

Comparative Statics of the Minimum-Effort Coordination Game

Noah Myung* and Julian Romero†

August 09, 2013

† Graduate School of Business & Public Policy, *Naval Postgraduate School*

‡ Department of Economics, *Purdue University*

Working Paper.

Approved for public release; distribution is unlimited.

Abstract:

We focus on the effects of changing costs of effort in the minimum-effort coordination game. We find three main results. First, as the cost of effort increases, the level of effort decreases. Second, as the cost of effort increases, the convergence speed to an equilibrium also increases. Third, the overall efficiency (average payoff) does not monotonically decrease as the cost of effort increases. Average payoff decreases for the most part but actually increases when the cost of effort is very high. Even though groups are converging towards worse equilibria as the cost increases, they are converging faster, and therefore lose less due to fewer periods of non-coordination. This non-monotonicity in the average payoff suggests that individuals may be better off with higher costs of effort.

Keywords: Coordination Game. Comparative Statics. Experiments.

JEL classification: C73, C91, C92, D60

*Email: noah.myung@nps.edu. Phone: 831-656-2811. Web: <http://faculty.nps.edu/nmyung>

†Email: jnromero@purdue.edu. Phone: 765-494-4271. Web: <http://jnromero.com>

1 Introduction

The inability to coordinate in economic interactions in which there are multiple equilibria can lead to significant welfare losses. Though all players may be better off in one equilibrium, other factors can make it difficult for players to coordinate to the Pareto-improved equilibrium. In these situations, it is important to know which equilibrium is best and what causes certain equilibria to be selected over others. The majority of work that has been done examining coordination problems looks at which environments are good for coordination and how to avoid getting stuck in a “bad” equilibrium. This paper differs from these works in that it not only examines the equilibrium reached, but also focuses on the process of reaching equilibrium. Though the same equilibrium may be reached in two different environments, the equilibrium may be reached more efficiently in one environment, which could make overall welfare higher.

We focus our attention on the minimum-effort coordination game (MECG). In the MECG, the player’s payoffs are determined by the group’s minimum effort while the cost is determined by the individual’s own choice of effort. The MECG has multiple Pareto-ranked pure-strategy Nash Equilibria in which each player exerts the same amount of effort. The MECG has been widely studied as a simplified model used to examine a group’s ability to coordinate.

We examine the impact of having different costs of effort on the MECG. We run experiments with five different cost parameters and provide three main results. First, there is a negative relationship between cost of effort and the average effort level. Therefore, as the cost of effort increases, the players tend to converge to a Pareto-dominated equilibrium. Second, we find that the game converges faster as the cost of effort increases. Furthermore, we find that the players deviate less frequently after the convergence to an equilibrium when the cost of effort is higher. This is because the cost of non-convergence is much higher when the cost of effort is higher. Lastly, we find a non-monotonic relationship between the cost of effort and average payoff. Not surprisingly, the average profit decreases as the cost of effort increases, for the most part. However, when the cost of effort is very high, the increase in the cost may lead to higher average payoffs. This result is due to a combination of negative and positive effects of increasing the cost of effort. The two negative effects come from 1) the first result, which is the negative relationship between cost of effort and the

average effort level, and 2) by the fact that for a given strategy profile, higher cost of effort provides lower payoff. The positive effect comes from the second result, which is the faster convergence in the game for higher cost of effort levels. Despite the two negative forces suggesting that payoffs should be decreasing as the cost of effort increases, the positive force can be significant enough to increase the average payoff. For relatively low costs, coordination failure is relatively cheap; therefore, in the early periods players routinely exert effort above the minimum effort. When the cost is very high, however, coordination failure is expensive; therefore, players are less likely to experiment and exert effort above the minimum effort. In sum, we find that the gain in efficiency from faster convergence actually outweighs the other forces, which are driving payoffs down as the cost of effort increases.

The MECG has intrigued experimental economists for many years. The experimental laboratory provides an ideal testing spot to determine which environments may lead to “good” and “bad” equilibria in the game. Typical studies have examined the effect of two different environments on a group’s ability to coordinate on the “good” equilibrium. Commonly studied parameters include group size (Cooper, DeJong, Forsythe, and Ross (1990), Knez and Camerer (1994), Van Huyck, Battalio, and Beil (1990), Weber (2006)) and cost of effort (Goeree and Holt (2005), Romero (2011)). These papers typically found that coordination becomes more difficult as the size of the group increased or as the cost of effort increased. Other papers have looked at the effect of adding additional characteristics to the environment on the groups’ ability to coordinate. To name a few, Cooper, DeJong, Forsythe, and Ross (1992) allowed group members to communicate, Cachon and Camerer (1996) required an entry fee to join the group, and Myung (2009) had multiple groups competing with each other. This paper is most similar to Goeree and Holt (2005) in which the researchers ran experiments with varying cost of effort. They examined the MECG with a continuous strategy space in which subjects faced one of two costs ($c = 0.25$ and $c = 0.75$). They found that in the low cost treatment, effort levels were higher and gradually increased over time, while in the high cost treatment, the effort levels were lower and typically decreased over time.

Our paper differs from the above works in several key aspects. First, rather than just analyzing two parameter values, we consider five different levels of effort cost. This is important because it

allows us to discover non-monotonicities which would be impossible to discover by testing only two parameter values. One difficulty in using a large number of parameter values is that it requires more experiments to be run, which requires more subjects. To better select the parameter values, a computational model proposed by Romero (2010) was used to run simulations and determine precise values for the parameters to be used in the experiments. In addition, we study the efficiency losses that are caused by slower convergence to an equilibrium. This sheds an interesting new light on the previously found result that groups with higher cost converge to lower effort equilibria. Though higher costs tend to lead to worse equilibria, they are also associated with faster convergence, which in the short-run can be beneficial to the group.

The paper is organized as follows. The next section contains a short introduction to the minimum-effort coordination game. Next, we proceed with the testable hypotheses and our experimental design. We then provide the experimental results and the concluding remarks.

