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Duffy, Sean and Naddeo, JJ and Owens, David and Smith, John

Rutgers University-Camden, Haverford College

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Sean Duffy† J. J. Naddeo‡ David Owens§ John Smith¶

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Abstract

It is well-known that laboratory subjects often do not play mixed strategy equilibrium games according to the equilibrium predictions. In particular, subjects often mix with the incorrect proportions and their actions often exhibit serial correlation. However, little is known about the role of cognition in these observations. We conduct an experiment where subjects play a repeated hide and seek game against a computer opponent programmed to play either a strategy that can be exploited by the subject (a naive strategy) or designed to exploit suboptimal play of the subject (an exploitative strategy). The subjects play with either fewer available cognitive resources (under a high cognitive load) or with more available cognitive resources (under a low cognitive load). While we observe that subjects do not mix in the predicted proportions and their actions exhibit serial correlation, we do not find strong evidence these are related to their available cognitive resources. This suggests that the standard laboratory results on mixed strategies are not associated with the availability of cognitive resources. Surprisingly, we find evidence that subjects under a high load earn more than subjects under a low load. However, we also find that subjects under a low cognitive load exhibit a greater rate of increase in earnings across rounds than subjects under a high load.

Keywords: bounded rationality, experimental economics, working memory load, cognition, learning, mixed strategies

JEL: C72, C91

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†Rutgers University-Camden, Department of Psychology

‡Rutgers University-Camden, Department of Economics

§Haverford College, Department of Economics

¶Corresponding Author; Rutgers University-Camden, Department of Economics, 311 North 5th Street, Camden, New Jersey, USA 08102; Email: smithj@camden.rutgers.edu; Phone: +1 856 225-6319; Fax: +1 856 225-6602.

1 Introduction

In experimental settings, subjects often do not mix according to the equilibrium predictions. Existing literature largely finds that subjects do not mix in the proportions predicted by equilibrium and that their actions exhibit serial correlation.[1] A critique of this literature is that subjects are often inexperienced in settings where strategic mixing is required. Prompted by this critique, many studies have examined mixing behavior in settings where decision makers have ample experience: the field.[2] Although some deviations are still detected, this literature mostly finds that the mixing in field settings is closer to the equilibrium predictions than that found in the laboratory.

In order to better understand the robustness of these deviations from equilibrium predictions, researchers have examined whether experience in mixing in a field setting translates to successfully mixing in a novel experimental setting.[3] Our paper is similar in that we seek to better understand the observed deviations from the mixed strategy equilibrium predictions by exploring the role of cognition.

To our knowledge, Geng, Peng, Shachat, and Zhong (2015) is the only other study that investigates the role of cognitive ability on mixing behavior.[4] The authors do not find evidence that higher measures of cognitive ability[5] are related to the behavior consistent with the equilibrium predictions: proportions of the mixture or serial correlation. Further, Geng et al. do not find a relationship between measures of cognitive ability and earnings in these games. However, one potential drawback of employing measures of cognitive ability is that these measures are possibly also correlated with other (observable or unobservable) characteristics

[1] See O'Neill (1987), Brown and Rosenthal (1990), Batzilis et al. (2016), Binmore, Swierzbinski, and Proulx (2001), Geng, Peng, Shachat, and Zhong (2014), Mookherjee and Sopher (1994, 1997), O'Neill (1991), Ochs (1995), Palacios-Huerta and Volij (2008), Rapoport and Amaldoss (2000, 2004), Rapoport and Boebel (1992), Rosenthal, Shachat, and Walker (2003), Shachat (2002), Van Essen and Wooders (2015). In fact, Martin et al. (2014) find evidence that chimpanzee subjects are closer to the equilibrium predictions than human subjects.

[2] See Azar and Bar-Eli (2011), Bailey and McGarrity (2012), Bar-Eli et al. (2007), Buzzacchi and Pedrini (2014), Chiappori, Levitt, and Groseclose (2002), Coloma (2007), Emara, Owens, Smith, and Wilmer (2016), Hsu, Huang, and Tang (2007), Kovash and Levitt (2009), McGarrity and Linnen (2010), Palacios-Huerta (2003a), Reed, Critchfield, and Martens (2006), Walker and Wooders (2001).

[3] See Palacios-Huerta and Volij (2008), Levitt, List, and Reiley (2010), and Van Essen and Wooders (2015).

[4] See Palacios-Huerta et al. (2014) for a study of brain activity during a game with a mixed strategy equilibrium.

[5] Raven's standard progressive matrices test (Raven and De Lemos, 1990) and a score on a math test.

of the subjects.

We take a complimentary approach as we seek to better understand the observed deviations from the equilibrium predictions by manipulating the available cognitive resources of the subjects. Our study follows other cognitive load experiments that observe behavior or judgments while the subject has some information committed to memory. This memorization task is designed to occupy a portion of the working memory of the subject so that fewer cognitive resources can be devoted to the decision or the judgment. This manipulation allows a within-subject design, whereby subjects can be placed under different cognitive loads.[6]

Our subjects are directed to play against computer opponents[7] that are programmed to play one of two exploitative strategies (designed to exploit suboptimal mixing by the subjects) and one of two naive strategies (designed to allow subjects the possibility of exploiting the computer). Further, using a computer opponent in an experiment that employs the cognitive load manipulation has the advantage that the subject's beliefs about the distribution of the cognitive load of the possible opponents, and the effects of the different cognitive loads on the potential opponents will not affect behavior.

Researchers have found that subjects have difficulty detecting and producing random sequences that are required for equilibrium.[8] If available cognitive resources are related to the ability to mix in a fashion that is consistent with equilibrium and to detect (and exploit) the deviation of opponents then the following hypotheses follow. We would expect that subjects with fewer cognitive resources would exhibit a mixing proportion further from the equilibrium prediction, exhibit more serial correlation, have less success detecting and exploiting naive computer strategies, and have less success against exploitative computer strategies.

Consistent with the previous literature, the behavior in our experiment exhibits mixture proportions and serial correlation that are inconsistent with the equilibrium predictions. How-

[6] We note that Carpenter, Graham, and Wolf (2013) find that the cognitive load manipulation is more effective on subjects with a higher measure of cognitive ability. However, Allred, Duffy, and Smith (2016) do not find such a relationship. Similarly, we do not find a relationship in our data.

[7] Also see Messick (1967), Fox (1972), Coricelli (2005), Levitt, List, and Reiley (2010), Shachat and Swarthout (2004, 2012), Spiliopoulos (2012, 2013), Shachat, Swarthout, and Wei (2015), and Bayer and Renou (2016a).

[8] For instance, see Wagenaar (1972), Bar-Hillel, and Wagenaar (1991), Rapoport and Budescu (1992), Budescu and Rapoport (1994), Rabin (2002), and Oskarsson et al. (2009).

ever, we do not find evidence that the available cognitive resources are related to either the mixing proportions or the observed serial correlation. To our surprise, subjects under high cognitive load earned a larger amount than subjects under low load. On the other hand, we find that subjects under low load exhibited an increase in earnings across rounds, whereas we do not find such a relationship for subjects under high load. In addition, we find that the response times of subjects under low load are decreasing at a faster rate than the response times of subjects under low load. We interpret these results as suggesting that subjects under low cognitive load exhibit a significantly faster rate of learning than do subjects under high load.

