.0011
	(0.0014)	(0.0009)
3-5 Moves x Match Number		0.0147***
		(0.0029)
7-9 Moves x Match Number		0.0050
		(0.0037)
More than 11 Moves x Match Number		-0.0018
		(0.0022)
Observations	3461	3461
Adjusted R^2	0.4541	0.4604

Note: Standard errors are clustered at the subject level.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Differential effects of experience by SPNE Moves Left in the MS Treatment

Dependent variable: SPNE Consistent Move		
	LPM (1)	LPM (2)
Intercept	0.9327***	0.9659***
	(0.0180)	(0.0171)
3-5 Moves	-0.2696***	-0.3736***
	(0.0235)	(0.0412)
7-9 Moves	-0.7221***	-0.7322***
	(0.0314)	(0.0626)
More than 11 Moves	-0.9502***	-0.9358***
	(0.0124)	(0.0243)
Match Number	0.0046***	0.0017
	(0.0013)	(0.0011)
3-5 Moves x Match Number		0.0086***
		(0.0028)
7-9 Moves x Match Number		0.0011
		(0.0042)
More than 11 Moves x Match Number		-0.0010
		(0.0015)
Observations	2094	2094
Adjusted R^2	0.5185	0.5206

Note: Standard errors are clustered at the subject level.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Differential effects of experience by SPNE Moves Left in the RO Treatment