2 Minimum-Effort Coordination Game

The minimum-effort coordination game (MECG), also known as the weakest-link game, is a game with N players in which each player chooses an effort level $s_i \in \{1, 2, \dots, M\}$, where M is finite. The players have payoff function

$$p_i = \alpha \min_{j \in N} \{s_j\} - cs_i + \delta, \quad (1)$$

where $\alpha > c > 0$ and $\delta \in \mathbb{R}$ for all players $i \in N$. The best response in this game is for player i to match the lowest effort from everyone else:

$$s_i = \min_{j \in N \setminus i} \{s_j\}. \quad (2)$$

Therefore, the set of pure-strategy Nash Equilibria contains any strategy profiles in which all players exert the same effort level: $\sigma = \{s_1, \dots, s_N\}$, where $s_1 = s_2 = \dots = s_N$. These equilibria are Pareto ranked, with $s_i = 1$ being the worst and $s_i = M$ being the Pareto optimal equilibrium.

2.1 Hypotheses

We propose three hypotheses for our experiments on the MECG. As the cost of effort increases,

Hypothesis 1 (Effort Level) average effort decreases,

Hypothesis 2 (Convergence Speed) the game converges faster, and

Hypothesis 3 (Average Payoff) average payoff does not decrease monotonically. Average payoff will decrease initially but will increase when the cost of effort is very high.

Hypothesis 1 is driven by the historical observation listed in the introduction as well as the increase in the risk-dominance of the inefficient equilibrium.¹ The previous literatures point to the inability to coordinate to payoff dominant equilibrium increases when the cost of effort is higher. Hypothesis 2 is driven simply by the structure of the game; not being able to coordinate causes higher penalty, in both absolute payoff as well as percentage of payoff, when the cost of effort is high. Lastly, hypothesis 3 is driven by the negative welfare effect of the higher cost of effort and the positive welfare effect of the increase in the convergence speed of the game. When the convergence speed is not fast, the lower average effort and the higher cost of effort decreases the average payoff. When the cost is extremely high, the increase in the convergence speed decreases the loss in payoff due to miscoordination. In other words, the ability to correctly coordinate to even the inefficient equilibrium is better than attempting to coordinate to a Pareto-improving equilibrium but failing to do so.

3 Experimental Design

3.1 Overview

The experiments were conducted at the California Social Science Laboratory (CASSEL) located in the University of California, Los Angeles (UCLA). A total of 60 subjects participated in the experiments. The average performance-based payment was 20USD with the standard deviation of \$1.55. All students were registered with the CASSEL and were recruited by the CASSEL's

¹For the MECG, for any two pair of equilibria, increasing cost of effort increases the risk-dominance of the inefficient equilibrium with everything else held constant.

electronic announcement system. The CASSEL consists of over 30 working computers divided into cubicles, which prevents participants from viewing other participants' screens.

The experiments were programmed and conducted with the experiment software z-Tree (Fischbacher 2007). The instructions were available both in print as well as on screen for the participants. The experimenter explained the instructions in detail out loud. Participants were also given a brief quiz after the instructions to ensure proper understanding of the game and the software. A copy of the instructions and a sample screenshot are available in the appendix.

The subjects were randomly assigned to their roles in the experiment. Furthermore, everyone participated in only one session. The identity of the participants as well as their individual decisions were kept as private information. The experiments used a fictitious currency called francs. The participants were fully aware of the sequence, payoff structure, and length of the experiment.

3.2 Details of the Experiment

There were a total of three sessions, and each session had 20 subjects. Each session consisted of five blocks. At the beginning of each block, subjects were divided into five groups of four subjects each. Each group of four subjects then proceeded to play a MECG repeatedly for 15 periods. After each block, the subjects were randomly rematched (with replacement) to another group of four subjects and were randomly reassigned another payoff parameter (with replacement). See Figure 1 for the timeline.

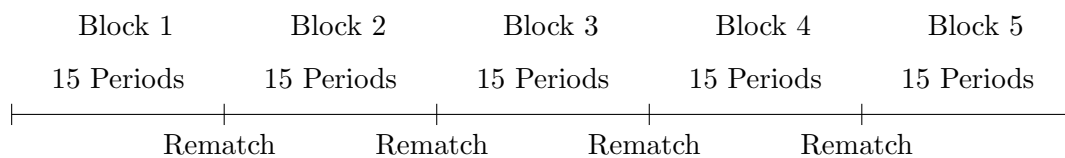


Figure 1: Timeline and Matching Structure for the Experiment

Players played a MECG in which they chose an effort level, $s_i \in \{1, \dots, 7\}$. Their payoff was determined by the following function:

$$p_i = 1000 \min_{j \in N} \{s_j\} - cs_i + 5950. \quad (3)$$

Five different cost parameters were tested, $c \in \{50, 500, 900, 950, 990\}$. These parameters were selected within the lower and upper bounds for the cost of effort, $c \in (0, 1000)$, and to highlight the extreme values as well as the middle value. The subjects were shown the payoff table displayed in Table 1, with the calculations already completed for the subjects. The group size, the randomization, and the fact that everyone in the group was using the same payoff table were common knowledge. However, the group's own minimum effort was private information for the group and was not available to the subjects outside of the group. Individuals were not told the effort levels of all members in their group, just the minimum effort of the group.

	Minimum Effort of All Players						
<i>i</i> 's Effort	7	6	5	4	3	2	1
7	$12950 - 7c$	$11950 - 7c$	$10950 - 7c$	$9950 - 7c$	$8950 - 7c$	$7950 - 7c$	$6950 - 7c$
6	—	$11950 - 6c$	$10950 - 6c$	$9950 - 6c$	$8950 - 6c$	$7950 - 6c$	$6950 - 6c$
5	—	—	$10950 - 5c$	$9950 - 5c$	$8950 - 5c$	$7950 - 5c$	$6950 - 5c$
4	—	—	—	$9950 - 4c$	$8950 - 4c$	$7950 - 4c$	$6950 - 4c$
3	—	—	—	—	$8950 - 3c$	$7950 - 3c$	$6950 - 3c$
2	—	—	—	—	—	$7950 - 2c$	$6950 - 2c$
1	—	—	—	—	—	—	$6950 - c$

Table 1: Sample Payoff Table That Was Used in the Experiment

Calculations were already filled in for the subjects.

4 Experimental Results

Figure 2 illustrates sample results from one block of sessions. Figure 2 (a) is an example in which there is coordination on the payoff-dominant Nash equilibrium (converging to an effort level of 7),

and Figure 2 (b) is an example in which there is a coordination on the worst equilibrium (converging to an effort level of 1).