Our results suggest that the behavioral observations on mixing (suboptimal mixture proportions and serial correlation) may not be related to the available cognitive resources of the subjects. Our results also suggest that subjects with fewer cognitive resources will not necessarily exhibit worse performance, particularly in the early rounds, than will subjects with more cognitive resources. It seems that executing a simple, stable strategy does not require a great deal of cognitive resources. On the other hand, early round experimentation, which would facilitate learning, can lead to lower payoffs in these rounds. However, our analysis suggests that subjects with more cognitive resources will exhibit more learning than will subjects with fewer cognitive resources. This is consistent with the contention that subjects under a low load had the available cognitive resources to sufficiently remember and analyze previous outcomes.

2 Related literature

There is a large and growing literature that examines the relationship between measures of cognitive ability and strategic behavior.[9] We take a complimentary approach in that, rather

[9] See Al-Ubaydli, Jones, and Weel (2016), Ballinger et al. (2011), Baghestanian and Frey (2016), Bayer and Renou (2016a,2016b), Benito-Ostolaza, Hernández, and Sanchis-Llopis (2016), Brañas-Garza, Espinosa, and Rey-Biel (2011), Brañas-Garza, Garcia-Muñoz, and Hernan Gonzalez (2012), Brañas-Garza and Smith (2016), Burks et al. (2009), Burnham et al. (2009), Carpenter, Graham, and Wolf (2013), Chen, Huang, and Wang (2013), Corgnet et al. (2016), Coricelli and Nagel (2009), Devetag and Warglien (2003), Fehr and Huck (2015), Georganas, Healy, and Weber (2015), Gill and Prowse (2015), Grimm and Mengel (2012), Jones (2014), Jones (2008), Kiss, Rodriguez-Lara, and Rosa-García (2016), Lohse (2016), Palacios-Huerta (2003b), Proto,

than measure cognitive ability, we manipulate the available cognitive resources of the subject.

The cognitive load manipulation is widely employed and its affects are well-understood in nonstrategic settings. Cognitive load has been found to make subjects more impulsive and less analytical (Hinson, Jameson, and Whitney, 2003), more risk averse (Whitney, Rinehart, and Hinson, 2008; Benjamin, Brown, and Shapiro, 2013), more impatient (Benjamin, Brown, and Shapiro, 2013), make more mistakes (Rydval, 2011), exhibit less self control over their actions (Shiv and Fedorikhin, 1999; Ward and Mann, 2000, Mann and Ward, 2007), fail to process available and relevant information (Gilbert, Pelham, and Krull, 1988; Swann et al., 1990), more susceptible to anchoring effects (Epley and Gilovich, 2006), perform worse on gambling tasks (Hinson, Jameson, and Whitney, 2002), perform worse on visual judgment tasks (Morey and Cowan, 2004; Allen, Baddeley, and Hitch, 2006; Morey and Bieler, 2013; Zokaei, Heider, and Husain, 2014; Allred, Crawford, Duffy, and Smith, 2016), affect choices in allocation decisions (Cornelissen, Dewitte, and Warlop, 2011; Schulz et al., 2014),[10] affect the evaluations of the fairness of outcomes (van den Bos et al., 2006), have more difficulty being dishonest (van't Veer, Stel, and van Beest, 2014), and exhibit choices that are more influenced by visual salience (Milosavljevic, Navalpakkam, Koch, and Rangel, 2012).[11]

On the other hand, few studies of strategic behavior employ the cognitive load manipulation. To our knowledge the only such examples are, Milinski and Wedekind (1998), Roch et al. (2000), Cappelletti, Güth, and Ploner (2011), Carpenter, Graham, and Wolf (2013), Duffy and Smith (2014), Buckert, Oechssler, and Schwieren (2014), Allred, Duffy, and Smith (2016), and Samson and Kostyszyn (2015).

With the exception of Carpenter et al. (2013) and Samson and Kostyszyn (2015), these papers describe experiments where the subjects are placed under a cognitive load and play against a human opponent who is either under a cognitive load or not. One of the drawbacks of conducting a cognitive load experiment in a strategic setting with a human opponent is that the subjects' beliefs about the distribution of the cognitive load of the opponents and

Rustichini, and Sofianos (2014), Putterman, Tyran, and Kamei (2011), Rydval (2011), Rydval and Ortmann (2004), and Schnusenberg and Gallo (2011).

[10] Although Hauge et al. (2015) does not find an effect.

[11] Deck and Jahedi (2015) study several effects at a time and find that subjects under a cognitive load are less patient, more risk averse, perform worse on arithmetic tasks, and are more prone to anchoring effects.

their beliefs about the effect of the cognitive load on their opponents are not well specified and are difficult to measure. A design such as ours, which employs a computer opponent, can address this critique. Further, it allows us to observe the effect of cognitive load on subjects playing against distinct varieties of opponents.

3 Experimental design

3.1 Hide and seek game

In our design, subjects played a repeated, deterministic version of the hide and seek game (Rosenthal, Shachat, and Walker, 2003) against a computer opponent while under a cognitive load. Each subject selected either "Up" or "Down" as the Evader and the computer selected either "Up" or "Down" as the Pursuer. If the computer correctly guessed the choice of the subject then the subject earned 0. Roughly half of the subjects were shown the game whereby successfully evading the computer with Up earned 1 point and successfully evading with Down earned 2 points. This version is illustrated in Figure 1 on the left. The other half of the subjects were shown the game whereby successfully evading the computer with Up earned 2 points and successfully evading with Down earned 1 point. This version is illustrated in Figure 1 on the right.[12]

		Pursuer	
		Up	Down
Evader	Up	0	1
	Down	2	0

		Pursuer	
		Up	Down
Evader	Up	0	2
	Down	1	0

Figure 1: Both versions of the hide and seek game, where Evader payoffs are provided

For subjects in either treatment, each point was worth \$1.50. In the analysis that follows, we recode the data from both treatments to correspond to the specification where successfully evading with Down earned 2. Each subject played 100 repetitions of the same version of the

[12] The computer's actions were presented in red, and the subject's actions and payoffs were presented in blue. A screenshot of the version where successfully evading with Down earned 2 is available in the Supplemental Online Appendix.

game. The subject was given feedback for that repetition, which specified their action, the selected action of the computer opponent, and the amount of points earned.

3.2 Memorization task

Before each repetition of the game, a cognitive load was imposed on subjects by directing them to remember a number. Subjects in the *low* cognitive load treatment were required to remember a one-digit number that ranged from 1 to 9. Subjects in the *high* cognitive load treatment were required to remember a six-digit number where the first digit ranged from 1 to 9, and the remaining digits ranged from 0 to 9.

In both treatments, a new number was given for each round. After making a decision in the game and after the given feedback, subjects were asked for the number. Each subject played 50 consecutive repetitions under a high load and 50 consecutive repetitions under a low load. Therefore, cognitive load was a within-subject manipulation. With probability 0.5 subjects played first under a high load. Subjects were not given feedback about their performance on the memorization tasks.

3.3 Computer opponent strategies

Subjects were told, "How does the computer decide what to play? A number of possible strategies have been programmed. Some computer strategies can be exploited by you. Some computer strategies are designed to exploit you. One of these possible strategies has been selected for the first 50 periods."

There are two naive computer strategies. One of these naive computer strategies mixes between the actions with equal probability. We refer to this as the *Naive* $50-50$ strategy. The best response to this strategy is to play Down.

The other naive computer strategy mixes with the overall frequency corresponding to the equilibrium prediction, but exhibits a pattern of Up-Down-Down-(repeat). We refer to this as the *Naive Pattern* strategy. The best response to this strategy is to play Down-Up-Up-(repeat).