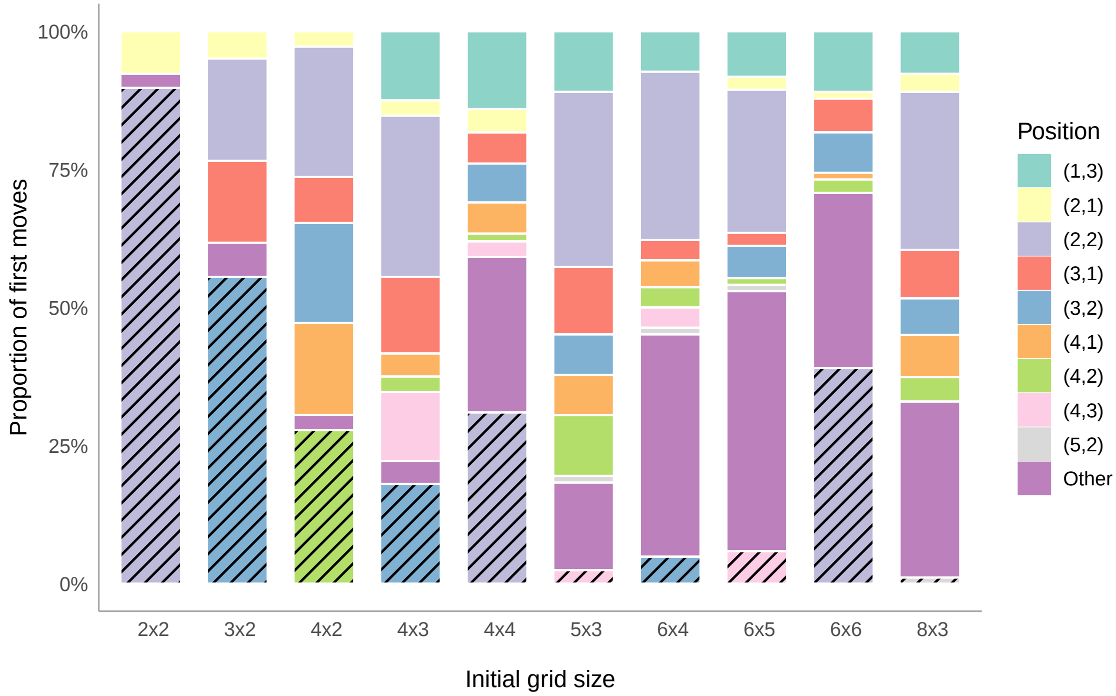


Figure 21: Proportion of initial choice by grid size in the MS Treatment

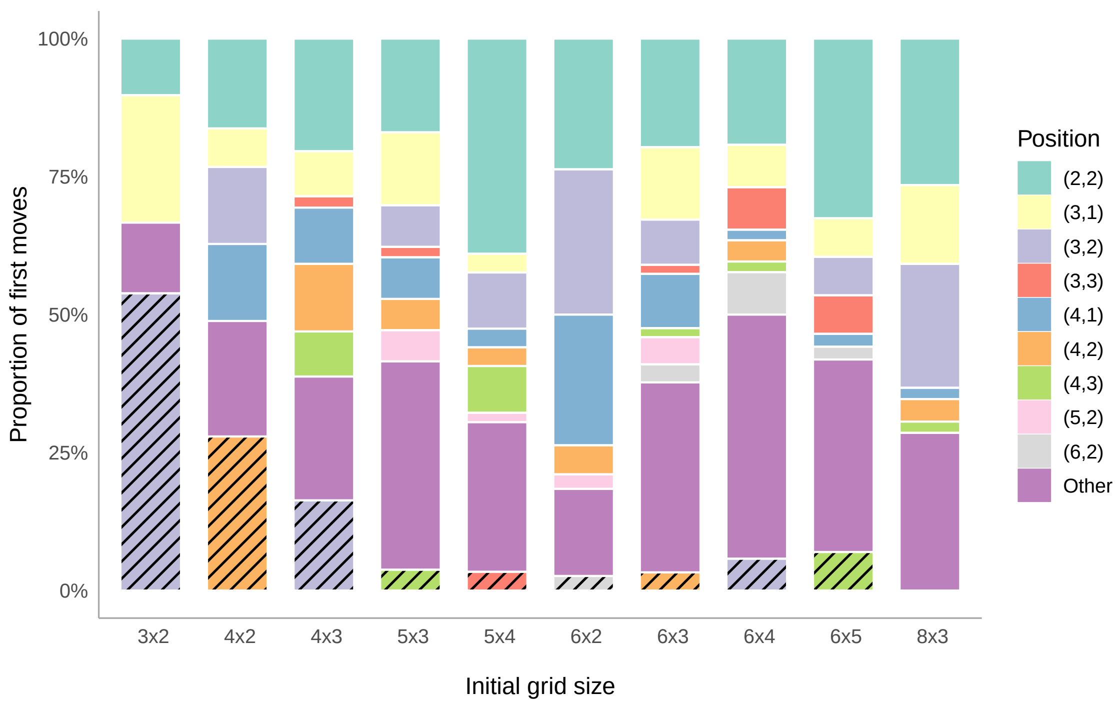


Figure 22: Proportion of initial choice by grid size in the RO Treament

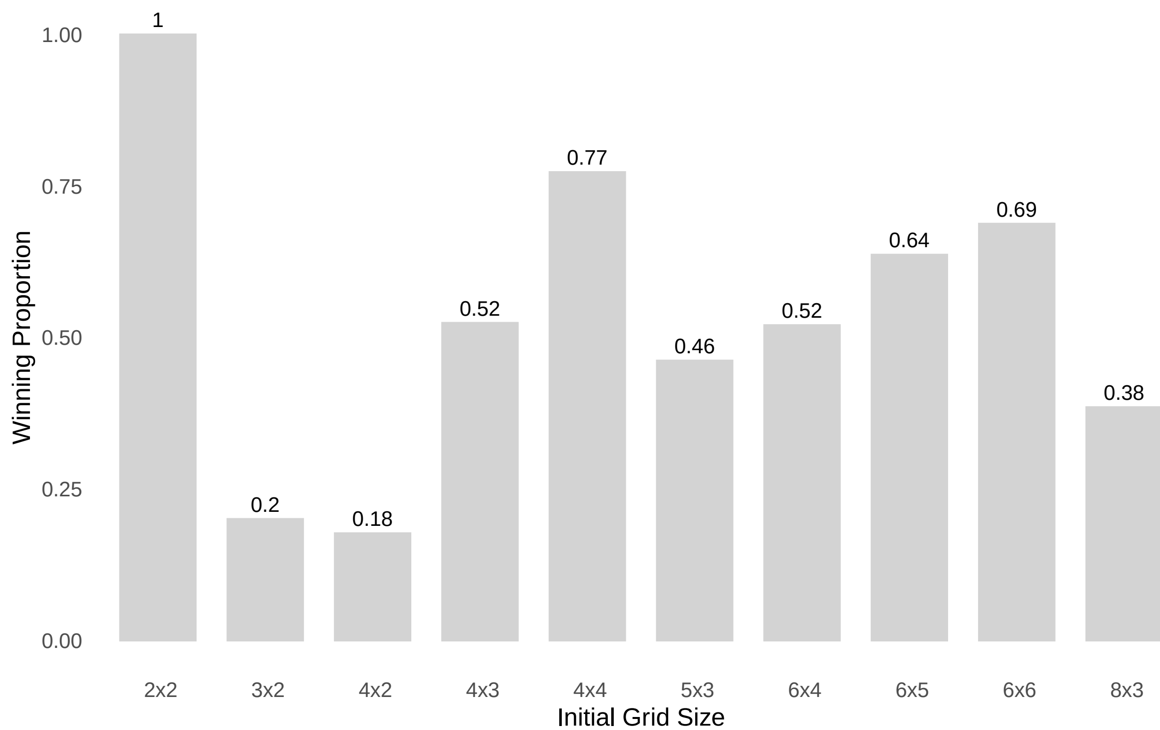


Figure 23: Winning proportion when choosing initial choice $(2, 2)$ by grid sizes in the MS Treatment

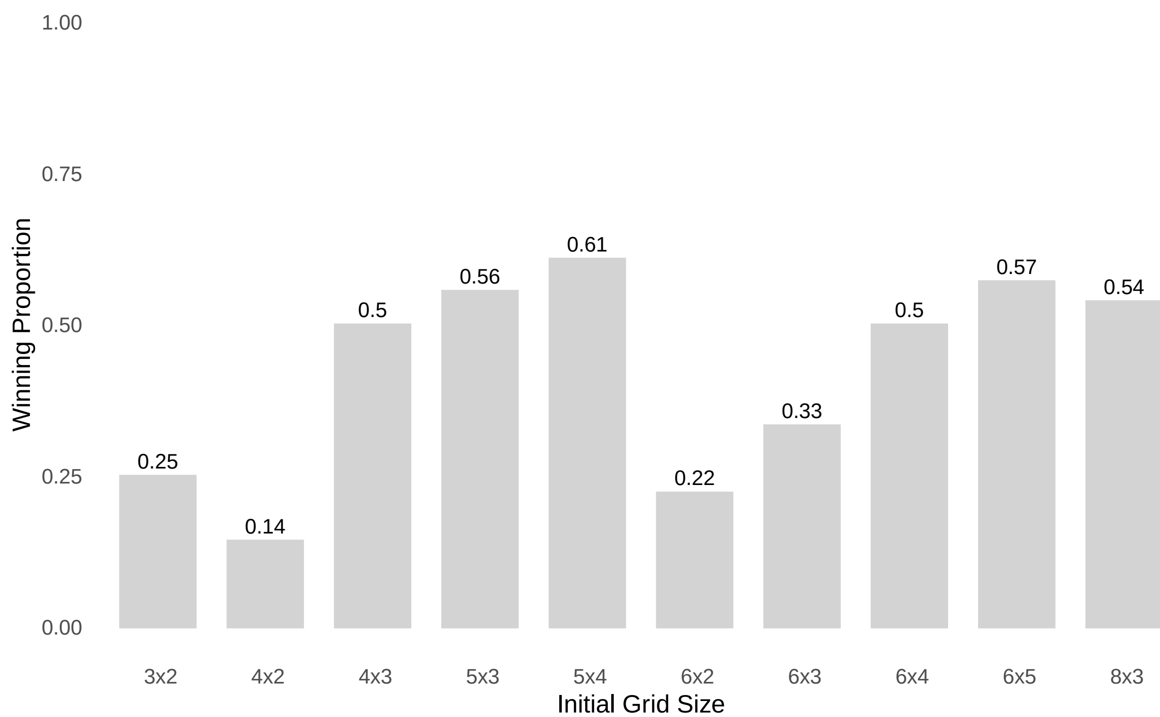


Figure 24: Winning proportion when choosing initial choice $(2, 2)$ by grid sizes in the RO Treatment

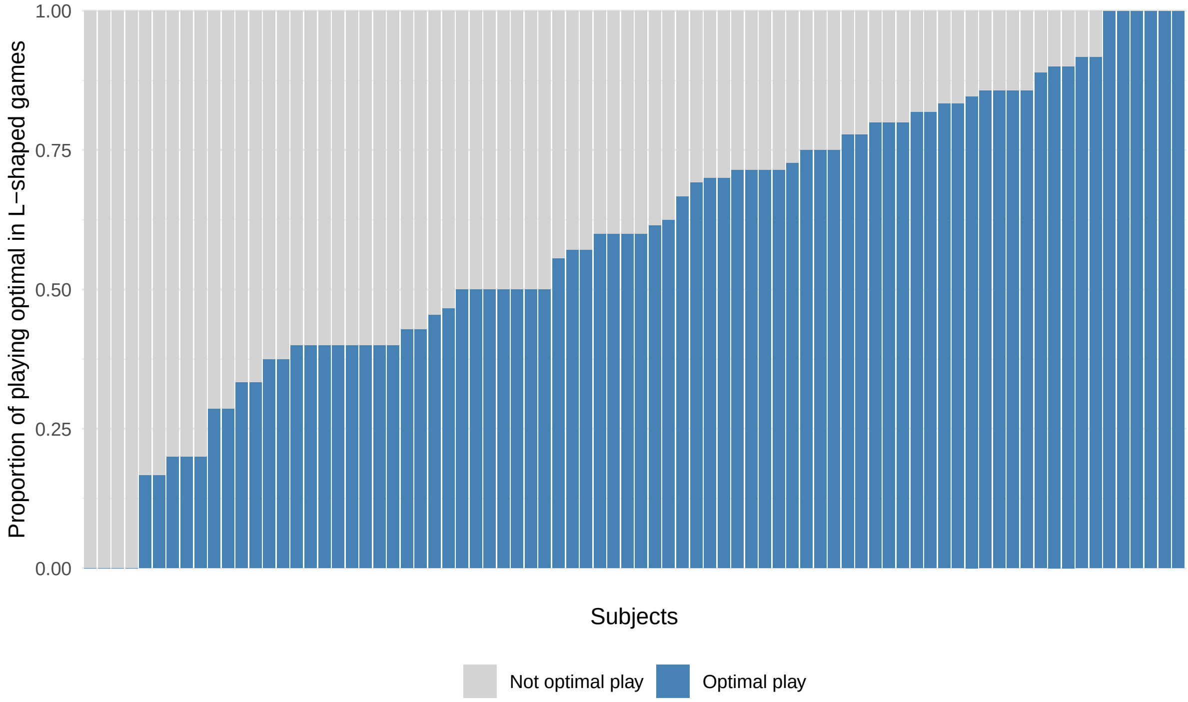


Figure 25: Probability of making a winning move in L-shaped games in the MS Treatment