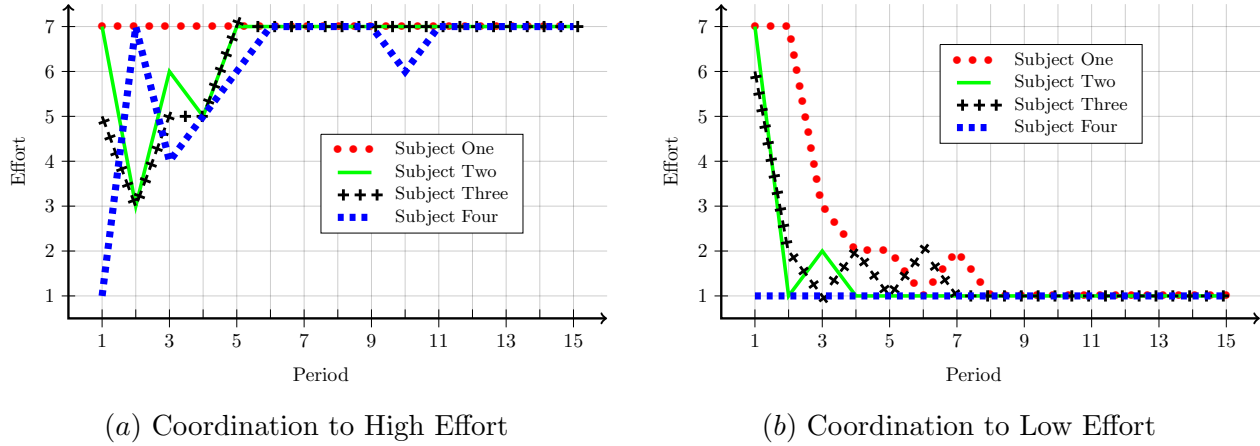


Figure 2: Sample Results from Single Block of Session for Illustration Purposes

Otherwise specified, we treated each block as an independent observation. Therefore, the sample size for each cost parameter c is $n = 60$.

4.1 Effort Level

The average effort level chosen in each period is displayed in Figure 3. First, we tested the hypothesis that higher cost of effort leads to lower effort levels by the players. Results are taken from the average effort level of the last five periods ($\sum_{t=11}^{15} \frac{s_{i,t}}{5}$) as one observation and are displayed in Figure 4 and Table 2. Confirming our hypothesis, the mean effort level drops from 4.917 to 1.06 as the the cost parameter increases. When we focus our attention to blocks 3, 4, and 5 (the experienced players), we obtain a stronger support for our hypothesis; the lowest effort level, equal to one, occurs at $c = 990$, and the differences in means between various cost parameters are all significant at $p < 0.05$ except when comparing the differences between $c = 900$ and $c = 950$ (*n.s.*).

4.2 Convergence Speed

Comparing convergence speed is not as straightforward as comparing average effort level. Consider the following example in Figure 5, which shows the period-by-period effort choices of one group of players. If one were to use a rule that the convergence occurs when there are no deviations (i.e., everyone is best responding), then there would not have been any convergence until period 13 in the example. However, starting in period 4, there were only two deviations in the final 11 periods. This rule may be too conservative when studying experimental results. We compared the convergence speed in three different ways. Each one of these measures has its strengths and weaknesses. First, we compared the standard deviation of the effort levels. Next, we compared the best-response rate. Finally, for any given period, we considered the number of different effort levels that were played each period (the fewer, the more converged the group is).

We first consider the standard deviation of the effort levels being played in each period. Figure 6 graphs the standard deviation of the effort levels being played by various cost parameters. The general idea is that the standard deviation should be low when a game converges to a pure-strategy equilibrium. We break the analysis of standard deviation into two parts. First, we considered how fast the standard deviation decreases in the first one-third of the game. We measured the rate of change in the standard deviation per period by looking at the slope of the regression ($SD = \alpha + \beta t$, Table 3). Conditional on the initial starting point of the standard deviation, steepest downward slope would indicate the fastest convergence.² Supporting our hypothesis, the coefficients for $c = 900$, $c = 950$, and $c = 990$ are all negative and are steeper for higher costs of effort ($p < 0.05$). The slope for $c = 50$ is no different from 0 and the slope at $c = 500$ is upward sloping ($p < 0.05$), which indicates a lack of convergence.³ Second, we considered the average standard deviation for the final two-thirds of the game ($\sum_{t=6}^{15} \frac{SD_{c,t}}{10}$, Table 4). The magnitudes of the average standard deviation are $SD_{c=500} = 2.538 > SD_{c=50} = 2.430 > SD_{c=950} = 0.973 > SD_{c=900} = 0.842 > SD_{c=990} = 0.522$; all but the difference between $c = 900$ and $c = 950$ are significant at $p < 0.05$. What we conclude from

²Of course, this would not be a fair measurement if the starting standard deviation is very small to begin with. Our data does not have such a problem.

³Finding a slope of 0 for $c = 50$ and a positive slope of 0.043 for $c = 500$ added the following result. First, it is harder to coordinate to the payoff-dominant equilibrium in the $c = 500$ case compared to the $c = 50$ case. Given that the cost of effort is relatively low when $c = 500$, the players may be trying even harder to increase to the payoff-dominant equilibrium, in turn, increasing the standard deviation of the effort levels.

the average standard deviation is that the standard deviation is low (below 1) when cost is high ($c = \{900, 950, 990\}$) and is high (above 2) when the cost is low ($c = \{50, 500\}$). Combining the results from the speed of convergence in the first one-third of the game and the average standard deviation in the last two-thirds of the game, we conclude that the game does indeed converge faster with higher cost. When the cost is low, $c = \{50, 500\}$, we in fact do not see any convergence. This is because the cost of miscoordination is relatively low. When the cost is the highest at $c = 990$, we see the fastest decrease in the standard deviation and maintain the lowest average standard deviation of the effort levels throughout.⁴

Next, we considered the best-response rate of the effort levels played across different costs of effort (Figure 7). The best-response rate measures the percentage of players who are best responding in the current period.⁵ Unlike using the standard deviation of effort levels, the best-response rate is insensitive to how close or far a single player is from the equilibrium strategy. However, it also penalizes severely in a situation in which three players may be playing the same effort level while one player selects an effort level lower than others: $\{s, s, s, s - 1\}$; this has a best-response rate of 0.25. Table 5 shows the averages of the best-response rates during the first five periods ($\sum_{t=1}^5 \frac{BR_{i,t}}{5}$). The best-response rate is the lowest (average of 0.468) when the cost of effort is low ($c = \{50, 500\}$) and highest (average of 0.708) when the cost of effort is high ($c = \{900, 950, 990\}$) with the difference being significant at $p < 0.01$. When we subdivide the groups by each cost level, the best-response rates between $c = 50$ and $c = 500$, and between $c = 900$ and $c = 950$, are not statistically different from one another. The best-response rate at $c = 990$ is six percentage points higher than the best-response rate at $c = 950$ ($p = 0.102$) with an even stronger difference when we focus on the experienced players (blocks 3, 4, and 5): a difference of 16.7 percentage points, $p < 0.01$. Considering the average of the first five periods gives an indication of how fast the game initially converges. Analyzing the average of the last five periods provides an indication of sustaining the convergence as well as how well the game continues to converge. First, the best-response rates are higher in the last five periods than the first five periods. Second, similar to the

⁴As a robustness check, we also regressed the entire 15 periods as $SD = \alpha + \beta(1/t)$. The slopes are all significant at $p < 0.02$ and the results are consistent with the results in this section.

