Time-pressure improves decisions in generalized Colonel Blotto games

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Abstract

We report data from generalized Colonel Blotto game experiments using human participants. When played with complete information, our game has a unique pure strategy Nash Equilibrium which we use as a baseline against which to measure actual play. We show that humans are better able to achieve Nash Equilibrium, and make empirically better decisions, when playing the game under time pressure and with imperfect information. These results caution against 'overthinking' strategic decisions and highlight the importance of 'gut' reasoning during combat.

Keywords: Time Pressure, Nash Equilibrium, Generalized Colonel Blotto Game, Decision making under imperfect information

1 Introduction

In many conflict environments (e.g. combats during war, sport games), one is required to make a decision under time pressure. In some cases, these constraints can be extremely tight. Consequently, it is important to develop an understanding of how people

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make decisions under time pressure. This challenge has been taken up by a recent literature that investigates human decisions under time constraint(Spiliopoulos and Ortmann, 2018). While valuable, these studies generally focus either on non-strategic decisions (Rubinstein, 2013, 2007; Capraro, 2017; Lohse et al., 2018; Barcelo and Capraro, 2018; Capraro et al., 2019; McKinney Jr and Van Huyck, 2013) or prosocial vs. antisocial behaviors in strategic interactions (Brañas-Garza et al., 2017; Cappelen et al., 2016; Nishi et al., 2016; Evans et al., 2015; Oechssler et al., 2015; Cone and Rand, 2014; Fischbacher et al., 2013) under time limits [1]. In this paper, we study how time pressure impacts decision making in strategic interactions that model combat. In particular, we ask whether time constraints affect the likelihood of playing the Nash Equilibrium, and ultimately the chance that one defeats one's enemy.

We test the effect of time pressure using a constrained Blotto game in which some forces are pre-allocated to battlefields and the remaining forces need to be allocated to one and only one battlefield. This constrained Blotto game has a unique pure strategy Nash Equilibrium, which we use as a baseline against which we compare actual play. Assuming common knowledge of full rationality, playing Nash Equilibrium is the best response for both players. Our interest is to discover the extent to which participants play (or deviate from) Nash Equilibrium, and to know how their play in different situations influences their likelihood of winning the game. In particular, we consider human Blotto game decisions in time-unconstrained and time-constrained environments.

Our main finding is that subjects play significantly more of the equilibrium strategy under time-constrained than in the time-unconstrained environment. In relation to the time-unconstrained environment, equilibrium play in the time-constrained environment increases by more than 5%. Further, we find that time-to-decision affects the chance of equilibrium play within both the time-unconstrained and time-constrained environments. In the time-unconstrained environment, on average, each 10 seconds of decision time decreases the rate of equilibrium play by 1%. Surprisingly, under the 15 seconds time-constraint, each additional second spent making a decision decreases the rate of equilibrium play by 1%. Moreover, our data show that when playing the equilibrium strategy, the probability of defeating one's enemy is significantly higher than when playing a non-equilibrium strategy. Importantly, even under time pressure, spending more time making decisions significantly reduces the chance of defeating one's enemy.

[1] Spiliopoulos and Ortmann (2018) provides a literature review.

Our study is the first to document the positive effect of time pressure on decisions in environments that involve conflict, though related results have appeared in other contexts. Gill and Prowse (2017) finds that 'overthinking' is detrimental to performance in a beauty contest game. A person wins this game when they guess a number that is closest to 1/3 times the average of other people's guesses. They document that when a person thinks longer she wins less frequently and earns less. The behavioral mechanism that drives the reduction in performance is a tendency for extra thinking to move one away from Nash equilibrium play. One important distinction between their study and our own is that in their case decision time is endogenous. In particular, their study includes only a (generally non-binding) 90 second time constraint, and they do not consider other environments. Because they do not have exogenous variation in the time constraint, Thus, whether a person makes their decision quickly is endogenous. Here we report data from two treatments, one without time constraints, the other with a tight and binding time constraint (15 seconds) in which subjects are required to make decision quickly.

The remainder of this paper is organized as follows. Section 2 provides an overview of the Blotto game. Section 3 describes the experiment design and procedures. Section 4 reports our findings. Section 5 concludes and discusses.