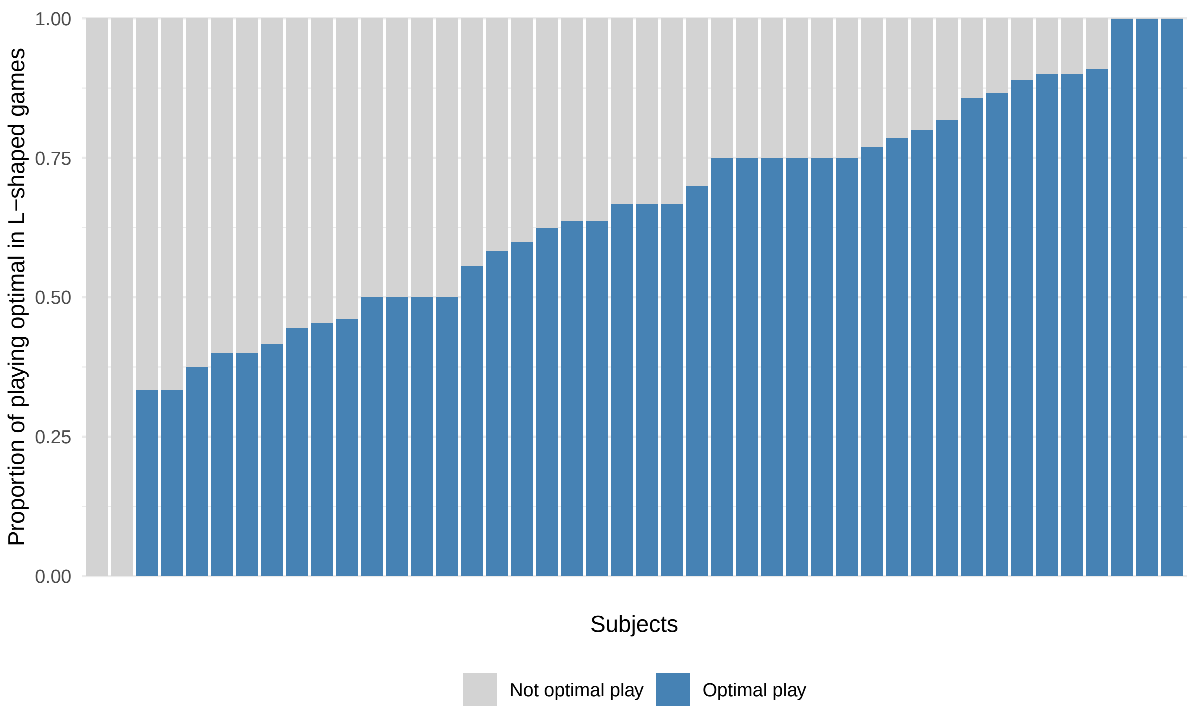


Figure 26: Probability of making a winning move in L-shaped games in the RO Treatment

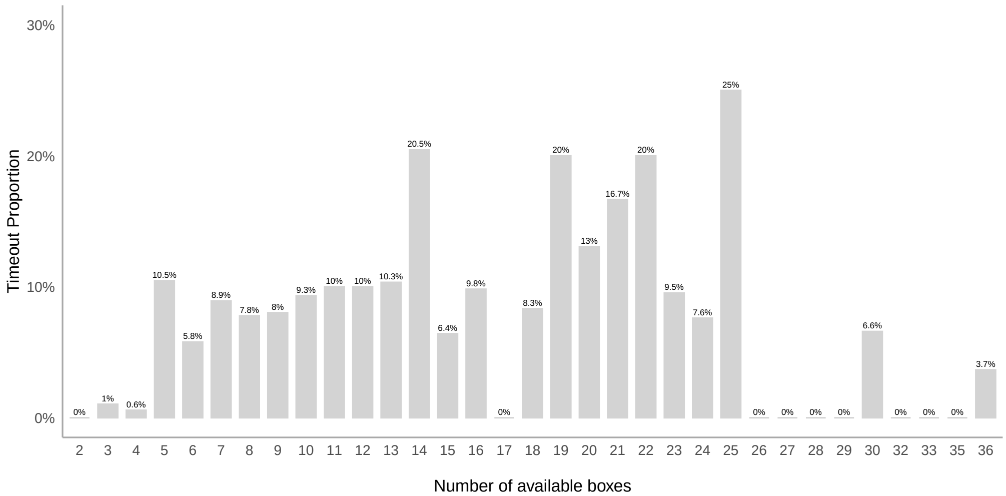


Figure 27: Timeouts by number of available boxes in the MS Treatment

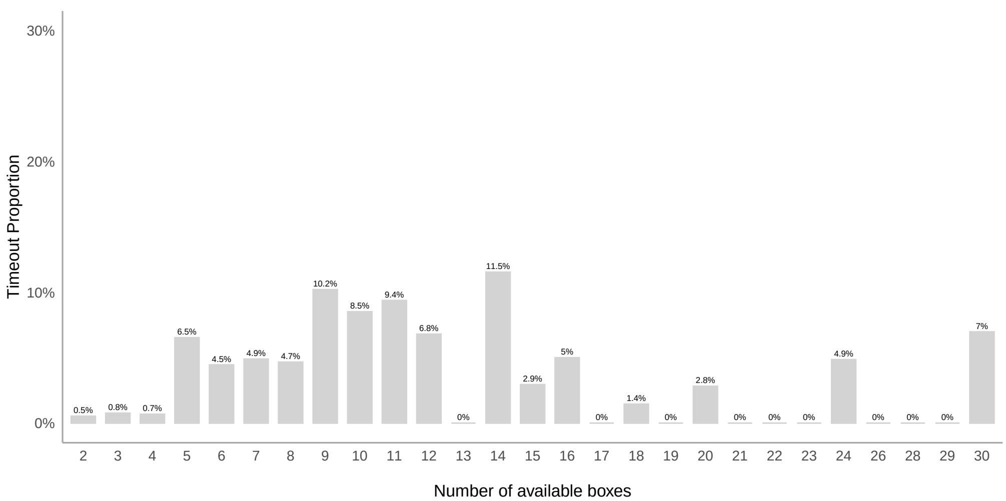


Figure 28: Timeouts by number of available boxes in the RO Treatment

	Mean	Std. Dev.
CRT Score	1.35	1.19
Male	0.38	0.49
Age	23.02	4.60
English	0.20	0.40
Economics	0.28	0.45
Subjects	80.00	

Notes: CRT Score is the number of correct answers on a Cognitive Reflection Test, ranging from 0 to 3. Male, English, and Economics are equal to one if the subjects report being male, speaking English as a first language, and majoring in Economics, respectively.

Table 17: Summary statistics for the MS Treatment

	Mean	Std. Dev.
CRT Score	1.50	1.13
Male	0.48	0.51
Age	23.73	5.35
English	0.20	0.41
Economics	0.43	0.50
Subjects	44.00	

Notes: CRT Score is the number of correct answers on a Cognitive Reflection Test, ranging from 0 to 3. Male, English, and Economics are equal to one if the subjects report being male, speaking English as a first language, and majoring in Economics, respectively.