⁵As a robustness check, we also measured the best-response rate as the percentage of players who are best responding to the previous period's minimum effort. The results are consistent.

first five periods, the best-response rate is the lowest (average of 0.867) when the cost of effort is low ($c = \{50, 500\}$) and highest (average of 0.960) when the cost of effort is high ($c = \{900, 950, 990\}$) with difference being significant at $p < 0.01$. However, we do not obtain significant differences when we subdivide the groups by each cost level. In summary, we are only able to draw a weak conclusion that best-response rate tends to increase as the cost of effort increases.

Finally, we considered both the number of effort levels being played in each group in each period. Therefore, we would consider the game to be more converged if there were fewer effort levels being played in a given period. We define this as *similarness condition*. The added benefit of the similarness condition is that it does not unreasonably penalize cases in which one person may deviate significantly away from the best response for just one period. By the same token, it also means that this measure treats the following two strategy profiles as equally converged: $\{2, 2, 2, 3\}$ and $\{1, 7, 7, 7\}$. In addition, unlike the best response measure, similarness condition does distinguish between $\{2, 2, 3, 3\}$ and $\{2, 2, 3, 4\}$. Both strategy profiles have a best-response rate of 2, but the former only has two effort levels being played while the latter has three. Therefore, the former strategy profile should be considered closer to being converged than the latter.

Figure 8 shows the frequency of different numbers of effort levels being played for various costs of effort. If the game is indeed converging faster under the similarness condition, we expect to see a higher frequency of red and green, which indicates everyone playing the same effort level and three people playing the same effort level, respectively. As the cost of effort increases, we observe an increase in frequency of red and green. Furthermore, the frequency of red and green also increases as the experiment proceeds (number of period increases). In other words, there are many different effort levels being played in the initial period but the game converges as the periods continue.

Considering the evidence from three different ways of measuring convergence, we conclude that the game converges faster to an equilibrium as the cost of effort increases. Furthermore, the fastest sustained convergence is when the cost of effort is $c = 990$.

4.3 Average Payoff

Lastly, we analyzed the average payoff as a function of cost of effort. We hypothesized that the average payoff will first decrease as the cost of effort increases but the average payoff will increase when the cost is extremely high. Tables 7 and 8 show the average payoff of the first five periods ($\sum_{t=1}^5 \frac{p_{i,t}}{5}$) and of the entire 15 periods by each cost parameter. As hypothesized, the average payoff generally decreases as the cost of effort increases. This is expected due to the negative welfare effect of the higher cost in effort and convergence to a lower equilibrium. When considering the first five periods, average payoff is the highest at 9,148 when $c = 50$ ($p < 0.01$), and second highest at 6,732 when $c = 500$ ($p < 0.01$). The average payoff level is not significantly different when comparing the difference between $c = 900$ and $c = 950$ (5,159 and 5031, respectively). This is the case when the positive effect of faster convergence offsets the average payoff of higher cost. In fact, when the cost is $c = 990$, the average payoff is 5,261 and is higher than the average payoff at $c = 950$ by 230 francs ($p < 0.12$). Furthermore, this effect is even stronger as the players gain experience: the payoff at $c = 990$ is 415.7 francs higher than the payoff at $c = 950$ ($p < 0.05$).

The general results of the average payoff behavior do not change when we use the average of 15 periods (an entire block) instead of the average of the first five periods. However, as more periods are played, the positive welfare (convergence speed) from the high cost of effort averages out with the negative welfare (lower convergence point and higher cost of effort). Meaning, the difference in average payoff, $\mu_{990} - \mu_{950}$, will decrease as more periods are played. The difference in average is 230 francs when looking at the first five period averages, but the difference decreases to 90 francs when looking at the 15 period averages. The same is true even with the experienced players; the difference drops from 415.7 to 179.1. In other words, the non-monotonicity of average payoff is most salient at the earlier phase of the game. This is due to the fact that the effects of non-convergence in the early periods are diluted after many periods of convergence.

These results support our hypothesis of the non-monotonicity of the average payoff as a function of cost of effort; the average payoff decreases as cost of effort increases, for the most part, but increases when the cost of effort is very high.

5 Conclusion

We performed a comparative statics of the minimum-effort coordination game via experiments. The experiments are a nice tool to use for the comparative statics given the Pareto-ranked strict Nash Equilibria structure of the MECG. In particular, we showed how the outcomes and behaviors changed as the cost of effort changed. By running experiments across various cost parameters, we were able to find results that may have been overlooked by experimenting over just two cost parameters.

First, we showed that players exerted less effort and converged to a Pareto-dominated equilibrium as the cost of effort increased. Second, our results showed that the players also converged faster to an equilibrium for higher levels of cost of effort. Lastly, the average payoff did not strictly decrease as the cost of effort increased. In fact, the average payoff function is U-shaped, providing an increasing average payoff as the cost of effort becomes very high.

The behavior in the average payoff is due to the welfare effects of the game. There are two negative welfare effects and one positive welfare effect. The negative effect is from the convergence to the lower minimum effort level and the fact that the players receive lower payoff for the exact same strategy profile. The positive effect is from the increase in the convergence speed of the game. Hence, the net outcome depends on the difference between the negative and the positive welfare effects of having a higher cost of effort. This suggests that in certain situations, players may be better off with higher effort costs as it means they will converge more quickly than they would with intermediate effort costs.

References

- CACHON, G. P., AND C. F. CAMERER (1996): “Loss-Avoidance and Forward Induction in Experimental Coordination Games,” *The Quarterly Journal of Economics*, 111(1), 165–194.
- COOPER, R., D. V. DEJONG, R. FORSYTHE, AND T. W. ROSS (1992): “Communication in Coordination Games,” *The Quarterly Journal of Economics*, 107(2), 739–771.