2 Blotto Game Overview

We study Blotto games with two human subjects i.e. players 1 and 2, each endowed with X tokens. Tokens do not have value outside the game – we operate within a "use-it-or-lose-it" setting. There are 4 battlefields, indexed by $i \in \{1, 2, 3, 4\}$. Winning battlefield i is worth W_i points, denoted by $W = (W_1, W_2, W_3, W_4)$ and let $w = \sum_{i=1}^{4} W_i$. The player who earns more than $w/2$ points wins the game and receives payoff Y. The losing player earns nothing.

Denote by x_i^j the number of tokens placed by player j on battlefield i. Then, the strategy of player j can be defined as $x^j = (x_1^j, x_2^j, x_3^j, x_4^j)$ such that $\sum_{i=1}^{4} x_i^j = X$. The probability that player j wins the battlefield i is determined by bids of both players, according to:

$$Pr(winner = j|x_i) = \frac{x_i^j}{x_i^j + x_i^{-j}}$$

Therefore every battle is a lottery with the probability of winning as defined above. Using this, the Colonel Blotto game can be defined by $G = (W, X, Y)$.

Let $t = (t_1, t_2, t_3, t_4)$ be an index vector indicating a subset of whether each of the battlefields i is a winning battle field. Then, we need to make the following assumption:

$$\sum_{i=1}^{4} t_i W_i \neq w/2 \ foranysubset \tag{1}$$

If the above assumption is satisfied and both players face the the same endowed tokens, then every such game has the unique pure strategy Nash equilibrium[2], specified as follows.

Following Duffy and Matros (2015), we have:

Definition: a battle field is pivotal in subset (t_1, t_2, t_3, t_4) if $(t_i = 1, t_{-i})$ is a winning subset and $(t_i = 0, t_{-i})$ is a losing subset, where t_{-i} denotes all battlefields except t_i. In other words, in a winning subset, battlefield i is the one which makes the total number of points earned exceed $w/2$. That is, *ceteris paribus*, winning battle field i will lead to the winning the game but losing battle field i will lead to losing the game. Denote by V_i a set of the winning subsets in which battlefield i is pivotal, then for every player $j \in N$ the equilibrium allocation would be[3]

$$\hat{x}_i^j = X \frac{|V_i|}{\sum\limits_{k=1}^{4} |V_k|} \tag{2}$$

Intuitively, one allocates to every battlefield the share of one's endowed tokens equal to the probability that winning this battlefield would lead you to win the game. Our interest is in discovering, using a laboratory experiment, whether people's actual play of this game is impacted by constraints on the time available to make a force-allocation decision. We implement the game in imperfect information environment as will introduced in the next section.

[2]For proof, see Duffy and Matros (2015).
[3]For proof, see Duffy and Matros (2015).

3 Experimental Design

Our experimental design is a modification of the game described above. This modification is designed to facilitate subject comprehension of the environment, without sacrificing the ecological validity of the game. We start by explaining the single-round game.

1 Subjects play the Blotto game $G = (W, X, Y)$

2 Subjects see the public information including preallocated tokens $\tilde{x}^j$ such that $\sum_{i=1}^{4} \tilde{x}_i^j = X - \delta^j$

3 Subject can allocate δ^j tokens to exactly one of the four battlefields

Now, denote the Blotto game with pre-allocations by $G = (W, X, Y, \tilde{x})$ where $\tilde{x}$ is the vector of pre-allocations for every player. We denote this as a **constrained Blotto game**. Note that in this case the strategy of every player is reduced to $s^j \in \{1, 2, 3, 4\}$ since she simply decides to which single battlefield it is best to allocate additional tokens.

3.1 Treatments

We designed the following treatments on the base of the constrained Blotto game described above.

Imperfect Information. In this treatment, a player can see the true value of her own preallocated tokens $\tilde{x}_i^j$ and remaining tokens δ^j. However, as for her opponent's preallcoated tokens $\tilde{x}_i^{-j}$ and remaining tokens δ^{-j}, she will only see the approximate values. The approximate values $\hat{\tilde{x}}_i^{-j}$ and $\hat{\delta}^{-j}$ are determined randomly by an error term ϵ.

$\hat{\tilde{x}}_i^{-j} = \tilde{x}_i^{-j} + \epsilon$

$\hat{\delta}^{-j} = \delta^{-j} + \epsilon$

Where $\epsilon \sim$ U{-5,5}.

Time Constraint. In this treatment, in addition to imperfect information described above, players have only 15 seconds to reach to a decision. If time is out before a decision is made, the remaining forces will be wasted.