Table 18: Summary statistics for the RO Treatment

Dependent variable:	Player 1 Winning		Perfect Play
	LPM (1)	LPM (2)	LPM (3)
Intercept	0.6552***	0.4456***	0.4353***
	(0.0872)	(0.0935)	(0.0644)
Square	0.1473**	0.0056	0.3281***
	(0.0601)	(0.0607)	(0.0541)
Nx2 Grid	-0.0698	-0.1322**	0.1115**
	(0.0634)	(0.0565)	(0.0482)
Num. Available Boxes	-0.0026	-0.0014	-0.0117***
	(0.0039)	(0.0039)	(0.0028)
SPNE Moves Left	-0.0096	0.0033	-0.0135*
	(0.0119)	(0.0121)	(0.0081)
First Move SPNE		0.4381***	
		(0.0512)	
Observations	796	796	796
Adjusted R^2	0.0362	0.1421	0.3400

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 19: Effects of initial game state on winning and playing perfectly in the MS Treatment

Dependent variable:	Player 1 Winning		Perfect Play
	LPM (1)	LPM (2)	LPM (3)
Intercept	0.4387***	0.2808***	0.3085***
	(0.1087)	(0.1035)	(0.0772)
Nx2 Grid	-0.0062	-0.0802	0.1601***
	(0.0625)	(0.0668)	(0.0466)
Num. Available Boxes	-0.0007	-0.0062	0.0088***
	(0.0077)	(0.0076)	(0.0029)
SPNE Moves Left	0.0042	0.0257*	-0.0398***
	(0.0150)	(0.0146)	(0.0091)
First Move SPNE		0.4073***	
		(0.0755)	
Observations	486	486	486
Adjusted R^2	-0.0058	0.0473	0.1627

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 20: Effects of initial game state on winning and playing perfectly in the RO Treatment

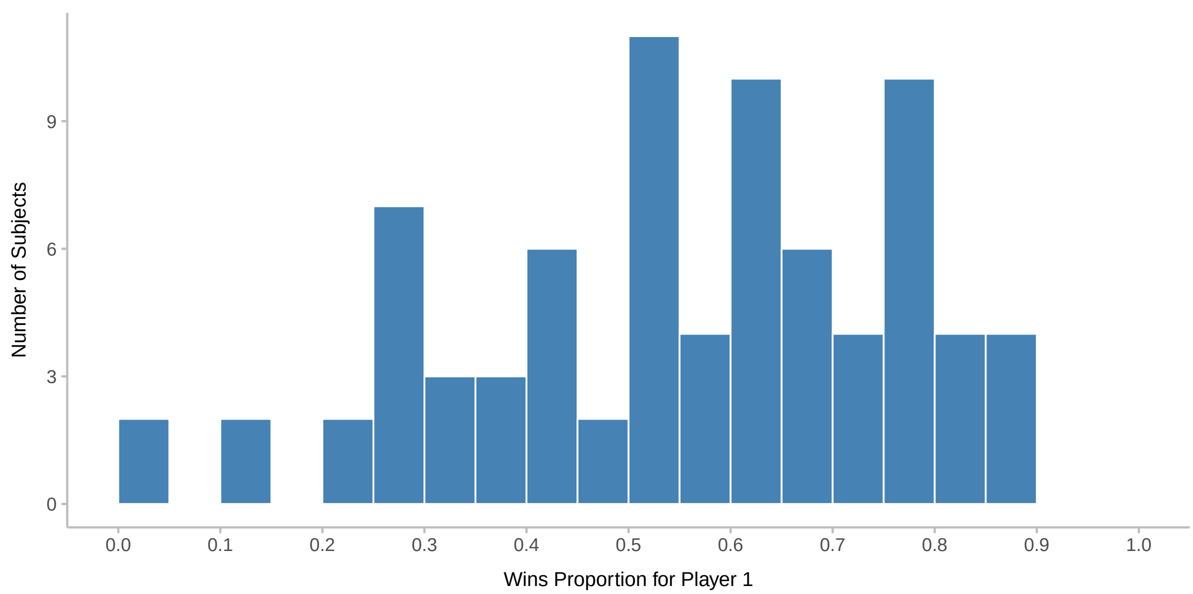


Figure 29: Histogram of proportion of winning as Player 1 in the first 18 round in the MS Treatment

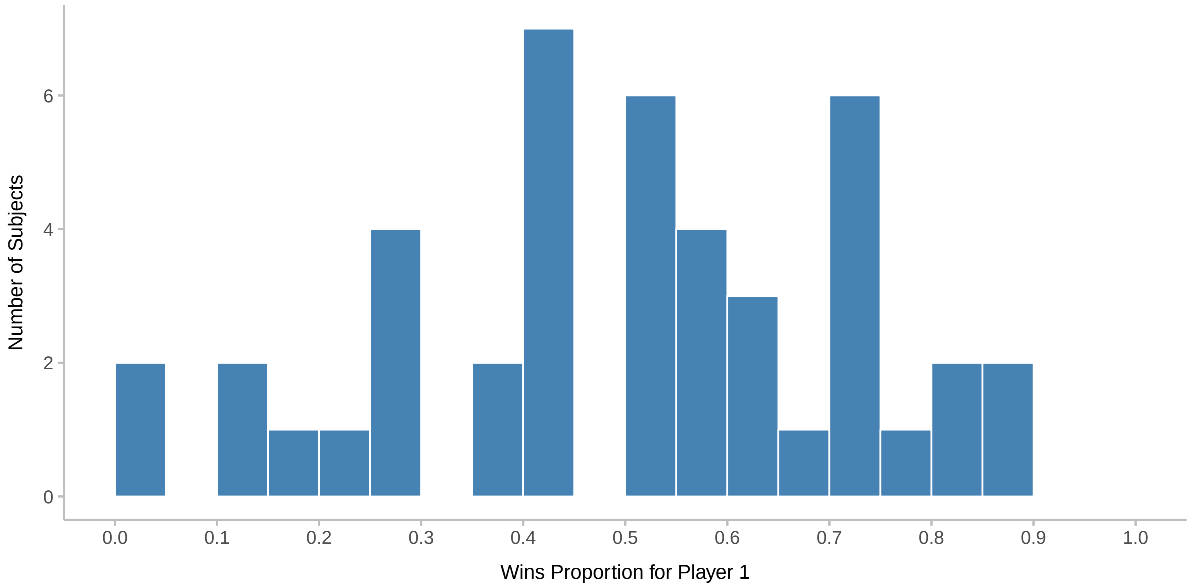
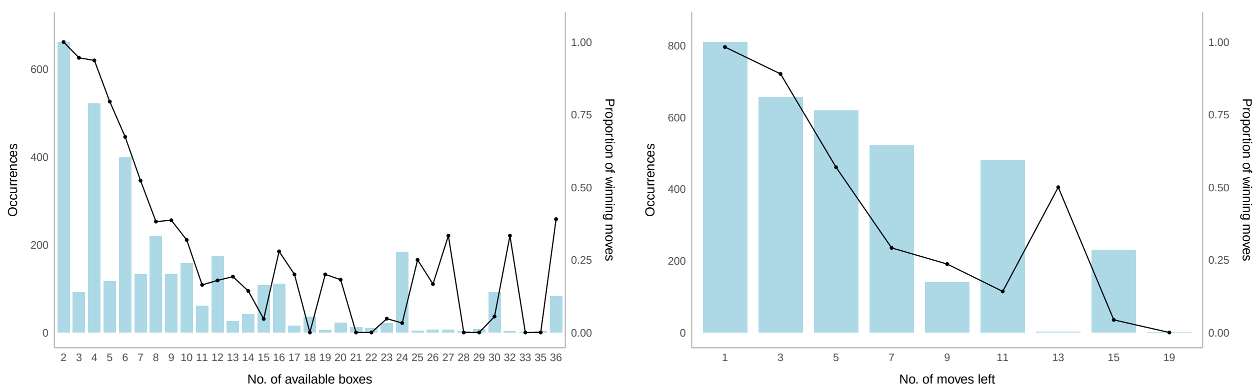