There are two exploitative computer strategies. One starts by playing the first 5 periods according to the equilibrium strategy: Up with probability $\frac{1}{3}$ and Down with probability $\frac{2}{3}$. Then in the remaining 45 repetitions the computer plays the equilibrium strategy with probability 0.5 and plays the best response to the subject's previous 4 decisions with probability 0.5. We refer to this as the *Exploitative Mix* strategy.

The other exploitative strategy also begins playing the equilibrium strategy for the first 5 periods, then in the remaining 45 repetitions plays the equilibrium strategy with probability 0.5 and best responds to the Win-Stay-Lose-Shift tendency[13] with probability 0.5. In particular, if the subject displayed behavior consistent with the Win-Stay-Lose-Shift strategy in 2 or 3 of the previous 3 decisions then the computer best responds to the Win-Stay-Lose-Shift strategy. On the other hand, if the subject exhibited behavior consistent with the Win-Stay-Lose-Shift strategy in 0 or 1 of the previous 3 decisions then the computer best responds to the Win-Shift-Lose-Stay strategy. We refer to this as the *Exploitative WSLS* strategy.

Each subject played 50 consecutive rounds against a Naive computer strategy and 50 consecutive rounds against a Exploitative computer strategy. With probability 0.5 subjects first played against a Naive computer opponent.

3.4 Experimental procedure

Subjects were paid a \$5 show-up fee. Additional payments were designed to decouple the material incentives from the game in any period with material incentives from the memorization task in that period. Subjects completed 100 repetitions of the game and 100 memorization tasks. Those who correctly completed all 100 memorization tasks were paid for 30 randomly selected game outcomes, those who correctly completed 99 were paid for 29, those who correctly completed 98 were paid for 28, and so on, until subjects who correctly completed 70 or fewer memorization tasks were not paid for any of the game outcomes.

Prior to the incentivized games and memorization tasks, subjects were given an unincen-

[13] See Imhof, Fudenberg, and Nowak (2007), Spiliopoulos (2013), Wang and Xu (2014), and Wang, Xu, and Zhou (2014).

tivized test of their understanding of the hide and seek game. In particular, the subjects were asked about the points that they would obtain for all 4 combinations of own actions and computer actions. Subjects were given feedback on their responses. In addition, the subjects were given an unincentivized opportunity to memorize a six-digit number and an unincentivized opportunity to memorize a one-digit number. Unlike the incentivized portion of the experiment, subjects were given feedback about their performance on these memorization tasks.

After completing the incentivized portion of the experiment, subjects reported their gender, whether they were an economics major, whether they have taken a game theory course, an optional estimate of their grade point average[14] (GPA), and a rating of the difficulty in recalling the large and the small memorization numbers. These difficulty ratings were elicited on a scale of 1 ("Very Difficult") to 7 ("Not Very Difficult"). After these questions were completed, the subjects were told their amount earned. Subsequently the experimenter took an image of the right hand of the subjects with a digital scanner[15] then subjects were paid in cash.

A total of 130 subjects participated in the experiment. The experiment was programmed and conducted with the software z-Tree (Fischbacher, 2007).[16] Of the 130 subjects, 78 were students at Rutgers University-Camden and 52 were students at Haverford College.[17] There were 13 Camden sessions and 3 Haverford sessions. None of the 16 sessions lasted longer than 60 minutes.

4 Results

4.1 Summary statistics

We begin with the summary statistics of the variables of interest. Correct is a dummy variable indicating whether the memorization task was correctly completed. Down is a dummy indicating whether the Down action was selected. Earnings refers to the amount earned in a particular game outcome: 0, 1, or 2. Female, Economics, and Game Theory are dummies

[14] Grade point average ranges from 0.0 to 4.0.

[15] We employed a Canon CanoScan 4507B002 LiDE110 Color Image Scanner. We report the analysis of this data in Duffy et al. (2016).

[16] The z-Tree code is available from the corresponding author upon request.

[17] The Haverford subjects were recruited via ORSEE (Greiner, 2015).

indicating gender, whether the subject was an economics major and whether reported having taken a game theory course. GPA refers to the subject's self-reported grade point average. Table 1 lists the means of these variables, while Table 2 reports the Spearman correlation coefficients.

Table 1: Summary statistics

	Mean
Correct	0.929
Down	0.555
Earnings	0.733
Female	0.531
Economics	0.169
Game Theory	0.177
GPA (optional)	3.365

Correct, Down, and Earnings have 13,000 observations. Female, Economics, and Game Theory have 130 observations. GPA has 103 observations.

Table 2: Spearman non-parametric correlation coefficients

	1	2	3	4	5	6
1 Correct	1.00					
2 Down	0.0110	1.00				
3 Earnings	0.0075	0.0343***	1.00			
4 Female	−0.0142	−0.0044	−0.0228**	1.00		
5 Economics	−0.0083	−0.0050	0.0049	−0.316***	1.00	
6 Game Theory	−0.0073	−0.0180*	0.0122	−0.210*	0.436***	1.00
7 GPA (optional)	0.0767***	0.0066	0.0254**	0.0767	−0.234*	−0.0649

Each correlation between variables 1, 2, or 3, and variables 4, 5, or 6 has 13,000 observations. Each correlation between variables 1, 2, or 3, and variable 7 has 10,3000 observations. Each correlation between variables 4, 5, or 6, and variable 7 has 103 observations. Each correlation among variables 1, 2, and 3 has $13,000$ observations. Each correlation among variables 4, 5, and 6 has 130 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, and * denotes $p < 0.05$

We observe that higher GPA subjects tend to earn more and are more likely to correctly perform the memorization task. Further, we do not observe a relationship between Earnings and either Economics or Game Theory, we do observe a negative relationship between Earnings and Female.[18]

We note that the high load memorization tasks were correct (87.97%, 5718 of 6500) with a significantly lower frequency than the low load memorization tasks (97.88%, 6362 of 6500), according to a Mann-Whitney test $Z = -22.03$, $p < 0.001$. This suggests that our manipulation was successful. As each of the 130 subjects attempted 50 high load memorization tasks and 50 low load memorization tasks, Table 3 presents a characterization of the subject-level distribution of number of correct memorization tasks by cognitive load treatment.

Table 3: Number of subjects by cognitive load treatment and number of correct memorization tasks

	$46-50$	$41-45$	$36-40$	$31-35$	$26-30$	$23-25$	Total
High load	72	30	13	10	2	3	130
Low load	125	5	0	0	0	0	130

In Table 4, we provide a characterization of the aggregate behavior by cognitive load and computer opponent treatments. We also provide the *Optimal* fraction of Down actions against each computer opponent treatment. Against the Naive 50-50 opponent, the best response is to always play Down, therefore Optimal is 1. Against the Naive pattern opponent, best responding to the pattern implies that Optimal is 0.333. Against the Exploitative opponents, playing the equilibrium strategy would prevent the computer from exploiting the subject, therefore Optimal is 0.333.