Framing. In this treatment, in addition to imperfect information, players will also be framed of a winning or losing history of other's previous battles in this war i.e. "Suppose, in the past, your side has often lost/won in this environment because of bad/good guesses about your opponent's actual number of forces and deployment decisions".

3.2 Within subject design

Players are matched against one another in the very first game, and continue to play against the same opponent for the 15 rounds. Each round can been seen as an independent Blotto game. The 15 rounds include three 5-round sub-games. In each of the sub-games, players are assigned to one of the three treatments: Imperfect Information, Time Constraint or Framing. To prevent potential order effects, we arrange the order of the treatments in two ways, one in which Time Constraint precedes Imperfect Information, the other in which Time Constraint follows Imperfect Information. The details of the ordering are displayed in Table 1 below.

Order	Round 1-5	Round 6-10	Round 11-15
ITF	Imperfect Information	Time Constraint	Framing
FTI	Framing	Time Constraint	Imperfect Information

Table 1: Order of Treatments

3.3 Parameters and equilibrium of the game

In each of the sub-games, the players play the same constrained Blotto game. We set $W = (W_1, W_2, W_3, W_4) = (20, 20, 20, 40)$, that is, the points assigned to each of the four battlefields are 20, 20, 20 and 40. We set $X = 120$, that is the total number of tokens each player owns is 120.

As shown in table 2, since there are four battle fields, there are 16 subsets(combinations) of whether each of the battle fields is a winning battle filed. Eight of the 16 subsets are winning subsets.

From equation (2),

$$\sum_{k=1}^{4} |V_k| = 12 \tag{3}$$

Therefore, the equilibrium allocation for each battle field is:
$(\hat{x}_1, \hat{x}_2, \hat{x}_3, \hat{x}_4) = (2/12, 2/12, 2/12, 6/12) \times 120 = (20, 20, 20, 60)$.

	W_1	W_2	W_3	W_4	Win Game	W_1 Pivotal	W_2 Pivotal	W_3 Pivotal	W_4 Pivotal
1	0	0	0	0	No	0	0	0	0
2	0	0	0	1	No	0	0	0	0
3	0	0	1	0	No	0	0	0	0
4	0	0	1	1	Yes	0	0	1	1
5	0	1	0	0	No	0	0	0	0
6	0	1	0	1	Yes	0	1	0	1
7	0	1	1	0	No	0	0	0	0
8	0	1	1	1	Yes	0	0	0	1
9	1	0	0	0	No	0	0	0	0
10	1	0	0	1	Yes	1	0	0	1
11	1	0	1	0	No	0	0	0	0
12	1	0	1	1	Yes	0	0	0	1
13	1	1	0	0	No	0	0	0	0
14	1	1	0	1	Yes	0	0	0	1
15	1	1	1	0	Yes	1	1	1	0
16	1	1	1	1	Yes	0	0	0	0
Total Pivotals						2	2	2	6
Equilibrium Allocation						20	20	20	60

Table 2: Equilibrium of the Blotto Games

We set the pre-allocated and remaining tokens in five different ways, as table 3 describes. Each player makes decisions under each of the five parameter sets, once in each of the three environments, presented to the player in random order. The first row is a symmetric game, where both players play under the parameters in set 1. The second and the third rows are asymmetric. In the second row, one player will play either 2a or 2b, the other will play 2b or 2a. Similarly, in the third row, one player will play 3a or 3b, the other will play 3b or 3a. The table also shows the battlefield to which the remaining forces are allocated in equilibrium (the column titled "NE Field" is the Nash equilibrium allocation).

3.4 Procedures

We conducted the experiment in the Interdisciplinary Center for Economic Science(ICES) lab at George Mason university. We recruited students across all disciplines at George

Set(Player a)	$\tilde{x}_1^a$	$\tilde{x}_2^a$	$\tilde{x}_3^a$	$\tilde{x}_4^a$	δ^a	NE Field	Set(Player b)	$\tilde{x}_1^b$	$\tilde{x}_2^b$	$\tilde{x}_3^b$	$\tilde{x}_4^b$	δ^b	NE Field
1	20	20	20	40	**20**	4	1	20	20	20	40	**20**	4
2a	20	20	**0**	60	20	3	2b	20	20	20	30	**30**	4
3a	**10**	20	20	60	10	1	3b	**15**	20	20	60	5	1

Table 3: Parameters for Constrained Blotto Games

Mason University using the ICES online recruiting system. A total of 168 subjects participated in one of 10 different sessions, in which 5 sessions were in the order: Imperfect Information, Time Constraint and then Framing. The other 5 sessions were in the order: Framing, Time Constraint and then Imperfect Information. Each session lasted for about one and half hours, including instructions reading, quiz, game playing and payment. All subjects received a show-up fee of $5. At the end of each session, one of the 15 rounds was randomly chosen for payment. The winner of the chosen round earned an extra $15, in addition to the $5 show-up fee. The loser did not earn any extra payment. Therefore, the total payoff for one participant in each session was either $20 or $5, and the average payoff was $12.5.