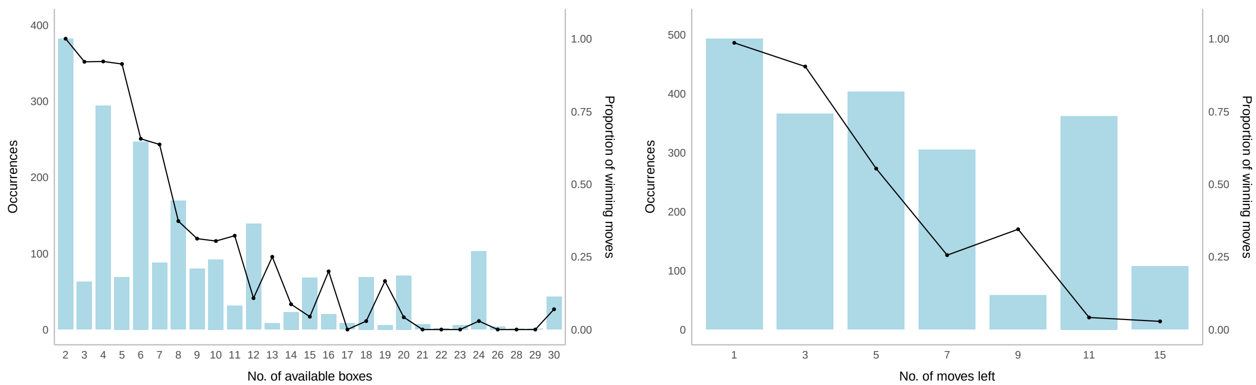
Figure 30: Histogram of proportion of winning as Player 1 in the first 18 round in the RO Treatment



(a) Available Boxes

(b) SPNE Moves Left

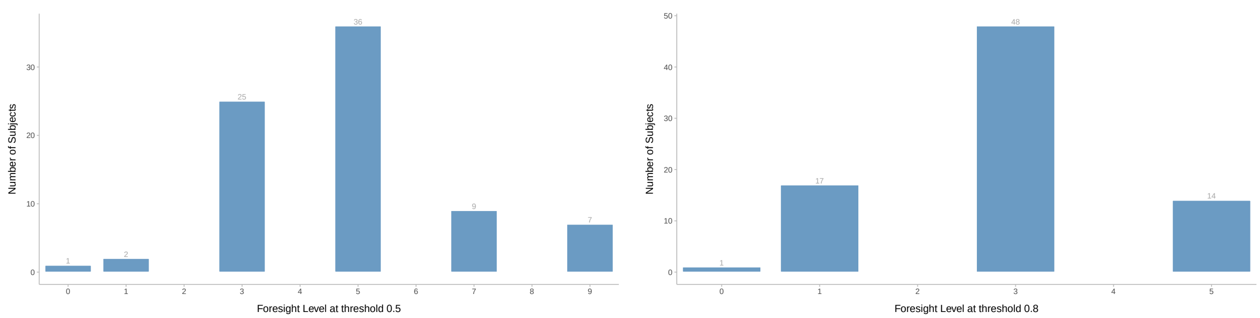
Figure 31: Relationship between complexity measures and making a winning move in the MS Treatment



(a) Available Boxes

(b) SPNE Moves Left

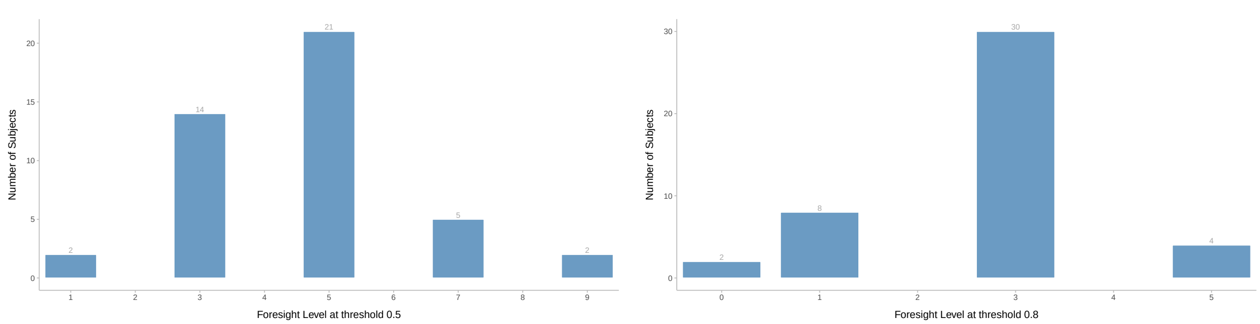
Figure 32: Relationship between complexity measures and making a winning move in the RO Treatment



(a) Threshold of 0.5

(b) Threshold of 0.8

Figure 33: Foresight Levels under alternative thresholds in the MS Treatment



(a) Threshold of 0.5

(b) Threshold of 0.8

Figure 34: Foresight Levels under alternative thresholds in the RO Treatment

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0054***	0.0062***	0.0048***	0.0052***
	(0.0015)	(0.0014)	(0.0014)	(0.0014)
Num. Available Boxes	0.0024	-0.0005	0.0028	0.0013
	(0.0022)	(0.0022)	(0.0022)	(0.0022)
SPNE Moves Left	-0.0770***	-0.0597***	-0.0706***	-0.0567***
	(0.0038)	(0.0051)	(0.0041)	(0.0051)
Square Game State	0.1336***	0.1738***	0.1568***	0.1995***
	(0.0226)	(0.0231)	(0.0233)	(0.0241)
Nx2 Game State	0.0418	0.0553	0.0738**	0.0922***
	(0.0335)	(0.0350)	(0.0337)	(0.0352)
Moves Made	0.0319***			-0.0085
	(0.0071)			(0.0062)
Fraction of Available Winning Moves		0.2894***		0.2413***
		(0.0402)		(0.0404)
OppMistake1			0.0175	0.0303
			(0.0239)	(0.0232)
WinAgain			0.0418*	0.0710**
			(0.0253)	(0.0281)
StayedWin			0.1927***	0.1665***
			(0.0290)	(0.0326)
RecoveredWin			0.0953**	0.1364***
			(0.0471)	(0.0486)
Observations	3461	3461	3461	3461
Adjusted R^2	0.4458	0.4599	0.4567	0.4664

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 21: Robustness of the effects of complexity in the MS Treatment

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0032**	0.0042***	0.0029**	0.0032**
	(0.0015)	(0.0013)	(0.0013)	(0.0013)
Num. Available Boxes	0.0045	0.0017	0.0070*	0.0066*
	(0.0040)	(0.0039)	(0.0038)	(0.0037)
SPNE Moves Left	-0.0829***	-0.0759***	-0.0816***	-0.0755***
	(0.0070)	(0.0067)	(0.0067)	(0.0069)
Square Game State	0.0862***	0.1022***	0.0787***	0.0955***
	(0.0258)	(0.0279)	(0.0273)	(0.0279)
Nx2 Game State	0.0037	-0.0120	0.0275	0.0338
	(0.0437)	(0.0444)	(0.0440)	(0.0443)
Moves Made	0.0507***			-0.0148
	(0.0117)			(0.0119)
Fraction of Available Winning Moves		0.1833***		0.1198***
		(0.0387)		(0.0368)
OppMistake1			-0.0050	0.0034
			(0.0306)	(0.0309)
WinAgain			0.0753**	0.1011***
			(0.0368)	(0.0354)
StayedWin			0.1958***	0.2007***
			(0.0459)	(0.0491)
RecoveredWin			0.1864**	0.2127***
			(0.0733)	(0.0692)
Observations	2094	2094	2094	2094
Adjusted R^2	0.5046	0.5049	0.5126	0.5143

