Organizational and Financial Economics

Thesis by

Noah Myung

In Partial Fulfillment of the Requirements
for the Degree of
Doctor of Philosophy

California Institute of Technology
Pasadena, California

2009

(Defended May 15, 2009)

To my little brother and my parents.

Acknowledgements

Overall:

This section is by far the toughest section for me to write. Mostly because I know that I could not have completed my dissertation without the support of so many people and it does not do justice acknowledging them in this short section.[1]

First, I thank the Lord for taking every step of my life with me.

It gives me great pleasure to be able to thank my family in this section. My family has sacrificed so much to provide me this life filled with countless opportunities. To see the permanent damage left on my mother's wrist due to taping boxes after boxes every day so that my younger brother and I can attend school in US is truly heart breaking. Surely, I could not have achieved even half as much without their loving support.

I honestly believe that I had the best set of advisors. I have always thought of my advisors as my academic family: from a big brother to my parents and a grandfather. Jaksa Cvitanic, Federico Echenique, Charlie Plott and Colin Camerer have all helped me to mature as a scholar that I am today.

Caltech was definitely a love-hate relationship for me; just like anything that is really worth pursuing in life. My classmates and fellow HSS graduate students made my time here much more enjoyable. Christoph Brunner, Guido Maretto and Alan Miller were especially influential during my time here at Caltech and I am grateful that we had the opportunity to cross paths. Do not take Math 110 (inside joke). Camerer Lab members were also an important part of my academic life: Ming Hsu,

[1]Disclaimer: I only acknowledged people who played a direct role on my dissertation or my education at Caltech. Surely, non-academic friends are very dear to me. For example, Yiting was my roommate for two years and was one of the best roommate!

Min Kang, Ian Krajbich, Tomomi Tanaka, Lauren Feiler and Joseph Wang. Due to this lab, I even had the chance to engage in scholarly discussions about neuroscience and scan human brains using fMRI! (Yes, I am an economist). I will cherish the memories we have built together and deeply appreciate all the mentoring.

In addition to my advisors, the following professors have influenced my way of thinking during my time here at Caltech through their classes and discussions: Chris Chambers, Jacob Goeree, Peter Ordeshook, Mike Alvarez, John Ledyard, Matt Jackson, Simon Wilkie, Bob Sherman, David Grether, Bill Zame, John ODoherty, Matt Spitzer, Tim Groseclose, Preston McAfee, Peter Bossaerts and Jean-Laurent Rosenthal.

One of the biggest tasks we are faced with during economics Ph.D program is the economics job market. Many people were vital to my success in the job market despite the horrible economic recession. How I dreaded receiving those job-search cancellation emails... In addition to my advisors, the following people were extremely generous during my job market: Jean-Laurent Rosenthal, Rod Kiewiet, Laurel Auchampaugh and Joseph Wang.

Last but not least, I like to thank Eileen Chou for all her support. Although Eileen and I both attended UCLA, we met only after starting our Ph.D program here at Caltech. I truly appreciate Caltech for giving us this opportunity. Eileen has been a strong encouragement and a good friend for the four years of my program. We were geographically apart due to her program at Northwestern, but our hearts were never really distant.

By Chapters:

Chapter 2: I owe many thanks to Charlie Plott, Jaksa Cvitanic, Colin Camerer, Joseph Wang, Matt Rabin, Tom Palfrey, Andrea Mattozzi, Federico Echenique and Eileen Chou for their helpful comments and discussions. The experiments were graciously funded by Charlie Plott. I am also grateful to seminar participants at Caltech, UMASS, Fordham University, Naval Postgraduate School, UCSD Rady, George Mason University IFREE, ESA North American Meeting and ESA International Meeting.

Chapter 3: This chapter is a joint work with Julian Romero. My research was graciously funded by Jaksa Cvitanic and Romero's research was graciously funded by SISL. We are grateful to seminar participants at Caltech and ESA North America Meeting.

Chapter 4: I owe many thanks to Ming Hsu, Colin Camerer, Peter Bossaerts, John O'Doherty, David Grether, Jaksa Cvitanic and Eileen Chou for their helpful comments and discussions. The experiments were graciously funded by Colin Camerer. I also thank Walter Yuan for introducing me to the world of PHP, MySQL and Apache server. The designing and data collection of the indices section was a joint work with Ming Hsu though the analysis and production of result is my own. I am grateful to seminar participants at Caltech, ESA International Meeting and BDRM Conference.

Abstract

We investigate behaviors in organizational and financial economics by utilizing and developing the latest techniques from game theory, experimental economics, computational testbed, and decision-making under risk and uncertainty.

In the first chapter, we use game theory and experimental economics approaches to analyze the relationships between corporate culture and the persistent performance differences among seemingly similar enterprises. First, we show that competition leads to higher minimum effort levels in the minimum effort coordination game. Furthermore, we show that organizations with better coordination also lead to higher rates of cooperation in the prisoner's dilemma game. This supports the theory that the high-efficiency culture developed in coordination games act as a focal point for the outcome of subsequent prisoner's dilemma game. In turn, we argue that these endogenous features of culture developed from coordination and cooperation can help explain the persistent performance differences.

In the second chapter, using a computational testbed, we theoretically predict and experimentally show that in the minimum effort coordination game, as the cost of effort increases: 1. the game converges to lower effort levels, 2. convergence speed increases, and 3. average payoff is not monotonically decreasing. In fact, the average profit is an U-shaped curve as a function of cost. Therefore, contrary to the intuition, one can obtain a higher average profit by increasing the cost of effort.

In the last chapter, we investigate a well-known paradox in finance. The equity market home bias occurs when the investors over-invest in their home country assets. The equity market home bias is a paradox because the investors are not hedging their risk optimally. Even with unrealistic levels of risk aversion, the equity market home bias cannot be explained using the standard mean-variance model. We propose ambiguity aversion to be the behavioral explanation. We design six experiments using real-world assets and derivatives to show the relationship between ambiguity aversion and home bias. We tested for ambiguity aversion by showing that the investor's subjective probability is sub-additive. The result from the experiment provides support for the assertion that ambiguity aversion is related to the equity market home bias paradox.

Keywords: Experiments, Coordination Game, Competition, Corporate Culture, Equilibrium Selection, Organization, Prisoner's Dilemma, Computational Testbed, Equity Market Home Bias, Mean-Variance Model, Ambiguity Aversion.

JEL Classification: C63, C72, C73, C91, C92, D02, D23 , G11, G15.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This dissertation is divided into the advancement of two topics: organizational economics and financial economics. We investigate these topics by utilizing and developing the latest techniques and theories from game theory, experimental economics, computational testbed, and the field of decision-making under risk and uncertainty.

Organizational economics is a relatively new and interdisciplinary field. It can be defined as the study of within-firm behavior. Organizational economics is an intersection of the following fields that help explain the economics behind an organization: contract theory (agency theory), theory of the firm, institutions, labor economics, law and economics (property rights and transaction cost), organizational behavior (team theory), industrial organization, and others. Figure 1.1 provides a general positioning of organizational economics. Although these intersecting fields are much older, such as transaction cost theory by Coase (1937) or even the later days of Williamson (1975)'s theory of why a single market cannot replace every individual firms, the name *organizational economics* have only begun to be used 20 years ago. In the organizational economics portion of the dissertation, we address the question of how to improve the efficiency of an organization by changing the organizational environment.

In comparison, financial economics is much more established and easier to define than organizational economics. Financial economics is a field which is interested in market equilibrium and optimal investment decisions across time and uncertainty. For example, financial economics addresses question such as "how much should one spend today and save for future consumptions?" In the financial economics portion of the dissertation, we focus primary on a specific type of uncertainty called ambiguity and develop how individuals invest when faced with such an uncertainty.

We begin with Chapter 2 titled *Improving Coordination and Cooperation Through Competition* and Chapter 3 titled *Designing Experiments with Computational Testbeds: Effects of Convergence Speed in Coordination Games* which are dedicated to the advancement of organizational economics. In Chapter 2, we use game theory and experimental economics approaches to analyze the relationships between corporate culture and the persistent performance differences among seemingly similar enterprises. First, we show that competition leads to higher minimum effort levels in the minimum effort coordination game. This implies that organizations with competitive institutional design are more likely to have better coordination, hence better performance outcome. Furthermore, we show that organizations with better coordination also lead to higher rates of cooperation in the prisoner's dilemma game. In other words, workers from an organization that coordinates well are also more likely to cooperate with one another. This supports the theory that the high-efficiency culture developed in coordination games act as a focal point for the outcome of subsequent prisoner's dilemma game. In turn, we argue that these endogenous features of culture developed from coordination and cooperation can help explain the persistent performance differences.

In Chapter 3, using a computational testbed, we theoretically predict and experimentally show that in the minimum effort coordination game, as the cost of effort increases: 1. the game converges to lower effort levels, 2. convergence speed increases, and 3. average payoff is not monotonically decreasing. In fact, the average profit is an U-shaped curve as a function of cost. Therefore, contrary to the intuition, one can obtain a higher average profit by increasing the cost of effort.

The last chapter, Chapter 4 titled *Ambiguity Aversion in Asset Markets: Experimental Study of Home Bias*, is dedicated to the advancement of financial economics. We investigate a well-known paradox in finance called the *home bias paradox*. The equity market home bias occurs when the investors over-invest in their home country assets. The equity market home bias is a paradox because the investors are not hedging their risk optimally. Even with unrealistic levels of risk aversion, the equity market home bias cannot be explained using the standard mean-variance model. We propose ambiguity aversion to be the behavioral explanation. We design six experiments using real-world assets and derivatives to show the relationship between ambiguity aversion and home bias. We tested for ambiguity aversion by showing that the investor's subjective probability is sub-additive. The result from the experiment provides support for the assertion that ambiguity aversion is related to the equity market home bias paradox. This result has an implication that people are willing to lose money in order to investing in a more familiar company or index.

The topics of organizational economics and financial economics are intertwined in many ways beyond addressing the classic question of how to efficiently allocate scares resources. One of the main reasons why this dissertation covers both organizational and financial economics is to make aware the importance of understanding the relationship between the insider and outsider's investment behaviors and the organization of a firm. As depicted in Chapter 2, inside or outside investors may not invest even when they face no downside risk. Furthermore, it shows how utilizing a different organizational structure with investment scheme can select a pareto dominating (i.e. social welfare enhancing) equilibrium. Chapter 3 shows that higher cost can improve coordination and attain higher profit but investors may not be aware of such possibility. Chapter 4 presents why brand recognition is so powerful for an organization to attract outside investment. It is our hope that scholars will further develop the link between internal and external financial decision-making to organization structure.

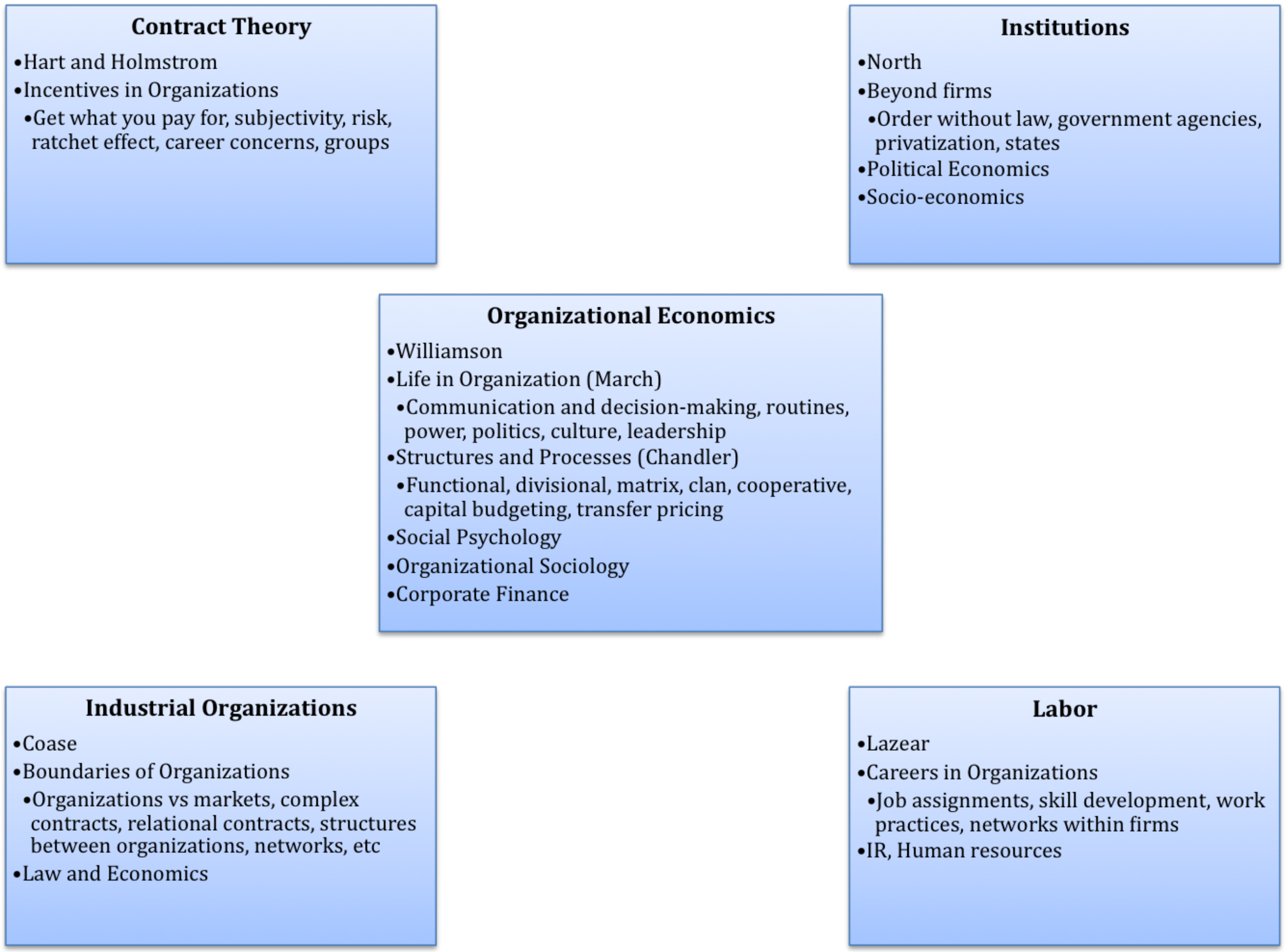


Figure 1.1: Organizational Economics
Adapted from Robert Gibbon's Econ 15.945 doctoral course in organizational economics syllabus at MIT

Chapter 2

Improving Coordination and Cooperation Through Competition

2.1 Introduction

Industrial, labor, and organizational economists are intrigued by the existence of persistent performance differences (PPD) among seemingly similar enterprises (SSE). Many empirical researches demonstrated that performance differences do exist, whether measured in productivity or profit in various sectors of industry. These results are prevalent between and within countries and even at the more narrow level of 5-digit industries. For example, there is a 156% difference in productivity between the top 10 and bottom 10 decile in UK manufacturing industries (Disney, Haskel, and Heden 2003), corporate effects alone can explain up to 18% of variance in profit in the US (Brush, Bromiley, and Hendrickx (1999) and Roquebert, Phillips, and Westfall (1996)), and initial defect rates varies by factor of five in the semiconductor manufacturing industry (Macher and Mowery 2003). We refer the readers to an excellent survey paper by Gibbons, Henderson, Repenning, and Sterman (In Press) for a more detailed discussion of empirical results regarding performance differences.

Because an organization is in essence a repeated game, the folk theorem argues that any outcome we observe is just different equilibria reached by the organizations. This paper takes it one step further and states how certain equilibrium results may occur. Various studies explained some of the reasoning behind the PPD among SSE. For example, in addition to Gibbons, Henderson, Repenning, and Sterman (In Press), Bloom and van Reenen (2007) presents well-studied empirical data which argues that management skills are part of the explanation for PPD.[1] However, management skill is just another form of labor input. Something that is more general and endogenous to the firm is *corporate culture*. Our paper shows the importance of culture that is developed from coordination and cooperation among the individuals which can help explain the performance differences among seemingly similar enterprises.

Corporations evolve through different phases as they develop. At the initial stage, the coordination and the cooperation phases have long-lasting effects on corporate performance. Consider the following thought exercise: At the initial phase, an organization deals with many coordination problems. Members in the organization may come from different social cultures, experiences, ethics, linguistics, or educational backgrounds. Is working overtime expected? Should people work individually or in teams? Is email an acceptable form of communication? It may take some time before the organization establishes a particular corporate culture. We denote this phase as the coordination phase. After corporate culture matures, individuals can choose to cooperate or to defect for self-benefit. For example, if email has become an acceptable form of communication even in urgent matters, one employee may deny receiving it when it is to his advantage to do so. Or the culture could be such that the management usually gives proper credit to subordinates, but takes sole credit when an extraordinary idea is suggested. We denote this as the cooperation phase. Our experiment replicates a similar time line. We show, in a laboratory setting, that we can endogenously generate different corporate cultures for a group in the coordination phase by using different organizational structures, and predict their individual behavior in the cooperation phase.

In short, our experiment shows the following two main results. First, to show that organizations with competitive institutional design are more likely to have better co-

[1] In fact, they detail other interesting results. US companies are usually better managed, competition leads to better management, and family-owned firms that pass down control to the eldest son usually do worse.

ordination, and, in turn, better performance outcome, we show that that competition leads to higher minimum effort levels in the minimum effort coordination game. Next, to support the theory that the high-efficiency culture developed in coordination games acts as a focal point in the cooperation phase, we show that organizations with higher minimum effort in the coordination game also have a higher rate of cooperation in the prisoner's dilemma game, and, in turn, a better performance outcome. These two endogenous features have significant performance differences in our experiment.

2.1.1 Corporate Culture

Corporate culture is broadly defined as "the specific collection of values and norms that are shared by people and groups in an organization and that control the way they interact with each other..." (Hill and Jones 2001). Corporate culture is undeniably prevalent and influential. Many organizational theorists have studied the psychological and sociological impacts and the measurements of corporate culture (e.g., Cameron and Quinn (2005), Kotter and Haskett (1992), Sorensen (2002)) and some have studied formation of norms (Bettenhausen and Murnighan (1991), and Bettenhausen and Murnighan (1985)). Southwest Airline once used an ad depicting a multiple choice exam which question asked "A customer forgets to pack extra baby formula and has an hour layover in Albuquerque. What do you do?" (Figure 2.1). The choices of answers were a) Wish her luck, b) Suggest an excellent restaurant across town, or c) Go find some formula and pick up a coloring book for her older child. Answer c) is going beyond what is expected of an employee at a typical airline but it portrays that Southwest airline's culture is to do exactly that: go beyond what is expected (Camerer and Malmendier 2007).

Another example is the culture at the California Institute of Technology (Caltech). Although not a corporation in the usual sense, Caltech operates under a honor code system that states that a student will not take advantage of another Caltech member. Students from other universities may have hard time grasping the concept and how it is enforced. However, Caltech's honor code system works extremely well; students are usually given take home exams that may be timed or un-timed, closed or open book, but ultimately self administered.[2] Lastly, one of the most important cultural understandings of the US military is the retrieval of US soldiers. If there is even a remote chance that a fellow soldier is alive, the soldiers do everything within their means to save the fellow soldier, even if it threatens additional lives. This type of culture helped develop the US military to be the most elite all-volunteer military force in the world. Consider for a second that the corporate culture was to leave the soldier behind enemy lines. How dedicated would the soldier be in dangerous missions?

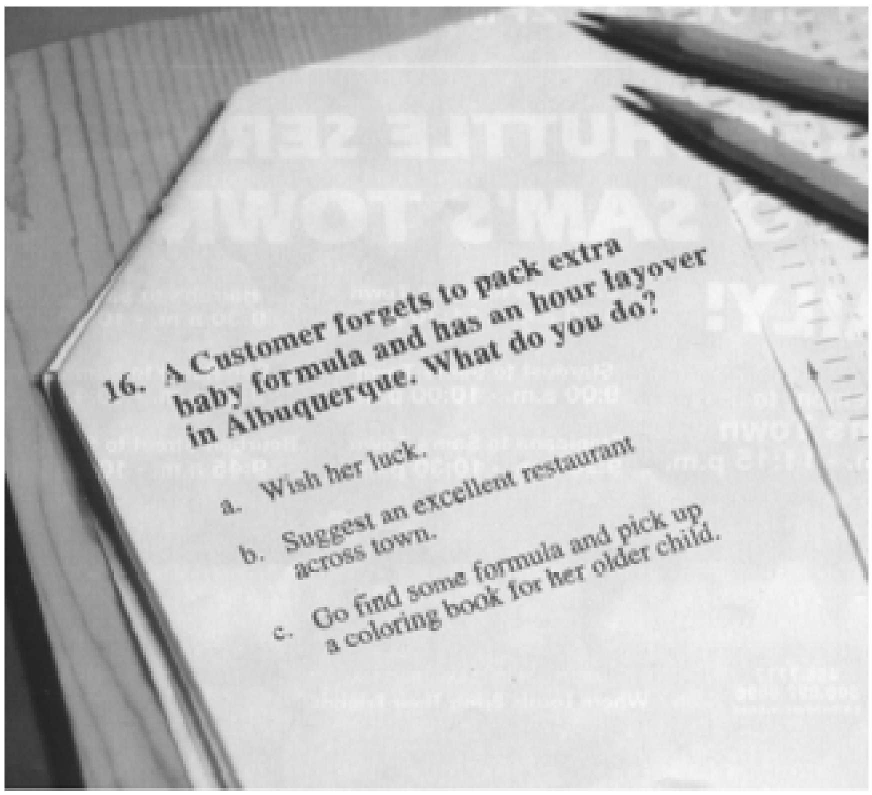


Figure 2.1: Ad from Southwest Airline Inflight Magazine

Although it is not as widely studied nor as mature as it is in management science, economists have begun to acknowledge that corporate culture is an integral part of studying the theory of firm. Culture is studied indirectly by using a relational contract in a repeated game theory framework (Baker, Gibbons, and Murphy 2002). It is

[2]Having done my undergrad education at another university and being an economist, I too was very surprised by Caltech's system. However, I too saw myself self-enforcing the honor code system.

also studied in a direct manner: Kreps (1990) emphasized the culture as a focal point (Schelling 1960), Cremer (1993) and Cremer (1986) viewed culture as an investment, and Hermalin (2001) argued culture as an efficiency improving mechanism. Hermalin (In Press) provides a helpful literature review of where the economic field is in terms of corporate culture. Furthermore, experimental economists contributed to a complementary ways of studying corporate culture. Feiler and Camerer (In Press) and Weber and Camerer (2003) have conducted an experimental study of how firms may endogenously create codes to communicate and how mergers will create a disruption in production due to “language barrier” in codes.

Although corporate cultures can be seen as a firm-specific technology, it cannot be easily transferred or purchased even in similar industries.[3] These literature all point to the crucial roles corporate culture plays in affecting corporate performance. First, it is a cheap way of increasing productivity. For example, having a well-implemented culture of “do no evil”, like Google, Inc., can reduce principal’s monitoring cost. Second, it provides us researchers with an equilibrium prediction. With a good understanding of the culture, we can better predict whether the members in the organization will be more self-serving or cooperative.

2.1.2 Overview of the Paper

In this paper, we use both game theory and experimental economics approaches to demonstrate two relationships between corporate culture and PPD among SSE. First, we show that competition leads to better coordination in the minimum effort coordination game: organizations with institutional design that induces competition are more likely to have better coordination. This result is consistent with previous findings where competition provides higher performance, such as in the tournament structure (Lazear and Rosen 1981) or managerial performance (Bloom and van Reenen 2007). Furthermore, we show that stronger coordination also leads to higher rate of cooperation in the prisoner’s dilemma game, even when non-cooperation is individually

[3]It is probably harder for a similar industry to adopt since there is a first mover’s advantage.

beneficial. In sum, we show that high-efficiency culture developed in coordination games act as a focal point for the outcome of a subsequent prisoner's dilemma game.

We operationalize minimum effort coordination games as organizations' coordination problems, and prisoner's dilemma game as cooperation problems. We have two experimental treatments for the coordination phase: competitive and non-competitive setting. In the competitive treatment, there are two firms, where firms are independently playing the minimum effort coordination game. In the non-competitive setting, there is only one firm. In both treatments, there are external investors whose payoff is determined by the performance of the firm. Furthermore, the investment linearly increases the payoff for the workers in the firm, and they know the investment prior to any decision making. As will be detailed in the experimental design section, this procedure is done to control for risk-dominance. Our experimental design benefited greatly from Bornstein, Gneezy, and Nagel (2002)'s (BGN) experiment that supports the idea that competition can improve coordination. Three major differences distinguish our research from BGN's. First, as mentioned, we control for risk-dominance in the competition setting. Second, our investment is constructed endogenously and is more aligned with the principal-agent framework. Lastly, both the competitive and non-competitive setting has investors in our design, providing a way to compare one-firm and two-firm treatments. Our design also benefited from results by Brandts and Cooper (2006) and Hamman, Rick, and Weber (2007) (HRW). Both papers are excellent experimental papers that study the relationship between effort choices and exogenous one-time changes to the payoff function. Here, exogenous change means that the change is not controlled by anyone participating in the experiment. Brandts and Cooper and HRW showed that, after observing coordination failure, periodic and exogenous changes of the payoff function in a non-affine manner[4] to increase the benefits from coordinating (compared to previous period's payoff) improve coordination. Adapting from their studies, our experiment deals with endogenous changes and affine transformations to the payoff function. We show that the effort levels from the com-

[4]A non-affine transformation may change risk-domiance. An affine function is a function that is both concave and convex.

petitive setting stochastically dominate the non-competitive setting. Interestingly, the distribution of effort levels from the one-firm treatment is not statistically different from the distribution of effort levels made by the lower performing firm in the competitive setting. Furthermore, even though the experiment was designed so that the investors cannot lose any of their investments, we observe that the investors do not fully invest their endowment in the poor performing firm even in the non-competitive setting. This punishment mechanism does not increase the effort levels.