At the beginning of each session, the experimenter read the instructions to the subjects aloud. Then subjects were asked to answer a short quiz about the experiment to ensure they understood the game. Once all participants completed the quiz successfully, they would proceed to the game. At any time, subjects could ask the experimenters questions, which would be answered privately. The game was programmed and conducted with the software z-Tree (Fischbacher, 2007). The treatment information was displayed to subjects using a computer interface prior to round 1, 6 and 11. The result of each battle and the winner of the war in each round were revealed before the next round began. When all groups finished the 15 rounds, the randomly chosen round and the final payoff was displayed to the participants.

4 Results

4.1 Sample

As mentioned, to account for potential order effects we ran sessions in which the Time Constraint treatment either preceded or followed the Imperfect Information treatment. The sample distribution in these two orders are shown in table 4. In sessions where

Time Constraint precedes Imperfect Information, there are 100 subjects, in sessions where Time Constraint follows Imperfect Information, there are 68 subjects.

Order	Session 1	Session 2	Session 3	Session 4	Session 5	Total
ITF	16	24	24	16	20	100
FTI	12	20	14	14	8	68
Total						168

Table 4: Sample Distribution

4.2 Equilibrium Play in each Treatment

We first compare the frequency with which the remaining forces were allocated to the equilibrium battle field. Figure 1 displays the comparison of the rate of equilibrium allocation between time-unconstrained and time-constrained treatments [4]. Without time pressure, the rate of following the equilibrium strategy is 38.7%, on average. Under time pressure, it increases to 44.0%. The difference is statistically significant at the 5% level (p=0.0318, two-sided t-test).

Table 5 reports equilibrium allocation rate in each of the individual set of parameters for pre-allocated and remaining forces. The rate of equilibrium play under time constraints is higher than in the time-unconstrained treatment in all of the five sets. In two of the sets, i.e. 2b and 3a, the differences are statistically significant, and increases in the equilibrium allocation rate exceed 10%.

Treatments $\backslash Set$	1	2a	2b	3a	3b
Time-Unconstrained	0.548	0.464	0.506	0.214	0.202
Time-Constrained	0.561	0.467	0.611	0.359	0.203
Difference	0.013	0.003	0.105^{*}	0.145^{***}	0.001
p-value	0.815	0.960	0.061	0.004	0.994

P-value is from two-sided t-test. *,**,*** indicate 10%, 5%, 1% significant level, respectively.

Table 5: Equilibrium allocation in each individual set.

[4]Since this paper focuses on the effect of time constraints, we don't include data from Framing treatment in our analysis.