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 22: Robustness of the effects of complexity in the RO Treatment

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0065***	0.0069***	0.0072***	0.0067***
	(0.0015)	(0.0013)	(0.0013)	(0.0013)
Num. Available Boxes	0.0019	-0.0762***	-0.0002	
	(0.0022)	(0.0081)	(0.0024)	
Num. Available Boxes^2		0.0016***		
		(0.0002)		
SPNE Moves Left	-0.0814***	-0.0594***		-0.0153**
	(0.0038)	(0.0144)		(0.0075)
SPNE Moves Left^2		0.0025***		
		(0.0007)		
Square Game State	0.1121***	0.1575***	0.1381***	0.0652***
	(0.0226)	(0.0208)	(0.0254)	(0.0245)
Nx2 Game State	0.0191	0.0184	0.1318***	0.0142
	(0.0331)	(0.0354)	(0.0369)	(0.0438)
SPNE Moves Left FE	No	No	Yes	No
Num. Available Boxes FE	No	No	No	Yes
Observations	3461	3461	3461	3461
Adjusted R^2	0.4420	0.5046	0.4960	0.5161

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 23: Nonlinear complexity effects in the MS Treatment

Dependent variable: SPNE Consistent Move				
	FE (1)	FE (2)	FE (3)	FE (4)
Match Number	0.0044***	0.0045***	0.0048***	0.0047***
	(0.0014)	(0.0012)	(0.0012)	(0.0012)
Num. Available Boxes	0.0028	-0.0729***	-0.0074**	
	(0.0040)	(0.0137)	(0.0036)	
Num. Available Boxes^2		0.0018***		
		(0.0003)		
SPNE Moves Left	-0.0888***	-0.0591***		-0.0358***
	(0.0068)	(0.0225)		(0.0090)
SPNE Moves Left^2		0.0014		
		(0.0011)		
Square Game State	0.0627**	0.0900***	0.0122	0.0555**
	(0.0281)	(0.0275)	(0.0301)	(0.0264)
Nx2 Game State	-0.0309	-0.0372	0.0323	-0.0391
	(0.0438)	(0.0454)	(0.0464)	(0.0503)
SPNE Moves Left FE	No	No	Yes	No
Num. Available Boxes FE	No	No	No	Yes
Observations	2094	2094	2094	2094
Adjusted R^2	0.4980	0.5398	0.5476	0.5526

Note: Standard errors are clustered at the subject level, and subject fixed effects are included. Significance: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 24: Nonlinear complexity effects in the RO Treatment

Dependent variable: SPNE Consistent Move		
	LPM (1)	LPM (2)
Intercept	0.9041***	0.9317***
	(0.0168)	(0.0150)
5-9 Boxes	-0.4060***	-0.5425***
	(0.0241)	(0.0442)
More than 10 Boxes	-0.8103***	-0.7735***
	(0.0138)	(0.0281)
Match Number	0.0063***	0.0036***
	(0.0014)	(0.0010)
5-9 Boxes x Match Number		0.0127***
		(0.0035)
More than 10 Boxes x Match Number		-0.0031
		(0.0023)
Observations	3461	3461
Adjusted R^2	0.4778	0.4833

Note: Standard errors are clustered at the subject level.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 25: Learning by number of boxes left in the MS Treatment.

Dependent variable: SPNE Consistent Move		
	LPM (1)	LPM (2)
Intercept	0.9112***	0.9349***
	(0.0193)	(0.0194)
5-9 Boxes	-0.3985***	-0.4754***
	(0.0283)	(0.0501)
More than 10 Boxes	-0.8558***	-0.8543***
	(0.0171)	(0.0314)
Match Number	0.0043***	0.0023*
	(0.0012)	(0.0013)
5-9 Boxes x Match Number		0.0063*
		(0.0033)
More than 10 Boxes x Match Number		-0.0000
		(0.0021)
Observations	2094	2094
Adjusted R^2	0.5094	0.5103

Note: Standard errors are clustered at the subject level.
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 26: Learning by number of boxes left in the RO Treatment.

	(1)	(2)	(3)
Intercept	0.4894***	2.3246*	0.6140***
	(0.0873)	(1.2822)	(0.1379)
Male	0.0755***	0.8786**	0.0971**
	(0.0277)	(0.3582)	(0.0463)
Age	-0.0001	0.0231	-0.0030
	(0.0036)	(0.0525)	(0.0061)
English	-0.0356	-0.4238	-0.0325
	(0.0376)	(0.3904)	(0.0692)
Economics	0.0538	0.3574	0.0892*
	(0.0327)	(0.3903)	(0.0474)
CRT Score	0.0370***	0.2502*	0.0716***
	(0.0115)	(0.1443)	(0.0171)
Observations	3461	80	769
Adjusted R^2	0.0141	0.0774	0.0385

Note: Standard errors are clustered at the subject level.
(1) SPNE Consistent Move
(2) Foresight Level at threshold 0.7
(3) SPNE Consistent Move in L-shaped Game
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 27: Relationship between demographics and consistency with SPNE in the MS Treatment

	(1)	(2)	(3)
Intercept	0.4492***	2.9954***	0.6647***
	(0.0902)	(0.9751)	(0.0989)
Male	-0.0271	0.1001	0.0188
	(0.0385)	(0.3917)	(0.0616)
Age	0.0023	-0.0034	-0.0008
	(0.0042)	(0.0379)	(0.0050)
English	-0.0585*	-0.3999	-0.0174
	(0.0347)	(0.3530)	(0.0503)
Economics	-0.0938**	-0.9131**	-0.0700
	(0.0409)	(0.4033)	(0.0676)
CRT Score	0.0711***	0.4638***	0.0675***
	(0.0141)	(0.1443)	(0.0221)
Observations	2094	44	506
Adjusted R^2	0.0292	0.2679	0.0285

Note: Standard errors are clustered at the subject level.
(1) SPNE Consistent Move
(2) Foresight Level at threshold 0.7
(3) SPNE Consistent Move in L-shaped Game
Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 28: Relationship between demographics and consistency with SPNE in the RO Treatment

C Screenshots from the experiment

Introduction

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

Thank you for participating in this study. This study is about decision-making. It should take about 90 minutes, and you will be paid based on your earnings from the experiment. The money you earn will be paid either in cash at the end of the study or electronically within a few days of the end of the study.

Please do not use any electronic devices or talk with other participants during this study.

There will be no deception in this study. Every decision you make will be carried out exactly as it is described in the instructions. Anything else would violate the human ethics protocol under which we run the study (UQ Human Research Ethics Approval 2024/HE001275).

In the study you will make decisions that will affect the amount of money you earn. The study will consist of games that you will play with other randomly selected players. The players that you are paired with in a match are selected independently of who you play with in any other match.

Please pay close attention to the instructions on the next page.

If you have questions at any point, please raise your hand and we will answer your questions privately.

Next

Figure 35: Introduction page

Instructions

PLEASE READ CAREFULLY AND DO NOT PRESS NEXT UNTIL INSTRUCTED TO DO SO.

All participants will receive a minimum of $15 regardless of what happens during the study.

In each match of the game that you play in this study, you will be matched with another player. One player will be randomly selected as "Player 1" and the other player will be "Player 2". "Player 1" will play first. At the beginning of the next match, all players will be matched with different opponents.