Similar to Knez and Camerer (2000)'s design, given that the corporation has developed a culture of high levels of coordination, we also find that this induces the agents to be more likely to cooperate even in the one-shot prisoner's dilemma game. Our paper provides a stronger result in that our prisoner's dilemma game is a one-shot game rather than a repeated game. Furthermore, unlike Knez and Camerer (2000), our organization for the coordination game consists of group size strictly greater than 2.[5] When we present the subjects with a prisoner's dilemma game which is played with another member from the group with whom they played the coordination game, cooperation is approximately 30% more likely than defection when there is a higher level of coordination.[6]

[5] A problem with having a coordination game with group size of 2 is that the individuals coordinate very well. Therefore, Knez's study was not able to get much variation in level of coordination (they all fully coordinated) to genuinely study the relationship between coordination and cooperation.

[6] One caveat we like to acknowledge from the start is that an experiment conducted at an university with group of students cannot fully generalize the complexity of standard organization in the business world. For example, this experiment is done without communication which surely exist in a typical corporation. However, one of the objectives of this paper is to study how the initial equilibrium selection of an organization effects the future selections. When an organization first begins, there is a coordination problem (due to language barrier, cultural differences, jargons, etc.) which becomes an obstacle to communication. One can see this no-communication experiment as an extreme version of that scenario. There have been studies which state that student's behavior at the lab is a good predictor of professional's behavior in these abstract settings (Ball and Cech 1996) but further studies of how the short-run organizational behavior in lab will generalize to the long-run organizational behavior is definitely needed. Experiments are extreme simplifications but that is their advantage. We view experiments as another form of methodology to gain data and insights. By using this controlled and simple environment, we are able to better understand how certain features will effect the organization.

2.1.3 Agenda

The paper proceeds as follows. We first introduce the general setup and review of the game of interest. Then we present the experimental design and the main hypotheses. We then follow with detailed analysis in the result section. We finish with a summarizing conclusion.

2.2 General Setup and Review

2.2.1 Minimum Effort Coordination Game

Minimum effort coordination game (MECG, and also known as the weak-link game) takes the following form: Given N agents, every agent chooses an effort level $e_i \in \{1, 2, ..., M\}$, M finite, with payoff function

$$p_i = \alpha \left(\min_{j \in N} \{e_j\} \right) - \beta(e_i) + \delta \text{ where } \alpha > \beta > 0, \delta \in \mathbb{R} \text{ for all agents } i \in N \quad (2.1)$$

Best response in this game is for agent i to match the lowest effort from everyone else:

$$e_i = \min_{j \in N \setminus i} \{e_j\}$$

Hence, there are M many pure strategy equilibria: everyone choosing $e_i = 1$, everyone choosing $e_i = 2$ and so on. Let's consider an example of which $M = 7, \alpha = 400, \beta = 200$, and $\delta = 1100$. The game can be then summarized by Table 2.1.

	Minimum effort of all the agents						
Agent i's effort	7	6	5	4	3	2	1
7	2500	2100	1700	1300	900	500	100
6	-	2300	1900	1500	1100	700	300
5	-	-	2100	1700	1300	900	500
4	-	-	-	1900	1500	1100	700
3	-	-	-	-	1700	1300	900
2	-	-	-	-	-	1500	1100
1	-	-	-	-	-	-	1300

Table 2.1: Minimum Effort Coordination Game Payoff for Agent i

This game has several features. First off, it has 7 pure strategy Nash Equilibria: $e_i = 1\ \forall i \in N$, $e_i = 2\ \forall i \in N$, ..., $e_i = 7\ \forall i \in N$. An interesting question to address in games with multiple equilibria is the equilibrium selection. However, given this particular game structure with strict Nash Equilibria, many of the standard notions of refinements, such as *trembling hand perfection*, will not help to reduce any equilibria. Using the reasoning of Harsanyi and Selton (1988), we are able to focus on two particularly interesting equilibria: the *payoff dominant equilibrium* and the *risk dominant equilibrium.* Everyone choosing effort level 7 is the payoff dominant equilibrium since this equilibrium pareto dominates all other equilibria. Choosing an effort level 1 is the least-efficient equilibrium but it can be seen as maximizing the worst-case scenario. In terms of Harsanyi and Selten, this equilibrium is the risk dominant equilibrium; by choosing an effort level of 1, the agent minimizes the uncertainty and, in MECG, secures a specific payoff regardless of the actions of other agents. Harsanyi and Selten further argue that payoff dominance should be the first criterion applied.

However, in tacit environment, experiments have shown that people fail to coordinate to a payoff dominant equilibrium. Rather they end up at the risk dominant equilibrium. The leading example is produced by van Huyck, Battalio, and Beil (1990) (VHBB). In VHBB's experiment, participants played the minimum effort coordination game without communication. The only statistics observable by the participant was the minimum effort of the group. The size of the group consisted of 14-16 participants and each were instructed to choose an integer effort level of 1 to 7 with 1 being the risk dominant and 7 being the payoff dominant equilibrium. In this and other similar experiments (See Camerer (2003) for survey), the game generally converges to a minimum effort of 1 by the 5th period when $N > 3$. One of the intuitions behind this experimental result is *strategic uncertainty.* In short, strategic uncertainty is the uncertainty arising from not knowing which equilibrium strategy the other players will implement. The strategic uncertainty increases as the group size increases (N increases) since agents now have more people to consider, and as the number of strategies increase (M increases) since the agent now has more Nash Equilibria to consider.

One of the leading theories of behavior we observe in these experiments is provided by Crawford, who uses the adaptive learning framework to explain the data for VHBB (Crawford 1995). After observing the minimum effort level that is weakly lower than the effort level any one agent has chosen ($e_i = \min_{j \in N \setminus i}\{e_j\}$), the agent uses the new information to update his next period strategy, in turn, converging to a minimum effort level of 1.

Two questions one might ask are 1. what would happen if group size is $N \leq 3$? and 2. if the distribution of choices were available instead of just the minimum effort statistics? VHBB also addresses those two questions. When the group size is small, the participants coordinate very well. However, with a bigger group size, showing the distribution of choices does not improve coordination. This can be because when the group size is small, there is hope in leading by example and being patient. However, when the group size is 'big', seeing the distribution of many low-effort levels is not much of an encouragement.

Many variations of the minimum effort coordination game have shown improvement of minimum effort in addition to the papers pervious mentioned by Bornstein, Gneezy, and Nagel (2002), Brandts and Cooper (2006), and Hamman, Rick, and Weber (2007). For example, Cooper, DeJong, Forsythe, and Ross (1992) showed that having a non-binding pregame communication improves coordination. Even without communication, Weber (2006) provides an experimental result where one slowly grows the organization to improve coordination. Schmidt, Shupp, Walker, and Ostrom (2003) provide experimental data that shows coordination improves when risk dominance is weaker. Furthermore, Cachon and Camerer (1996) showed that people coordinate better when they are charged a fee to participate which leads to losses of money in poor equilibrium (loss-avoidance).

2.2.2 Prisoner's Dilemma Game

Given the heavy exposure of prisoner's dilemma game, we will not cover the related literature in this paper. However, we briefly touch on the game in the experimental design section.

2.3 Experimental Design

The experiments were conducted at 2 laboratories: the Social Science Experimental Laboratory (SSEL) at the California Institute of Technology (Caltech), Pasadena, CA, and the California Social Science Laboratory (CASSEL) at the University of California, Los Angeles (UCLA). A total of 128 subjects participated in the experiments. The average performance-based payment was 19USD. All students were registered subjects with SSEL / CASSEL (signed a general consent form) and the experiment was approved by the local research ethics committee at both universities. These labs consist of over 30 working computers divided into cubical setting, which prevents the students from viewing another student's screen.

The experiment was 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 and the Experimenter explained the instructions in detail out-loud. Participants were also given a brief quiz after instruction to insure proper understanding of the game and the software. A sample instruction that was provided to the participants is attached at the Appendix.

The subjects were randomly assigned their roles in the experiment and did not change their roles for the entire experiment. Furthermore, no subjects participated in more than one experiment. The identity of the participants as well as their individual decisions were kept as private information. However, each group knew the total investment their group received, their own group's minimum effort (not the other group's effort level), and the investors only knew their own investment level as well as the minimum effort of all the groups. The experiment used fictitious currency called francs and the expected payment for the investors and group members were comparable. The participants were told that the experiment consisted of undetermined number of rounds to prevent end game effect. All participants filled out a survey immediately after the experiment.

Terminology: In terms of terminology, we avoided any priming effects by using neutral language during the experiment. More specifically, we used language such as *groups* and *numbers* instead of *firms* and *effort levels*. For consistency of this paper, we will refer to groups as *firms* and *investors* henceforth. The members in a firm will be called *workers*. However, we can consider these not only as firms but also as different divisions within a firm. In other words, this setting can be applied to both inter- and intra-organization levels. Lastly, we will refer to the number chosen by the subject as *effort level* throughout the paper.

2.3.1 Two-Firm (Competitive) Treatment

Below is the sequence of the experiment.

1. Investors privately decide on how much to invest in Firm 1 and Firm 2.

2. The workers observe the aggregate investment for their firm.

3. The workers privately select a number between 1 - 7.

4. The minimum number for each firm is shown to the investors along with their current period payoff and total payoff.

5. The workers are shown the minimum number selected with their own firm. In addition, the workers are shown their individual payoff for the current period and the total payoff.

6. The period comes to an end and the next period begins.

7. Experiment concludes at an indefinite period.

We conducted 4 sessions of the two-firm treatment (3 at UCLA and 1 at Caltech). Subjects in the two-firm treatment were divided into three groups: Firm 1, Firm 2, and Investors. Each of the firms had 6 workers and there were total of 4 investors.

Investors: In each period, investors were given 100 francs to invest. Investors were allowed to invest in any combination such that for any investor i, investment to Firm 1 is $I_1^i \geq 0$, investment to Firm 2 is $I_2^i \geq 0$ and $I_1^i + I_2^i \leq 100$. Investors kept any endowment not invested. The payoffs from the investment were determined by the performance of the two firms

$$R\left(\min_{i\in firm1}\{e_i\}\right) \times I_1^i + R\left(\min_{j\in firm2}\{e_j\}\right) \times I_2^i \tag{2.2}$$

where $R(min\{e_i\})$ represents the following multiplier in Table 2.2.

$min\{e_i\}$	7	6	5	4	3	2	1
$R(min\{e_i\})$	2.5	2.25	2.0	1.75	1.5	1.25	1.0

Table 2.2: Multiplier for $R(min\{e_i\})$ for Both Firms

These multipliers are standard in experimental economics, such as the trust game, centipede game, and many others. Notice that investors cannot lose money from investment and it is weakly dominant to always invest.

Workers: Each firm consisted of 6 people and the composition of the firm did not change for the entire experiment. The workers played the MECG explained before with the following variation. Worker i in firm j was choosing a number $e_i \in \{1, 2, ..., 7\}$ with his payoff given by

$$p_i = 400\left(\min_{i\in N} e_i\right) - 200e_i + 1100 + I_j \tag{2.3}$$

where $I_j = \sum_{k\in investors} I_j^k$, the sum of total investment made to the firm j. Notice that the best response does not change: $e_i = \min_{j\in N\backslash i}\{e_j\}$. Furthermore, the entire equilibrium structure remains the same. In particular, risk dominance is invariant with respect to isomorphisms (Harsanyi and Selton 1988). The worker's payoff matrix can be summarized by Table 2.3. These parameters were chosen so that in the worst case the worker will end with at least 100 francs and not a negative amount. This is to reduce confounding effects such as loss aversion.

The design choice was made with simplicity in mind. Obviously, there are more complex contracts that can induce better performance than a fixed-wage contract, such as an option-based or benchmark contract. Our goal was to design a simple wage

	Minimum effort of all the agents						
Agent i's effort	7	6	5	4	3	2	1
7	$2500 + I_j$	$2100 + I_j$	$1700 + I_j$	$1300 + I_j$	$900 + I_j$	$500 + I_j$	$100 + I_j$
6	-	$2300 + I_j$	$1900 + I_j$	$1500 + I_j$	$1100 + I_j$	$700 + I_j$	$300 + I_j$
5	-	-	$2100 + I_j$	$1700 + I_j$	$1300 + I_j$	$900 + I_j$	$500 + I_j$
4	-	-	-	$1900 + I_j$	$1500 + I_j$	$1100 + I_j$	$700 + I_j$
3	-	-	-	-	$1700 + I_j$	$1300 + I_j$	$900 + I_j$
2	-	-	-	-	-	$1500 + I_j$	$1100 + I_j$
1	-	-	-	-	-	-	$1300 + I_j$

Table 2.3: MECG with Investment Payoff for Agent i in Firm j

schedule that is less likely to induce coordination improvement. The focus of the study is not whether different contracts can induce coordination but whether competition can help improve coordination. We want to minimize the confounding effects. The design of the I_j parameters were again chosen for simplicity of computation during the experiment, as well as to not change the risk dominance of the game. Instead of using the payoff to workers $p_i = 400\left(\min_{i \in N} e_i\right) - 200e_i + 1100 + I_j$, we could have also used the payoff $p_i = 400\left(\min_{i \in N} e_i\right) - 200e_i + 1100 + \frac{I_j}{N}$, but there is no a priori reason to think scalar multiplication of investment will make a difference. The profit function for firm j which constructs the model above is $\prod_j = I_j(R(min(e_i)) + 6) + 6(\alpha min(e_i) + \delta)$ and was not shown to the subjects in the experiment.

2.3.2 One-Firm (Non-Competitive) Treatment

The one-firm treatment is identical to the two-firm treatment except that there is now only one firm. We conducted 4 sessions of the one-firm treatment (3 at UCLA and 1 at Caltech). Again, the equilibrium structure does not change. The comparison between the design of the two treatments can be summarized by the Table 2.4.

	Two-Firm Treatment	One-Firm Treatment
Investor's Choice: How much to invest in	Firm 1, Firm 2, and Nobody	Firm 1 and Nobody
Performance knowledge	Investors: All Workers: Own Firm	Investors: All Workers: Own Firm
Investment Knowledge	Own Firm	Own Firm
Can investors lose money?	No	No

Table 2.4: Comparing the Two-Firm and One-Firm Treatments

2.3.3 Standard Treatment

We ran 2 sessions at UCLA and 2 at Caltech of the standard minimum effort coordination game using the payoff from Table 2.1.

2.3.4 Cooperation Design

We used a one-shot prisoner's dilemma game to test whether subjects are more likely to cooperate (Table 2.5).

		Your pair's decision A	Your pair's decision B
Your decision	A	\$3, \$3	\$1, \$4
	B	\$4, \$1	\$2, \$2

Table 2.5: Prisoner's Dilemma Game

We did not inform the subjects beforehand that they would be playing a prisoner's dilemma game. The subjects were randomly (anonymously) matched to one other person from the same group that they were part of during the coordination game. For example, someone from Firm 1 was paired with another person from Firm 1. Subjects were clearly told that this was being played only once and we have obtained the data from the cooperation design only from the UCLA subjects.[7] We chose the prisoner's dilemma game because this game has one pure strategy Nash equilibrium which is dominant solvable. In the example from Table 2.5, the pareto-efficient outcome is to cooperate-cooperate but it is not an equilibrium. Nash equilibrium is to chose B. Following the standard prisoner's dilemma terminology, we consider choosing A as *cooperating* while choosing strategy B as *not cooperating*. Given the structure of the game, choosing to cooperate in one shot prisoner's dilemma provides a strong result.

2.3.5 Hypothesis

For the coordination phase, we tested whether the workers in the two-firm treatment coordinated better than in the one-firm treatment. Better coordination can mean three things: 1. achieve higher minimum effort level, 2. achieve lower wasted effort, or 3. achieve faster convergence to an equilibrium. For consistency with other literatures, we are referring to *higher minimum effort* level when we state that some setting has a better coordination. However, we will show that there is no difference in wasted effort and rate of convergence between different settings in the result section. For the cooperation phase, we test whether subjects coming from a better-coordinating firm are also more likely to cooperate.

Hypothesis 1 *Higher Minimum Effort. Subjects in the two-firm treatment will choose higher minimum effort level than the one-firm treatment.*

Hypothesis 2 *Likelihood of Cooperation. Subjects are more likely to cooperate in the prisoner's dilemma game if they have also coordinated well in the MECG.*

[7] We only obtained the data from UCLA because this part of the experiment was incorporated after we had already finished running the experiments at Caltech.

2.4 Results

2.4.1 Two Firm

Figure 2.2 and 2.3 show the summary results aggregated over all four sessions of the two-firm treatment. For the analysis, we have separated the sample into two sets. The first set, denoted *higher performing firm*, consists of firms that had higher minimum effort for a given session. The second set, denoted *lower performing firm*, is the complement set of the *higher performing firm*. Of the two firms per session, we define a firm as higher performing if it achieves a higher minimum effort by period 5. There were no cases in which a firm with a higher effort by period 5 ended up having a lower minimum effort at any time from period 5 to 10 (10 being the last period).

We observe that mean choice of effort was between 6-3 with all firms, while the mean choice of effort was between 6-4 and 5-2 for the higher and lower performing firm, respectively (Figure 2.3). The average minimum effort was between 3-4 with all firms, while the average minimum effort was between 3-5 and 1-3 for the higher and lower performing firm, respectively (Figure 2.2). We compared the distribution of average choice per period of each subsample to show that the difference in performance between higher and lower performing firms is statistically significant. Table 2.6 contains the results from the two-sample Kolmogorov-Smirnov test. Furthermore, Figure 2.4 graphs the kernel estimated cumulative distribution function of each of the subsamples. Results from the KS test and the CDF graph show that the higher performing firm indeed chose statistically significantly higher (p-value of 0) effort levels than the lower performing firm.[8] Lastly, we conclude from Table 2.7, a cross-sectional time series FGLS regression for average effort level, that average effort level for period t is predominately determined by firm's previous period's minimum effort (coefficient: 0.699 for higher performing firm and 0.91 for the lower performing firm), and minimally, but statically significantly, determined by the percent wealth invested to the firm. The effect of investment for the higher performing firms is negative (coefficient:

[8]The cdf of the higher performing firm stochastically dominates the cdf of the lower performing firm.

-0.016) while for the lower performing firm is positive (coefficient: 0.0145). This is because there is an upper and lower bound to the possible effort and investment level. The investors will end up investing 100% of their wealth in the higher performing firm, so decrease in average effort in time will show up as a negative effect. Yet, the investors have no reason to shift their investment from higher performing to lower performing firm as long as the higher performing firm is indeed outperforming the lower firm. Also, as the average effort approaches 1 for the lower performing firm, even modest investment will show up as a positive effect.

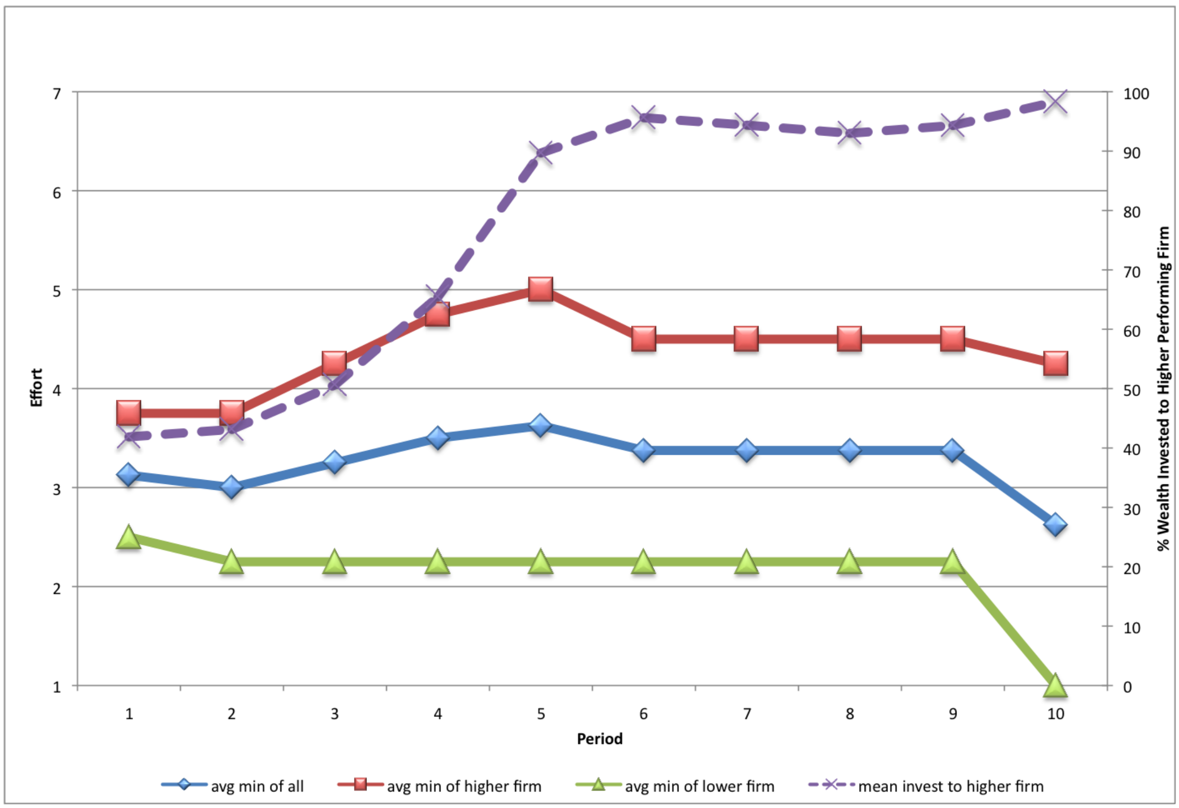


Figure 2.2: Average Minimum Effort for Two-Firm Treatment

Table 2.8 and 2.9 further analyzes the investment behavior. Although investors start out by investing 50-50 between both firms[9], Table 2.8 shows that on the last period, over 98% of the wealth is invested to the higher performing firm. These means are significantly different ($p<0.000$). Another important feature is that the investors

[9]From Figure 2.2 and 2.3, it may seem as if the investors invested more in the lower performing firm at first but that is not the case. The investors did invest 50-50 but did not invest their entire endowment in the first period

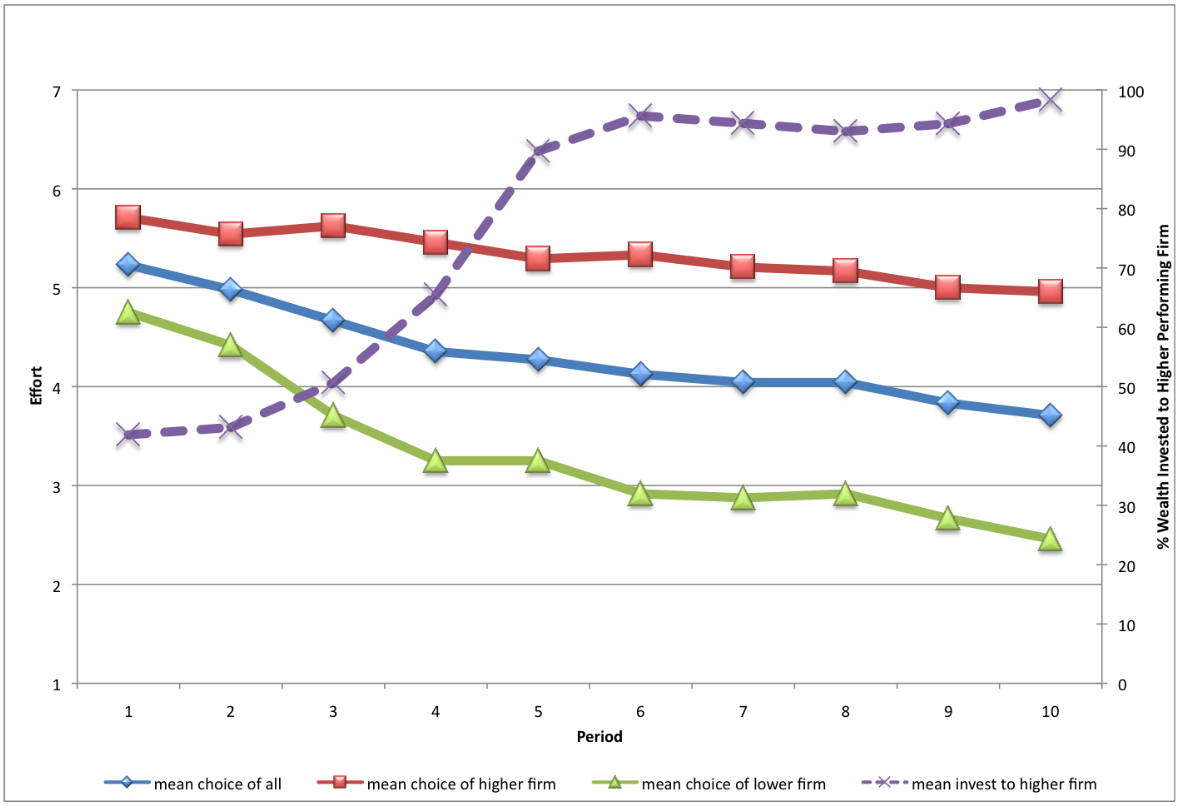


Figure 2.3: Mean Choice of Effort for Two-Firm Treatment

	Smaller group	D	P-value
2 firm setting: higher of the two per session	lower	1	0
vs	higher	0	1
2 firm setting: lower of the two per session	Combined K-S	1	0
2 firm setting: both firms	1 firm	0.567	0.008
vs	2 firm	-0.033	0.983
1 firm setting	Combined K-S	0.567	0.012
2 firm setting: only higher of the two per session	1 firm	0.9	0
vs	2 firm	0	1
1 firm setting	Combined K-S	0.9	0
2 firm setting: only lower of the two per session	1 firm	0.3	0.407
vs	2 firm	-0.1	0.905
1 firm setting	Combined K-S	0.3	0.418