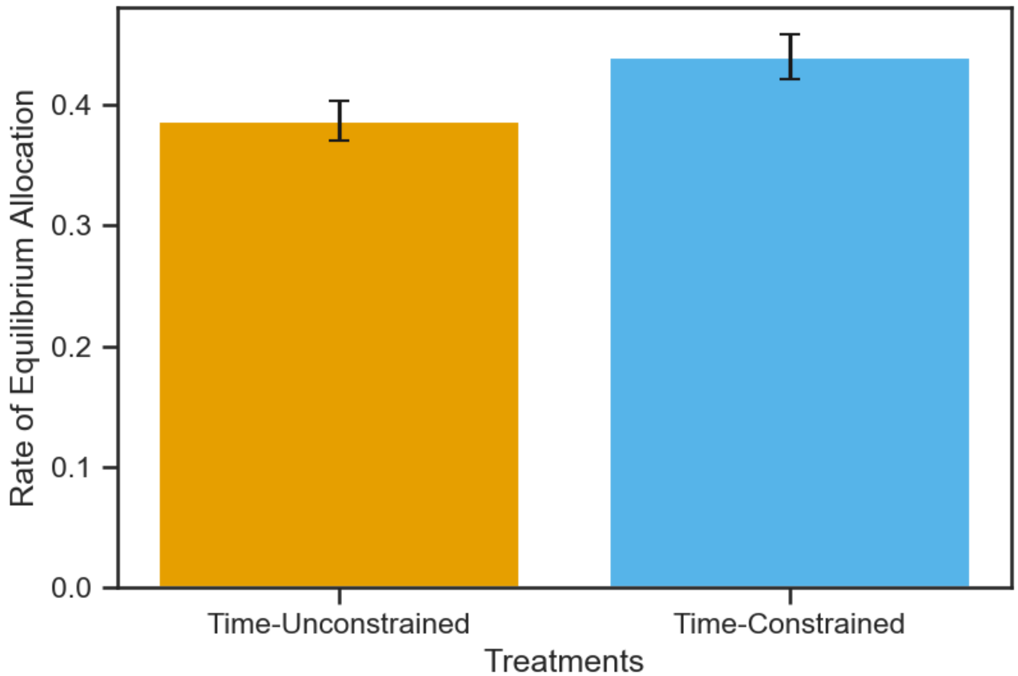

Figure 1: Equilibrium allocation

4.3 Equilibrium Play Within Treatments

To test whether longer time-to-decision is detrimental to equilibrium playing behavior, we conducted a Logit regression of equilibrium play on time spent to decision, in both the time-unconstrained treatment and the time-constrained treatment. Table 6 Panel A shows the regression results in time-unconstrained treatment. In column (1), we first ran a simple regression, then we control for the parameter set in column (2), and then round in column(3). In all three models, time-to-decision ('allocate time') is statistically significantly negative. The marginal effect indicates every 10 seconds of additional thinking decreases the probability of equilibrium strategy play by about 1% to 2%. Panel B shows the regression results in time-constrained treatment. Again, 'allocate time' is significantly negative in all three models. The marginal effect shows, under a 15 seconds time constraint, an even stronger detrimental effect of deliberation. In particular, every additional second of decision time lead to a decrease of more than 1% in the probability of making an equilibrium decision.

Panel A: Time-unconstrained						
	(1)		(2)		(3)	
	Original	Marginal	Original	Marginal	Original	Marginal
AllocateTime	-0.007***	-0.002***	-0.007***	-0.002***	-0.005*	-0.001*
	(0.003)		(0.003)		(0.003)	
ParameterSet			-0.417***	-0.098***	-0.424***	-0.099***
			(0.054)		(0.055)	
Round					0.045***	0.010***
					(0.015)	
Constant	-0.226**	**	0.992***	***	0.621***	***
	(0.110)		(0.193)		(0.227)	
Observations	840		840		840	
Pseudo R^2	0.007		0.064		0.072	
LR chi2	8.256		72.118		80.918	
Prob > chi2	0.004		0.000		0.000	
Panel B: Time-constrained						
	(4)		(5)		(6)	
	Original	Marginal	Original	Marginal	Original	Marginal
AllocateTime	-0.053**	-0.013**	-0.055**	-0.014**	-0.054**	-0.013**
	(0.023)		(0.023)		(0.023)	
ParameterSet			-0.347***	-0.085***	-0.346***	-0.085***
			(0.055)		(0.055)	
Round					0.029	0.007
					(0.054)	
Constant	0.344		1.396***	***	1.150**	**
	(0.261)		(0.318)		(0.560)	
Observations	750		750		750	
Pseudo R^2	0.005		0.046		0.046	
LR chi2	5.463		47.151		47.433	
Prob > chi2	0.019		0.000		0.000	

Independent variable is dummy variable Equilibrium, which equals to 1 if one played equilibrium strategy, 0, otherwise. Standard error in parenthesis. *,**,*** indicate 10%, 5%, 1% significant level, respectively.

Table 6: Logit regression of equilibrium playing on allocated time.

4.4 Defeating the Enemy

We have shown above that subjects are more likely to play the equilibrium strategy under time pressure. We now test whether equilibrium play increases the probability of defeating the enemy (or 'war winning'). The first two columns in Figure 2 show the comparison in the time-unconstrained treatment. The probability of war-winning is 48.5% when making out-of-equilibrium allocations and 52.3% when making equilibrium allocations. The difference is substantively meaningful (more likely to lose vs. more likely to win) and statistically significant($p<0.001$, two-sided t-test, $n=840$). The third and fourth columns show the comparison in the time-constrained treatment. The probability of war-winning is 48.7% using out-of-equilibrium allocations and 52.1% under in-equilibrium allocation. The difference is again substantively meaningful, and also statistically significant($p<0.001$, two-sided t-test, $n=750$). The last two columns show, in the pooled sample, the probability of winning when making an out-of-equilibrium allocation is 48.6%, significantly lower than 52.7% of when making in-equilibrium decisions ($p<0.001$).