Table 4: Fraction of Down by computer strategy treatment and cognitive load treatment

	Optimal	High load	Low load	$MW\ Z-$stat	Observations
Naive 50-50	1.000	0.615	0.585	$1.769^{\dagger}$	3450
Naive pattern	0.333	0.494	0.524	-1.589	3050
Exploitative WSLS	0.333	0.559	0.568	-0.520	3200
Exploitative Mix	0.333	0.523	0.561	-2.134^{*}	3300

The optimal fraction of Down actions by computer opponent treatment and cognitive load treatment. Mann-Whitney tests were conducted on the difference between the high and low load. The Mann-Whitney Z-statistic is reported. * denotes $p < 0.05$ and † denotes $p < 0.1$

[18] Apparently being an economics major is not good for one's GPA: we note a negative relationship between GPA and Economics.

From the analysis summarized in Table 4, we observe that subjects under a high load play Down with a significantly different probability than subjects under a low load against both the Naive 50-50 strategy and the Exploitative Mix strategy.[19] We also note that in these two cases, subjects under a high load are closer to the optimal mixture than are subjects under a low load. Although we do not find a significant difference in the overall rate of playing Down against the Naive pattern strategy there are meaningful differences in behavior. Subjects under a high load best respond to the action of the Naive pattern strategy (62.8%), more frequently than do subjects under a low load (55.1%) according to a Mann-Whitney test, $Z = 4.103$, $p < 0.001$.

However, we cannot conclude that subjects under a high load were more likely to have discerned the pattern than subjects under a low load. This is because there is not a significant difference between the number of consecutive periods at the end of the Naive pattern treatment in which the subject under a high load earned a payoff greater than zero ($Mean = 5.82$, $SD = 1.63$) and that for a subject under a low load ($Mean = 6.54$, $SD = 2.47$), $Z = 0.50$, $p = 0.61$.

4.2 Mixture proportions

We now test whether the subjects mixed in the proportions as predicted by equilibrium: Up with probability 0.6667 and Down with probability 0.3333. Here we restrict attention to observations against Exploitative computer strategies. This is because there are difficulties interpreting the mixing proportions against the Naive computer strategies.

We conduct a binomial χ^2 test on each subject.[20,21] Performing a joint test on the 76 subjects under a high load by summing their test statistics, we reject the hypothesis that, on aggregate, they mix with these proportions, $\chi^2(76, 1) = 1026.22$, $p < 0.001$. We also conduct a joint binomial χ^2 test on 53 the subjects under a low load by summing their test statistics,

[19] As a robustness check, we run a repeated measures regression with the action as the dependent variable and treatment dummies as independent variables. The qualitative results of Table 4 hold, with the exception that the Exploitative Mix difference is not signficant.

[20] See the Supplemental Online Appendix for the subject-level data. Note that one subject selected Down in every period and therefore we cannot perform a binomial χ^2 test on this subject.

[21] We note that there does not exist a significant Spearman correlation between the χ^2 statistic and the Female, Game Theory, Economics, and GPA variables.

and again we reject the hypothesis that they mix with the Nash equilibrium proportions, $\chi^2(53, 1) = 774.08$, $p < 0.001$.

Next we test the hypothesis that the subjects under high and low load are significantly different in this regard. We conduct a two-sample Kolmogorov-Smirnov test[22] on the distribution of the individual χ^2 test statistics and find that they are not significantly different, $K = 0.164$, $p = 0.37$. This qualitative result is not changed when we restrict attention to the last 25 periods of each 50 period block, $K = 0.129$, $p = 0.70$. We also test for differences between the treatments using a Mann-Whitney test on the percentage of Down actions against an exploitative computer opponent. We find that the subjects under a high load (54.05%) had a significantly different mixture than subjects under a low load (56.44%), $Z = 1.910$, $p = 0.056$. However, the difference between subjects under high load (53.42%) and low load (56.30%) is not significant when we restrict attention to the final 25 periods of the 50 period block, $Z = 1.622$, $p = 0.105$.

Therefore, consistent with the previous literature, we find that the subjects do not mix in the equilibrium proportions. However, we do not find strong evidence of a significant difference between the mixture proportions of subjects under a high load and subjects under a low load. This suggests that the availability of cognitive resources is not related to the observed deviations from the equilibrium mixture proportions in this game.

4.3 Serial correlation

Next we investigate whether the actions in our data exhibit serial correlation. As in the previous subsection, we restrict attention to observations against an Exploitative opponent. This is because exhibiting a mixture with serial correlation against a Naive opponent is a best response.

In order to detect serial correlation, we perform test of runs, as described in Gibbons and Chakraborti (1992). A run (r) is defined to be a sequence of one or more identical actions followed by a different action or no action at all. Given the number of Up actions (n_U) and the number of Down actions (n_D) selected by a subject, we are able to calculate the probability

[22] See Gibbons and Chakraborti (1992).

of observing any feasible number of runs.[23] For every subject, given n_D and n_U we calculate the probability density function of the number of runs:

$$f(r|n_U, n_D) = \begin{cases} \dfrac{2\binom{n_U-1}{(\frac{r}{2})-1}\binom{n_D-1}{(\frac{r}{2})-1}}{\binom{n_D+n_U}{n_U}} & \text{if } r \text{ is even} \\ \\ \dfrac{\binom{n_U-1}{\frac{r-1}{2}}\binom{n_D-1}{\frac{r-3}{2}}+\binom{n_U-1}{\frac{r-3}{2}}\binom{n_D-1}{\frac{r-1}{2}}}{\binom{n_D+n_U}{n_U}} & \text{if } r \text{ is odd.} \end{cases}$$

From the density function, we can calculate the cumulative distribution function:

$$F(r|n_U, n_D) = \sum_{k=1}^{r} f(k|n_U, n_D),$$

which is the probability of observing r or fewer runs. Similar to Walker and Wooders (2001), Palacios-Huerta and Volij (2008), and Levitt, List, and Reiley (2010), we calculate two statistics, $F(r-1|n_U, n_D)$ and $F(r|n_U, n_D)$, for each subject.[24] At a 5% level of significance, we would reject the null hypothesis of independence, if either $F(r|n_U, n_D) < 0.025$ or if $1 - F(r-1|n_U, n_D) < 0.025$. Because we plan to run one-sample Kolmogorov-Smirnov tests on these probabilities, as Walker and Wooders (2001), for each subject we take a draw from the uniform distribution with $F(r|n_U, n_D)$ as the upper bound and $F(r-1|n_U, n_D)$ as the lower bound. This leaves us with a single probability estimate for each subject.[25] If the actions are selected independently then these probabilities would be distributed as a uniform between 0 and 1.

We perform a one-sample Kolmogorov-Smirnov test that the 53 probabilities associated with subjects under a low load are uniformly distributed between 0 and 1. We reject the hypothesis that the probabilities are distributed as a uniform, $K = 0.174$, $p = 0.071$. Figure 1 illustrates the test on subjects under a low load. We also perform a one-sample Kolmogorov-Smirnov test that the 76 probabilities associated with subjects under a high load are uniformly

[23] Given $n_U > 0$ and $n_D > 0$, there must be at least 2 runs and the maximum possible number of runs is equal to $2 * \min(n_U, n_D) + 1$.

[24] See the Supplemental Online Appendix for the subject-level data.

[25] We note that there does not exist a significant Spearman correlation between these probability estimates, and the Female, Game Theory, Economics, and GPA variables.

distributed between 0 and 1. Again, we reject the hypothesis, $K = 0.246$, $p < 0.001$. Figure 2 illustrates the test on the subjects under a high load.