- COOPER, R. W., D. V. DEJONG, R. FORSYTHE, AND T. W. ROSS (1990): "Selection Criteria in Coordination Games: Some Experimental Results," *American Economic Review*, 80(1), 218–233.
- FISCHBACHER, U. (2007): "z-Tree: Zurich toolbox for ready-made economic experiments," *Experimental Economics*, 10(2), 171–178.
- GOEREE, J. K., AND C. A. HOLT (2005): "An experimental study of costly coordination," *Games and Economic Behavior*, 51(2), 349–364, Special Issue in Honor of Richard D. McKelvey.
- KNEZ, M., AND C. CAMERER (1994): "Creating Expectational Assets in the Laboratory: Coordination in 'Weakest- Link' Games," *Strategic Management Journal*, 15, 101–119.
- MYUNG, N. (2009): "Improving Coordination and Cooperation Through Competition," Caltech Working Paper.
- ROMERO, J. (2010): "Essays on cooperation and coordination," Ph.D. thesis, California Institute of Technology.
- (2011): "The Effect of Hysteresis on Equilibrium Selection in Coordination Games," Purdue University Economics Working Papers 1265, Purdue University, Department of Economics.
- VAN HUYCK, J. B., R. C. BATTALIO, AND R. O. BEIL (1990): "Tacit Coordination Games, Strategic Uncertainty, and Coordination Failure," *American Economic Review*, 80(1), 234–248.
- WEBER, R. A. (2006): "Managing Growth to Achieve Efficient Coordination in Large Groups," *American Economic Review*, 96(1), 114–126.

Appendix

A Tables

	Blocks 1 through 5: n=60			Blocks 3, 4, and 5: n=36		
	Mean	SE	P-value	Mean	SE	P-value
$c = 50$	4.917	0.314	0.167	4.489	0.423	0.045
$c = 500$	4.457	0.328		3.506	0.386	
$c = 500$	4.457	0.328	0.000	3.506	0.386	0.000
$c = 900$	1.187	0.076		1.150	0.067	
$c = 900$	1.187	0.076	0.692	1.150	0.067	0.677
$c = 950$	1.257	0.117		1.217	0.128	
$c = 950$	1.257	0.117	0.061	1.217	0.128	0.048
$c = 990$	1.060	0.042		1.00	0.00	

Table 2: Average Effort of Last Five Periods by Cost
 Ho: mean(lower cost) - mean(higher cost) = diff = 0
 Ha: diff > 0

Independent Variable	Dependent Variables: Standard Deviation of Effort Levels				
	$c = 50$	$c = 500$	$c = 900$	$c = 950$	$c = 990$
Constant	2.135*** (0.096)	2.112*** (0.044)	2.777*** (0.129)	2.936*** (0.070)	2.630*** (0.340)
Period	0.008 (0.029)	0.043** (0.013)	-0.309*** (0.039)	-0.376*** (0.021)	-0.417** (0.103)
R-squared	0.025	0.780	0.955	0.991	0.846

*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test).

Number of obs: 5 for each cost. Numbers in parentheses are standard errors.

Table 3: Regression: Standard Deviation of Effort Levels During First Five Periods

	Mean	SE	P-value
$c = 50$	2.430	0.018	0.001
$c = 500$	2.538	0.021	
$c = 500$	2.538	0.021	0.000
$c = 900$	0.842	0.093	
$c = 900$	0.842	0.093	0.286
$c = 950$	0.973	0.075	
$c = 950$	0.973	0.075	0.002
$c = 990$	0.522	0.099	

Table 4: Average Standard Deviation of Effort Levels During Last 10 Periods by Cost

Ho: mean(lower cost) - mean(higher cost) = diff = 0

Ha: diff != 0. n = 10 for each cost

	Blocks 1 through 5: n=60			Blocks 3, 4, and 5: n=36		
	Mean	SE	P-value	Mean	SE	P-value
$c = 50$	0.457	0.045	0.353	0.500	0.058	0.607
$c = 500$	0.480	0.042				
$c = 500$	0.480	0.042	0.000	0.478	0.057	0.000
$c = 900$	0.687	0.032				
$c = 900$	0.687	0.032	0.500	0.739	0.038	0.793
$c = 950$	0.687	0.039				
$c = 950$	0.687	0.039	0.107	0.689	0.047	0.002
$c = 990$	0.750	0.033				

Table 5: Average Best-Response Rate During First Five Periods

Ho: mean(lower cost) - mean(higher cost) = diff = 0

Ha: diff < 0

	Blocks 1 through 5: n=60			Blocks 3, 4, and 5: n=36		
	Mean	SE	P-value	Mean	SE	P-value
$c = 50$	0.860	0.037	0.397	0.844	0.054	0.236
$c = 500$	0.873	0.035				
$c = 500$	0.873	0.035	0.044	0.894	0.044	0.085
$c = 900$	0.943	0.021				
$c = 900$	0.943	0.021	0.330	0.961	0.019	0.427
$c = 950$	0.957	0.022				
$c = 950$	0.957	0.022	0.173	0.967	0.023	0.078
$c = 990$	0.980	0.011				

Table 6: Average Best-Response Rate During Last Five Periods
 H_0 : mean(lower cost) - mean(higher cost) = diff = 0
 H_a : diff < 0

	Blocks 1 through 5: n=60			Blocks 3, 4, and 5: n=36		
	Mean	SE	P-value	Mean	SE	P-value
$c = 50$	9148.167	223.659	0.000	9134.722	328.020	0.000
$c = 500$	6731.667	166.324				
$c = 500$	6731.667	166.324	0.000	6447.222	179.792	0.000
$c = 900$	5158.667	98.490				
$c = 900$	5158.667	98.490	0.240	5358.333	107.397	0.165
$c = 950$	5030.667	151.618				
$c = 950$	5030.667	151.618	0.113	5175.833	152.232	0.013
$c = 990$	5261.067	113.684				

Table 7: Average Payoff of First Five Periods by Cost
 H_0 : mean(lower cost) - mean(higher cost) = diff = 0
 H_a : diff > 0 for $c \in \{50, 500, 900, 950\}$. H_a : diff < 0 for $c \in \{950, 990\}$