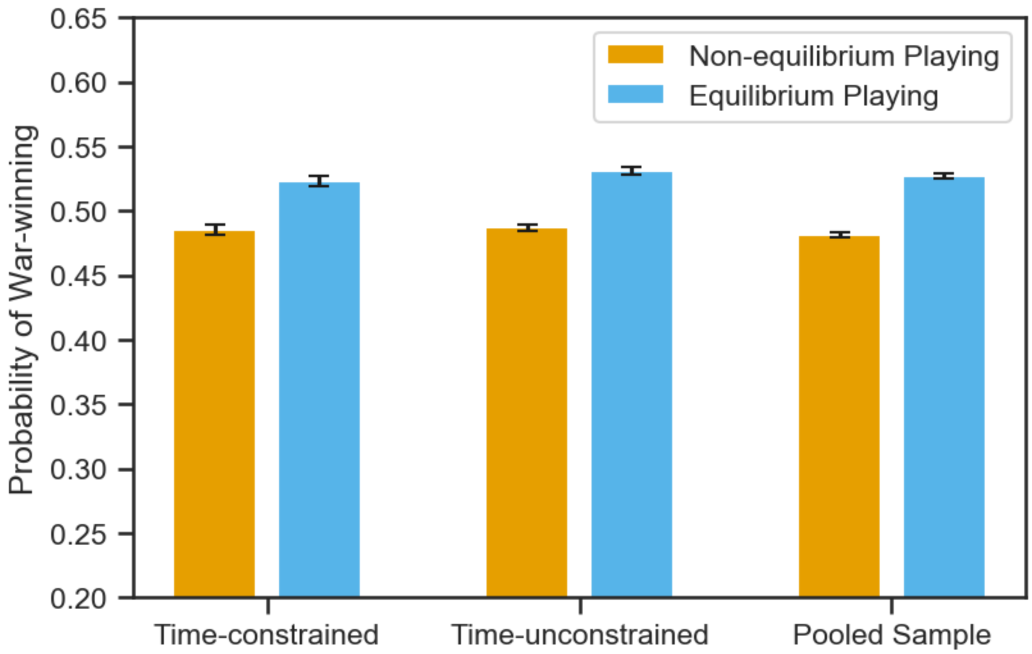

Figure 2: Probability of War-Winning

We further investigate whether spending more time making decisions leads to a lower probability of defeating the enemy, in time-unconstrained and time-constrained treatments. Table 7 shows the results of regressing the probability of war-winning on time to allocation. As in Table 6, we conducted a simple regression, then controlled for the parameter set and finally for the round. The first three columns show the results in the time-unconstrained treatment. The coefficient of AllocateTime is negative but not significant. The last three columns detail the regression results in time-constrained treatment. AllocateTime is negatively correlated with the probability of war-winning, and the effect is statistically significant at 1% level.

	Time-free			Time-constraint		
	(1)	(2)	(3)	(4)	(5)	(6)
AllocateTime	-0.00003	-0.00003	-0.00003	-0.00131***	-0.00131***	-0.00134***
	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.0005)	(0.0005)
ParameterSet		0.00442***	0.00442***		0.00011	0.00009
		(0.0014)	(0.0014)		(0.0011)	(0.0011)
Period			-0.00006			-0.00074
			(0.0004)			(0.0011)
_cons	0.50088***	0.48777***	0.48824***	0.52092***	0.52058***	0.52693***
	(0.0030)	(0.0052)	(0.0062)	(0.0055)	(0.0064)	(0.0114)
N	840	840	840	750	750	750
adj. R^2	-0.001	0.009	0.008	0.009	0.007	0.007

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Independent variable is the probability of war-winning rate.

Table 7: Regression of the Probability of War-winning on Allocated Time.

5 Concluding Discussion

We experimentally tested the effect of time pressure on strategic decision making in generalized Colonel Blotto games. We found participants are more likely to play optimally under time pressure. Also, even under time constraints, spending less time on decisions leads to more equilibrium play.