<<Figures 1 and 2 about here>>

While subjects in neither cognitive load treatments appear to be mixing in an independent fashion, it remains to be seen whether the distribution associated with subjects under a high load is different from the distribution associated with subjects under a low load. We perform a two-sample Kolmogorov-Smirnov test and we fail to reject the hypothesis that the distributions are different, $K = 0.158$, $p = 0.42$. This qualitative result remains unchanged when we restrict the analysis to the final 25 periods in the 50 period block, $K = 0.091$, $p = 0.97$.

Another test of serial correlation examines the rate at which subjects switch their action from one decision to the next. We find that there is not a significant difference in switching rates for subjects under a high load (49.54%) and subjects under a low load (48.00%), $Z = 1.217$, $p = 0.224$.[26,27] Therefore, while we observe serial correlation in both of our cognitive load treatments, we do not detect differences in the serial correlation between these treatments.

4.4 Earnings differences

Now we examine difference in earnings by cognitive load treatment. We observe that earnings of subjects under a high load ($Mean = 0.737$, $SD = 0.806$) are not different than those of subjects under a low load ($Mean = 0.730$, $SD = 0.805$), according to a Mann-Whitney test, $Z = 0.52$, $p = 0.61$. However, when we examine these corresponding differences within computer opponent treatments, differences do appear. Table 5 lists the differences in earnings within computer opponents, and the corresponding Mann-Whitney tests.

[26] We obtain similar results when we restrict attention to the final 25 periods in the 50 period block. This analysis is available from the corresponding author upon request.

[27] Interestingly, differences in switching emerge when we restrict attention to particular computer strategies. Against the Exploitative WSLS computer strategy, subjects under a high load switch (46.22%) less than subjects under a low load (50.87%), $Z = 2.572$, $p = 0.005$. However, against the Exploitative Mix computer strategy, subjects under a high load switch (52.69%) more than subjects under a low load (45.12%), $Z = 4.233$, $p < 0.001$.

Table 5: Average amount earned by computer opponent treatment and load treatment

	High load	Low load	$MW\ Z-stat$	Observations
Naive 50-50	0.779	0.794	-0.595	3450
Naive pattern	0.855	0.753	3.686^{***}	3050
Exploitative WSLS	0.707	0.735	-0.997	3200
Exploitative Mix	0.664	0.602	2.395^{*}	3300

The average amount earned by computer opponent treatment and cognitive load treatment. Mann-Whitney tests were conducted on the difference between the high and low load observations. The Mann-Whitney Z-statistic is reported. *** denotes $p < 0.001$ and * denotes $p < 0.05$

The results in Table 5 suggest that the investigation of earnings should account for the computer opponent treatment. Therefore, in each of the regressions below we include dummy variables indicating the computer opponent treatment and the interaction of these dummies with the high load dummy. Additionally, we consider specifications that account for the repeated nature of the observations. In these repeated measures regressions, we estimate an exchangeable covariance matrix, clustered by subject. In other words, we assume a unique correlation between any two observations involving a particular subject. However, we assume that observations involving two different subjects are statistically independent. We also consider specifications that control for Female, Economics, and Game Theory. We refer to this collection of variables as *Demographics*. We also account for self-reported GPA. Recall that a response to GPA was optional and only 103 of 130 subjects provided a response. This analysis is summarized in Table 6.

Table 6: Regressions of earnings

	(1)	(2)	(3)	(4)
High load	0.0626^{*}	0.0692^{*}	0.0791^{*}	0.0968^{**}
	(0.0284)	(0.0327)	(0.0333)	(0.0369)
GPA	–	–	–	0.0457^{*}
				(0.0229)
Strategy dummies	Yes	Yes	Yes	Yes
Repeated measures	No	Yes	Yes	Yes
Demographics	No	No	Yes	Yes
AIC	31221.7	31199.0	31212.3	24767.3
Observations	13,000	13,000	13,000	10,300

The repeated measures regressions estimate an exchangeable covariance matrix, clustered by subject. We do not provide the estimates of the intercepts, the individual demographics variables, the covariance estimates, or the strategy dummies. Each specification has 13,000 observations. AIC refers to the Akaike information criterion (Akaike, 1974). ** denotes $p < 0.01$, and * denotes $p < 0.05$

Although the less detailed analysis does not find a relationship between cognitive load and earnings, in each of the specifications in our regressions we find that subjects under a high cognitive load earn a significantly larger amount than subjects under a low load. We also find a positive relationship between GPA and earnings.

4.5 Earnings differences over time

In order to better understand the result that subjects under a high cognitive load have higher earnings than subjects under a low cognitive load, we now consider the trajectory of earnings. We define Round to be the number of periods under a particular computer opponent treatment and a particular cognitive load treatment. Therefore, Round ranges from 1 to 50. Other than the inclusion of the Round variable and the interaction of Round and cognitive load treatment, the analysis is identical to that summarized in Table 6. This analysis is summarized in Table 7.

Table 7: Regressions of earnings across rounds

	(1)	(2)	(3)	(4)
High load	0.114**	0.120**	0.130**	0.146**
	(0.0378)	(0.0410)	(0.0415)	(0.0462)
Round	0.00190**	0.00190**	0.00190**	0.00198*
	(0.00069)	(0.00069)	(0.00069)	(0.00077)
Round*High load	−0.00201*	−0.00201*	−0.00201*	−0.00193†
	(0.000976)	(0.000972)	(0.000972)	(0.00109)
GPA	–	–	–	0.0457*
				(0.0229)
Strategy dummies	*Yes*	*Yes*	*Yes*	*Yes*
Repeated measures	*No*	*Yes*	*Yes*	*Yes*
Demographics	*No*	*No*	*Yes*	*Yes*
AIC	31239.6	31216.8	31230.1	24785.8
Observations	13,000	13,000	13,000	10,300

The repeated measures regressions estimate an exchangeable covariance matrix, clustered by subject. We do not provide the estimates of the intercepts, the individual demographics variables, the covariance estimates, or the strategy dummies. Each specification has 13,000 observations. AIC refers to the Akaike information criterion (Akaike, 1974). ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$

The positive and significant high load coefficient suggests that subjects under a high load earn more in the early rounds. However, we observe a positive and significant Round coefficient in addition to a negative and significant Round-High load interaction. This indicates that the subjects under a low load exhibit an improved earnings across rounds, however, the subjects under a high load do not exhibit such an improvement. This finding is robust to the specification of the analysis. This suggests that while subjects under a low load earn less than subjects under a high load in the early rounds the subjects under a low load appear to be catching up. This result is consistent with the interpretation that subjects under a low load exhibit a greater learning across rounds.

4.6 Differences in response time

Research finds a positive relationship between the time spent deciding on a choice and the difficulty of the choice.[28] In other words, decisions where one option is clearly better than the others tends to take less time than decisions where this is not the case. In order to better understand the analysis of earnings across rounds, here we study the response times across rounds. We run the analogous regressions as summarized in Table 7 but we employ the response time of the game decision as the dependent variable. Therefore, a higher value indicates that the decision was selected in a longer time period. As response times are bounded below by 0, we perform the analysis by taking the natural log of the response times. This analysis is summarized in Table 8.

[28] See Wilcox (1993), Moffatt (2005), Rubinstein (2007), Alós-Ferrer, Granić, Shi, and Wagner (2012), Chen and Fischbacher (2015), and Alós-Ferrer, Granić, Kern, and Wagner (2016).