	Blocks 1 through 5: n=60			Blocks 3, 4, and 5: n=36		
	Mean	SE	P-value	Mean	SE	P-value
$c = 50$	9791.333	268.269	0.000	9587.037	375.927	0.000
$c = 500$	7489.444	166.577		7075.000	196.268	
$c = 500$	7489.444	166.577	0.000	7075.000	196.268	0.000
$c = 900$	5652.667	54.150		5769.630	46.402	
$c = 900$	5652.667	54.150	0.204	5769.630	46.402	0.134
$c = 950$	5559.833	97.730		5628.704	117.619	
$c = 950$	5559.833	97.730	0.210	5628.704	117.619	0.079
$c = 990$	5650.022	53.773		5807.833	43.352	

Table 8: Average Payoff of 15 Periods by Cost
 H_0 : mean(lower cost) - mean(higher cost) = diff = 0
 H_a : diff > 0 for $c \in \{50, 500, 900, 950\}$. H_a : diff < 0 for $c \in \{950, 990\}$

B Figures

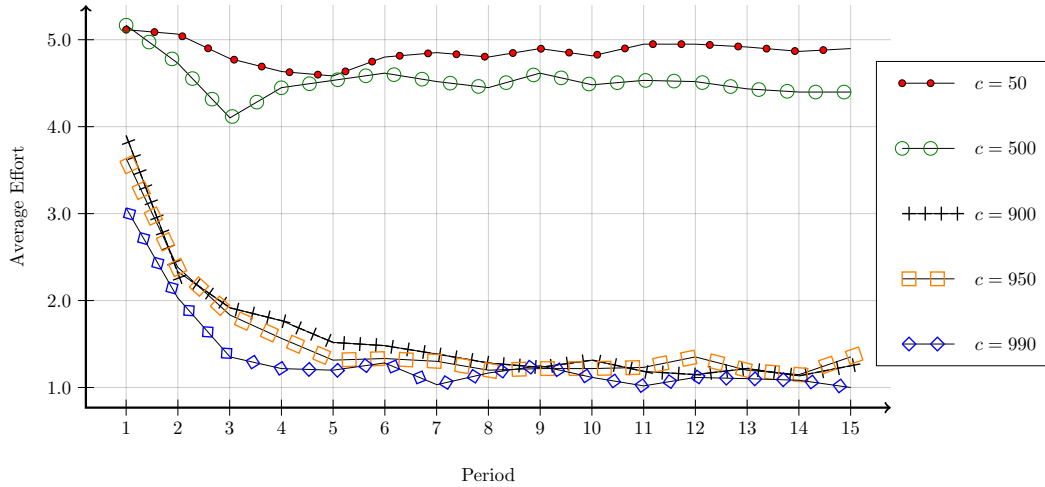


Figure 3: Average Effort Level by Cost

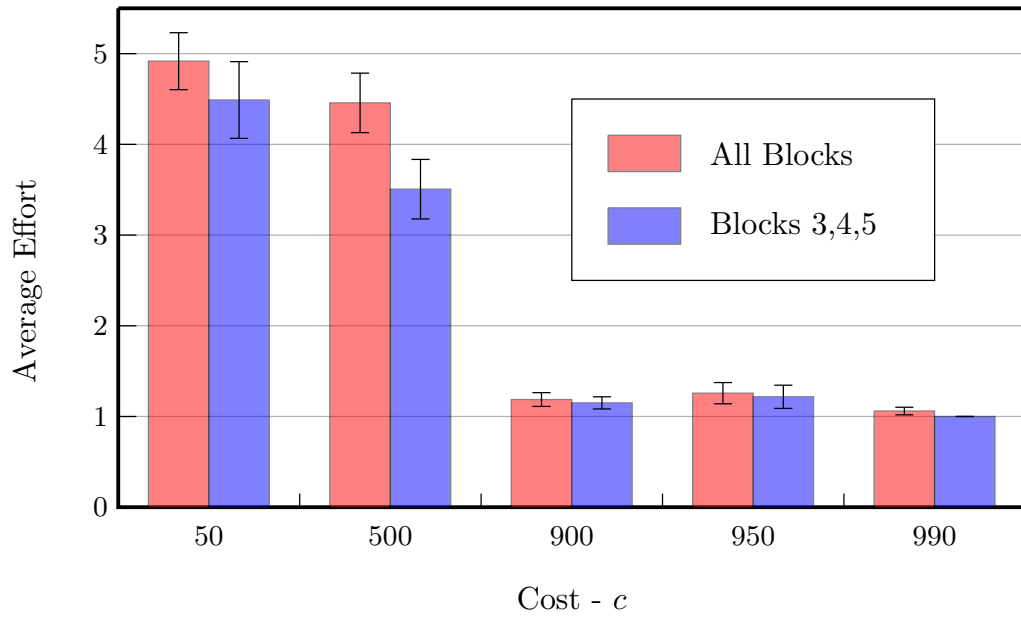


Figure 4: Average Effort of Last Five Periods by Cost (See Table 2 for Numbers)