We reported data revealing that deliberation has a detrimental impact on decision making in a strategic environment that includes combat. Whether this result extends to other contexts remains an important open question. For example, the effects we observed may depend on the difficulty of the decision environment. Further, these effects may rely on repeat play. It would be profitable for future studies to investigate the impact of deliberation in multiple related environments.

Limitations of this study include that, within a game, we assumed opponents always faced symmetric time constraints. That is, players participated in a no-time-pressure or time-pressure treatment. In some cases of interest, opponents may face different time pressure to form a decision. In addition, we assumed that players knew their own force allocations perfectly, and the uncertainty was only over the opponents allocations. In natural environments, one might anticipate some uncertainty over one's own forces as well as one's opponents, though perhaps better information would be available regarding one's own allocations. Future studies that relaxed these assumptions would shed additional light on the role of time-pressure in strategic decision-making during combat.

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Appendix

Instructions

Welcome to today's experiment! During the experiment, please keep your cellphone turned off, and refrain from talking to other participants. If at some point you have a question, please raise your hand and we will address it with you privately.

You've already earned a $5 show-up bonus. The remainder of your earnings will be determined by the choices you and another participant make in this experiment. One of the 15 rounds you'll play will be randomly chosen for payment. Between you and your paired participant, the winner of the randomly chosen round will receive an extra $15, in addition to the show-up bonus.

You will be paired with the same participant, your "opponent", throughout this experiment. Each round works in the same way as described below.

Each round, you and your opponent both have deployable forces that you will use to try to win a "war". The number of your own forces will be displayed to you. However, while you know the approximate number of forces available to your opponent, you do not know the exact number. The war involves four "battlefields", namely, B1, B2, B3 and B4. The battlefields are each worth a different number of points, though the total value of all four battlefields is always 100 points. If you win a battlefield you earn its corresponding points, and the winner of the war is the person who wins enough battles to earn more than 50 points.

Whether you win a battlefield is determined by the number of forces deployed to it, by both you and your opponent. Specifically, if the number of your forces deployed to a battlefield is A, and the number of your opponent's forces deployed to it is B, the probability you win this battlefield would be

Your Probability of Winning= A/(A+B)

This means that if you and your opponent have the same number of forces on a battlefield, then you both have a 50% chance of winning the battle. If you have more than your opponent, then you have a higher than 50% chance of winning. This means that the more forces you deploy to a battlefield, the higher the chance you win it. Of course, winning an individual battlefield doesn't necessarily mean you'll win that round's war. You can only win a war if you obtain more than 50 points in total from all the battlefields you win in that round.

Process of Each Round

When a round begins, you will find that some of your and your opponent's forces are already deployed to battlefields. You and your opponent will also have some remaining forces not yet deployed. Your own deployed and remaining forces will be displayed to you. However, you will know the approximate number of your opponent's forces, but not the exact number. The actual forces may be higher than, lower than or equal to the approximate value. You and your opponent must decide where to deploy your respective remaining forces.

Let's look at Figure 1. This figure describes the "gameboard" where you'll make your decisions. Numbers in the figure are for demonstration purposes: you will see different sets of numbers in the real "wars". The four battlefields are labeled as B1, B2, B3 and B4, with their values displayed in the middle. You can see in this example that B1 is worth 19 points, B2 is worth 21 points, and so on. On the upper part of the board you find how, on average, your opponent's forces are currently deployed. For example, in this war your opponent has already deployed to the first battlefield approximately 17 forces, approximately 11 to the second battlefield, and so on. Also, your opponent will have approximately 22 additional forces to deploy. After all decisions have been made, the actual number of forces on each battlefield will be revealed to you. Deployment of your forces is on the lower part of the board. In this example you have 20 forces deployed to the first battlefield, 20 forces deployed to the second battlefield, etc. and 20 remaining forces to deploy.

In this example, if you deploy 20 of your remaining forces to B1, you will have 40 forces on B1. Suppose your opponent has 25 additional forces to deploy and deploys them to B1, and suppose her already deployed forces in B1 is 15, your opponent has 40 forces on it. Thus your probability of winning B1 is

40/(40+40)=1/2 .

All battlefields follow this same rule.

Suppose that you win B1 and B3, and your opponent wins B2 and B4 in this "war". Then you obtain 19+30=49 points, and your opponent obtains 21+30=51 points. The winner of this war is your opponent, as she obtains more than 50 points. If this is the payment round, your opponent will earn an extra $15.