Table 8: Regressions of the natural log of response times across rounds

	(1)	(2)	(3)	(4)
High load	-0.166^{***}	-0.214^{***}	-0.187^{***}	-0.172^{**}
	(0.0270)	(0.0465)	(0.0471)	(0.0534)
Round	-0.00781^{***}	-0.0083^{***}	-0.0083^{***}	-0.0072^{***}
	(0.00050)	(0.00045)	(0.00045)	(0.00051)
Round*High load	0.00238^{***}	0.00243^{***}	0.00243^{***}	$0.00127^{\dagger}$
	(0.00071)	(0.00064)	(0.00064)	(0.00072)
GPA	–	–	–	-0.00404
				(0.0473)
Strategy dummies	Yes	Yes	Yes	Yes
Repeated measures	No	Yes	Yes	Yes
Demographics	No	No	Yes	Yes
AIC	14000.3	12427.1	12431.7	9930.9
Observations	13,000	13,000	13,000	10,300

The repeated measures regressions estimate an exchangeable covariance matrix, clustered by subject. We do not provide the estimates of the intercepts, the individual demographics variables, the covariance estimates, or the strategy dummies. Each specification has 13,000 observations. AIC refers to the Akaike information criterion (Akaike, 1974). *** denotes $p < 0.001$, ** denotes $p < 0.01$, and † denotes $p < 0.1$

Table 8 provides evidence that subjects under a high load take less time to reach their decisions, and that this time decreases by round for subjects under a low load. The Round-High load interaction, however, suggests that subjects under a low load exhibit a greater increase in the decision speed across rounds than subjects under a high load. This is consistent with the interpretation of the analysis summarized in Table 7 that subjects under a low load exhibit a greater amount of learning than subjects under a high load. Interestingly, we do not find a relationship between response time and GPA.

5 Discussion

The experimental literature largely finds that subjects do not mix in the proportions predicted by equilibrium and that actions exhibit serial correlation. We find these features in our data however we do not find evidence that they are related to the cognitive load treatment. Therefore, we do not find evidence that the standard experimental results on mixing are associated with the available cognitive resources of the subject.

These results are reminiscent of the findings reported in Geng et al. (2015). These authors do not find a relationship between measures of cognitive ability and either the mixture proportions or the serial correlation of actions. Although the design of Geng et al. (2015) exhibits (adolescent subjects, human opponents, measures of cognitive ability) notable differences from our design (college student subjects, computer opponents, cognitive load manipulation), neither study finds a relationship between cognition and either mixing proportions or serially correlated actions. However, more work needs to be done in order to better understand the relationship between cognition and the standard mixed strategy experimental results.

We also find surprising evidence that subjects under a high cognitive load earn more than subjects under a low cognitive load, particularly in the early rounds. This is consistent with the explanation that subjects under a high load are employing a simple, stable strategy and subjects under a low load are engaging in experimentation during those early rounds.

However, we also find that subjects under a low cognitive load exhibit increases in earnings across rounds, while those under a high cognitive load do not.[29] An interpretation of this result is that the subjects under a low load exhibit more learning than subjects under high load. Our analysis of the response times is also consistent with this interpretation. This result has an intuitive appeal because remembering and analyzing previous outcomes would seem to require available cognitive resources.

Gill and Prowse (2015) find a similar result, albeit in a different setting. These authors observe that subjects with higher measured cognitive ability exhibit a faster convergence to the equilibrium prediction in a repeated beauty contest game.

We acknowledge that there is much work to be done on the topic. We leave it to future research to determine whether there is a sufficient number of rounds where subjects under a low load would earn more than subjects under a high load. Also, it is possible that subjects play a computer opponent differently than a human opponent because the computer might be expected to employ a more stable strategy. These and other interesting questions are a matter for future research.

[29] Geng et al. (2015) did not study the trajectory of earnings across rounds,

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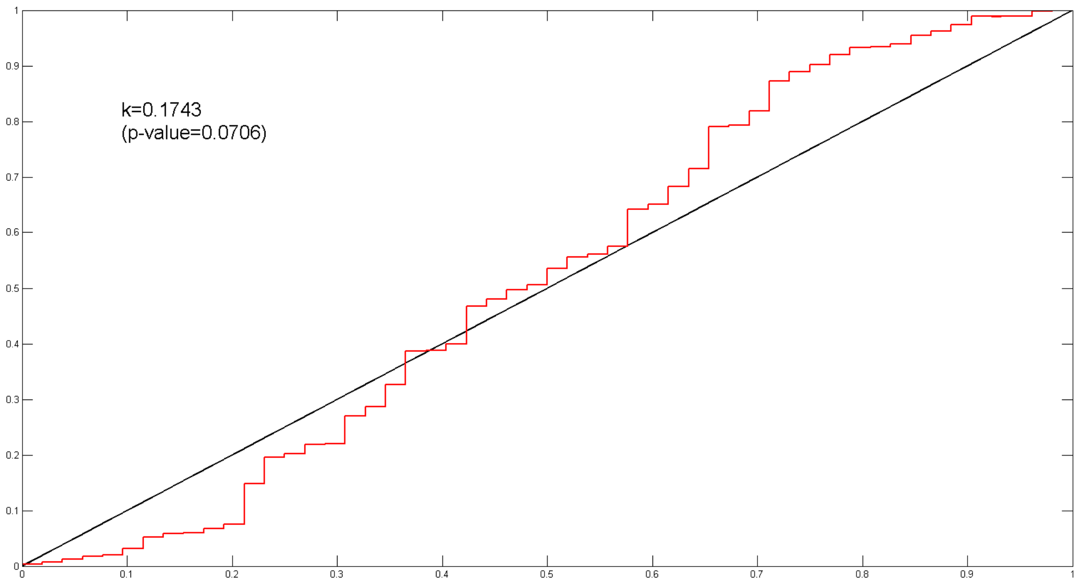


Figure 1: Kolmogorov-Smirnov Test of Runs for subjects under a low load.