Table 2.6: Two-Sample Kolmogorov-Smirnov Test: Average Effort Choice Per Period

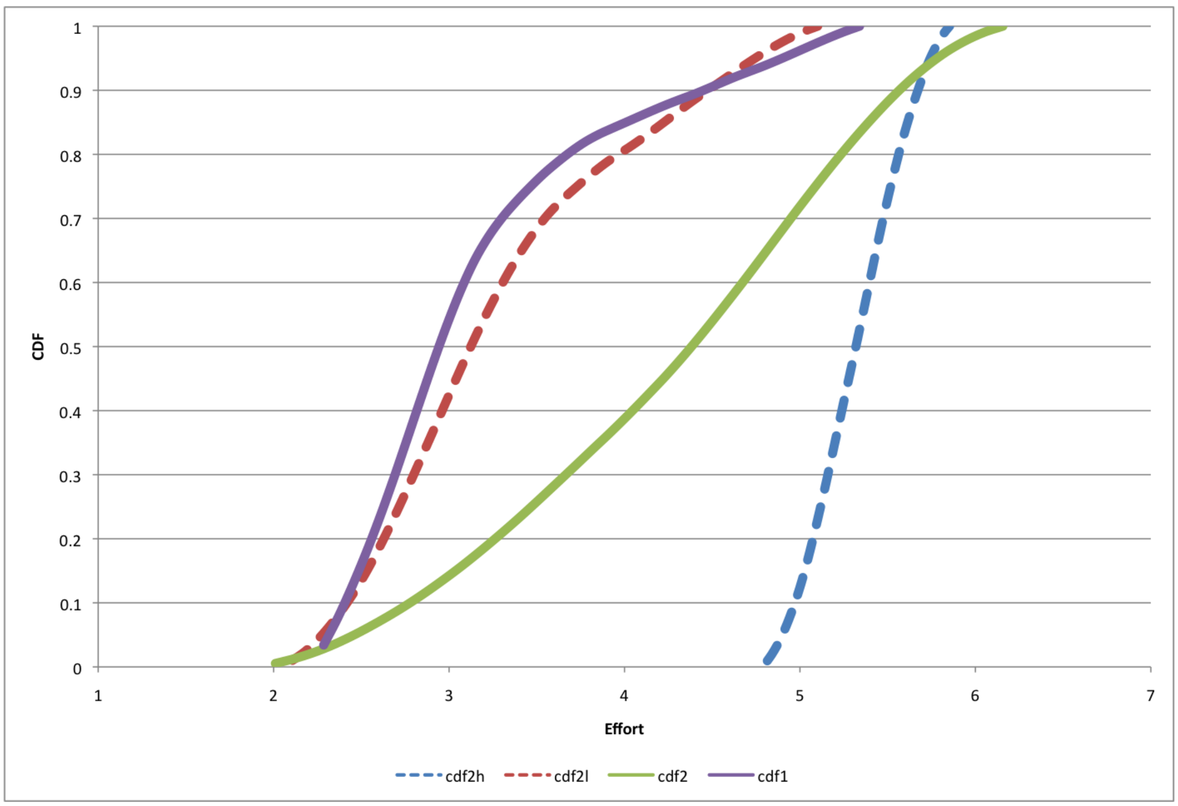


Figure 2.4: Kernel Estimated CDF of Average Effort Choice

cdf2h is the CDF of the higher performing firm from the two-firm treatment. cdf2l is the CDF of the lower performing firm from the two-firm treatment. cdf2 is the CDF of the two-firm treatment and cdf1 is the CDF of the one-firm treatment. These CDFs were generated using the Kernel estimation.

Independent Variable	Dependent Variables: Average Effort Level			
	1 Firm	2 Firm (higher performer)	2 Firm (lower performer)	2 Firm (difference)
Constant	-0.049	3.540***	0.831***	0.443*
	(0.278)	(0.305)	(0.197)	(0.247)
Firm's minimum (lag 1 period)	0.917***	0.699***	0.909***	
	(0.085)	(0.052)	(0.061)	
% wealth invested	0.013***	-0.016***	0.014***	
	(0.005)	(0.003)	(0.005)	
Minimum difference (lag 1 period)				0.864***
				(0.100)
Investment difference				-0.002
				(0.003)
Common AR(1) for all panels	-0.041	0.297	0.121	0.248
Log likelihood	-22.833	-15.105	-36.884	-36.528
Number of obs: 36. Number of panels: 4. Time period: 9				
*p < 0.1, **p < 0.05, ***p <0.01. (Two-tailed test). Numbers in parentheses are standard errors				

Table 2.7: Cross-Sectional Time Series FGLS Regression for Average Effort Level
Difference: Higher performing firm - Lower performing firm

invest their entire endowment, which is not the case in the one-firm treatment. Table 2.9 suggests that the investment behavior at period t is not driven by the firm's minimum effort in period $t-1$ but by the *difference* in the two firm's minimum effort in period $t-1$. The difference in the two firm's minimum effort is higher performing firm's minimum effort minus the lower performing firm's minimum effort. Unsurprisingly, the investment has gravitated towards the higher performing firm such that bigger differences in minimum effort level cause bigger differences in investment level.

Subject Categories	Mean	SE	Min	Max	Obs	P-value
Higher performing firm	98.313	1.305	94.5	100	4	0
Lower performing firm	1.688	1.305	0	5.5	4	
All firms	100	0	100	100	8	
Ho: mean(higher performing) - mean(lower performing) = diff = 0. Ha: diff != 0						

Table 2.8: Descriptive Statistics & T-Test of % Wealth Invested in Two-Firm Treatment at Last Period

Independent Variable	Dependent Variables: Investment			
	1 Firm	2 Firm (higher performer)	2 Firm (lower performer)	2 Firm (difference)
Constant	51.229***	54.265***	45.615***	24.536*
	(6.412)	(12.990)	(11.942)	(14.405)
Firm's minimum (lag 1 period)	11.475***	2.219	-2.24	
	(2.468)	(2.983)	(2.712)	
Minimum difference (lag 1 period)		7.068**	-10.122***	16.587***
		(2.818)	(2.983)	(5.051)
Common AR(1) for all panels	0.373	0.583	0.555	0.583
Log likelihood	-144.530	-148.378	-146.508	-172.381
Number of obs: 36. Number of panels: 4. Time period: 9				
*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test). Numbers in parentheses are standard errors				

Table 2.9: Cross-Sectional Time Series FGLS Regression for Investment
Difference: Higher performing firm - Lower performing firm

2.4.2 One Firm

Figure 2.5 shows the summary results aggregated over all four sessions of the one-firm treatment. Here we see that the mean choice (average minimum) effort level ranges from 2-5 (2-3). According to the FGLS of average effort level in Table 2.7, we find that the average effort level is predominately determined by the firm's minimum in the previous period (coefficient: 0.917), while the percent of wealth invested only has a small but statistically significant effect (coefficient: 0.013).

One might think that investors will always invest everything since they have nothing to lose, given that they are guaranteed at least their investment in return (firm's minimum effort of 1). However, that is not the case. Investors start out by investing over 90% (not 100%) of their wealth in the first period and invest even smaller percentage of their wealth in later periods. Referring to Table 2.10, by last period, the investors are only investing on average of 66% of their wealth. If we subdivide the sample to two groups, firms with minimum higher than 1 and firms with minimum equal to 1, we observe that the average investment to the firm with minimum effort of 1 is only 37.75%. However, over 95% of the wealth is invested whenever the firm's minimum effort is greater than 1. The investment level difference is statistically different at p-value of 0.047. In addition, according to the FGLS in Table 2.9, we conclude that the investment is significantly driven by the previous period's firm's minimum in a positive manner (coefficient: 11.47). Although we cannot distinguish whether the lack of investment is due to spitefulness or a punishment to encourage a higher effort level, we observe that there are lower investments to firms performing poorly. However, withholding investment does not accomplish an increase in effort level since, according to Table 2.7, the investment variable has a positive coefficient of 0.013, which suggests that lowering investment does not increase average effort level.

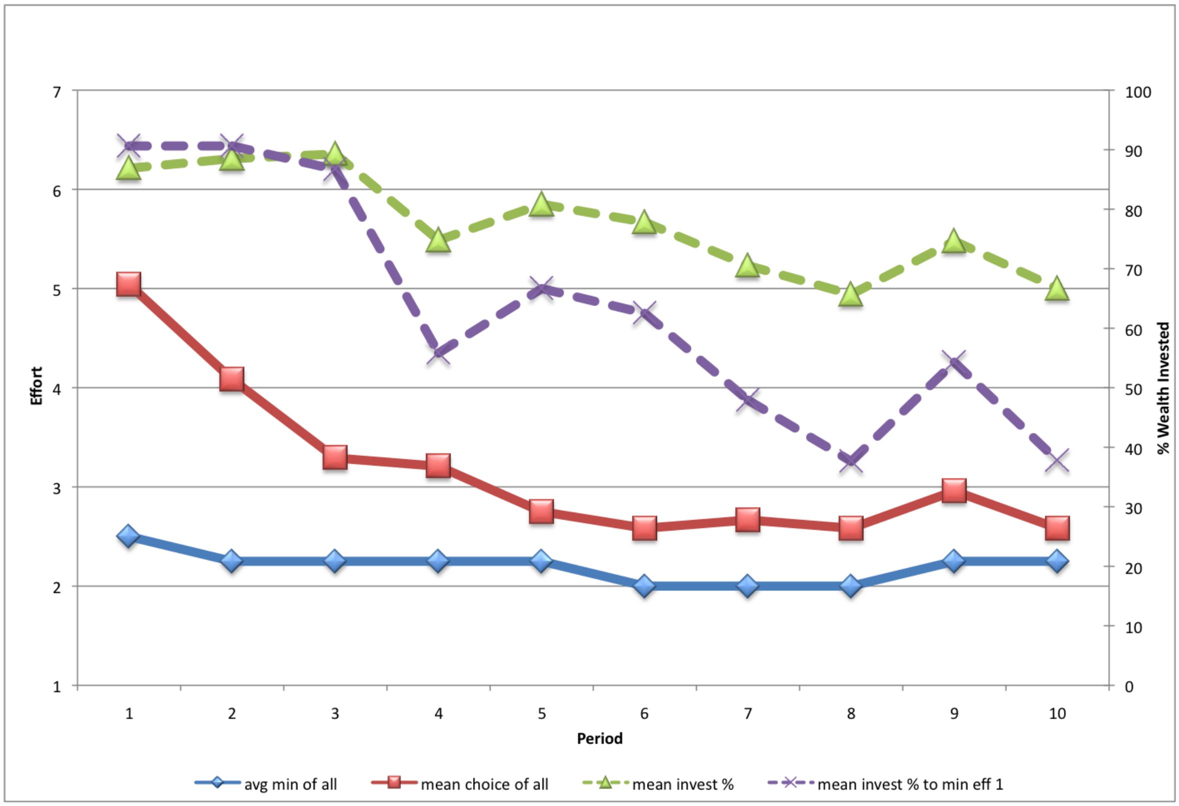


Figure 2.5: Mean Choice and Average Minimum Effort for One-Firm Treatment

Subject Categories	Mean	SE	Min	Max	Obs	P-value
Firms with min > 1	95.625	4.375	91.25	100	2	0.047
Firms with min = 1	37.75	12.250	25.5	50	2	
All firms	66.688	17.531	25.5	100	4	
Ho: mean(firms with min>1) - mean(firms with min=1) = diff = 0. Ha: diff != 0						

Table 2.10: Descriptive Statistics & T-Test of % Wealth Invested in One-Firm Treatment at Last Period

2.4.3 Two Firm vs One Firm

Recall that the difference between one-firm and two-firm treatment is on the investor's outside option depicted by Table 2.4. Figure 2.6 and 2.7 are the pooled graph from the one-firm and two-firm treatment. An important feature of the graph is that the mean choice (average minimum) of effort of the one-firm treatment is statistically no different from the lower performing firm in the two-firm treatment. If there were no effects between having two firms or one firm, we would expect that mean choice (average minimum) of the one firm to be statistically no different compared to the mean choice (average minimum) of both the higher and lower performing firms combined. Referring back to Table 2.6, the two-sample K-S test comparing the distribution of average effort choices, and Figure 2.4 (the CDF of average choices), we can make the following conclusions regarding the comparison of one-firm and two-firm treatment. First, we can reject the null that the distributions from one-firm and two-firm treatment are not different ($p<0.05$). Furthermore, we can state that the two-firm treatment stochastically dominates the one-firm treatment ($p<0.01$). Next, when we compare the higher performing of the two-firm treatment to one-firm treatment, we can reject the null at p-value of 0 that they have the same distribution. In addition, we conclude that the higher performing of two-firm treatment also dominates the one-firm treatment ($p<0.01$). However, when comparing the lower performer of the two-firm treatment to the one-firm treatment, we cannot reject the null that (i) the distributions are the same (p-value of 0.418), (ii) neither one-firm treatment nor the lower performer dominate one another (p-value of 0.407 and 0.905, respectively). In sum, our data supports hypothesis 1. The subjects in two-firm treatment choose a higher minimum effort level than the one-firm treatment. Furthermore, we observe that the results from the one-firm treatment are similar to the results from the lower performing firm.

One reason why we might see such a difference between one-firm and two-firm treatment is that workers start out with only about half of the wealth invested in each firm. Therefore, they work "harder" to earn the rest of the investment. However,

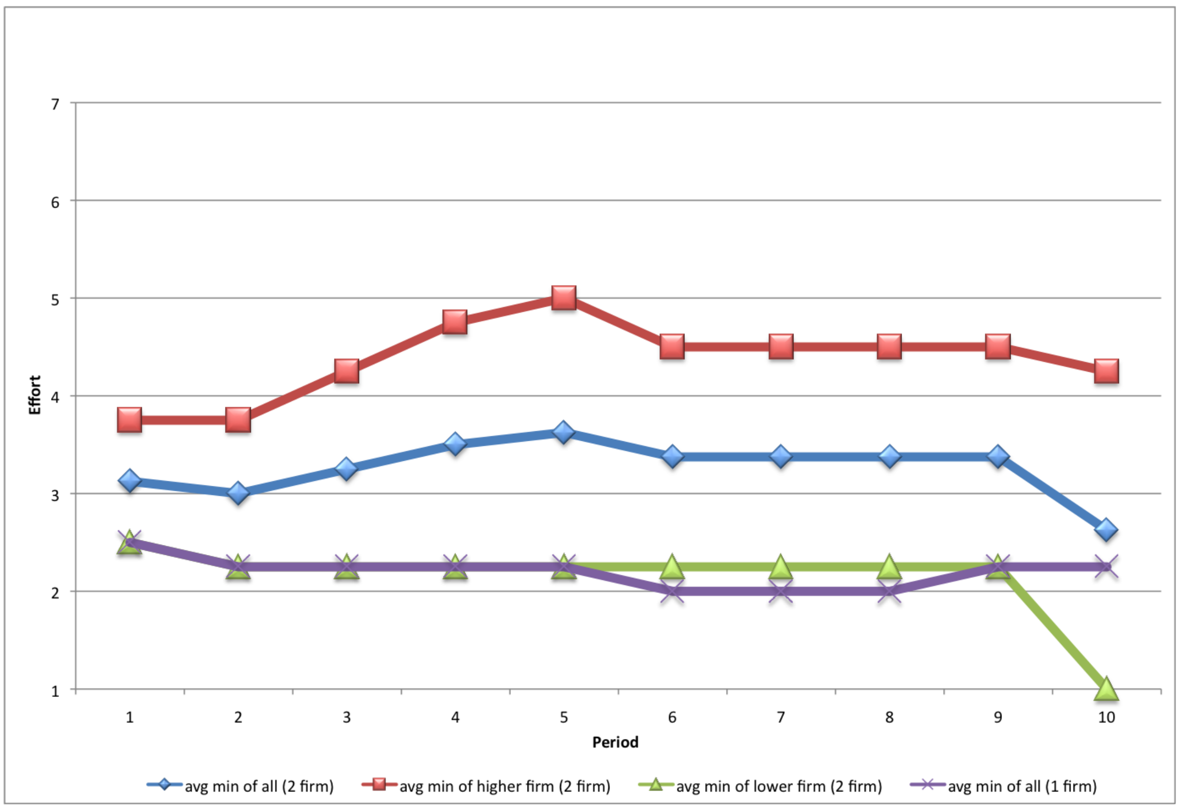


Figure 2.6: Average Minimum Effort: One-Firm Treatment vs Two-Firm Treatment

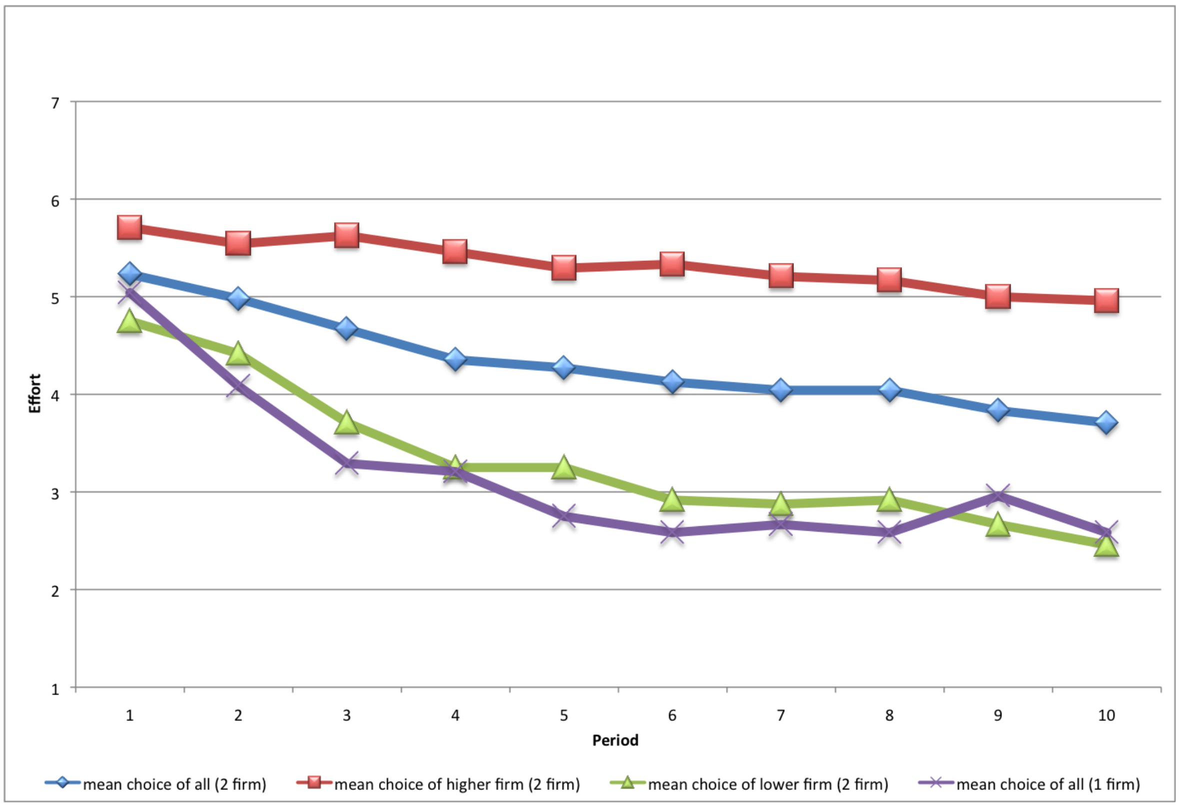


Figure 2.7: Mean Choice of Effort: One-Firm Treatment vs Two-Firm Treatment

in the one-firm treatment, they are offered almost the entire investment from the beginning. Although, it does not change the fact that everyone exerting higher effort, in turn getting a higher minimum effort, is pareto improvement regardless of the treatment, we tested whether firms who had lower levels of initial investment also coordinate to the higher minimum effort in the one-firm treatment. The idea is that the workers will work "harder" to earn the rest of the investment. Our data shows that the initial investment level has no significant effect on individual's initial effort level. By regressing period 1's individual effort level on the first period's investment[10], we obtain a negative but statistically insignificant coefficient of -0.0235 with SE of 0.04737. This is evidence against the argument that workers are exerting higher efforts when they observe low investment in the first period because they want to "earn" higher level of investment in the subsequent period.

[10]Recall that investment decisions are made and shown to the workers before effort levels are chosen.

2.4.4 Wasted Effort

So far we have only considered having a higher minimum effort as an indicator of better coordination. Table 2.11 and Figure 2.8 present the average wasted effort per period by each individual. Comparing various combinations of two-firm treatment and one-firm treatment, and just the high performer of two firm and low performer of two-firm treatment, we do not get any statistically significant differences between the average wasted effort. At best, the p-value is 0.372 and at worst, it is 0.9 in a two-tailed t-test. The average wasted effort across both the one-firm and two-firm treatment is 1.033 per period with standard error of 0.087. Therefore, we conclude that amount of effort wasted does not vary much between treatments.

	Mean	SE	Num of Obs	P-value	
(A) 2 firm setting	1.063	0.120	48	(A) & (B)	0.640
(B) 1 firm setting	0.975	0.109	24	(B) & (C)	0.9
(C) 2 firm setting (higher only)	0.954	0.124	24	(B) & (D)	0.404
(D) 2 firm setting (lower only)	1.171	0.206	24	(C) & (D)	0.372
everyone	1.033	0.087	72		
Ho: mean(X) - mean(Y) = diff = 0. Ha: diff != 0					

Table 2.11: T-Test: Average Wasted Effort Per Period

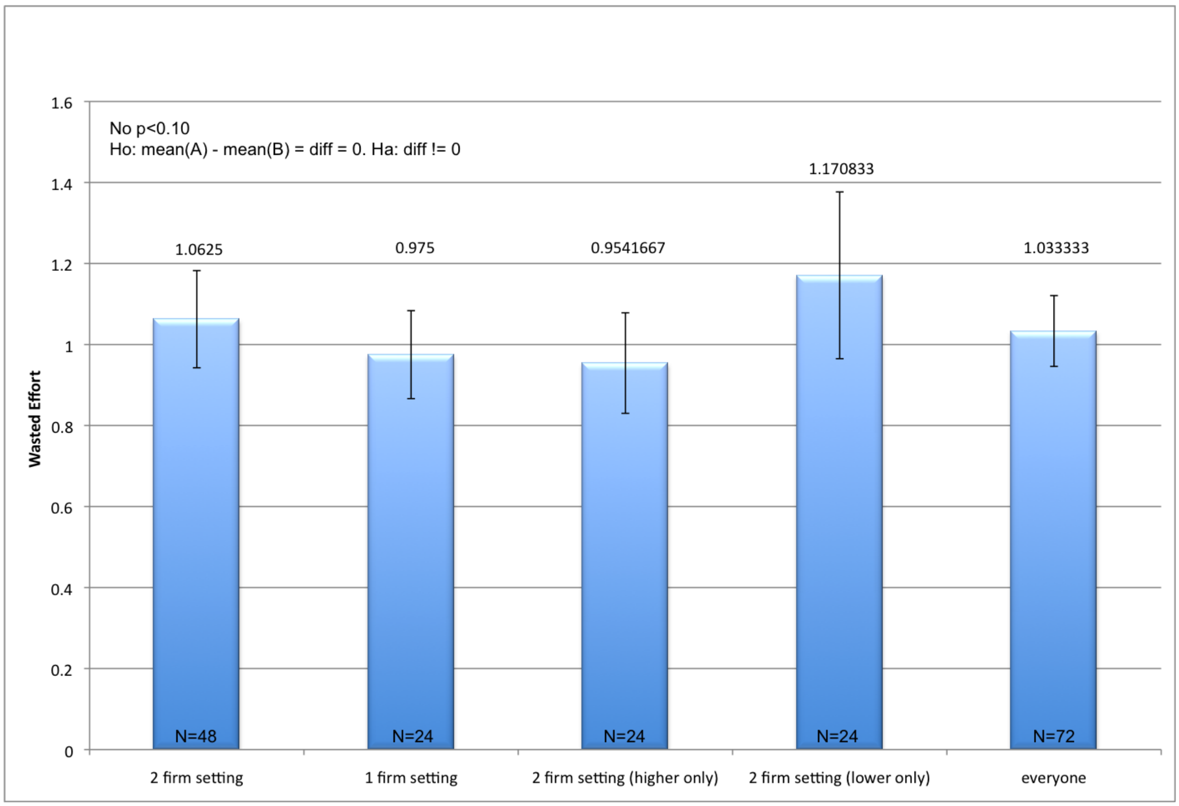


Figure 2.8: Average Wasted Effort Per Period

2.4.5 Convergence

Another method in measuring coordination is the rate of convergence speed to an equilibrium. Figure 2.9 presents the average number of best responses per period. For example, if the average rate of best response is 3, this means that on average, 3 agents are best responding in that period. As the graph depicts, there are no major differences between one-firm or two-firm treatment or between higher or lower performing firm. In all cases, the average rate of best response starts out low, between 1-1.5, and converges to 3.5-4 by the end of the experiment. Therefore, we conclude that the rate of convergence speed does not vary much between treatments.