The game will begin as a grid of squares. Two players take turns choosing squares. With each choice, all boxes **below** and **to the right** of the selected box turn green and are removed from the grid after the player clicks the "Submit" button. Each player has 30 seconds to make their choice in each turn. After making the final decision, the player clicks the "Submit" button to proceed to the next turn. If the player fails to click the submit button before the timeout, the computer will randomly select a box from the grid.

The player who is forced to choose the yellow box in the top left loses the game. The game will end when only the yellow box remains.

At the end of the study, the computer will randomly select a single match that will count for your payment. If you won that match, you will receive $65. If you lost that match, you will receive $15.

You can try to click on any box:

Figure 36: Instruction page

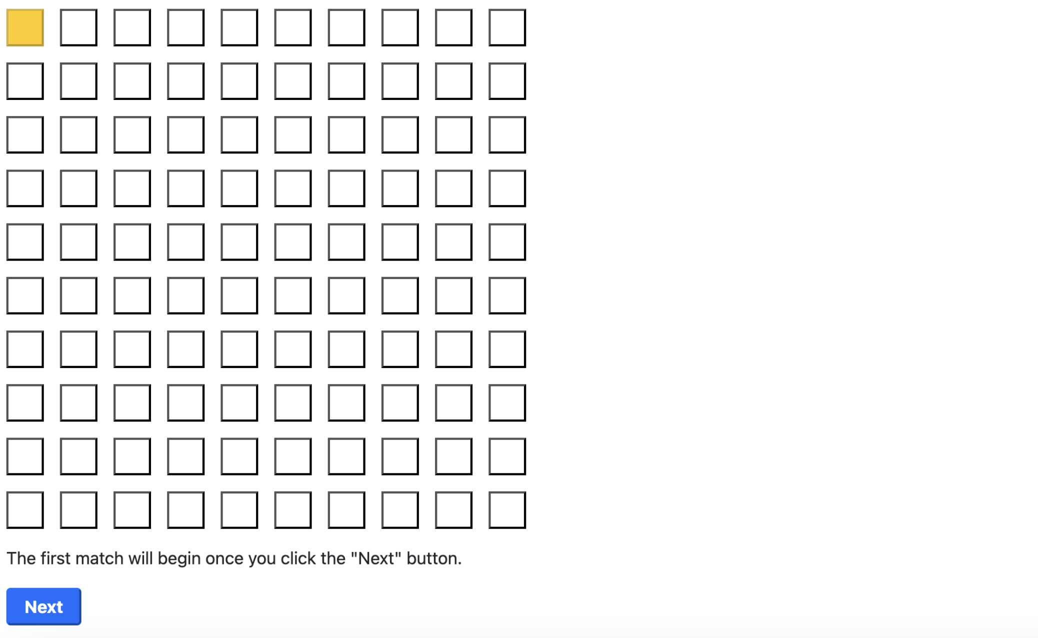


Figure 37: Instruction page (cont)

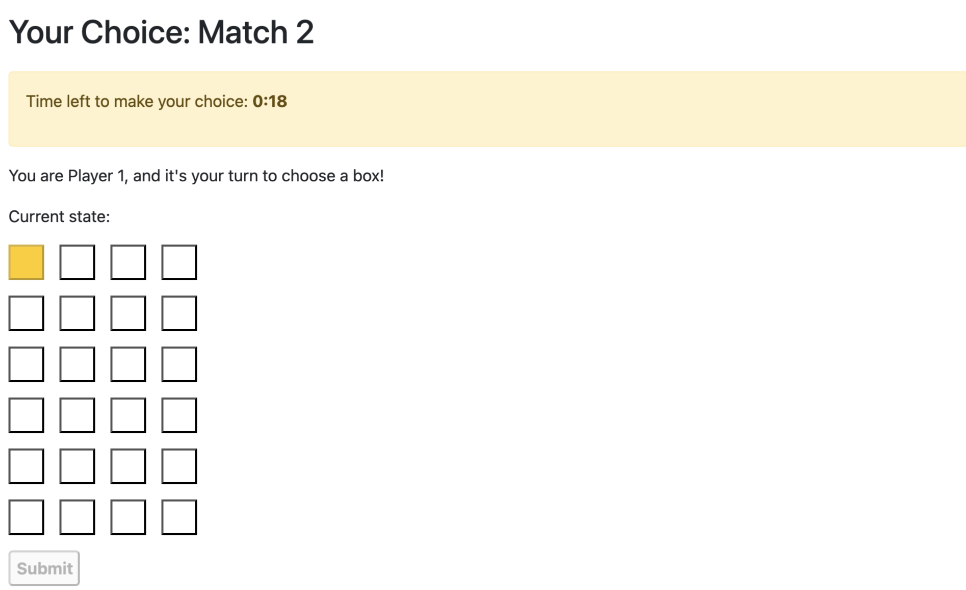


Figure 38: Choice page of Player 1

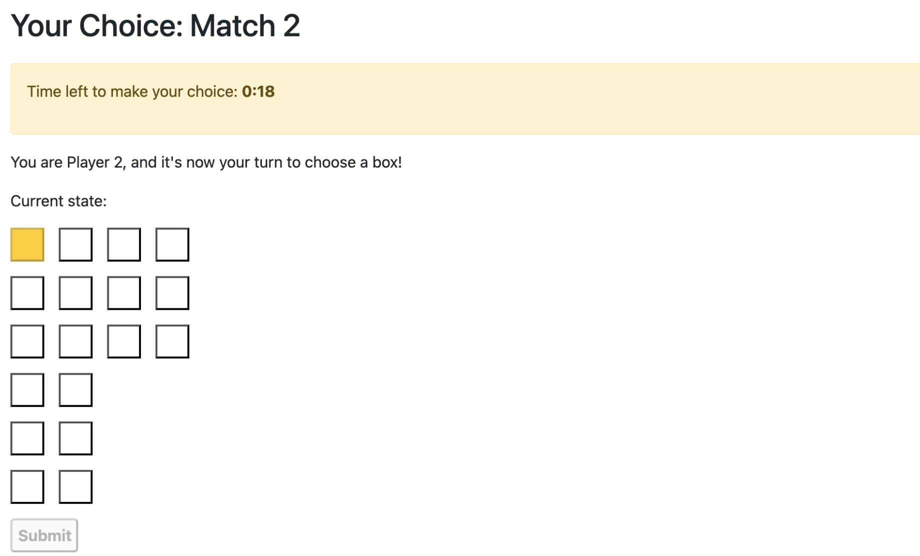


Figure 39: Choice page of Player 2

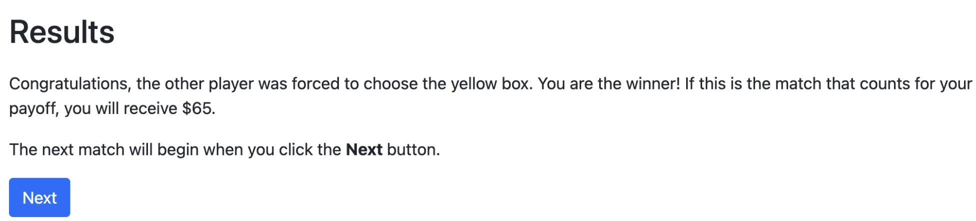


Figure 40: Result page for winner in each match

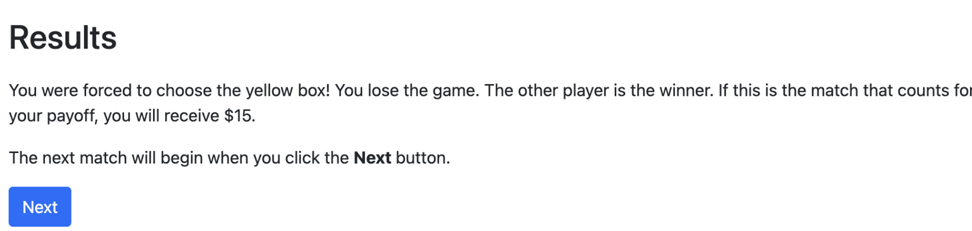
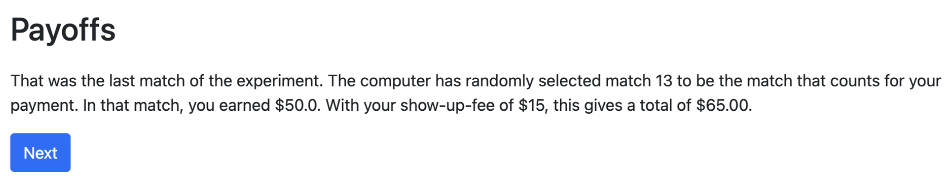