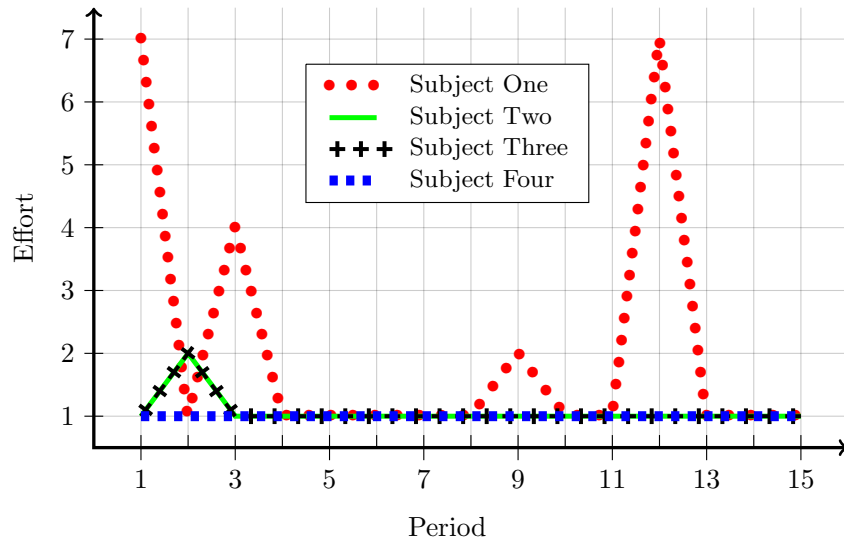


Figure 5: A Sample Result From a Block of Sessions

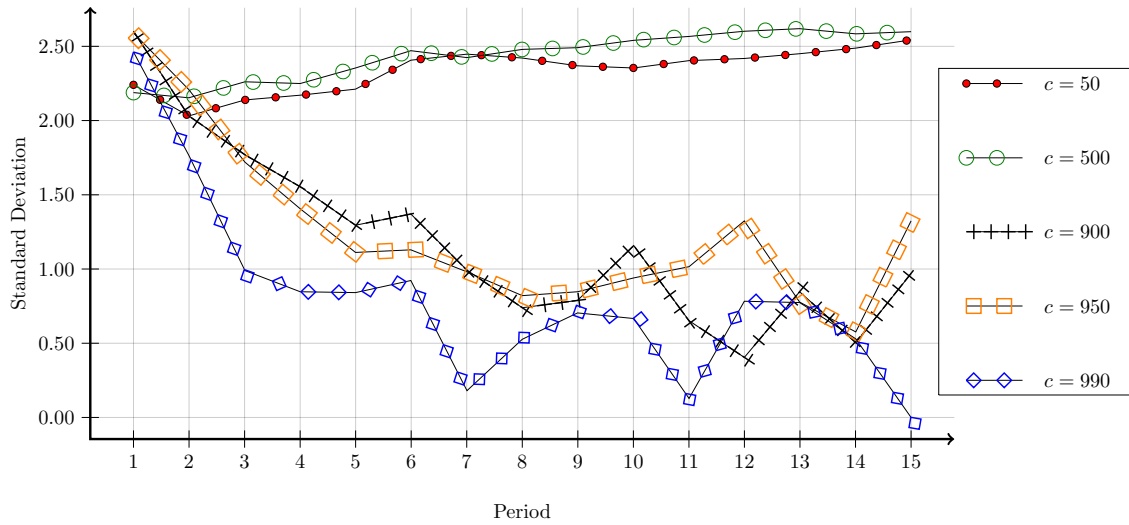


Figure 6: Standard Deviation of Effort Levels by Cost

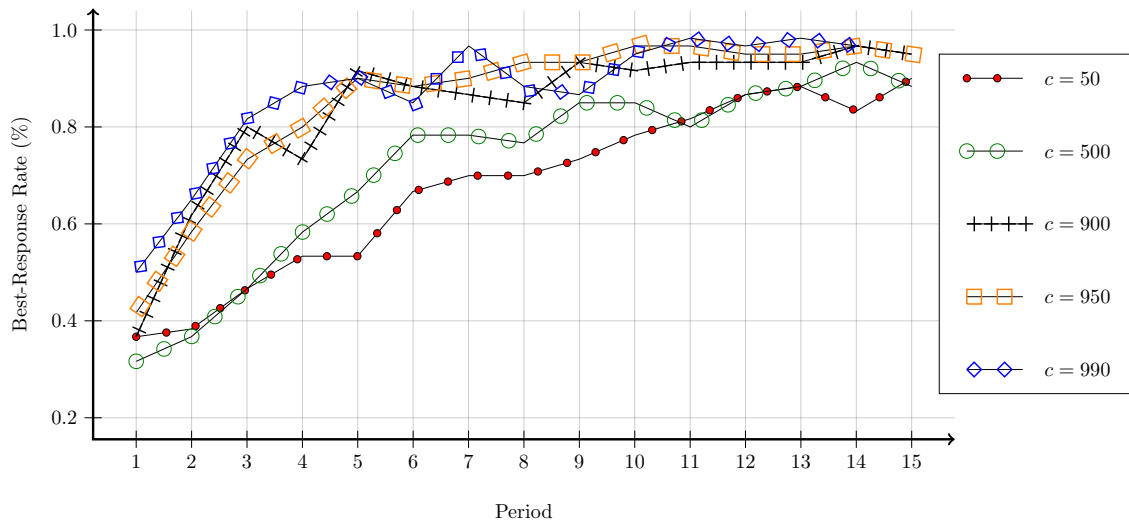


Figure 7: Best-Response Rate of Effort Levels by Cost