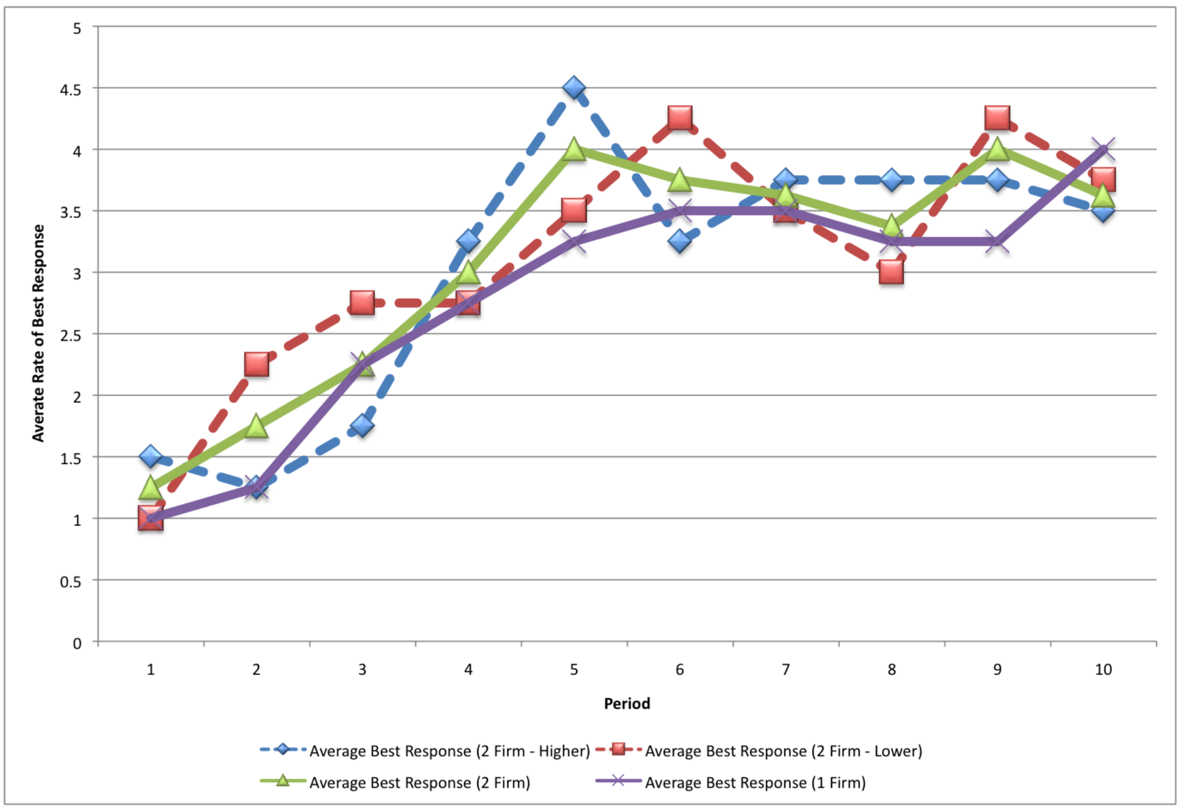


Figure 2.9: Average Rate of Best Response

2.4.6 Cooperation

Here, we address the relationship between the likelihood of cooperation conditioned on a firm's coordination outcome. Table 4.3 is the correlation matrix of our explanatory variables. While one may think that the last period's minimum effort from the coordination game would have the most significant relationship on cooperation, the first period's minimum effort decision had the strongest relationship ($\rho = 0.296$ and p-value of 0.018). This may be the case because when the cooperation treatment was induced by pairing the subjects randomly within the firm, the subjects are conditioning their expectation on the how others behaved at the beginning of the coordination treatment. Not surprisingly, the correlation between firm's minimum effort at period 1 has correlation of 0.77 with firm's minimum effort at period 10.

	pd	gpmin1	gpmin10	gender	exptype	p1	p10
pd	1						
gpmin1	0.296**	1					
gpmin10	0.227*	0.772***	1				
gender	0.244*	-0.196	-0.238*	1			
exptype	0.143	0.346***	0	-0.011	1		
p1	0.037	0.556***	0.422***	-0.144	0.168	1	
p10	0.197	0.726***	0.916***	-0.262**	0.022	0.409***	1
*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test); n=64							

Table 2.12: Correlation Relationship

By running a logit regression of cooperation (1 if cooperated and 0 otherwise, Table 4.4) we are able to make the following conclusions. When looking at the sole effect of individual effort choice, this has no significant effects to the likelihood of cooperation. However, when looking at the sole effect of firm's minimum on the first period, this has a positive significant effect (coefficient: 0.398) on the likelihood of cooperation. This may suggest that the individual's likelihood of cooperation is not based on whether the individual is likely to put in high effort in the first period but whether he comes from a firm that coordinated well. When looking at the multivariable logit regression, we can make the following conclusions. First, the three significant variables are individual choice in period 1 (coefficient: 0.723), firm's minimum in period 1 (coefficient: 2.88), and the interaction effect of firm's minimum in period 1 with individual effort in period 1 (coefficient: -0.424). This result suggests that people who chose higher effort levels in first period are also more likely to choose to cooperate. Furthermore, when a firm has a higher minimum effort, workers in that firm are more likely to choose to cooperate. Therefore, it is not that the subjects are trying to take advantage of fellow subjects who seem to be more trusting, but instead are choosing to cooperate. However, when looking at the interaction effect which has a negative coefficient, this suggests that a person who initially chose a high effort and was damaged by low firm's minimum effort is more likely to choose to defect.[11] The variables relating to period 10's efforts are not significant.

Ind. Variable	Dependent Variable: PD = 1 if cooperate and PD = 0 if defect				
Constant	-0.725	-1.215**	-1.809***	-1.291**	-5.217**
	(0.777)	(0.534)	(0.647)	(0.520)	(2.289)
p1	0.041				0.723*
	(0.140)				(0.408)
p10		0.228			-0.532
		(0.147)			(0.443)
gpmin1			0.398**		2.880***
			(0.173)		(0.935)
gpmin10				0.302*	0.003
				(0.169)	(1.248)
gpmin1xp1					-0.434***
					(0.160)
gpmin1xgpmin10					0.126
					(0.233)
Number of Obs	64	64	64	64	64
Pseudo R2	0.001	0.030	0.068	0.039	0.205

*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test).
numbers in parentheses are standard errors

Table 2.13: Logit Regression: Cooperation

We further subdivide the population to different groups based on effort levels to determine the types and proportion of the subgroup who cooperate in Figure 2.10 and

[11] Recall that $p1 \geq gpmin1$. Therefore, this does not state the converse which suggests that people who initially chosen low effort and realized that $gpmin1$ was higher than his effort are more likely to take advantage of fellow workers in the cooperation treatment.

2.11 and Table 2.14 and 2.15 to supplement the result from the logit regression on Table 4.4. The results from Figure 2.10 and Table 2.14 support the idea that people who come from firms with higher minimum efforts are more likely to cooperate than those from lower minimum efforts. This occurs in two ways. First, when comparing between groups, for example min $< j$ to min $\geq j$, there generally is a statistically significant effect that min $\geq j$ has higher proportion of cooperation. Secondly, when comparing within groups, for example min $< j$ to min $< j+1$, although the effects are not statistically significant, we do observe the the proportion of cooperation is higher for min $< j+1$. In terms of individual choices, the results from Figure 2.11 and Table 2.15 supports that individual effort choices are a poor predictor of the proportion of cooperation.

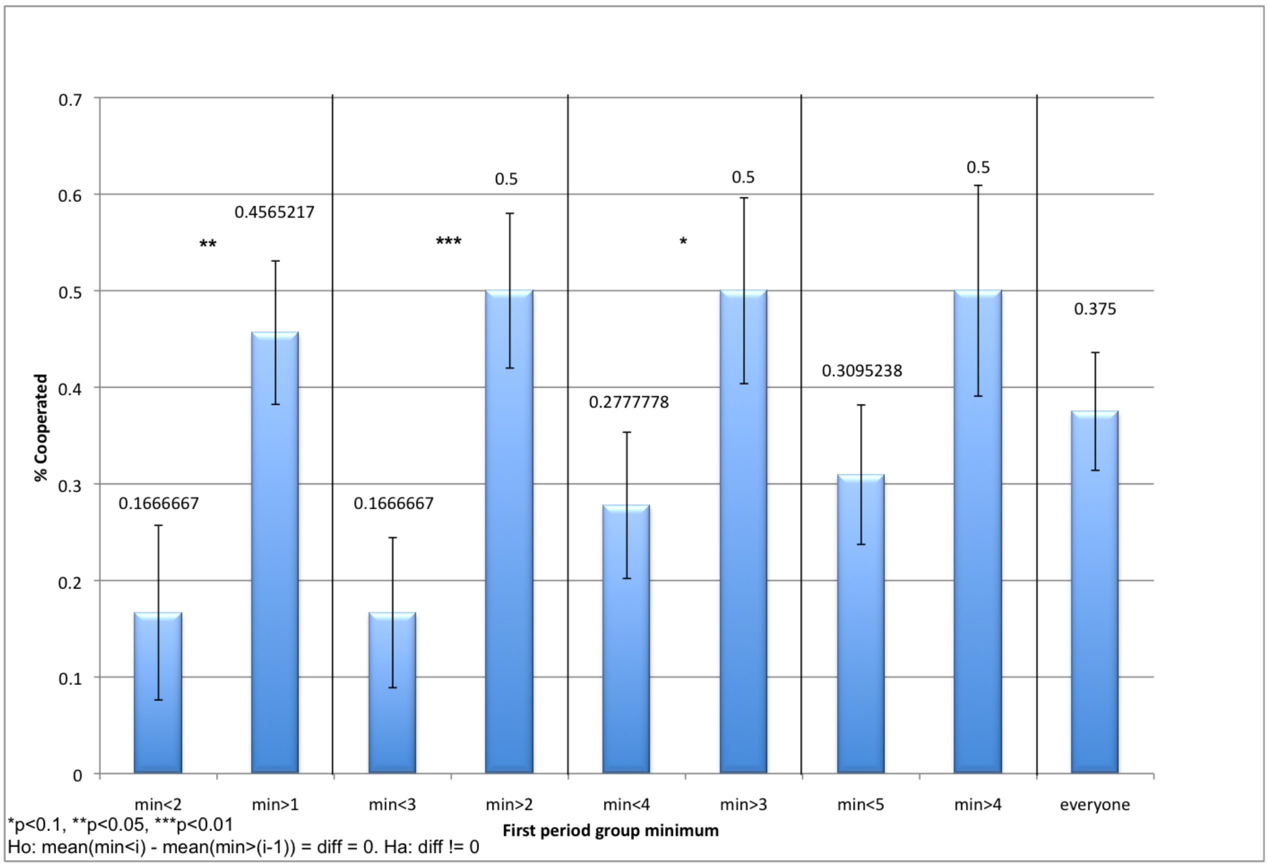


Figure 2.10: T-Test: Average Cooperation Conditional on First Period Firm's Minimum

First Period Firm Min	% Cooperated	SE	Num of Obs	P-value
min<2	0.1667	0.0904	18	0.0315
min>1	0.4565	0.0743	46	
min<3	0.1667	0.0777	24	0.0071
min>2	0.5000	0.0801	40	
min<4	0.2778	0.0757	36	0.0704
min>3	0.5000	0.0962	28	
min<5	0.3095	0.0722	42	0.1393
min>4	0.5000	0.1091	22	
everyone	0.3750	0.0610	64	
Ho: mean(min<i) - mean(min>(i-1)) = diff = 0. Ha: diff != 0				

Table 2.14: T-Test: Average Cooperation Conditional on First Period Firm's Minimum

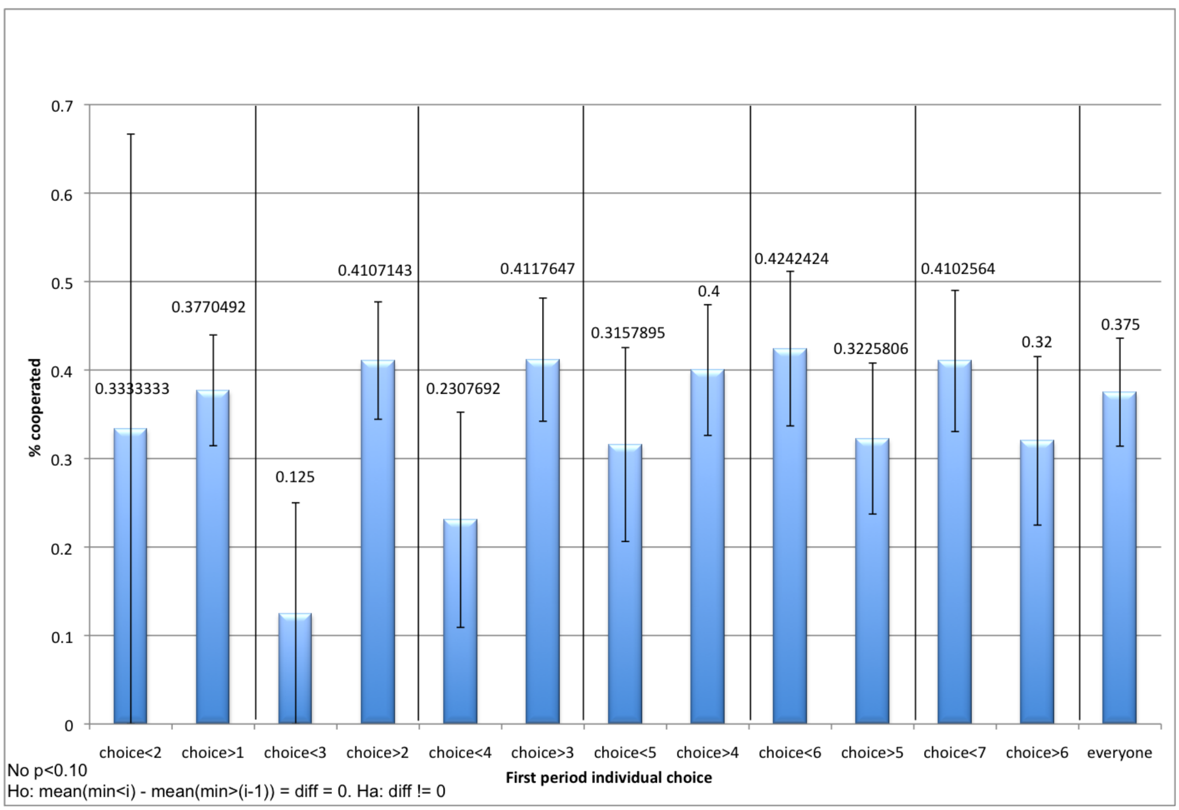


Figure 2.11: T-Test: Average Cooperation Conditional on First Period's Individual Choice

First Period Individual Choice	% Cooperated	SE	Num of Obs	P-value
choice<2	0.3333	0.3333	3	0.8810
choice>1	0.3770	0.0626	61	
choice<3	0.1250	0.1250	8	0.1222
choice>2	0.4107	0.0663	56	
choice<4	0.2308	0.1216	13	0.2355
choice>3	0.4118	0.0696	51	
choice<5	0.3158	0.1096	19	0.5325
choice>4	0.4000	0.0739	45	
choice<6	0.4242	0.0874	33	0.4092
choice>5	0.3226	0.0853	31	
choice<7	0.4103	0.0798	39	0.4747
choice>6	0.3200	0.0952	25	
everyone	0.3750	0.0610	64	
Ho: mean(min<i) - mean(min>(i-1)) = diff = 0. Ha: diff != 0				

Table 2.15: T-Test: Average Cooperation Conditional on First Period's Choice

2.5 Conclusion

We set out to study the relationship of persistent performance differences among seemingly similar enterprises and used corporate culture as part of the explanation. We defined corporate culture as the ability to coordinate and cooperate. Our contributions are twofold: The experimental results support that competition significantly improves coordination which pareto improves everyone's payoff. Furthermore, this increase in coordination also improves the likelihood of cooperating even when defecting is individually beneficial. That is also a pareto improvement in everyone's payoff. An organizational culture of coordinating to an efficient outcome determines the ability to cooperate even when there is no monitoring by the principal. We conclude that the results provided in our experiment supports the theory that the endogenous features of culture developed from coordination and cooperation can help explain the persistent performance differences.

As economists, not only are we concerned with existence of equilibrium and its selection but also efficiency. We have shown that in the coordination game we have studied, higher levels of coordination lead to higher social surplus. Hence the natural question to ask is how to improve coordination and we have provided one way in doing so. In the prisoner's dilemma game, the pareto-efficient outcome is not an equilibrium, but an organization was better able to achieve such outcome for greater social surplus due to the institutional design and corporate culture.

There are many open questions left in this field of study. For example, one can start focusing on different types of contracts for coordination. Furthermore, unlike our design, it would be interesting to see how well the firms in one-firm treatment will coordinate if the investors are not allowed to invest until the 5th period. Of course, the idea of studying coordination and cooperation in organization can be extended to different games as well, such as, the battle of the sexes and the trust game in different organizational structure.

2.6 Appendix

The following 3 pages are sample instructions used in the experiment.

Appendix: Experimental Instructions

Experiment Overview

You are about to participate in an experiment in the economics of decision making. If you listen carefully and make good decisions, you could earn a considerable amount of money that will be paid to you in cash at the end of the experiment.

Please do not talk or communicate with other participants. Feel free to ask questions by raising your hand or signaling to the experimenter.

You will be working with a fictitious currency called Francs. The exchange rate will be specified in the instructions. You will be paid in cash at the end of the experiment.

The experiment consists of a sequence of periods. The total number of periods is unknown.

In this experiment, you will be divided into three groups called Group1, Group 2 and Investors.

Specific Instructions to Group 1 and Group 2

Exchange rate: ______ Francs = _____ USD.

You are assigned to this group with ____ many other participants. Your job is to choose one of the following numbers: {1, 2, 3, 4, 5, 6, 7}. The number you choose will remain anonymous. Your individual payoff is determined by your choice, the choice of others in your group and the investment in your group. The following shows the relationships:

Table 1: Group member's payoff in francs

Your choice of number	Lowest choice of number from all the participants (including you)						
	7	6	5	4	3	2	1
7	2500 + Investment	2100 + Investment	1700 + Investment	1300 + Investment	900 + Investment	500 + Investment	100 + Investment
6	-	2300 + Investment	1900 + Investment	1500 + Investment	1100 + Investment	700 + Investment	300 + Investment
5	-	-	2100 + Investment	1700 + Investment	1300 + Investment	900 + Investment	500 + Investment
4	-	-	-	1900 + Investment	1500 + Investment	1100 + Investment	700 + Investment
3	-	-	-	-	1700 + Investment	1300 + Investment	900 + Investment
2	-	-	-	-	-	1500 + Investment	1100 + Investment
1	-	-	-	-	-	-	1300 + Investment

Investment: The investment made to your group will be known to you prior to your decision making.

Example 1: Let's say your group consists of 5 participants (including yourself). Investment made to your group is 250 francs. You chose number 3 and others chose numbers 5, 4, 2, and 1. The lowest number in your group is 1. Since your choice of number is 3 and lowest number is 1, the table 1 tells you that your payoff is 900 + investment = 900 + 250 = 1150.

Example 2: Let's say your group consists of 3 participants (including yourself). Investment made to your group is 50 francs. You chose number 3 and the other two participants chose numbers 6 and 7. The lowest number in your group is 3. Since your choice was 3 and the lowest number is 3, table 1 tells you that your payoff is 1700 + investment = 1700 + 50 = 1750.

Notice that the more money is invested to your group by investors, then higher is your payoff.

Quiz 1: Let's say your group consists of 2 participants (including yourself). Investment made to your group is 350 francs. You chose number 1. The other participant in the group chose number 2. What is your payoff? What is the other member's payoff?

Specific instructions to investors:

Exchange rate: ______ Francs = _____ USD.

Your decisions, as well as other people's decisions, may affect your outcome. You will be given ____ francs each period. Your job in each period is to determine how much to invest in which of the two groups: group 1 and group 2. You are allowed to invest any amount in any group of your choice. In addition, you are allowed to invest in any combination as you wish. Lastly, you are not obligated to invest your entire endowment at any time. The only restriction is that you cannot invest more than ____ francs in each period. Your individual investment is kept private and only the total investment will be known to the group members.

Example 3: Suppose you have 100 Francs. You can choose to invest 10 francs to one group and 30 francs to the other group and do nothing with the remaining 60 francs. Or you can choose to invest 50 to one group and 50 to the other group.

Your payoffs from the investment are determined by the following table:

Table 2: Investor's payoff for every franc invested in a particular group.

	Lowest choice of number from all the participants within a group you invested						
	7	6	5	4	3	2	1
Payoff	2.5× Investment	2.25× Investment	2× Investment	1.75× Investment	1.5× Investment	1.25× Investment	1× Investment

Notice that with respect to your payoff the groups are identical.

Example 4: you invested 10 francs to group A and 5 francs to group B. The lowest choice of number from group A was 3. From table 2, your payoff from investing in group A is: $1.5 \times 10 = 15$ francs. The lowest choice of number from group B was 1. From table 2, your payoff from investing in group B is: $1 \times 5 = 5$ francs. Total payoff from this period is 15 francs (from group A) + 5 francs (from group B) = 20 francs.

Quiz 2: Let's say you know that the lowest number chosen by group A will be 2 and the lowest number chosen by group B will be 3. You have 10 francs to invest. How much will you invest in group A? How much will you invest in group B? What will be your total payoff at the end of the period?

Procedure Summary

The period will begin and all investors will be given an opportunity to input their investment choices: First for group 1 and then for group 2. Each investor's decision will remain private. If you belong in a group, your screen will not do anything at this time until all decisions have been made. The total investment for each group will be computed and be shown to the members of the group. Members will only observe the total amount invested to the group he belongs.

After groups have been told the investment, group members will then privately choose their number and enter it to the computer. The computer will determine for each group the lowest number chosen within the group. If you are an investor, your screen will not do anything at this time until all decisions have been made. The lowest number for each group will be shown to the members of the same group and to the investors.

Your payoff for the period and your total payoff will be shown. Press continue to begin the next round.

Computer number: _________

Please circle one:
In the experiment, I was
- ♦ an Investor
- ♦ a Group member

If you were a group member, you will be anonymously paired with another person from your previous group.

If you were an investor, you'll be anonymously paired with another investor.

You and the person you are paired with will be playing the following game.

		Your pair's decision	
		A	B
Your decision	A	\$3, \$3	\$1, \$4
	B	\$4, \$1	\$2, \$2

Your decision is?
- ♦ A
- ♦ B

Chapter 3

Designing Experiments with Computational Testbeds: Effects of Convergence Speed in Coordination Games

3.1 Introduction

This paper makes two contributions: First, we use a computational testbed to determine the experimental parameters. Testbeds are useful because they allow us to run many simulations over wide range of parameters very cheaply instead of experimenting with the parameters via pilot sessions. Second, we run the actual experiment using subjects in a laboratory setting to test the predictions made using our testbed. We make the following three predictions using the testbed which are indeed confirmed by subjects in experimental laboratory.

In a minimum effort coordination game, increasing the cost of effort causes:

1. The game converge to a lower minimum effort.

2. An increase in convergence speed to an equilibrium.

3. A non-monotonic change in average payoffs.

The intuition behind the results of the minimum effort coordination game is that there are both negative and positive effects on welfare as cost increases. We use the standard notion of welfare; total surplus or in our case, average payoff. The negative effects of higher cost are in two parts. First, lower payoffs are obtained from the same strategy profile for a higher cost in effort. In addition, the game also converges to a lower effort, which causes a lower payoff in general. The positive effects of higher costs is the faster rate of convergence to an equilibrium. Therefore, there is less wasted effort from agents searching for the equilibrium to converge. In sum, the average payoff increases if positive effects outweigh the negative effects, while the average payoff decreases if the negative effects outweigh the positive effects.

One reason why we implement computation testbed is the general difficulty in determining the specific parameters to use for the results stated above. One may guess and run many pilot sessions to guess the exact parameters but this can be a costly procedure. We propose that a computational testbed, which is often used in other areas of experimental science such as chemistry, offers an alternative solution to this problem.

3.1.1 Agenda

We first start with the theory section where we introduce the minimum effort coordination game, computational testbed, and our theoretical predictions. The details of the computational testbed and its algorithm are provided in the Appendix. Next, we proceed with testable hypotheses and our experimental design. We then provide the experimental results and concluding remarks.

3.2 Theory

3.2.1 Minimum Effort Coordination Game

Minimum effort coordination game, also known as a weakest-link game, takes the following form: Given N agents, every agent chooses an effort level $s_i \in \{1, 2, ..., M\}$, M finite, with payoff function

$$p_i = \alpha \left(\min_{j \in N} \{s_j\} \right) - c(s_i) + \delta \text{ where } \alpha > c > 0, \delta \in \mathbb{R} \text{ for all agents } i \in N \quad (3.1)$$

Best response in this game is for agent i to match the lowest effort from everyone else:

$$s_i = \min_{j \in N \setminus i} \{s_j\}$$

Notice that the minimum effort coordination game is a game of strictly complementarity. In turn, it has multiple equilibria. For this particular class of game, we get pure strategy equilibria that are pareto ranked. The Nash Equilibria for this game are any strategy profile that satisfies the following condition: $\sigma = \{s_1, ..., s_N\}$ where $s_1 = s_2 = ... = s_N$. For example, everyone choosing $s_i = 3 \; \forall i \in N$ is a Nash Equilibrium. Among these M pure strategy equilibria, a strategy profile $\sigma = \{s_1, ..., s_N\} = \{M, ..., M\}$ is the payoff dominant equilibrium, while $\sigma = \{s_1, ..., s_N\} = \{1, ..., 1\}$ is the worst, but is a risk dominant equilibrium.

Please refer to Myung (2008 Working Paper) for a more detailed review and the experimental background of this particular game.