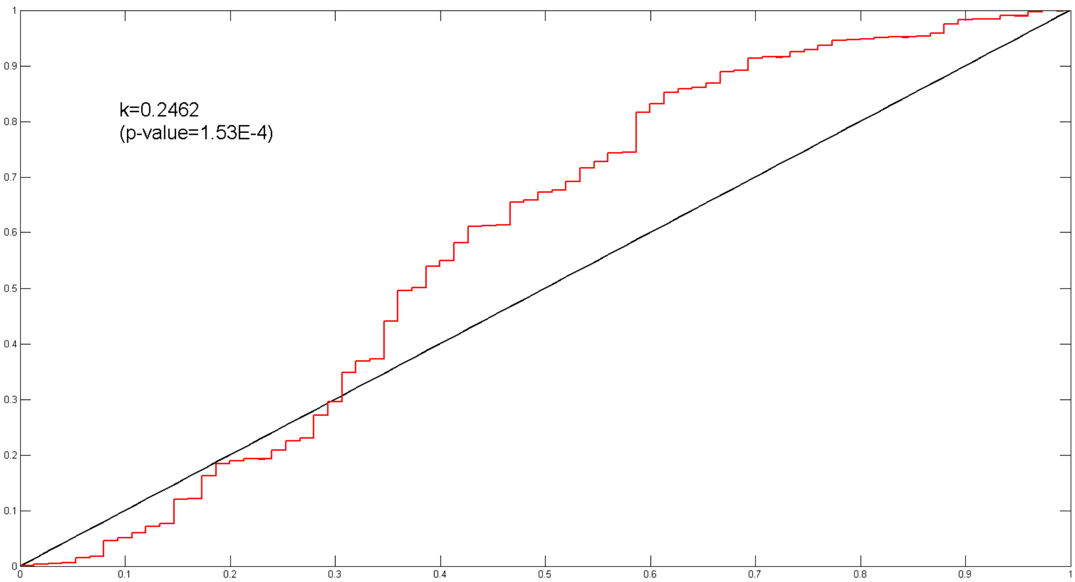
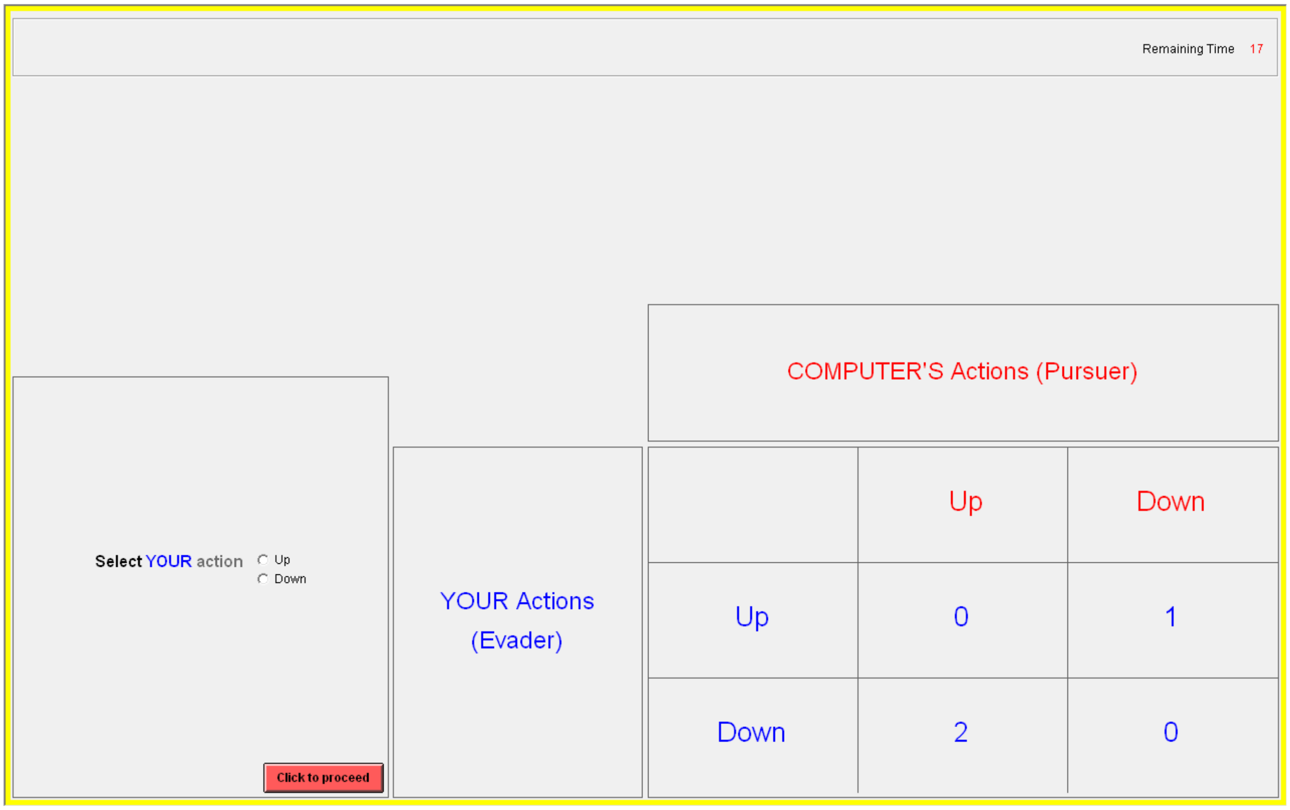


Figure 2: Kolmogorov-Smirnov Test of Runs for subjects under a high load.

Supplemental Online Appendix

Screenshot of game



Low Load against Exploitative opponent

Subject	#Down	χ^2	p-value	Runs	$F(r)$	$F(r-1)$	U draw
2	22	2.56	0.110	25	0.483	0.371	0.387
3	22	2.56	0.110	31	0.956	0.921	0.939
4	25	6.25	0.012	21	0.099	0.058	0.058
6	23	3.61	0.057	19	0.033	0.017	0.031
9	28	11.56	< 0.001	32	0.977	0.956	0.962
13	27	9.61	0.002	26	0.576	0.460	0.506
16	28	11.56	< 0.001	20	0.068	0.037	0.060
20	22	2.56	0.110	42	0.999	0.999	0.999
22	49	94.09	< 0.001	3	1.000	0.040	0.202
27	24	4.84	0.028	37	0.999	0.999	0.999
30	22	2.56	0.110	34	0.995	0.989	0.990
31	29	13.69	< 0.001	33	0.992	0.983	0.989
33	25	6.25	0.012	32	0.969	0.942	0.955
34	18	0.16	0.689	29	0.959	0.916	0.934
43	31	18.49	< 0.001	26	0.718	0.612	0.650
47	33	24.01	< 0.001	16	0.014	0.006	0.012
49	27	9.61	0.002	34	0.994	0.987	0.990
52	22	2.56	0.110	28	0.796	0.704	0.714
53	27	9.61	0.002	24	0.351	0.250	0.286
62	25	6.25	0.0124	30	0.902	0.841	0.872
64	17	0.01	0.9203	21	0.270	0.172	0.218
65	32	21.16	< 0.001	24	0.550	0.434	0.497
67	50	–	–	1	0	0	0
68	29	13.69	< 0.001	26	0.629	0.516	0.556
70	24	4.84	0.028	19	0.0314	0.016	0.020
71	28	11.56	< 0.001	30	0.921	0.869	0.902
77	27	9.61	0.002	31	0.949	0.911	0.920
78	33	24.01	< 0.001	15	0.0061	0.002	0.003
102	30	16.00	< 0.001	25	0.559	0.438	0.535

Camden subjects are labeled $1-78$. Haverford subjects are labeled $101-152$. Among the 50 decisions against an exploitative opponent, we report the number of down actions, the χ^2 statistic and the corresponding p-value as discussed in subsection 4.2. We report the number of runs, the two CDF statistics, and the draw of the uniform between these, as discussed in subsection 4.3.

Low Load against Exploitative opponent

Subject	#Down	χ^2	p-value	Runs	$F(r)$	$F(r-1)$	U draw
103	34	27.04	< 0.001	21	0.341	0.223	0.326
105	48	88.36	< 0.001	4	0.118	0.041	0.075
110	25	6.25	0.012	21	0.098	0.058	0.067
112	35	30.25	< 0.001	26	0.936	0.892	0.932
119	28	11.56	< 0.001	26	0.598	0.483	0.575
120	25	6.25	0.012	26	0.558	0.442	0.467
121	34	27.04	< 0.001	16	0.021	0.009	0.017
125	27	9.61	0.002	36	0.999	0.998	0.998
128	36	33.64	< 0.001	23	0.805	0.663	0.793
130	30	16.00	< 0.001	25	0.559	0.438	0.480
131	25	6.25	0.012	25	0.442	0.335	0.388
134	22	2.56	0.110	28	0.796	0.704	0.791
136	25	6.25	0.012	22	0.159	0.098	0.149
137	27	9.61	0.002	17	0.008	0.003	0.007
140	41	53.29	< 0.001	14	0.237	0.151	0.195
141	24	4.84	0.028	25	0.447	0.339	0.399
142	25	6.25	0.012	28	0.763	0.665	0.683
144	23	3.61	0.057	20	0.062	0.033	0.052
145	28	11.56	< 0.001	26	0.598	0.483	0.561
146	25	6.25	0.012	29	0.841	0.763	0.818
147	24	4.84	0.028	24	0.339	0.240	0.270
149	36	33.64	< 0.001	19	0.282	0.167	0.219
150	25	6.25	0.012	27	0.665	0.558	0.641
151	30	16.00	< 0.001	29	0.912	0.850	0.889
152	23	3.61	0.057	33	0.987	0.973	0.973

Camden subjects are labeled $1-78$. Haverford subjects are labeled $101-152$. Among the 50 decisions against an exploitative opponent, we report the number of down actions, the χ^2 statistic and the corresponding p-value as discussed in subsection 4.2. We report the number of runs, the two CDF statistics, and the draw of the uniform between these, as discussed in subsection 4.3.