Note that the game board will change from round-to-round. That is, your approximation of the deployed and remaining forces as well as the point values of battlefields

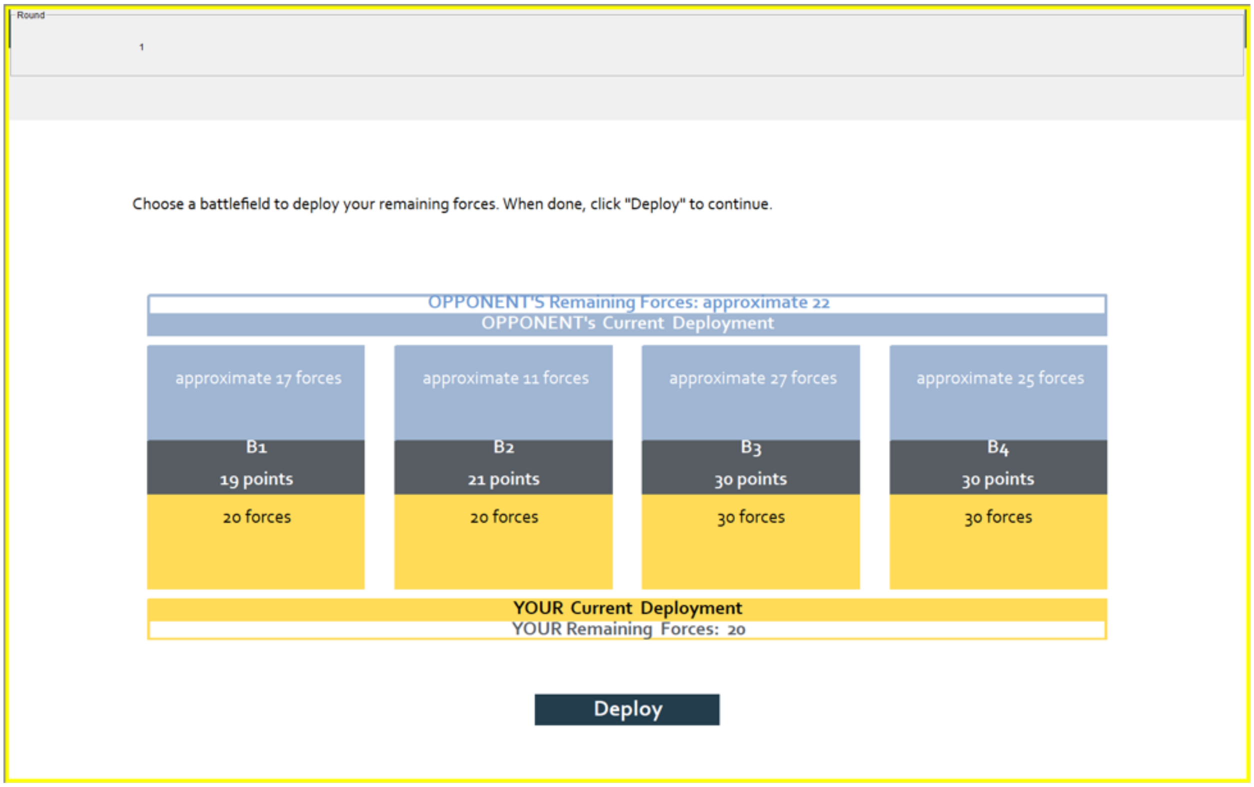

Figure 1: Example of Interface

will vary from round to round.

You won't see your opponent's decision until both of you have deployed your respective remaining forces, nor will your opponent see your deployment decision.

After both you and your opponent deploy your respective remaining forces, the probability that you win each battlefield will be calculated according to the formula above. The computer will then make a random draw to determine the winner of each battlefield, according to the calculated probabilities. The result of each battle and the winner of the war will be revealed before the next round begins.

Note: the decision environments will be different in round 1-5, round 6-10 and round 11-15. You will be informed of the environment prior to round 1, round 6 and round 11 on your screen. Please read them carefully!

Payment

As mentioned before, at the end of the experiment, one of the 15 rounds you will play will be randomly chosen for payment. Besides the $5 show-up bonus, you will earn an extra \$15 if you win the war in that round.

This is the end of the instructions. You will now be given a short quiz to ensure you understand the game. Once you complete the quiz successfully, you'll proceed to the game.

If you have any question at any point during the experiment, please raise your hand and an experimenter will assist you.