3.2.2 Computational Testbed

A computational testbed is a computer environment that allows us to run simulations in order to make predictions about human behavior. Though these testbeds will likely never be able to perfectly predict human behavior, they are still a useful tool for making these predictions. These testbeds allow us to run simulations of an experiment over a wide variety of parameters. Based on the simulations, we can develop behavioral hypotheses in these games, as well as select interesting parameters to be used in a laboratory experimental setting.

Others have developed computational testbeds in order to design experiments. Arifovic and Ledyard (2005 Working Paper) build computational agents to be used as a testbed for experiments on the Groves-Ledyard mechanism. In particular, the mechanism has one parameter that plays an important role in the speed of convergence. Arifovic and Ledyard make predictions about optimal values of this parameter with their computational testbed, and then confirm these predictions with experiments. Their learning algorithm is a combination of a genetic algorithm with some behavioral intuition. Their computational agents are able to converge quickly, on average in 20 rounds. Their algorithm strongly favors convergence to a single point. Therefore in a game like battle of the sexes, their algorithm cannot support the commonly observed behavior where players learn to alternate meeting places. Our algorithm uses pattern recognition, and is therefore able to capture this behavior.

For our study, the algorithm determines which choice each agent makes in each period of a repeated game. This choice depends on the history of play as well as the agent's current state. After each agent made their choice, the choices and payoffs are revealed to all agents. The agents then update their history and current state, and make their choice for the following round.

Two main features of this algorithm are the pattern recognition scheme and the agent's states. The experiments of Sonsino and Sirota (2003) show that subjects are able to sustain patterns of Nash equilibria (alternate, not randomly mixed, between multiple equilibria). Even in 2-by-2 games, the probability of sustaining a pattern of Nash equilibria for n rounds by random choice decreases exponentially as n increases; yet subjects are still able to sustain these patterns. People's ability to sustain these patterns of equilibria provide evidence that they are in fact recognizing these patterns. Therefore, pattern recognition is a natural feature when modeling human behavior in repeated interactions. Our pattern recognition scheme is a modification of the k-nearest neighbor classification algorithm from machine learning (Dasarathy 1991). Patterns are recognized by first identifying the current play (the most recent choices in the history) and then finding previous plays that are similar to the current play. The prediction for next round is a weighted average of the outcomes of these similar plays. In each round, agents make their choice based on their current state, which are given by two parameters, γ and σ. The γ parameter represents an agent's current level of confidence. This is determined by how well that agent predicts what the other agents will do. The σ parameter represents the agent's satisfaction of the current play of the game. If the agent is not satisfied and wants to change what is happening in the game, then σ is close to 1. If the agent is satisfied with how the game is going then σ is close to 0. When all agents have high values of γ and low values of σ, then each agent's choice has low variance and each agent is satisfied with the predicted outcome of their choice, so the algorithm has converged.

Another important aspect in the algorithm is that agents are not able to calculate exact best-responses to their predictions. Instead, agents determine best responses by randomly sampling from the strategy space, and keeping the strategy that gives the highest payoff. This is important for two reasons. First, it allows for completely general payoff functions. Because the explicit best response function isn't required, the payoff functions need not be continuous nor differentiable. Also, it allows agents to have different levels of intelligence by changing the number of samples they take. For example, a very intelligent agent has a good grasp of the payoff function, and therefore is able to find the best response. This can be modeled by an agent who takes a large number of random samples to find the best response. Conversely, a very unintelligent agent is not able to find the best response. This can be modeled as an agent that takes a very small number of samples to find the best response.

For a more detailed description of computational testbeds in economics, see Romero (2008 Working Paper). We have attached the algorithm and a detailed mathematical description in the Appendix.

3.3 Prediction

We run simulations using the algorithm on the minimum effort coordination games and develop testable experimental hypotheses. The benefit of using computational agents is that simulations are essentially costless, which allows us to run many trials for each parameter value.

Previous experiments on the minimum effort coordination game have focused on differences in cost and group size. The experiments have typically compared two different parameter values: a low and high cost or a small and large group (Goeree and Holt 2005). Experiments examining a large set of parameters are difficult due to constraints on the number of subjects in a given subject pool, as well as monetary costs for running large experiments. Simulations using the algorithm provide a testbed to simulate these experiments for many different parameter values. Unlike the binary comparisons, examining a larger set of parameters will give us a better understanding of the behavior which may have been overlooked in the past.

From the minimum effort coordination game defined in the previous section using equation 3.1, we run simulations with $\alpha = 1$, $\delta = 0$, $s_i \in [0, 1]$ for groups of four agents with 9 different costs, varying from $c = 0.1$ to $c = 0.9$. At each parameter value, we run 300 simulations lasting for 50 rounds.

Convergence Point: We find that higher costs lead to lower convergence points. Convergence points are the average play over the last 10 periods of the repeated game. The convergence points of these simulations are displayed in Figure 3.1. This is consistent with experimental results from minimum effort coordination games as shown in Goeree and Holt (2005).

Convergence Speed: We then examine the effect of different costs on speed of convergence.[1]

Based on the simulations, we find that the number of rounds required to converge increases with c. A plot of convergence as a function of c is displayed in Figure 3.2 (higher bars mean slower convergence). The intuition for increase in speed of

[1] We will use convergence in γ as a measure of convergence. See Appendix.

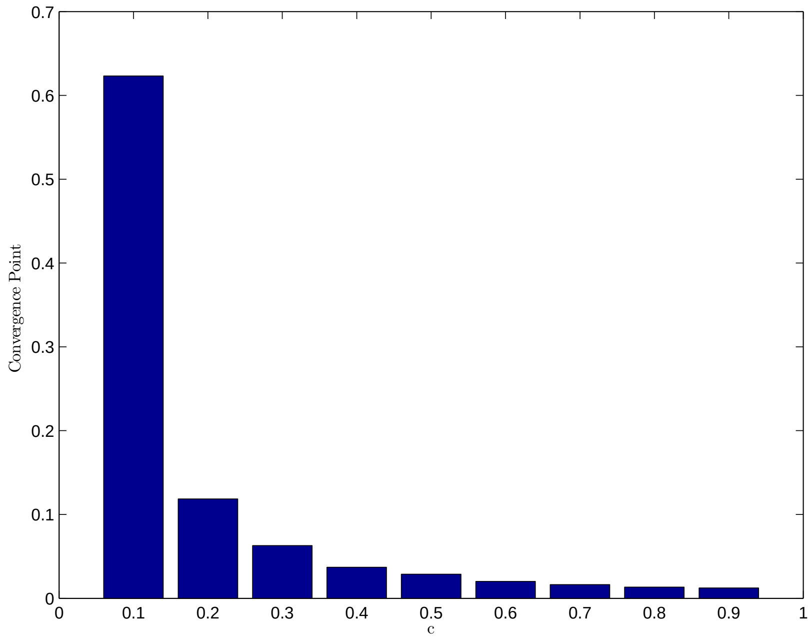


Figure 3.1: Convergence Points as a Function of Cost

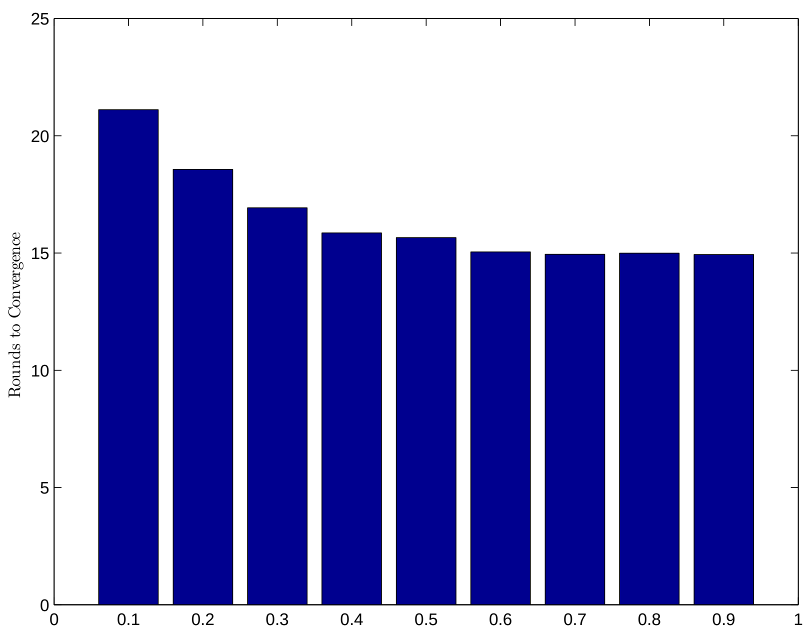


Figure 3.2: Convergence Speed as a Function of Cost
Higher bars indicate slower convergence

convergence for higher cost is simple; it is more expensive for agents to search for different outcomes or experiment with different strategies.

Average Payoff: These convergence results have some interesting effects on the agent's payoffs. When agents do not all choose the same effort (i.e., best respond), the outcome is pareto inefficient. If all agents chose the minimum effort for a given strategy profile, then everyone's payoff would be weakly higher, with at least one receiving a strictly higher payoff. Since it is inefficient when all agents are not choosing the same effort, slow convergence may lead to lower average payoffs. The average payoff per agent for different costs is displayed in Figure 3.3. It is difficult to compare the welfare between two experiments with different costs because they have different payoff functions. Even though welfare is difficult to compare, the payoff for any given strategy profile is lower when the cost of effort is higher. Intuition thus suggests that higher cost of effort should lead to lower average payoffs in the repeated game. However, we argue that higher cost can actually lead to higher payoffs. The increase in payoffs due to faster convergence outweighs the decrease in payoffs due to higher cost. Note that the difference in average payoff shrinks as number of rounds increases in Figure 3.3. This result is due to the fact that the positive welfare of faster convergence gets averaged out by the negative welfare of higher cost in effort as the game is played for more periods.

3.3.1 Hypotheses

We test the following three hypotheses that were generated by the computational testbed in the experimental laboratory:

Hypothesis 1. Convergence Point: The game will converge to a pareto dominated payoff as the cost of effort increases.

Hypothesis 2. Convergence Speed: The game will converge faster to an equilibrium as the cost of effort increases.

Hypothesis 3. Average Payoff: The average payoff does not monotonically decrease as the cost of effort increases.

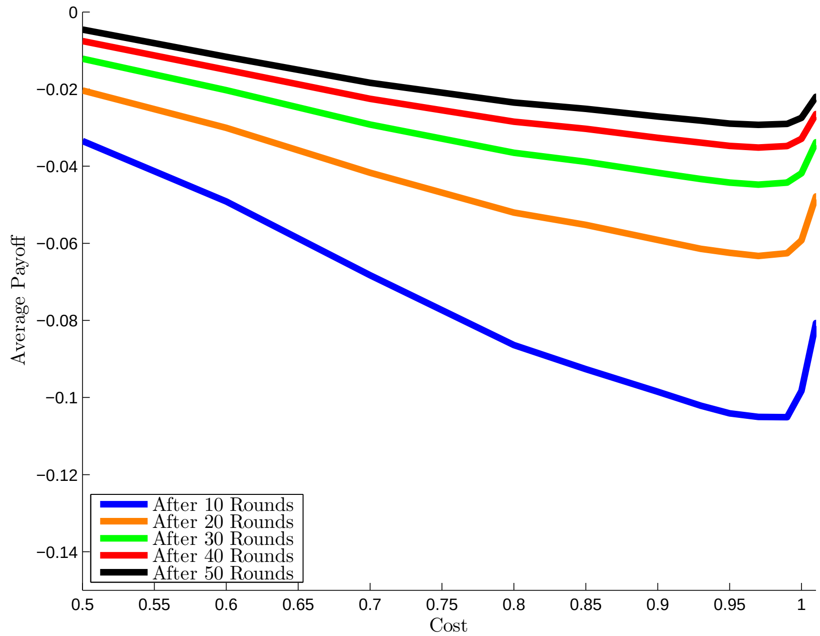


Figure 3.3: Average Payoffs for Different Costs in Minimum Effort Coordination Game as a Function of Number of Rounds

3.4 Experimental Design

3.4.1 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. All students were registered as subjects with CASSEL (signed a general consent form) and the experiment was approved by the local research ethics committee at both universities. These labs consist of over 30 working computers divided into a cubicles, which prevents students from viewing another student's screen.

The experiment was 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, and the experimenter explained the instruction in detail out-loud. Participants were also given a brief quiz after instruction to insure proper understanding of the game and the software. A copy of the instruction, as well as the payoff tables, are available in the Appendix.

The subjects were randomly assigned to their roles in the experiment. Furthermore, no one participated in more than one experiment. The identity of the participants as well as their individual decisions were kept as private information. However, each groups knew their own minimum effort. Experiment used fictitious currency called francs. The participants were fully aware of the sequence, payoff structure, and the length of the experiment. All participants filled out a survey immediately after the experiment.

3.4.2 Details of the Experiment

A total of 20 subjects participated in each session. These 20 subjects were split into 5 groups of 4, and each group used a different cost parameter. The entire session was divided into 5 blocks, and each block was divided into 15 rounds. After each block, the subjects were randomly rematched (with replacement) to another group of 4 and were randomly reassigned another payoff parameter (with replacement). See Figure 3.4 for the time line.

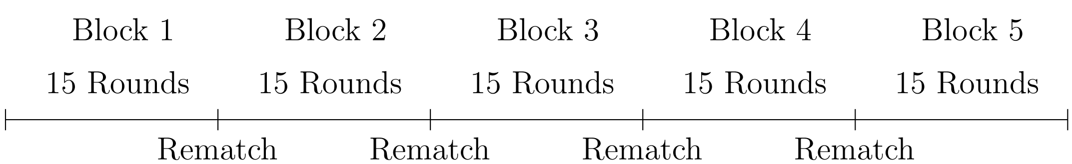


Figure 3.4: Timeline and Matching Structure for the Experiment

Subjects played a minimum effort coordination game per round. Their task was to choose an effort level,

$$s_i \in \{1, ..., 7\}$$

and their payments were determined by the following payoff function

$$p_i = 1000 \left(\min_{j \in N} \{s_j\} \right) - c(s_i) + 5950$$

In each block, there were 5 groups each with a different payoff matrix based on

$$c \in \{50, 500, 900, 950, 990\}$$

The subjects were shown the payoff table displayed in Table 3.1, with the calculation already completed for the subjects. The group size, randomization, and the fact that everyone in the group were using the same payoff table were common knowledge. However, the group's own minimum effort was private information to the group and was not available to the outside members.

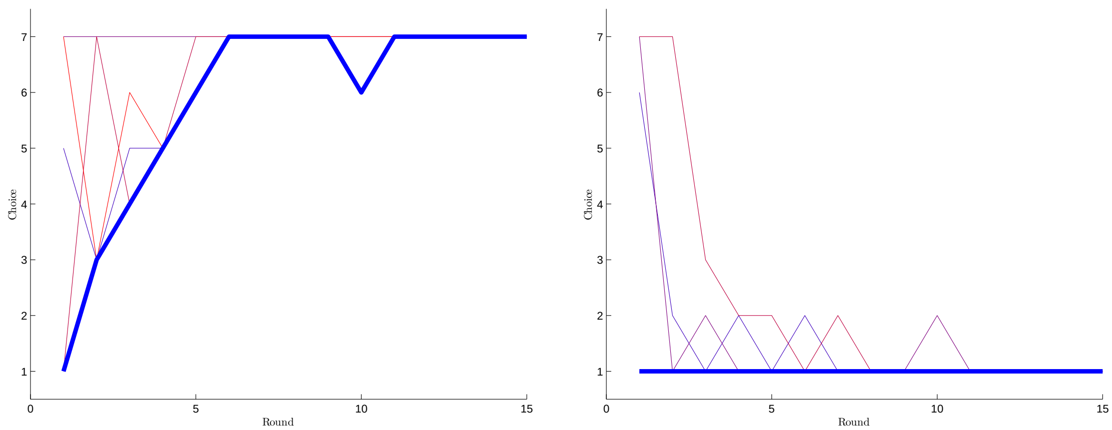
	Minimimum effort of all agents						
***i*'s Effort**	7	6	5	4	3	2	1
7	$12950 - 7c$	$11950 - 7c$	$10950 - 7c$	$9950 - 7c$	$8950 - 7c$	$7950 - 7c$	$6950 - 7c$
6	–	$11950 - 6c$	$10950 - 6c$	$9950 - 6c$	$8950 - 6c$	$7950 - 6c$	$6950 - 6c$
5	–	–	$10950 - 5c$	$9950 - 5c$	$8950 - 5c$	$7950 - 5c$	$6950 - 5c$
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 3.1: Sample Payoff Table that was used in the Experiment

Calculations were already filled in for the subjects

3.5 Experimental Results

Figure 3.5 illustrates sample results from one of the block of sessions. Figure 3.5 (a) is an example where there is a high level of coordination (converging to an effort level of 7) and Figure 3.5 (b) is an example where there is a low level of coordination (converging to an effort level of 1).



(a) Coordination to High Effort

(b) Coordination to Low Effort

Figure 3.5: Sample Results From One of The Block of Session for Illustration Purpose
The thin lines represent individual choices and the thick line represents the group's minimum choice

3.5.1 Convergence Points

First, we test the hypothesis that higher costs will lead to lower convergence points and provide the results in Table 3.2, Table 3.3, and Figure 3.6. These results are taken from the average choice of the last 5 rounds and it supports the hypothesis that the average choice drops as the cost parameter increases. While the cost parameter between $c \in \{50, 500\}$ provides a high level of average choice around 4.5 to 5, the average choice drops significantly lower to 1 to 1.2 for cost parameter between $c \in \{900, 950, 990\}$. Although we do not get a significant difference between the means from $c = 900$ and $c = 950$, we do obtain significant differences in the right direction for the rest of the mean comparisons.

	c = 50	c = 500	c = 900	c = 950	c = 990
Choice	4.8485	4.5000	1.2864	1.2606	1.1242
SE	0.0932	0.0975	0.0363	0.0391	0.0244

Table 3.2: Average Choice for Different Cost Parameters

	$\mu_{50} > \mu_{500}$	$\mu_{500} > \mu_{900}$	$\mu_{900} > \mu_{950}$	$\mu_{950} > \mu_{990}$
p-value	0.0126	0	0.1677	0.0023
t-value	2.2428	21.2006	-0.9642	2.8422

Table 3.3: Average Choice Comparison

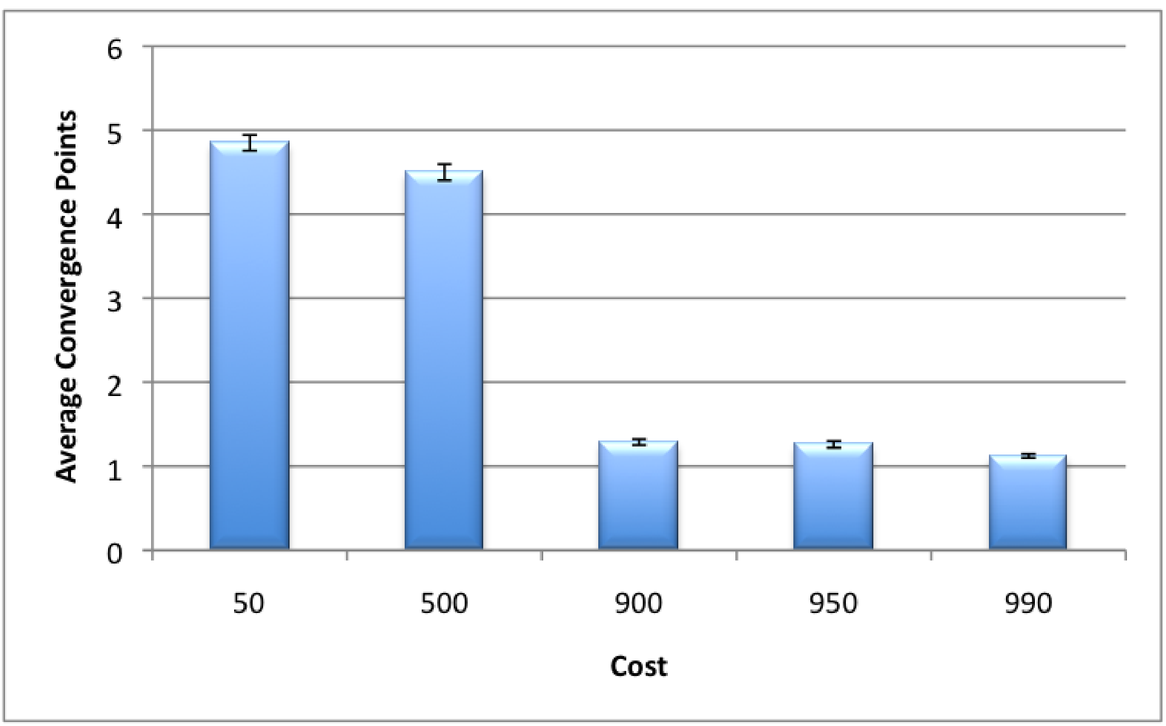


Figure 3.6: Average Convergence Points for Different Cost Parameters

3.5.2 Convergence Speed

Comparing convergence speed is bit trickier than comparing convergence points. Consider the following example in Figure 3.7. If one were to use a rule that the convergence occurs when there are no deviations (i.e., everyone is best responding), then there won't be any convergence until round 13 in the example. When studying experimental results with subjects from a laboratory, this may be too conservative of a criterion. Noisy choice in human behavior is often expected in experiments. Whether these noises are rational or not is another story. However, there are many different ways of modeling noisy choices, such as the Quantal Response Equilibrium (McKelvey and Palfrey 1995), the Level-K Model, and the Cognitive Hierarchy Model (Camerer, Ho, and Chong 2004), among others.

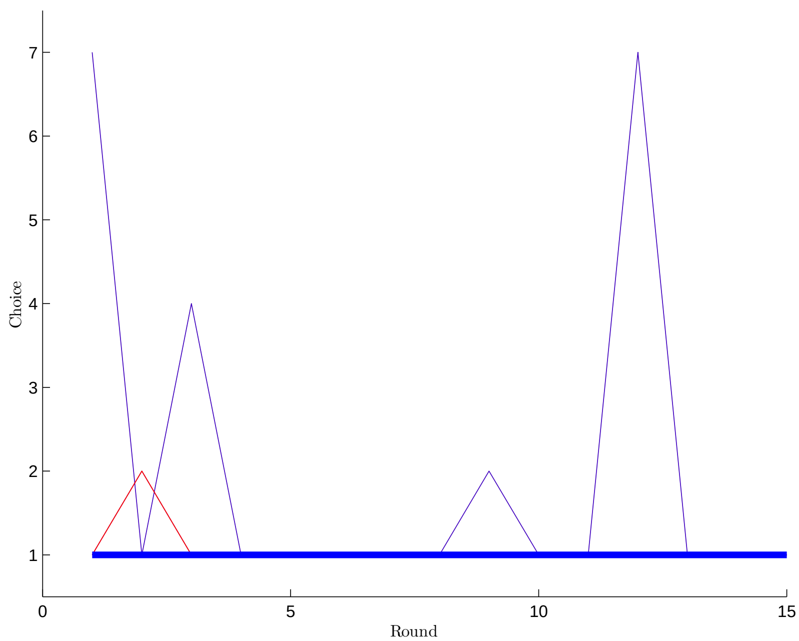


Figure 3.7: A Sample Result From a Block of Session
The thin lines represents individual choices and the tick line represents the group's minimum choice

Here, we provide two means of measuring convergence. First, we use a more quantitative measure of convergence called v-bounded condition. Then we introduce a more qualitative and intuitive measure of convergence called the similarness condition.

Definition: We say that the game has converged to a particular equilibrium at round t under *v-bounded condition* if the variance of number of strategies chosen is always less than v for every round starting from t. Specifically, $var_{t+m}(\sigma_1, ..., \sigma_n) \leq v$, $\forall m \geq 0$.

For example, if the strategy profile σ consists of $[3, 3, 3, 4]$, this will require that a variance parameter of $v \geq 0.25$ will be needed to consider this strategy profile as converged under the v-bounded condition. See Table 3.4 for other samples of strategy profile and its required variance parameter for v-bounded condition.

$\boldsymbol{\sigma}$	**Minimum** v
$[3, 3, 3, 4]$	.25
$[3, 3, 4, 4]$	.33
$[2, 3, 3, 4]$	.66
$[3, 3, 4, 4]$	.92
$[3, 3, 3, 5]$	1

Table 3.4: Samples of Strategy Profile and its Required v Parameter for v-bounded Condition

Using the v-bounded condition criterion for the notion of convergence, Figure 3.8 illustrates the average rounds it took for the game to converge.[2]Although convergence speed seems to be increasing as the cost parameter increases, differences are not statistically significant. Consider the following example from Figure 3.7 to illustrate why the v-bounded condition may not be a good criterion: We would require $v \geq 9$ in order to allow this particular example to be considered converged under v-bounded condition due to a large jump in choice of effort by one of the players in round 12. This does not take into account that the deviation is by one person for only one period. However, intuitively, one may think that this game has converged at round 4.

Therefore, we use a more intuitive and qualitative measure of convergence. We consider the number of different strategies being used from the strategy profile for a given round. We say the game has converged to a particular equilibrium if a high

[2]We drop the last round deviation because there may be end game effects.