Figure 41: Result page for loser in each match

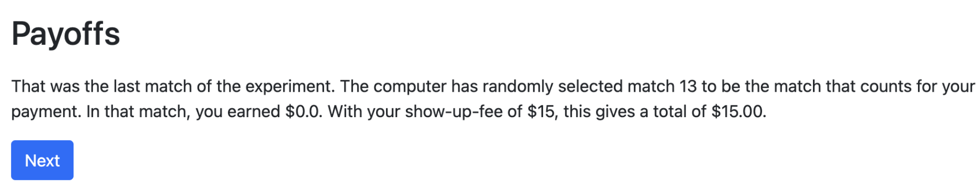


Payoffs

That was the last match of the experiment. The computer has randomly selected match 13 to be the match that counts for your payment. In that match, you earned $50.0. With your show-up-fee of $15, this gives a total of $65.00.

Next

Figure 42: Payoff for winner in the experiment

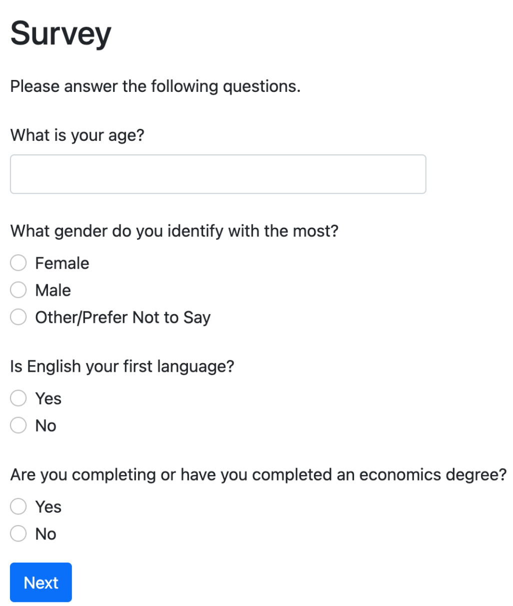


Payoffs

That was the last match of the experiment. The computer has randomly selected match 13 to be the match that counts for your payment. In that match, you earned $0.0. With your show-up-fee of $15, this gives a total of $15.00.

Next

Figure 43: Payoff for loser in the experiment



Survey

Please answer the following questions.

What is your age?

What gender do you identify with the most?

- Female
- Male
- Other/Prefer Not to Say

Is English your first language?

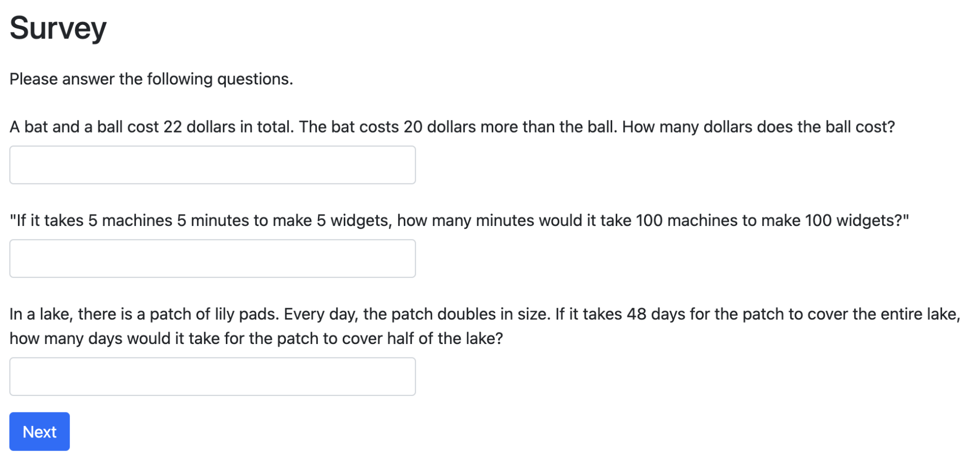
- Yes
- No

Are you completing or have you completed an economics degree?

- Yes
- No

Next

Figure 44: Demographics Page



Survey

Please answer the following questions.

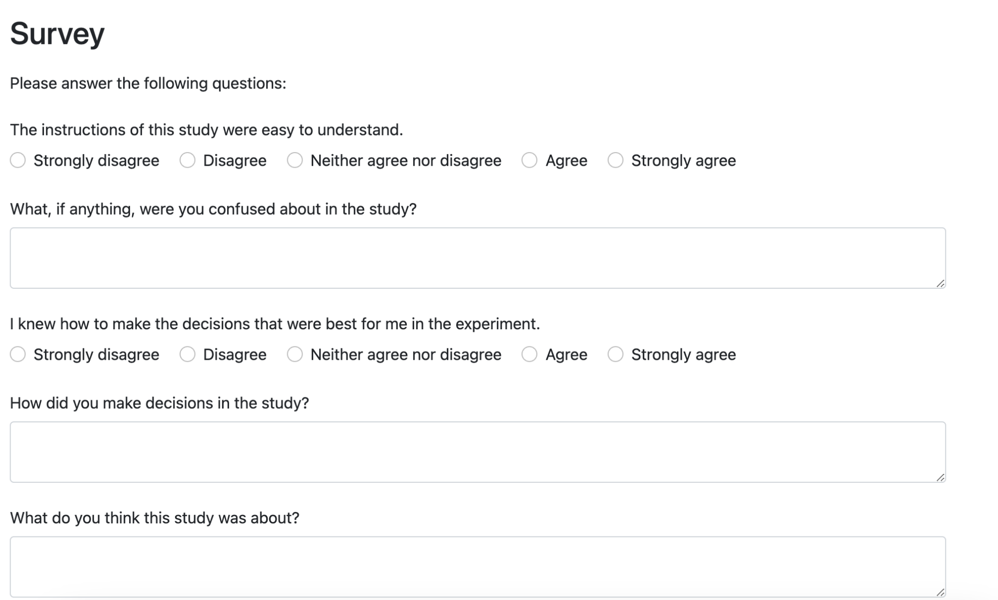
A bat and a ball cost 22 dollars in total. The bat costs 20 dollars more than the ball. How many dollars does the ball cost?

"If it takes 5 machines 5 minutes to make 5 widgets, how many 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 many days would it take for the patch to cover half of the lake?

Next

Figure 45: Cognitive Reflection Test



Survey

Please answer the following questions:

The instructions of this study were easy to understand.

Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree

What, if anything, were you confused about in the study?

I knew how to make the decisions that were best for me in the experiment.

Strongly disagree Disagree Neither agree nor disagree Agree Strongly agree

How did you make decisions in the study?

What do you think this study was about?

Figure 46: Experiment Feedback Page