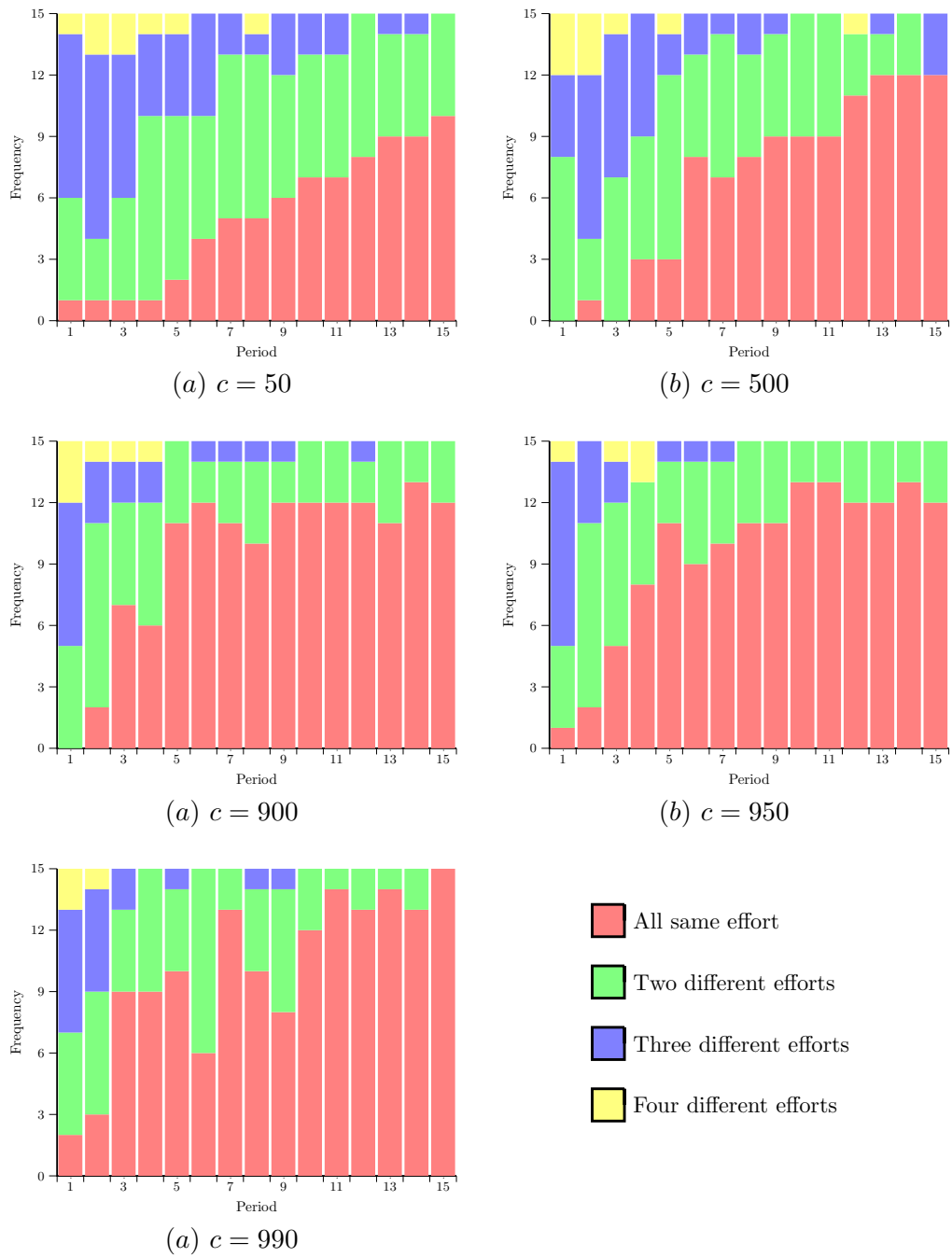


Figure 8: Frequency of Different Effort Levels Played by Cost

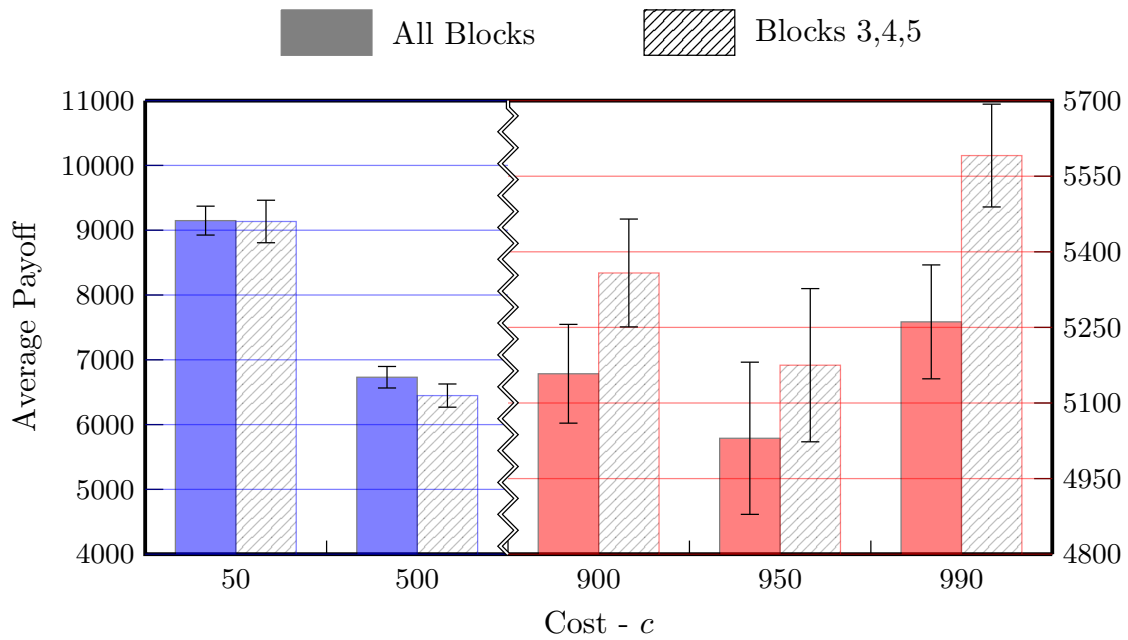


Figure 9: Average Payoff of First Five Period by Cost (All Blocks)

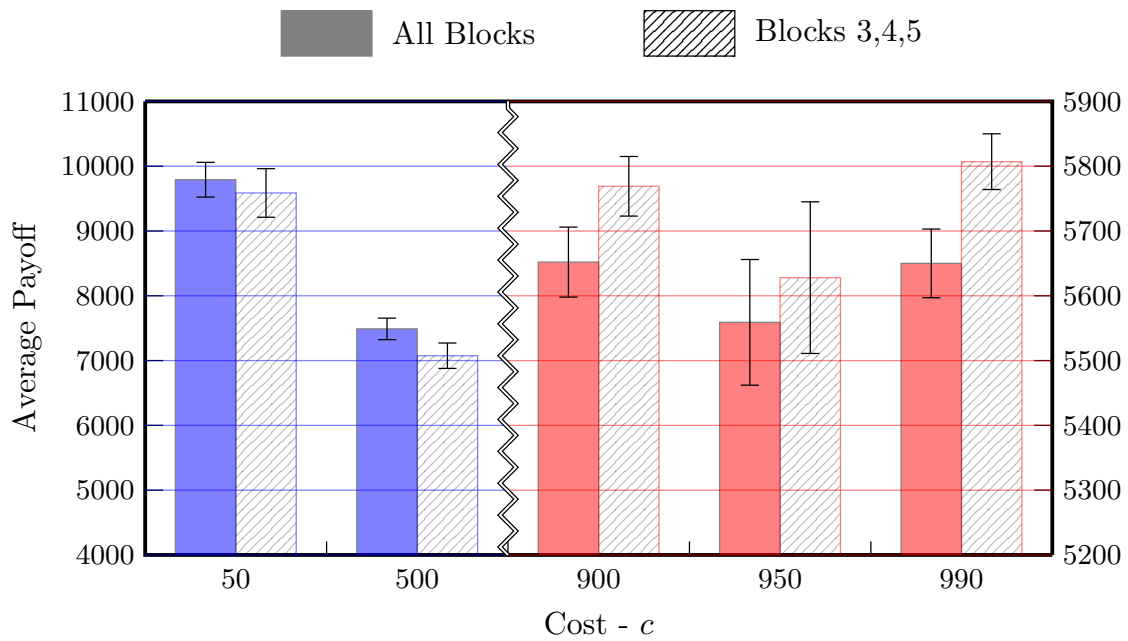


Figure 10: Average Payoff of 15 Periods by Cost (All Blocks)