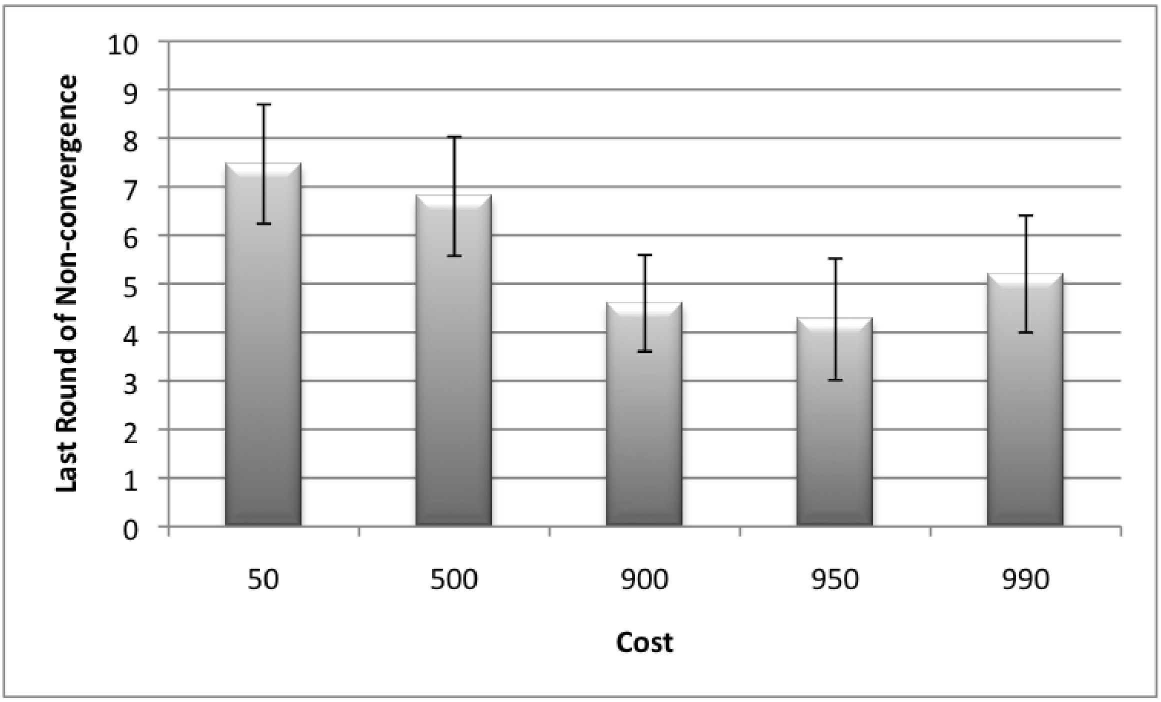
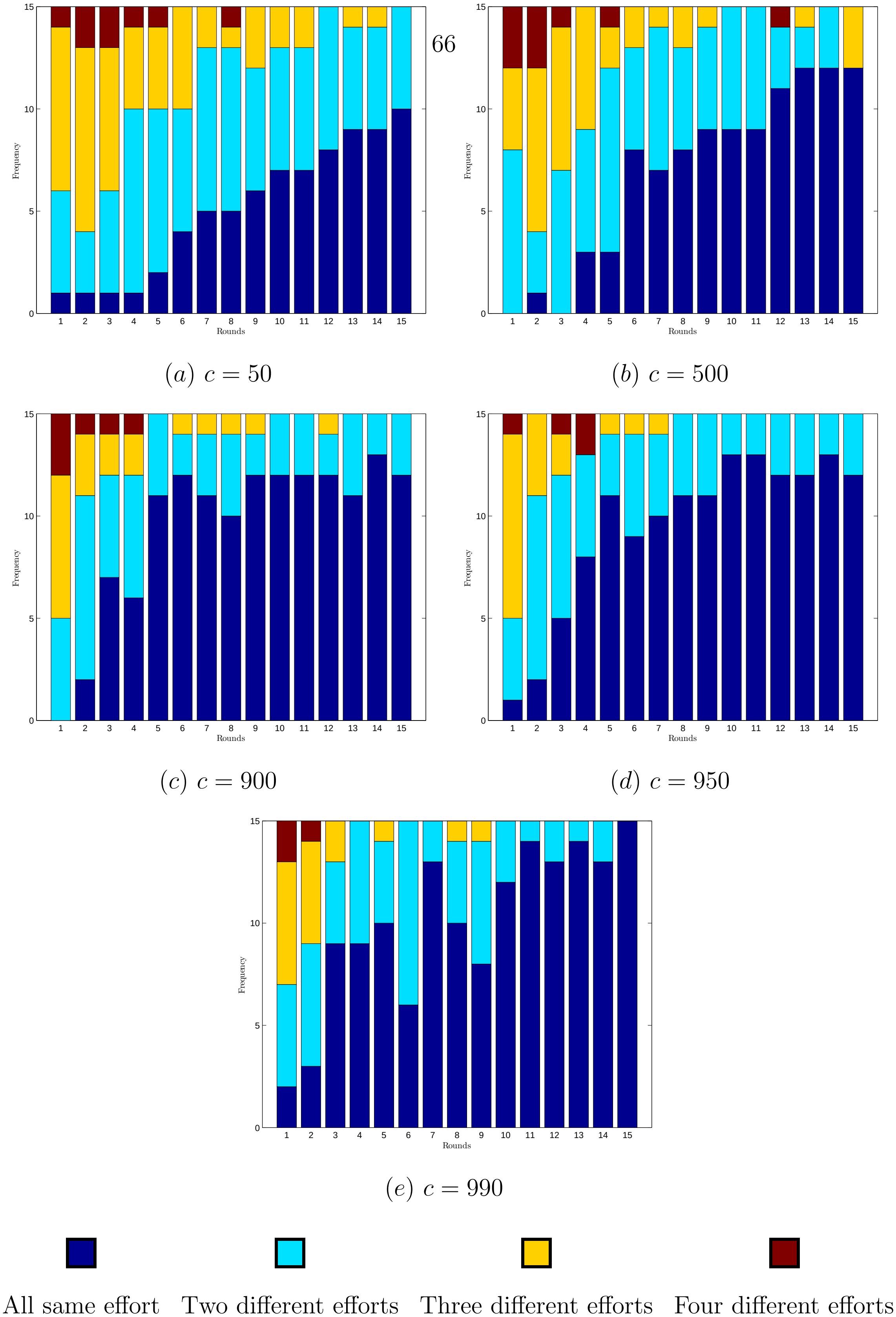


Figure 3.8: Number of Rounds Needed for Convergence for $v \leq 0.5$

proportion of people use the same strategy. We define this as *similarness condition*. The added benefit of the similarness condition is that it does not unreasonably penalize cases where 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 $[1, 1, 1, 7]$.

Figure 3.9 shows the frequency of different strategies played for various cost of effort. If the game is indeed converging faster under the similarness condition, we expect to see a higher frequency of blue and sky-blue, which indicates everyone playing the same strategy and three people playing the same strategy, respectively. As the cost of effort increases, we observe an increase in frequency of blue and sky-blue. This increase in frequency holds true for any given round. Furthermore, the frequency of blue and sky-blue also increases as the experiment proceeds (number of round increases). In other words, there are many different strategies being played in the initial round but subjects learn to best respond.

Using this similarness condition as a convergence criterion, we conclude that the game converges faster to a particular equilibrium as the cost of effort increases.



$(a)\ c = 50$ $(b)\ c = 500$ $(c)\ c = 900$ $(d)\ c = 950$ $(e)\ c = 990$

Figure 3.9: Frequency of Different Strategies Played for Various Costs

3.5.3 Average Payoff

Finally, we analyze the behavior of the average payoff as the cost increases. Refer to Figure 3.10 and Table 3.5 and 3.6 to see the average payoff and their mean comparisons up to 4 rounds for each of the cost parameters from the experiment. What we observe, and is statistically significant, is that the average payoff does decrease from $\mu_{50} = 9088$ at $c = 50$ to $\mu_{950} = 4846$ at $c = 950$. However, as the simulation has predicted, the average payoff at $c = 990$ of $\mu_{990} = 5136$ is significantly higher than the average payoff at $c = 950$ of $\mu_{950} = 4846$ ($p < 0.05$). Although the average payoff of $\mu_{900} = 4968$ at $c = 900$ is higher than the average payoff of $\mu_{950} = 4846$ at $c = 950$, they are not statistically different.

Given that we observe a non-monotonicity in average profit as a function of cost of effort in the first 4 rounds, we test the significance after the entire block of the experiment (15 rounds). The result is displayed in Figure 3.11 and Table 3.7 and 3.8. Again, we observe a similar pattern to the results from the first 4 rounds. The average payoff of $\mu_{990} = 5650$ at $c = 990$ is significantly greater than the average payoff of $\mu_{950} = 5560$ at $c = 950$ ($p < 0.1$). Furthermore, the average payoff in this setting is the lowest at $c = 950$, which is also lower than the average payoff of $\mu_{900} = 5652$ at $c = 900$ ($p < 0.1$).

Another topic worth mentioning is that the difference between the average payoff when $c = 990$ and $c = 950$ diminishes as more rounds are played. This confirms the prediction made by the simulation in Figure 3.3. As more rounds are played, the positive welfare from the lower cost averages out the negative welfare from the wasted effort. For example, after 4 rounds, the difference in average payoff is $\mu_{990} - \mu_{950} = 288.9583$. But, after 15 rounds, the difference decreases to $\mu_{990} - \mu_{950} = 90.1889$. In other words, the non-monotonicity of average payoff is most salient at the initial phase of the game.

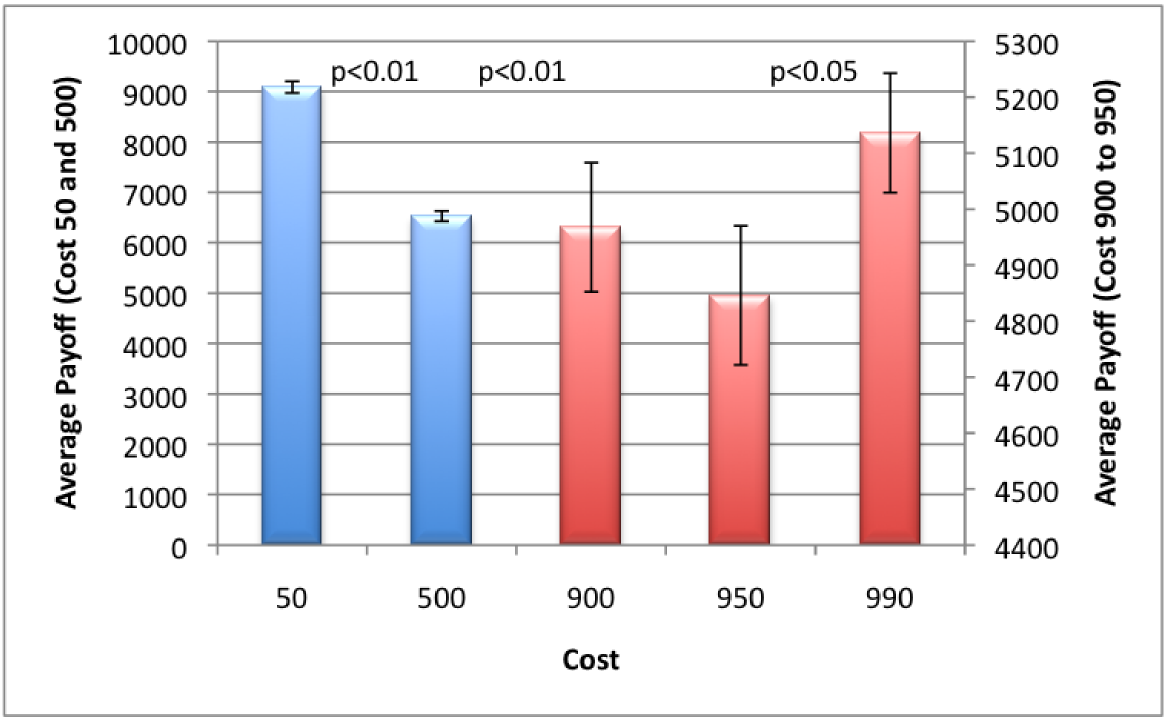


Figure 3.10: Average Payoff After 4 Rounds

	c = 50	**c = 500**	**c = 900**	**c = 950**	**c = 990**
μ	9088	6527	4968	4846	5136
SE_{μ}	118.05	103.36	115.42	124.51	106.56

Table 3.5: Average Payoffs for Different Cost Parameters After 4 Rounds

	$\mu_{50} > \mu_{500}$	$\mu_{500} > \mu_{900}$	$\mu_{900} > \mu_{950}$	$\mu_{950} < \mu_{990}$
p-value	0	0	0.2366	0.0393
t-value	16.3234	10.05	0.7178	1.7632

Table 3.6: Average Payoffs Comparison After 4 Rounds

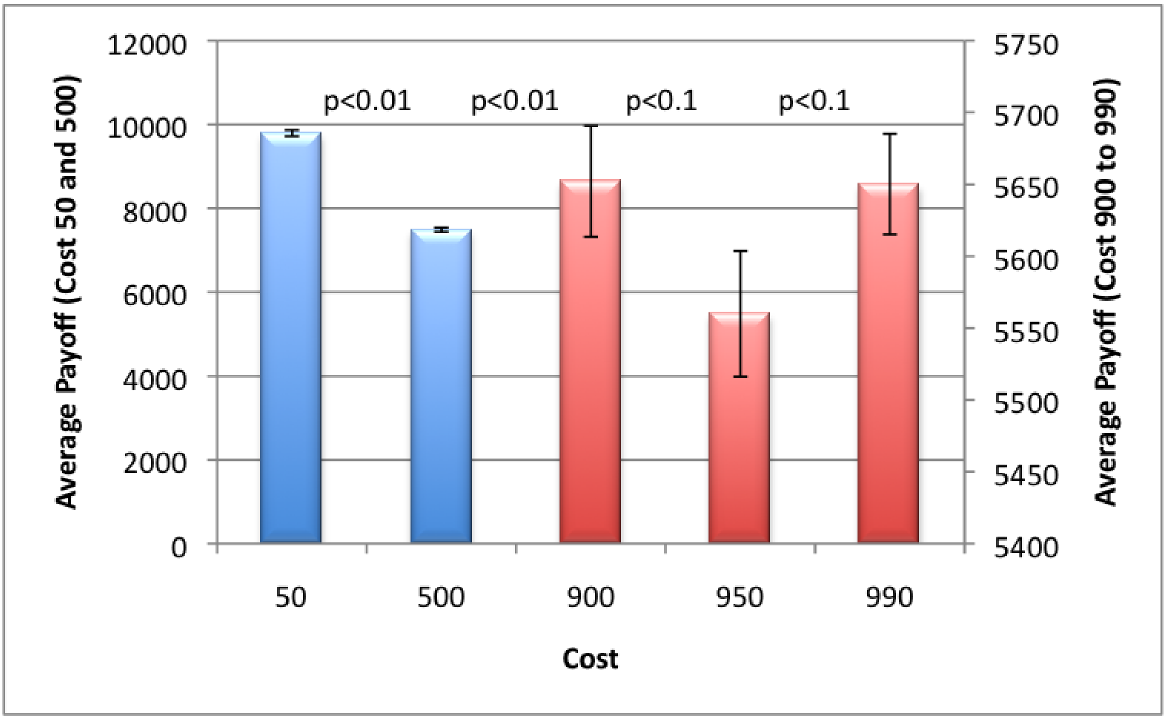


Figure 3.11: Average Payoff After 15 Rounds

	c = 50	**c = 500**	**c = 900**	**c = 950**	**c = 990**
μ	9791	7489	5652	5560	5650
SE_μ	76.23	53.75	38.61	43.66	35.02

Table 3.7: Average Payoffs for Different Cost Parameters After 15 Rounds

	$\mu_{50} > \mu_{500}$	$\mu_{500} > \mu_{900}$	$\mu_{900} > \mu_{950}$	$\mu_{950} < \mu_{990}$
p-value	0	0	0.0557	0.0536
t-value	24.6797	27.75	1.5928	1.6114

Table 3.8: Average Payoffs Comparison After 15 Rounds

3.6 Conclusion

We utilize a computational testbed to design a laboratory experiment to better understand the behavior of the minimum effort coordination game. Using the computational testbed, we are able to make predictions of interesting and un-intuitive behavioral features of the minimum effort coordination game. First, the game converges to a pareto dominated equilibrium as the cost of effort increases. Second, the game converges faster to an equilibrium as the cost of effort increases. Lastly, the average payoff does not monotonically decrease as cost of effort increases. Had we not used the testbed, the likelihood of running across these behavioral features would have been low and the cost of running multiple sessions to figure out the parameters would have been expensive.

Another important contribution from this research is to show that the testbed we have designed effectively predicts human behaviors in the minimum effort coordination game.

We focused primarily on the behavior of the minimum effort coordination game as a function of cost. However, our results also suggest predictions from changing the number of players in the game. These are testable hypotheses we encourage others to pursue. Furthermore, we have focused mainly on minimum effort coordination game but we are hopeful that our computational testbed would generalized to other class of coordination games such as battle of the sexes.

3.7 Appendix

The explanation of the algorithm is divided up into four parts: notation, preliminary initialization, round k action, and preparation for round $k + 1$. For notational purposes, the superscript typically denotes the agent and the subscript denotes the round.

3.7.1 Notation

Each agent has a database of information that is used to help make their choice in each round. At the start of each round, each agent has two parameters in their database, the confidence parameter γ and the satisfaction parameter σ. These parameters for agent i in round k are denoted by γ_k^i and σ_k^i. The agents use these parameters to help make their choice. Agent i's choice in round k is represented by $\mathbf{x}_k(i)$. The choice of all agents in round k is given by $\mathbf{x}_k$, which yields payoffs $\pi_i(\mathbf{x}_k) = \pi_k^i$ for agent i.

After the agents make their choices, they update their database of information in preparation for the next round. Each agent makes a prediction about what the other agents will play in the following round. Let $\hat{\mathbf{x}}_k^i(j)$ be agent i's prediction for agent j's play in round k. The full prediction vector, $\hat{\mathbf{x}}_k^i$, consists of predictions for all of the other agents.

As the game progresses, each agent creates a quasi-best-response matrix. Agent i's quasi-best response matrix at round k is denoted by Q_k^i. This matrix helps the agent determine what they should choose after they have made their prediction. To do this, the agent groups similar strategy profiles together in the quasi-best-response matrix. The agent then determines which play is best against these similar strategy profiles by randomly sampling responses from the strategy space. In the future, when a similar strategy profile arises, the agent uses this quasi-best-response matrix to help remember what they did in the past. From this quasi-best-response matrix, the agent determines the quasi-best-response for their prediction for round k, which is denoted by ${x_k^i}^*$. More details about the quasi-best-response are given below in the description of the algorithm in the preparation for round $k + 1$ section.

Each agent also keeps track of their best and worst outcomes. To do this, each agent randomly chooses J strategy profiles from the uniform distribution on the joint strategy space $S = [0,1]^N$. Next, they calculate the payoffs for each of these profiles, and save the strategy profiles which yield the highest and lowest payoffs, $\bar{\mathbf{x}}_k^i$ and $\underline{\mathbf{x}}_k^i$, respectively. These are referred to as the highest and lowest known choices for agent i in round k. The payoffs for these strategy profiles, $\bar{\pi}_k^i$ and $\underline{\pi}_k^i$, are referred to as the highest and lowest known payoffs for agent i at round k.

All of this information is stored in the agent's database, and is available when they are making their choice in round k.

3.7.2 Initialization

Many learning algorithms contain multiple initialization periods, where the agents choose randomly in the strategy space. Since the focus of this paper is not long run convergence, but rather short run behavior, the initialization period has to be short. Before the first choice is made, the agents randomly choose J strategy profiles to determine their initial highest and lowest known payoffs, $\bar{\mathbf{x}}_0^i$ and $\underline{\mathbf{x}}_0^i$, respectively. Each agent then makes the initial predictions about the other agents by randomly drawing a number from the uniform distribution on $[0,1]$, that is $\mathbf{x}_1^i(j) \sim U[0,1]$. Finally, each agent starts with the lowest possible confidence level, $\gamma_1^i = 10$. They also start with the highest satisfaction parameter, $\sigma_1^i = 1$, because they have no reason to try to change the outcome of the game yet. With these initial parameters, the algorithm is ready to run.

3.7.3 Round k

Entering round k, agent i has a database of information which is used to make a choice in round k. The choice in round k is a random number from a beta distribution with mean μ and variance ν^2. The mean of the distribution is a convex combination of the quasi-best-response, ${x^i}^*_k$, and the strategy which yields the highest known payoff for agent i at round k, $\bar{x}_k^i$. The weight on each term is determined by the current level of satisfaction. If the agent's satisfaction level is high ($\sigma_k^i = 1$) then they play the quasi-best-response for their prediction. If the agent is not satisfied ($\sigma_k^i < 1$), then they try to move the outcome towards the point which yields their highest known payoff. That is,

$$\mu = \sigma_i^k {x^{i*}}_k + (1 - \sigma_i^k)\bar{x}_k^i$$

The variance of the distribution is inversely proportional to the current level of confidence[3]. The proportionality constant is ρ, so the variance is,

$$\nu^2 = \frac{1}{\rho \gamma_k^i}$$

As the confidence level of the agent increases, the choice distribution has lower variance, and therefore the choice is more accurate. When the agent is not confident about what the other agents will do, then his choice distribution has high variance, and his choice is not as accurate.

After all agents have made their choices as described above, the payoffs are calculated. The agents then learn the choices of the other agents as well as the payoffs of all agents. At this point, the agents begin their preparation for round $k + 1$ by updating their database of information.

3.7.4 Preparation for Round $k + 1$

The agents have a variety of tasks to perform in preparation for round $k + 1$.

Update extremes As the game progresses the agents become more acquainted with the payoff function. To model this, each round the agents update their highest and lowest known payoffs by taking J random samples from the joint strategy space. For each random sample $\mathbf{z}_j$, the payoff vector is calculated. If the payoff for agent i from the sample is higher than the highest known payoff for agent i in round k,

[3] It is not possible to have a distribution over a closed region, if the variance is high, and the the mean is sufficiently close to the endpoints. If this is the case, then it is corrected by using a modified beta distribution with mass point on the endpoint.

then the agent sets the highest known choice for round $k+1$ to $\bar{\mathbf{x}}^i_{k+1} = \mathbf{z}_j$ and the highest known payoff round $k+1$ to $\bar{\pi}^i_{k+1} = \pi_i(\mathbf{z}_j)$. If none of the payoffs from the J sample points are higher than the highest known payoff for agent i at round k, then the highest known choice and payoff from round k are carried over to round $k+1$, i.e., $\bar{\mathbf{x}}^i_{k+1} = \bar{\mathbf{x}}^i_k$ and $\bar{\pi}^i_{k+1} = \bar{\pi}^i_k$. The same update is performed for the lowest known play and payoff.

Prediction for round $k+1$ In order to make a choice in round $k+1$ it is useful for the agents to have some prediction about what their opponents are going to do in round $k+1$. The prediction scheme used by the agents is a modification of the nearest neighbor classification algorithm from machine learning. The goal of the prediction scheme is to make a prediction for $\mathbf{x}_{k+1}$. Since there are N agents, the agents' choices at round k are given by the vector $\mathbf{x}_k \in \mathbb{R}^N$. A pattern is vector combining one or more of these choice vectors. For example, a pattern of length 3 is $[\ \mathbf{x}_k \quad \mathbf{x}_{k+1} \quad \mathbf{x}_{k+2}\ ]$. The agents divide the history of choice into the current pattern, previous patterns, and outcomes. Each previous pattern has a corresponding outcome. The algorithm makes a prediction for the outcome of the current pattern. The agents determine which of the previous patterns are closest to the current pattern. Then the agents' prediction is a weighted sum of the outcomes of the closest patterns. The agents repeat this process for patterns of different lengths, n. After the agent has done this for all values of n, he compares them, and determines which pattern length provides the best prediction.

For example, consider a two-player game with the history of play after eight rounds,

$$(0,0)\,,(1,1)\,,(1,1)\,,(0,0)\,,(1,1)\,,(1,1)\,,(0,0)\,,(1,1)$$

Let's examine the prediction by agent 1 of what agent 2 will play in the ninth round. First, agent 1 considers patterns of length 1. The current pattern is the most recent play, $(1,1)$. This has been played four previous times in rounds 2, 3, 5, and 6. These are the closest patterns. When these closest patterns have been played in the past, agent 2 has responded by playing 1, 0, 1, and 0 in the respective following rounds. These are the outcomes for the four closest patterns. This is not good, because agent 2 has played 0 half the time, and 1 half the time, so it is difficult to predict what agent 2 will play in the next round based on patterns of length 1.

Next, agent 1 looks at patterns of length 2. The current pattern in this case is the play in the previous 2 rounds, $(0,0),(1,1)$. This pattern has been played twice before in the past, in rounds 1-2 and 4-5. In response to this pattern, agent 2 has played 1 in both rounds 3 and 6. After patterns of length 2, agent 2 always chose 1. Therefore, patterns of length 2 are better for prediction that patterns of length 1.

More formally, at the end of the k^{th} round, each agent considers patterns of different lengths n. For each length, there are $k-n$ previous patterns of length nN each. The agent forms the previous patterns matrix $X \in \mathbb{R}^{k-n \times nN}$ and the output matrix $Y \in \mathbb{R}^{k-n \times N}$,

$$X = \begin{bmatrix} \mathbf{x}_1 & \cdots & \mathbf{x}_n \\ \mathbf{x}_2 & \cdots & \mathbf{x}_{n+1} \\ \vdots & & \vdots \\ \mathbf{x}_{k-n} & \cdots & \mathbf{x}_{k-1} \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_2 \end{bmatrix} \text{ and } Y = \begin{bmatrix} \mathbf{x}_{n+1} \\ \mathbf{x}_{n+2} \\ \vdots \\ \mathbf{x}_k \end{bmatrix}$$

Each row of the previous patterns matrix is a single pattern, and these are denoted by X_m for $m = 1, \ldots, k-n$. The current prediction is the vector $c \in \mathbb{R}^{nN}$

$$c = \begin{bmatrix} \mathbf{x}_{k-n+1} & \cdots & \mathbf{x}_k \end{bmatrix}$$

Next, the agent finds the j rows of X which are closest to the current pattern c in terms of Euclidean distance. To do this, the agent forms the distance vector by finding the length between the current point and each of the previous points,

$$\mathbf{d} = \begin{bmatrix} \|X_1 - c\| \\ \|X_2 - c\| \\ \vdots \\ \|X_{k-n} - c\| \end{bmatrix}$$

Let J be the set of indices of the j smallest terms in the distance vector $\mathbf{d}$. That is $d_j \leq d_k$ for $j \in J$ and $k \neq J$. These indices correspond to the j rows of X which are closest to the current point c.