High Load against Exploitative opponent

Subject	#Down	χ^2	p-value	Runs	$F(r)$	$F(r-1)$	U draw
1	36	33.64	< 0.001	19	0.282	0.167	0.189
5	24	4.84	0.028	28	0.767	0.669	0.716
7	26	7.84	0.005	28	0.767	0.669	0.743
8	28	11.56	< 0.001	26	0.598	0.483	0.501
10	9	5.29	0.021	17	0.829	0.576	0.613
11	31	18.49	< 0.001	19	0.063	0.033	0.059
12	31	18.49	< 0.001	21	0.177	0.109	0.122
14	22	2.56	0.110	32	0.977	0.956	0.974
15	30	16.00	< 0.001	19	0.051	0.026	0.045
17	23	3.61	0.057	31	0.949	0.911	0.925
18	22	2.56	0.110	16	0.004	0.001	0.003
19	20	1.00	0.317	33	0.995	0.988	0.990
21	40	49.00	< 0.001	16	0.368	0.260	0.349
23	35	30.25	< 0.001	23	0.699	0.551	0.581
24	32	21.16	< 0.001	17	0.021	0.001	0.014
25	37	37.21	< 0.001	24	0.942	0.902	0.916
26	29	13.69	< 0.001	32	0.983	0.966	0.983
28	38	40.96	< 0.001	17	0.254	0.135	0.208
29	21	1.69	0.194	25	0.516	0.399	0.496
32	32	21.16	< 0.001	28	0.916	0.862	0.913
35	25	6.25	0.012	23	0.237	0.159	0.163
36	26	7.84	0.005	37	0.999	0.998	0.999
37	20	1.00	0.317	30	0.950	0.912	0.947
38	28	11.56	< 0.001	25	0.483	0.371	0.440
39	28	11.56	< 0.001	30	0.921	0.869	0.869

Camden subjects are labeled $1-78$. Haverford subjects are labeled $101-152$. Among the 50 decisions against an exploitative opponent, we report the number of down actions, the χ^2 statistic and the corresponding p-value as discussed in subsection 4.2. We report the number of runs, the two CDF statistics, and the draw of the uniform between these, as discussed in subsection 4.3.

High Load against Exploitative opponent

Subject	#Down	χ^2	p-value	Runs	$F(r)$	$F(r-1)$	U draw
40	23	3.61	0.057	23	0.250	0.169	0.193
41	24	4.84	0.028	27	0.669	0.562	0.610
42	21	1.69	0.194	27	0.735	0.629	0.673
44	49	94.09	< 0.001	3	1	0.04	0.929
45	18	0.16	0.689	26	0.772	0.676	0.676
46	19	0.49	0.484	22	0.264	0.177	0.185
48	28	11.56	< 0.001	34	0.995	0.989	0.990
50	31	18.49	< 0.001	16	0.007	0.003	0.005
51	33	24.01	< 0.001	21	0.270	0.172	0.230
54	31	18.49	< 0.001	25	0.612	0.488	0.539
55	22	2.56	0.110	27	0.704	0.598	0.655
56	29	13.69	< 0.001	20	0.077	0.043	0.077
57	23	3.61	0.057	27	0.682	0.576	0.659
58	23	3.61	0.057	22	0.169	0.105	0.120
59	25	6.25	0.012	32	0.969	0.942	0.948
60	28	11.56	< 0.001	29	0.869	0.796	0.851
61	32	21.16	< 0.001	21	0.217	0.135	0.193
63	23	3.61	0.057	28	0.778	0.682	0.744
66	30	16.00	< 0.001	30	0.950	0.912	0.946
69	23	3.61	0.057	25	0.460	0.351	0.368
72	24	4.84	0.028	33	0.985	0.970	0.984
73	20	1.00	0.317	20	0.090	0.051	0.051
74	22	2.56	0.110	36	0.999	0.998	0.999
75	33	24.01	< 0.001	7	0.000	0.000	0.000
76	49	94.09	< 0.001	3	1	0.04	0.296

Camden subjects are labeled $1-78$. Haverford subjects are labeled $101-152$. Among the 50 decisions against an exploitative opponent, we report the number of down actions, the χ^2 statistic and the corresponding p-value as discussed in subsection 4.2. We report the number of runs, the two CDF statistics, and the draw of the uniform between these, as discussed in subsection 4.3.

High Load against Exploitative opponent

Subject	#Down	χ^2	p-value	Runs	$F(r)$	$F(r-1)$	U draw
101	31	18.49	< 0.001	30	0.965	0.936	0.951
104	31	18.49	< 0.001	27	0.815	0.718	0.727
106	27	9.61	0.002	35	0.998	0.994	0.997
107	28	11.56	< 0.001	31	0.956	0.921	0.952
108	24	4.84	0.028	24	0.339	0.240	0.271
109	23	3.61	0.057	23	0.250	0.169	0.224
111	21	1.69	0.194	26	0.629	0.516	0.549
113	24	4.84	0.028	29	0.844	0.767	0.816
114	20	1.00	0.317	31	0.975	0.950	0.952
115	20	1.00	0.317	24	0.438	0.327	0.372
116	24	4.84	0.028	29	0.844	0.767	0.832
117	24	4.84	0.028	33	0.985	0.970	0.984
118	24	4.84	0.028	32	0.970	0.944	0.953
122	19	0.49	0.484	16	0.007	0.003	0.004
123	29	13.69	< 0.001	18	0.022	0.010	0.017
124	27	9.61	0.002	27	0.682	0.576	0.612
126	24	4.84	0.028	30	0.904	0.844	0.861
127	30	16.00	< 0.001	31	0.975	0.950	0.958
129	42	57.76	< 0.001	17	1	0.822	0.937
132	24	4.84	0.028	40	0.999	0.999	0.999
133	29	13.69	< 0.001	30	0.935	0.889	0.891
135	24	4.84	0.028	30	0.904	0.844	0.858
138	26	7.84	0.005	28	0.767	0.669	0.691
139	26	7.84	0.005	30	0.904	0.844	0.889
143	26	7.84	0.005	21	0.100	0.059	0.071
148	31	18.49	< 0.001	29	0.936	0.883	0.916

Camden subjects are labeled $1-78$. Haverford subjects are labeled $101-152$. Among the 50 decisions against an exploitative opponent, we report the number of down actions, the χ^2 statistic and the corresponding p-value as discussed in subsection 4.2. We report the number of runs, the two CDF statistics, and the draw of the uniform between these, as discussed in subsection 4.3.