The agent now determines which pattern length gives the best prediction. As exhibited in the above example, the agent wants to choose the pattern length with the most similar outcomes. To determine the optimal pattern length for each n, the agent takes the outcome of the j closest points, and calculates the average of these points, $\bar{Y}$. Then the agent computes the variance of these j closest points,

$$V_n = \sum_{j \in J} \|Y_j - \bar{Y}\|$$

Now, the agent compares the variance for all considered pattern lengths and chooses the pattern length with the smallest variance. If there is a tie, then the agent chooses the shorter pattern. Note that average variances are higher in higher dimensions. This is not corrected for, which gives an additional benefit to the shorter patterns, because shorter patterns are easier to recognize.

Once the agent has selected which pattern length to use, he forms a weighted average of the closest outcomes. The closer the pattern is to the current outcome, the higher the weight is. The patterns are weighted using a logistic function. The prediction for the next period is thus,

$$\hat{\mathbf{x}}^i_{k+1} = \frac{\sum_{j \in J} Y_j e^{\mathbf{d}(j)}}{\sum_{j \in J} e^{\mathbf{d}(j)}}$$

Therefore, if the distance to each of the j closest patterns is 0, then the prediction is just the average outcome from those j closest patterns. The agent makes their choice for period $k+1$ based on this prediction.

Quasi-Best-Response The quasi-best-response helps the agent determine the best response for his prediction for round $k+1$. To do this the agent updates the quasi-best-response matrix from the previous period, Q^i_k. Each row of the quasi-best-response matrix consists of three items: prediction about what the other agents will do, what agent i should do given that prediction, and the payoff given that strategy profile. More formally row m has the terms,

$$Q_k^i = [\ \mathbf{q}_{-i}^m \quad \mathbf{q}_i^m \quad \pi_i\left(\mathbf{q}_i^m, \mathbf{q}_{-i}^m\right)\ ]$$

Here, $\mathbf{q}_{-i}^m$ are the choices of the other agents, and $\mathbf{q}_i^m$ is the choice of agent i. Agent i updates Q_k^i as follows. First, agent i determines if the current prediction is similar to any of the entries already in the quasi-best-response matrix. To do this, agent i chooses a set, R, of random strategies. For each row of the quasi-best-response matrix, agent i calculates the payoff difference,

$$pd_m = \sum_{r \in R} \left| \pi_i\left(r, \mathbf{q}_{-i}^m\right) - \pi_i\left(r, \hat{\mathbf{x}}_{k+1}^i\right) \right|$$

Next, the agents find the minimum payoff distance, $pd^* = \min pd_m$. If the distance is small, i.e., $pd^* < \delta$, then the two strategies are similar, and therefore are combined in the quasi-best-response matrix. If $pd^* > \delta$, then the two strategies are not similar, so a new entry is created in the quasi-best-response matrix. Let the threshold δ be a fraction of the difference between the highest and lowest payoff,

$$\delta = \frac{\bar{\pi}_i^k - \underline{\pi}_i^k}{20}$$

If $pd^* < \delta$, then the agent updates the row of the quasi-best-response matrix corresponding to pd^*, call this row m^*. The agent takes the set of R strategies, and calculates the payoffs $\pi_i\left(r, \hat{\mathbf{x}}_i^{k+1}\right)$. Let r^* denote the strategy from R which maximizes $\pi_i\left(r, \hat{\mathbf{x}}_i^{k+1}\right)$. If this new strategy yields a higher payoff than the current quasi-best-response, i.e., $\pi_i\left(r^*, \hat{\mathbf{x}}_i^{k+1}\right) > \pi_i\left(\mathbf{q}_i^m, \mathbf{q}_{-i}^m\right)$, then the row m^* is updated to $\mathbf{q}_{-i}^{m^*} = \hat{\mathbf{x}}_i^{k+1}$ and $\mathbf{q}_i^{m^*} = r^*$.

If $pd^* > \delta$, then the agent creates a new row for the quasi-best-response matrix, call this row $M+1$. Again, the agent calculates the payoffs $\pi_i\left(r, \hat{\mathbf{x}}_i^{k+1}\right)$ for all $r \in R$, with r^* being the strategy which yields the maximum payoff. The agent then updates the quasi-best-response matrix by setting $\mathbf{q}_{-i}^{M+1} = \hat{\mathbf{x}}_i^{k+1}$ and $\mathbf{q}_i^{M+1} = r^*$.

Update γ The parameter γ measures the current level of confidence of the agent. When the agent makes accurate predictions, his confidence increases. In preparation for round $k+1$, the agent compares his prediction for round k that was made in round $k-1$, $\hat{\mathbf{x}}_k^i$, with the actual play from round k, $\mathbf{x}_k$. Based on this prediction and outcome, the agent updates his confidence as follows,

$$\gamma_{k+1} = \frac{\alpha_1}{\|\hat{\mathbf{x}}_k^i - \mathbf{x}_k\| + \alpha_2}\gamma_k$$

Therefore, if the Euclidean distance between the prediction and the actual outcome is less than $\alpha_1 - \alpha_2$, then the confidence increases. The maximum possible increase in confidence is ${}^{\alpha_1}/_{\alpha_2}$.

Update σ The parameter σ represents the agent's satisfaction at the current state of the game. If the agent is not satisfied with the current outcome, then he may try to induce the other agents to play something else in order to change the current outcome. If the agent's attempt to move is unsuccessful, then he will stop trying. For example, suppose two agents are coordinating at one of the equilibria repeatedly in the battle of the sexes game. Agent 1 is at her optimal equilibrium, and Agent 2 is at his least favored equilibrium. Agent 2 realizes that he can receive a higher payoff at the other equilibrium. Therefore he will try to induce agent 1 to start playing the other equilibrium. However, agent 1 may not change the way she is playing, even when agent 2 is starts playing something else. If agent 2 has tried for a long time with no success, he will give up, and start playing the original equilibrium. The entire process of trying to move and giving up is called a *moving session*.

Agent i will start with the highest satisfaction possible. The satisfaction will remain at the highest level until some event causes agent i to start a moving session. In order for the agent to become dissatisfied, he has to have a good idea of what the other agents are going to play. Therefore, agent i must have a confidence greater than γ_{MS} in order to start a moving session. Given that agent i has confidence greater than γ_{MS}, he will start a moving session in two situations. If agent i knows that all agents receive higher payoffs at his highest known play, then he will try to move there because everyone will receive a higher payoff. Also if agent i's highest known payoff increases agent i's payoff by a large amount, and decreases the other agents' payoffs by only a small amount, then he will try to change the outcome. There are also some situations in which agent i will not start a moving session, even if his confidence is greater than γ_{MS}. If moving to agent i's highest known play will increase agent i's payoff by a small amount, but will decrease all other agents payoffs by a large amount, then agent i will not try to change the outcome. Also, if agent i has tried to move before unsuccessfully, then he will not try to move again until he has found a better strategy.

Once the moving session has started, agent i will try to induce the other agents to play his optimal strategy. If the play of the game is moving away from the play at the start of the moving session, and towards the highest play for agent i, then agent i will continue the moving session. If the play of the game does not move towards the highest play for agent i, then that round will be considered a *failure*. If the total number of failures become to high, then i will stop the moving session.

To more formally define this event that triggers a moving session, consider the term,

$$\Sigma_k^i = \frac{\pi_i\left(\bar{\mathbf{x}}_k^i\right) - \pi_i\left(\mathbf{x}_k\right)}{\frac{1}{N-1}\sum_{j\neq i}\pi_j\left(\bar{\mathbf{x}}_k^i\right) - \pi_j\left(\mathbf{x}_k\right)}$$

Σ_k^i will be referred to as the *relative gain* for agent i in round k. Agent i's payoff at the highest known play is always greater than his payoff at the current play, because the agent takes the current play into account when updating his highest known play. Therefore, switching from the current play $\mathbf{x}_k$ to agent i's highest known play $\hat{\mathbf{x}}_k^i$ will always increase agent i's payoff. So the numerator of Σ_k^i will always be weakly positive.

The agent will also keep track of the *maximum relative gain* for round k, $\bar{\Sigma}_k^i$, and the *minimum relative gain* for round k, $\underline{\Sigma}_k^i$. At the beginning of the game, agent i will start with maximum relative gain of $\bar{\Sigma}_0^i = 0$ and minimum relative gain of $\underline{\Sigma}_0^i = -1$. The agent will update these extreme relative gains with the current relative gain when the current relative gain is more extreme (higher than maximum or lower than minimum) and confidence is greater than γ_{MS}. The role of the extreme relative gains is to ensure that the agent does not continuously try to move to a point which the other agents refuse to move to.

Based on the current relative gain, the extremes relative gains, and the confidence, agent i will determine whether or not to start a moving session. When the denominator of Σ_k^i is positive, and hence $\Sigma_k^i > 0$, the other agents will benefit on average when switching from $\mathbf{x}_k$ to $\bar{\mathbf{x}}_k^i$. So, if $\Sigma_k^i > \bar{\Sigma}_k^i$ and $\gamma_k^i > \gamma_{MS}$, then the agent will start a moving session because all agents will have higher payoffs at $\bar{\mathbf{x}}_k^i$. When the denominator of Σ_k^i is negative, the other agents will get lower payoffs on average when switching from $\mathbf{x}_k$ to $\bar{\mathbf{x}}_k^i$. However, if Σ_k^i is very negative, then the average decrease of the other agents payoff will be small compared to the increase for agent i. So if $\Sigma_k^i < \underline{\Sigma}_k^i$ and $\gamma_k^i > \gamma_{MS}$ then the agent will also start a moving session. To summarize, agent i will try to move if $\Sigma_k^i \notin \left[\underline{\Sigma}_k^i, \bar{\Sigma}_k^i\right]$ and $\gamma_k^i > \gamma_{MS}$.

In the first round of the moving session, agent i will decrease from the full satisfaction level $\sigma = 1$ to the level $\sigma = \sigma_0 < 1$. Agent i will also set the number of failures to 0, $f = 0$. Agent i should not expect the other agents to respond to this move until they have seen the play in second round of the moving session and had a chance to respond to it in the third round of the moving session. So the agent will remain with satisfaction $\sigma = \sigma_0$ in the second round of the moving session, and this will not count as a failure. Starting in the third round, agent i's satisfaction and failures will depend on whether the other agents are responding to agent i's move. In particular, if the other agents are responding, and play is moving toward the highest known payoff, i.e.,

$$\|\mathbf{x}_k - \hat{\mathbf{x}}_k^i\| > \|\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1}^i\|$$

then the satisfaction will increase, $\sigma_{k+1} = \bar{\xi}\sigma_k$ and the number of failures will stay constant $f_{k+1} = f_k$ (for some $\bar{\xi} > 1$). Alternatively, if the other agents are not responding, so play is not moving toward agent i's highest known payoff, i.e.,

$$\|\mathbf{x}_k - \hat{\mathbf{x}}_k^i\| < \|\mathbf{x}_{k+1} - \hat{\mathbf{x}}_{k+1}^i\|$$

then the satisfaction will decrease, $\sigma_{k+1} = \underline{\xi}\sigma_k$ and the number of failures will increase by one, $f_{k+1} = f_k + 1$.

When the number of failures reaches the threshold $f_k = \bar{f}$, then the session ends because the other agents are not responding to the move. After the session ends, the amount of failures is set back to 0, and the satisfaction is set back to the highest level $\sigma = 1$.

3.7.5 Instructions

The following 2 pages are sample instructions used in the experiment.

Experiment Overview

You are about to participate in an experiment in the economics of decision making. If you listen carefully and make good decisions, you could earn a considerable amount of money that will be paid to you in cash at the end of the experiment.

Please do not talk or communicate with other participants. Feel free to ask questions by raising your hand or signaling to the experimenter.

You will be working with a fictitious currency called Francs. The exchange rate will be specified in the instructions. You will be paid in cash at the end of the experiment.

The experiment consists of a sequence of periods and blocks. There will be total of 5 blocks. For each block, there will be total of 15 periods.

Specific Instructions for Each Period

Exchange rate: ______ Francs = _____ USD.

Your group will consist of you and 3 other individuals (total of 4 people in your group). Your job is to choose one of the following numbers: {1, 2, 3, 4, 5, 6, 7}. The number you choose will remain anonymous. Your individual payoff is determined by your choice and the choice of others in your group. The following is a sample payoff table for illustration purposes only. Your actual payoff table will be using different numbers from this table. The overall ideal will be the same, however.

Table 1: Your payoff in francs

	Lowest choice of number from your group (including you)						
Your choice of number	7	6	5	4	3	2	1
7	25	21	17	13	9	5	1
6	-	23	19	15	11	7	3
5	-	-	21	17	13	9	5
4	-	-	-	19	15	11	7
3	-	-	-	-	17	13	9
2	-	-	-	-	-	15	11
1	-	-	-	-	-	-	13

Examples
- You chose 5 and the lowest choice of number from your group is 5. Then you win 21 francs.
- You chose 4 and the lowest choice of number from your group is 2. Then you win 11 francs.
- You chose 3 and the lowest choice of number from your group is 2. Then you win 13 francs.

Quiz
You chose 2 and the lowest choice of number from all the participants is 1. Then you win _____ francs.

Procedural Summary

There are five papers folded in half on each of your desk. They are labeled “Table 1”, “Table 2”, Table 3”, “Table 4” and “Table 5”. Each of these papers will present a different payoff table. The payoff from your paper labeled “Table 1” will be identical to everyone else’s paper labeled “Table 1”, the payoff from your “Table 2” will be identical to everyone else’s “Table 2” and so on. Please do not open any of these papers until you are instructed to do so.

The experiment consists of 5 blocks and each block will consist of 15 periods. You will be placed in a group with 3 others who are randomly chosen for each block. This means that at the beginning of each block, you will be randomly matched with 3 others individuals to be placed in a group size of 4.

Your payoff from each period will be determined by one of the 5 folded papers. You will be using one payoff table for the entire block. Everyone in your group will be using the exact same payoff table as you. Your group members are randomly chosen (via random number generator) and your payoff tables for each block are also randomly chosen (via random number generator). Your payment will be sum of your entire earnings from all 5 blocks.

Q: How do you know what period you are in? What Payoff table to use? Which block you are in?
A: Refer to Figure 1. Number of periods is denoted in the upper left corner. The first line of the computer’s instruction tells you what table your payoff is determined from.

Periods 1-15 is block one. Periods 16-30 is block two. Periods 31-45 is block three. Periods 46-60 is block four. Periods 61-75 is block five.

Note: There will be no sign that tells you that you are starting a new block. So pay attention to the period numbers.

Q: Is it possible to have the same table number from one block to another?
A: Yes, this is because you are randomly assigned a payoff table for each block.

Timeline and Summary

Block 1 begins. You’re randomly matched with 3 other people and everyone in your group is randomly assigned a same payoff table to use for this block. You may open the payoff table at this time. The period will begin and all the participants will make their choices privately through the computer. Press “okay” after you have made your decision. After all the participants have inputted their choices, the lowest number chosen from your group as well as your payoff will be displayed. Press continue to move on to the next period. You and your group will do this for 15 periods and block 1 will come to an end.

Block 2 begins. You’re randomly matched with 3 other people and everyone in your group is randomly assigned a same payoff table to use for this block. You may open the payoff table at this time. The period will begin and all the participants will make their choices privately through the computer. Press “okay” after you have made your decision. After all the participants have inputted their choices, the lowest number chosen from your group as well as your payoff will be displayed. Press continue to move on to the next period. You and your group will do this for 15 periods and block 2 will come to an end.

This continues until all 5 blocks are played. Your payment will be the sum of your payoff from each period in all 5 blocks.

Any questions?

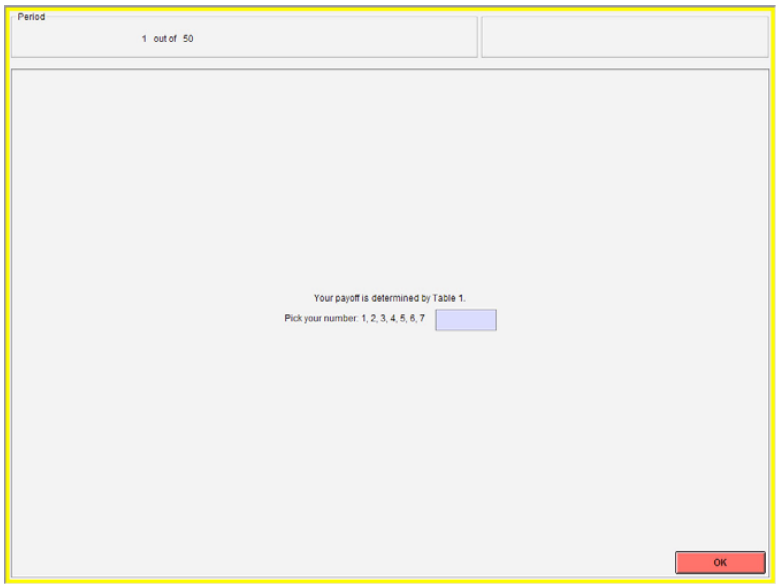


Figure 1: Sample Screenshot

Chapter 4

Ambiguity Aversion in Asset Market: Experimental Study of Home Bias

4.1 Introduction

Equity Home Bias is a phenomenon in which investors over-invest in home country assets compared to what the rational model predicts. Despite the fact that, in the past 4 years, foreign stocks have been outperforming domestic stocks on average, US investors still maintain a domestic-asset-heavy portfolio. Home bias is not limited to US investors but occurs worldwide (Figure 4.1). There has been strong empirical support for the existence of home bias paradox and many scholars have made various arguments trying to explain this puzzle. The inflation rate, exchange rate, information asymmetry, and information immobility are some of the popular choices but none of these have been generally accepted or empirically consistent. However, these explanations are all within a rational choice framework. Here, we propose a behavioral framework, ambiguity aversion, to help better understand the cause of equity market home bias. Simply put, we argue that ambiguity aversion inhibits people from investing in unfamiliar companies. Unlike previous studies, we use an experimental design with real world assets and test for ambiguity aversion instead of using fictitious assets or simply showing home bias without an explanation.

Equity market home bias[1] presents an interesting problem because the investors are being "irrational" in the sense that they are not investing in a pareto-optimal manner: there exists another portfolio allocation such that the investor does not face any higher risk (variance) but receives higher expected return. If people are indeed being irrational with their portfolio selection, then this presents an arbitrage opportunity. In addition, the irrational behavior raises the question of why investors are not allocating risks efficiently. Our paper shows that 1) using real world assets there is home bias, and 2) the bias is caused by ambiguity aversion by showing that the investor's subjective probability over foreign assets is sub-additive.

A common argument against ambiguity aversion is that an investor might want to invest in familiar companies because he knows how well the company will perform (i.e., informational advantage). Surely, rational choice theorists cannot use that as an argument with the Efficient Market Hypothesis looming over it (Fama 1970). However, as an outsider of the firm, it is highly unlikely that the investor has any useful knowledge. The term "familiarity" that the investor generally refers to is related to being able to answer nontechnical questions such as "What does the firm produce? Where are they located?" However, these things should be irrelevant when it comes to investing. As with the standard finance approach, what the investor truly needs to know is the expected cash flow and not what the company produces.[2]

The insights obtained through the study of home bias also help in explaining other similar behavioral phenomena. For example, an employee often times invests in the same company in which he works. However, this is not an optimal way to hedge one's risk. When Enron collapsed, the employees who also invested in Enron took a double loss by failing to insure themselves against risk. In a non-investment environment, our model can help explain some of the everyday consumer purchasing behavior, such as buying a toothpaste. Consumers are willing to pay the extra premium in order to buy toothpaste from a brand which is more familiar. Although our study is focused on the international asset market, the same phenomenon is applicable across contexts.

[1] We will drop the term "equity" from here on out.

[2] In terms of efficient market hypothesis, the prices should have already incorporated relevant informations.

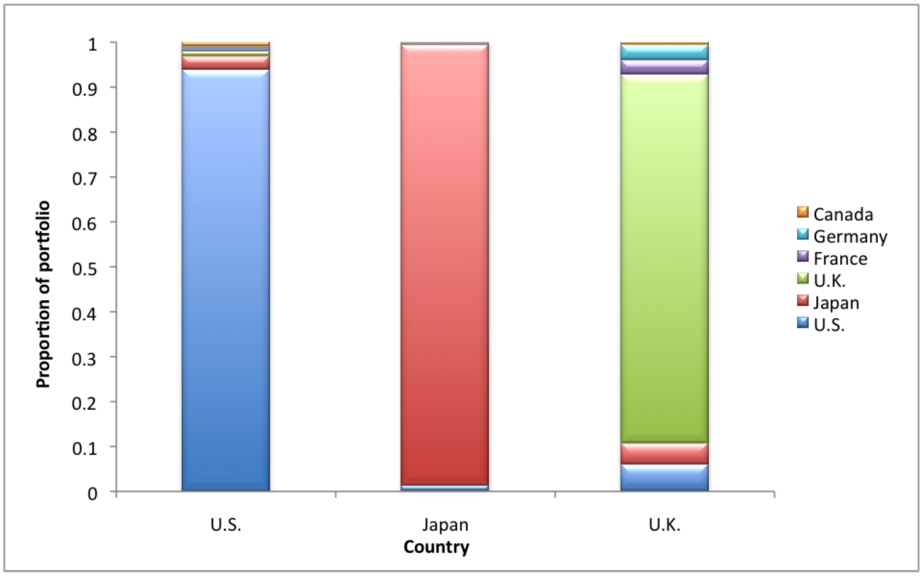


Figure 4.1: Portfolio Weights: US, Japanese and UK Investors
French and Poterba (1991)

4.1.1 Literature Review

In addition to French and Poterba (1991), many others have documented empirical support of home bias. Ahearne, Griever, and Warnock (2003) show that in 1997 the US stocks composed only 48.3% of the worlds stock portfolio yet US investors portfolios were composed of only 10.1% foreign stocks. Therefore, when considering the Capital Asset Pricing Model (CAPM) with the parameters specified using the world market, US investors are holding less than 1/5th of the foreign assets required to achieve the efficient frontier. Even in experimental setting, Kilka and Weber (2002) have shown the existence of home bias in Germany and United States.

To justify the discrepancy between the empirics and the rational model, a number of explanations have been suggested. One explanation is that there is capital immobility due to institutional structure. However, international barriers have been decreasing for the last 30 years yet there is no significant change in the US investors' portfolio. Moreover, most of the portfolio diversification can be obtained by trading in American Depositary Receipts (Errunza, Hogan, and Hung 1999). Also, we observe that the gross equity flow has increased while the net flow stayed constant (Bekaert and Harvey 1995). Glassman and Riddick (2001) showed that informational asymmetry cannot be a good explanation unless we are assuming that the market portfolio standard deviation is 2 to 5 times higher than what is empirically shown. Explanation using exchange rate bias is not plausible with CAPM because one can hedge the exchange rate risk by shorting risk free assets in foreign countries. Even without hedging, optimal portfolio shows that investors should diversify even with exchange rate risk. Another explanation is that the investors are trying to hedge the risk of inflation rate. However, Cooper and Kaplanis (1994) suggest that this too is not a plausible explanation unless one assumes a very high level of risk tolerance. Lastly, in theory, information asymmetry and immobility can help explain home bias (Nieuwerburgh and Veldkamp In Press) but one needs to assume that there is relevant information gained by non-professional traders. For more detailed review, see Karolyi and Stulz (2003) and Lewis (1999).

The study reported here provides a behavioral explanation of the home bias paradox. From the behavioral economics point of view, ambiguity aversion is a very good starting point as an explanation for the home bias paradox. For example, Bossaerts, Ghirardato, Guanaschelli, and Zame (2005) showed that asset markets do react to ambiguity aversion with fictitious assets. Our research is an experimental study which shows a positive relationship between ambiguity aversion and home bias. In particular, the experiments tested whether investors are more ambiguous when it comes to foreign stocks and how this relates to the level of home bias. Our experiments are built on Ellsberg (1961)'s example of showing ambiguity aversion.

4.1.2 Agenda

We begin by introducing the theory behind the mean-variance model and its implications, followed by various theories of ambiguity aversion, and non-additive subjective probability model we used for the experimental design. We present experimental results directly after presenting the design for all six experiments. First two designs target decision-making over individual companies while the last two designs target decision-making over indices. We end with a summarizing conclusion.

4.2 Theory

A short review of ambiguity aversion and the mean-variance model is discussed in the following two subsections. Readers who are familiar with the topic may go directly to the experimental design section. However, our experimental design is heavily based on the non-additive probability discussed in the Theory of Ambiguity Aversion section.

4.2.1 Mean-Variance Model and Empirical Data

We follow the argument made by Lewis (1999). The standard model used in finance is the *mean-variance* model. The utility function is called the mean-variance utility when it increases with respect to mean and decreases with respect to variance. In particular, it has the following form: $U = U(E_t W_{t+1}, Var(W_{t+1}))$ where W_t is the wealth at time t, $Var(\bullet)$ is the variance-covariance matrix and E_t is the expectations operator taken at time t. Furthermore, assume that $\frac{\partial U}{\partial W_t} > 0$ and $\frac{\partial^2 U}{\partial W_t^2} < 0$. Denote α_t, β_t as the proportion of wealth held in domestic and foreign assets at time t, respectively. Hence $\alpha_t + \beta_t = 1$. Define $r_t = (r_t^D, r_t^F)$ as turn on domestic assets and foreign assets at time t. For example, one may consider the following utility function with all the desired properties: $W_t(1 + E_t r_{t+1}) - \gamma Var(W_t E_t r_{t+1})$ where γ is the risk aversion parameter. Now, solving for the first order condition of the objective function, the optimal proportion of foreign holding is:

$$\beta_t = \frac{(E_t r_{t+1}^F - E_t r_{t+1}^D)/\gamma}{var(r^F - r^D)} + \frac{\sigma_D^2 - \sigma_{FD}^2}{var(r^F - r^D)} \tag{4.1}$$

where $\gamma = \frac{-2W_t U_2}{U_1}$ is the relative risk aversion.

Consider the result from Equation 4.1. As the level of relative risk aversion increases, foreign investment decreases. However, there is a bound on how little one should invest in foreign companies. In particular, the bound is $\frac{\sigma_D^2 - \sigma_{FD}^2}{var(r^F - r^D)}$, which is empirically greater than zero. Table 4.1 shows how much one should hold in foreign assets for a given relative risk aversion.

Using the empirical data provided from Table 4.1 and optimal foreign holdings

Summary Statistics of Returns								
	US	Canada	France	Germany	Italy	Japan	UK	EAFE
Mean	11.14	9.59	11.63	11.32	5.81	14.03	12.62	12.12
SD	15.07	18.66	23.33	20.28	26.18	22.50	23.97	16.85
Correlations								
US	1.00	0.70	0.44	0.36	0.22	0.26	0.51	0.48
Canada	-	1.00	0.43	0.31	0.29	0.27	0.52	0.49
France	-	-	1.00	0.60	0.42	0.39	0.54	0.65
Germany	-	-	-	1.00	0.37	0.37	0.43	0.62
Italy	-	-	-	-	1.00	0.38	0.35	0.51
Japan	-	-	-	-	-	1.00	0.36	0.86
UK	-	-	-	-	-	-	1.00	0.71
EAFE	-	-	-	-	-	-	-	1.00
Foreign Portfolio Shares in Percent of Wealth								
	Actual	$\gamma = 1$	$\gamma = 2$	$\gamma = 3$	$\gamma = 10$	Minimum Variance		
β	8.00	75.9	57.7	51.6	43.1	39.5		

Table 4.1: Summary Statistics of International Equity Market
Data are from Morgan Stanley, from Jan 1970 to Dec 1996

by Equation 4.1, even as relative risk aversion goes to infinity, one should still invest 39.5% of his shares in foreign assets. However, we observe approximately only 8% of the total investments are directed to foreign assets. Hence, using the mean-variance model, even with unrealistic amount of risk aversion, the level of home bias cannot be explained.

4.2.2 Theory of Ambiguity Aversion

Decision theorists have defined and modeled ambiguity in several ways. The most intuitive way of defining *ambiguity* is that the individual is uncertain about the distribution of the risk (Knight 1921). More uncertain the individual is about the distribution implies a higher level of ambiguity. For example, the probability distribution of a coin toss has very little ambiguity (close to 50/50) but the probability distribution of the weather in Tajikistan (without looking it up on the internet) is pretty uncertain. To say that a person is *ambiguity averse* is to say that a person prefers to bet on an event where he knows more about the distribution. For example, I would rather bet on whether the next coin toss will turn up heads than bet on whether the weather in Tajikistan today is between 40-50 degrees.

Although seemingly intuitive, formal modeling of ambiguity has taken many different approaches. One model assumes that the utility from ambiguous events are less than the utility from unambiguous events (Sarin and Winkler 1992, Smith 1969). Another approach lets the weights of ambiguous probability be different from the weights on unambiguous probability when calculating the expected utility (Einhorn and Hogarth 1985, Segal 1987). Epstein (1999) states that there are multiple priors to the probability distribution. Another popular model often used, similar to the multiple priors approach, provides a range of probability for an event (i.e., probability of $X \in [0.3, 0.7]$) instead of a point mass probability (i.e., probability of $X = 0.5$) (Gilboa and Schmeidler 1989). The approach we use is from Schmeidler (1989) which is derived from Choquet (1953-1954), where we relax the assumption that the probability must add up to 1. We call this approach the *non-additive probability* approach.

In non-additive probability approach, we keep the assumption that the probabilities are monotonic ($p(E) \leq p(F)$ if $E \subseteq F$) but not necessarily additive ($p(E \cup F) \neq p(E) + p(F) - p(E \cap F)$). In this model, we measure the level of ambiguity by the level of sub-additivity. In other words, while $p(A)$ and $p(B)$ are the likelihood of the events A and B, $1 - p(A) - p(B)$ measures the lack of "faith" in those likelihoods. Therefore, bigger sub-additivity ($1 - p(A) - p(B)$) implies higher levels of ambiguity.

Again, an interested reader may refer to Camerer and Weber (1992) for more detailed discussion and Epstein (1999) for more rigorous treatment.

4.3 Materials and Methods

A total of 55 people participated in this experiment; 47 were graduate and undergraduate students from the California Institute of Technology (Caltech) and 8 were not Caltech affiliates. The participants were recruited using the Social Science Experimental Laboratory (SSEL) announcement system and public fliers. All participants were registered subjects with SSEL (signed a general consent form) and this experiment was approved as an exemption by the local research ethics committee. The experiment was conducted at the SSEL located at Caltech, Pasadena, CA. The lab consists of 30 working computers divided into a cubical setting. Subjects were physically prevented from viewing another student's computer screen. The subjects were paid a show-up fee of $10 in addition to extra earnings based on their performance in the experiment.

The experimental designs dealing with individual companies (experiments 1-4) were programmed using PHP[3] and MySQL[4] and are divided into four parts plus a survey section. The experimental designs dealing with indices (experiments 5-6) were programmed using E-prime[5] and are divided into two parts plus a survey section. Instructions were given prior to each section and were available both in print as well as on screen. We quizzed the subjects after the instruction to insure they understood the experiment. The instructions provided to the participants are attached as an Appendix.

[3] www.php.net

[4] www.mysql.com

[5] www.pstnet.com/products/E-Prime

4.4 Control Experiment: Ellsberg Paradox

4.4.1 Experimental Summary and Motivation

We used the Ellsberg's standard two urns and two colored balls experiment as the control treatment (Ellsberg 1961). An ambiguous urn, urn 1, contains 100 balls with unknown distribution of red and black. A risky urn, urn 2, contains 100 balls of which 50 are red and 50 are black. There is risk with urn 2 while uncertainty with urn 1. This baseline treatment is conducted to obtain an approximation of which of the investors are ambiguity averse and not ambiguity averse. The experimental structure below depicts how we go about in eliciting preference for ambiguity.

4.4.2 Experimental Structure

Ellsbergs experiment was administered to the investors in the following manner:

1. Investor is presented with two urns.
   (a) Urn 1 contains 100 balls but the number of black or red balls is unknown.
   (b) Urn 2 contains 100 balls, of which 50 are black and 50 are red.
2. Setting one: Investor is asked to pick from the following two gambles.
   (a) $x dollar if red ball is drawn from urn 1.
   (b) $x dollar if red ball is drawn from urn 2.
   (c) Indifferent.
3. Setting two: Investor is asked to pick from the following two gambles.
   (a) $x dollar if black ball is drawn from urn 1.
   (b) $x dollar if black ball is drawn from urn 2.
   (c) Indifferent.

We determined whether the investor is ambiguity averse or not by the choices he makes in this Ellsberg experiment. In particular, if the investor chooses the gamble from urn 2 (risky urn) in both settings, then we inferred that the investor was ambiguity averse. By choosing urn 2 in the first setting, it implies that the expected utility from gamble two is greater than the expected utility from gamble one. If the investor chooses urn 2 in the second setting, it implies that the expected utility from the gamble two is greater than gamble one. The following proposition will show why this leads to sub-additive probability, and therefore, ambiguity aversion.

Proposition 4.4.1 *Under the expected utility maximization framework, choosing the risky urn in both setting implies sub-additive probability measure.*

Proof. Choosing gamble two in the first setting implies that

$$p(red\ ball|urn\ 2)u(\$x) > p(red\ ball|urn\ 1)u(\$x)$$

$$\Longleftrightarrow$$

$$p(red\ ball|urn\ 2) > p(red\ ball|urn\ 1) \tag{4.2}$$

Choosing gamble two in the second setting implies that

$$p(black\ ball|urn\ 2)u(\$x) > p(black\ ball|urn\ 1)u(\$x)$$

$$\Longleftrightarrow$$

$$p(black\ ball|urn\ 2) > p(black\ ball|urn\ 1) \tag{4.3}$$

Since urn 2 has 50 black and 50 red balls, it must be that $p(black\ ball|urn\ 2) + p(red\ ball|urn\ 2) = 1$. From Equation 4.2 and 4.3, this implies that $p(black\ ball|urn\ 1) + p(red\ ball|urn\ 1) < 1$, which leads to a sub-additive probability measure. ∎

4.4.3 Results

From the Ellsberg's urn experiment, we found 48.65% of the subjects to be *ambiguity averse*. We classified the subject as ambiguity averse if he chose option (b) in both settings one and two. If the subject chose a mixture of (a), (b) or (c), this classified him as *undetermined*, choosing option (a) in both settings classified him as *ambiguity preferred*, and choosing option (c) in both settings classified him as *ambiguity neutral*. Refer to Table 4.2 to see the complete breakdown. For the rest of the paper, when we refer to an *ambiguity averse* subjects, we are referring to the 48.65% of the subjects who were classified as ambiguity averse. We refer to the complement of the ambiguity averse population as the *non-ambiguity averse* subjects.[6] One caveat is that, just as people show different risk preference (although correlated) for different tasks, the same holds true for ambiguity preference for different tasks.

Type	Proportion (%)
Ambiguity Averse	48.65
Ambiguity Neutral	37.84
Ambiguity Preferred	2.70
Undetermined	10.81
Number of Obs: 37	

Table 4.2: Sample Population's Classification of Ambiguity Preference

[6]We do not have records of the results on the Ellberg's urn experiment for subjects from session 1 of the indices experiment due to technical error.

4.5 Experiment 1: Portfolio Building

Definition 1 *A derivative is called a **Digital Option** if it provides a fixed return after reaching the strike price on the maturity date.*

A digital option is often called an *Arrow Security* by economists. Consider the following example of a digital option. A *digital call option* with strike price k and payment r is denoted as $C(r, k)$ which pays zero if the stock price $s < k$ and r if $s \geq k$ at the maturity date. A *digital put option* with strike price k and payment r is denoted as $P(r, k)$ which pays zero if the stock price $s > k$ and r if $s \leq k$ at the maturity date.

4.5.1 Setup for Individual Stocks, Experimental Summary, and Motivation

A motivation for this experiment is to test whether there is home bias in our sample, as well as how the company choices are correlated with ambiguity aversion. We presented a collection of 23 domestic and 27 foreign companies to the investor in a random order. These companies were all from the technology and semiconductor industry to minimize the industry bias. In addition, these are companies listed as the 50 biggest companies in the world with respect to their industry by Forbes 2004 magazine.[7] Along with a company name the investors were given their company's ticker symbol, headquarter location, as well as a brief list of company information which was provided by finance.google.com. Investors were asked to choose 15 companies to place a digital put option order and 15 companies in a digital call option order. One option was given per company chosen by the investor. These digital options had a maturity date of one week and strike price equal to the stock price at the day of the experiment. The investors were restricted from using any tools other than the software required for the experiment. In addition, the investors were not allowed to list a company for both a put and a call option. The investors were paid based on the performance

[7] "Biggest company" was measured by a composite of sales, profits, assets, and market value. The list spans 51 countries and 27 industries.

of their portfolio after the maturity date of the options which paid \$0.50 per option exercised.

This study answers two major questions. 1. Do investors show signs of home bias? 2. What is the relationship between ambiguity aversion and home bias? We expect to see the proportion of domestic companies chosen to be greater than $23/50 = 46\%$. In addition, we expect to see a positive correlation between the level of home biasness and ambiguity.

4.5.2 Results

Refer to Figure 4.2 for the average portfolio composition. We tested the hypothesis of home bias. On average, US companies comprised 52.70% (SE=3.05) of the call options and 49.21% (SE=2.54) of the put options, which gave a total of 50.95% (SE=1.30) investment in US companies. The investors were no more likely to choose call options for US companies nor were they more likely to choose a put option for US companies. Given that the US companies consisted of only 46% of the possible companies available to choose, this suggests that there is a home bias level of 4.95% where the differences are significant at $p < 0.01$. This is a modest result but this may be caused by the fact that the experiment limits the industry choice and investors are required to choose 30 companies.

Despite the fact that half of our subjects were considered to be ambiguity averse from Ellsberg's experiment, we do not find a difference between the ambiguity averse and non-ambugity averse individual when it came to levels of home bias in their portfolio. In fact, we did not find any correlation between the result from the Ellsberg treatment and total composition of one's portfolio.

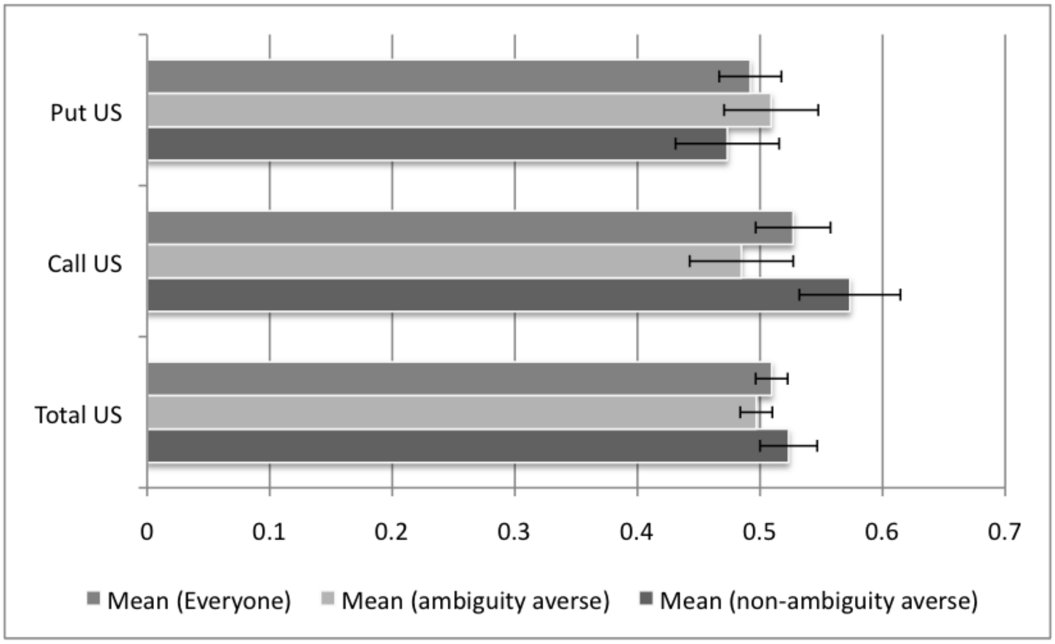


Figure 4.2: Share of US Companies in Portfolio

4.6 Experiment 2: Bond or Options?

4.6.1 Experimental Summary and Motivation

In this experimental design, the investor was shown one company at a time and was asked to choose one of the three gambles. *Gamble 1* is to receive a bond which pays \$1 one week later, *Gamble 2* is to receive a digital call option with exercise value \$1 and *Gamble 3* is to receive a digital put option with exercise value \$1. These options are identical to the previous section minus the exercise value. However, the investor also faced a known risk in a sense that, having chosen gamble 1, he has P probability of actually receiving the bond. Also, by choosing a gamble 2 or 3, he has $1 - P$ probability of actually receiving the options. In this setting, the probability of receiving the security of choice becomes an implied cost: lower the probability implies a higher cost. (Refer to the experimental instructions for a detailed example.)

Each investor gets three domestic companies with $P = 33\%$, three foreign companies with $P = 33\%$, three domestic companies with $P = 29\%$ and three foreign companies with $P = 29\%$. The companies were randomly selected for each investor.

Investors were paid based on the performance of every trial. After completing the entire experiment (after part 4), the investors were asked for the level of familiarity of these 12 companies in the survey section.

Implied assumption is that the subjective probability belief over the stock prices is independent of the probability of receiving the security (bond and options). With this assumption, Proposition 2 claims that regardless of the belief over the performance of the stocks, choosing a bond will imply that the investor is exerting ambiguity aversion (via sub-additive probability).

Proposition 4.6.1 *With any probability $p < 33\%$ in the above setting, selecting a bond will lead to a sub-additive probability measure. In addition, as p decreases, the level of sub-additivity of the probability measure increases, which implies higher level of ambiguity aversion.*

Proof. Denote x as an event of receiving the bond and y as an event of receiving the option. Denote v as an event of increase in price and w as an event of decrease in price of the company's stock. By assumption, $p(y \cap v) = p(y)p(v)$ and $p(y \cap w) = p(y)p(w)$. $bond \succ put \iff p(x)u(\$) > p(y \cap v)u(\$) = p(y)p(v)u(\$) \Rightarrow p(x) > p(y)p(v)$ hence $p(x)/p(y) > p(v)$. Similarly, $bond \succ call \iff p(x)/p(y) > p(w)$. We observe that $p(w) + p(v) < 2p(x)/p(y)$. If $p < 33\%$, then we have $p(w) + p(v) < 66/67 < 1$, hence sub-additive probability measure. Notice as p decreases, $2p(x)/p(y)$ also decreases. Therefore, the level of sub-addivity of the probability measure increases as p decreases.

■

This section addresses four major questions: 1. Is there a difference in the level of familiarity between domestic and foreign companies? 2. What is the relationship between the level of familiarity and individual choices? 3. Are investors more likely to show higher levels of ambiguity aversion in foreign companies compared to the domestic companies? And most importantly, 4. Are ambiguity averse investors more likely to choose bonds than others?

4.6.2 Results

This section provides the most significant result out of all designs related to individual companies.

The familiarity of companies were coded using the following method. Investors were asked during the survey section to state the level of familiarity from "never heard of it", "not familiar", "somewhat familiar", "familiar", and "very familiar." We then coded the dummy variable using 1 to 5 from "never heard of it" to "very familiar" in increasing order ($\mu = 2.18, \sigma = 1.30$).

Table 4.3 presents a simple relationship from the experimental data. In particular, it addresses whether there is a relationship between familiarity and individual choices. We see that investors are indeed more familiar with US companies than foreign companies ($\rho = 0.24$, $p < 0.01$). Next, we obtain a significant correlation between investment decision and ambiguity classification ($\rho = -0.16$, $p < 0.01$). This states that people who were classified as ambiguity averse are more likely to choose to receive a bond in this experimental treatment. Table 4.3 suggests that the type of option chosen (call vs put) is not influenced by ambiguity aversion, country origin of asset, level of ambiguity, or familiarity.

Refer to the graph in Figure 4.3. Here, we present the percentage that an option was chosen instead of a bond. On average, we find that an option was chosen in 73% of the trials. We further divide the group to compare the decisions made by ambiguity averse and non-ambiguity averse individuals, and then further divided the sample by focusing on domestic and foreign assets. First, we observe that investors classified as ambiguity averse are more likely to choose an option compared to non-ambiguity averse investors ($\mu_{non-ambiguity\ averse} = 0.81 \neq 0.67 = \mu_{ambiguity\ averse}$, $p < 0.01$). Furthermore, we observe that ambiguity averse individuals are more likely to receive a bond over option when faced with foreign companies ($\mu_{non-ambiguity\ averse} = 0.85 \neq 0.71 = \mu_{ambiguity\ averse}$, $p < 0.1$) or US companies ($\mu_{non-ambiguity\ averse} = 0.77 \neq 0.62 = \mu_{ambiguity\ averse}$, $p < 0.1$). Therefore, Figure 4.3 supports our theory and shows that ambiguity averse individuals are more likely to select a bond, in turn, showing a higher rate of sub-additivity in probability.

Next, we divide the sample to see the aggregate rate of option chosen for different levels of familiarity between ambiguity averse and non-ambiguity averse individuals in Figure 4.4. While we do not find significant difference between rate of option chosen between ambiguity averse and non-ambiguity averse investors for high levels of familiarity (≥ 3), we find significant differences when the familiarity is low. This is expected since ambiguity aversion is more salient when the asset is not familiar. When familiarity level is 1, we find that $\mu_{non-ambiguity\ averse} = 0.87 \neq 0.65 = \mu_{ambiguity\ averse}$, $p < 0.01$, which means ambiguity averse investors are more likely to choose a bond conditioning on familiarity level being 1. When familiarity level is 2, we also find a statically significant differences: $\mu_{non-ambiguity\ averse} = 0.81 \neq 0.58 = \mu_{ambiguity\ averse}$, $p < 0.1$. Again, these results support our theory: when people are unfamiliar with an asset, it creates higher rate of ambiguity, in turn, they are more likely to choose a bond. When people are familiar with an asset, the two class of investors behave in a similar manner.[8]

Table 4.4 represents three different random-effects logistical regression models. All three regressions takes the following functional form in Equation (4.4):

$$decision_{ij} = \alpha + \beta_1 \text{ambiguity averse}_i + \beta_2 \text{us asset}_j + \beta_3 \text{high ambiguity} + \beta_4 \text{familiarity}_{ij} \tag{4.4}$$

where i is the index for the individuals and j is the index for the companies. For example, familiarity$_{ij}$ means individual i's familiarity for company j. For the random-effects model, we panel the data by individual i: therefore, the number of groups equal the number of subjects and each panel contains all the choices made by that particular individual. The three different regression models are: *All Assets*, *Familiar Assets*, and *Unfamiliar Assets*. As the names indicate, we restrict our attention to a subset of observations for those analyses. *Familiar Assets* restricts attention to assets with familiarity levels 3 to 5 while *Unfamiliar Assets* are restricted to familiarity levels

[8]Although not statistically significant, what we observe is that with familiar assets, ambiguity averse individuals are more likely to take the option than the bond compared to non-ambiguity averse people.

1 and 2. The $decision_{ij}$ variable took a value of 1 if the investor i chose to receive an option for company j and 0 if a bond. Ambiguity averse took a value of 1 if the individual i was classified as ambiguity averse, 0 otherwise. US asset is a dummy variable representing whether the company j is from US. High ambiguity is also a dummy variable, taking a value of 1 during $P = 29$ treatment. Lastly, familiarity took a value ranging from 1 to 5, least to most familiar.

From *All Assets* regression, we find that investors are more likely to choose to receive an option when familiarity is higher ($\beta_4 = 0.262$, $p < 0.1$). As expected, familiarity plays a even a stronger and positive role when an asset is familiar ($\beta_4 = 1.584$, $p < 0.05$ under *Familiar Assets* regression), and it is not significant when it comes to *Unfamiliar Assets* regression. In other words, familiarity matters when the investor is familiar with the asset and the relationship is positive. The high ambiguity independent variable is positive in all 3 regressions, which means that investors are more likely to select an option if the required level of sub-additivity increases. Notice that the US assets independent variable is significant under *All Assets* and *Unfamiliar Assets* regressions only ($p < 0.05$). Furthermore, the coefficients are negative: $\beta_2^{allassets} = -0.765 > \beta_2^{unfamiliarassets} = -0.848$. This suggests that people are more ambiguity averse when it comes to unfamiliar US assets compared to unfamiliar foreign assets. This observation is also supported in Figure 4.3 by showing a higher rate of selecting the bond option for US compared to foreign assets. The key is that the β_2 is significant for the unfamiliar assets. Lastly, consider the independent variable titled ambiguity averse. This variable takes 1 if the investor is classified as ambiguity averse and 0 otherwise. Under the *All Assets* regression, it has a weakly significantly and negative coefficient ($\beta_1 = -1.015$, $p < 0.15$ two-tailed test), which correctly suggests that ambiguity averse individuals are more likely to take the bond over the asset. Furthermore, the ambiguity averse variable is not significant when it comes to *Familiar Assets* regression, since people are indeed not ambiguous when it comes to these assets. Lastly, when considering the *Unfamiliar Assets* regression, we obtain a even more negative and statistically significant coefficient, as one would expect if our theory were to hold true ($\beta_1 = -1.275$, $p < 0.05$).

In summary, our data suggests that: 1. subjects are more familiar with the US assets, 2. subjects are more likely to choose a bond when they are less familiar with the company, 3. subjects do not show higher rate of ambiguity aversion to foreign assets per se; they are ambiguity averse towards less familiar companies which are more likely to be foreign, 4. in fact, subjects are more likely to dislike unfamiliar US assets compared to unfamiliar foreign assets and 5. subjects who are classified as ambiguity averse are more likely to choose a bond.

	Ambiguity Averse	US Asset	High Ambiguity	Familiarity	Decision	Option Type
Ambiguity Averse	1					
US Asset	0	1				
High Ambiguity	0	0	1			
Familiarity	-0.05	0.24***	0.02	1		
Decision	-0.16***	-0.10	0.31***	0.07	1	
Option Type	0.11	0.06	-0.00	-0.03	.	1

*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test)
Number of Obs: 252. Number of Obs for Optiontype: 185

Table 4.3: Correlation Relationship
Ambiguity Averse: 1 if true, 0 otherwise. US Asset: 1 if true, 0 otherwise. High Ambiguity: 1 if P = 29%, 0 if P = 33%
Familiarity: from 1-5. Decision: 1 if Option, 0 if Bond. Option Type: 1 if Call, 0 if Put

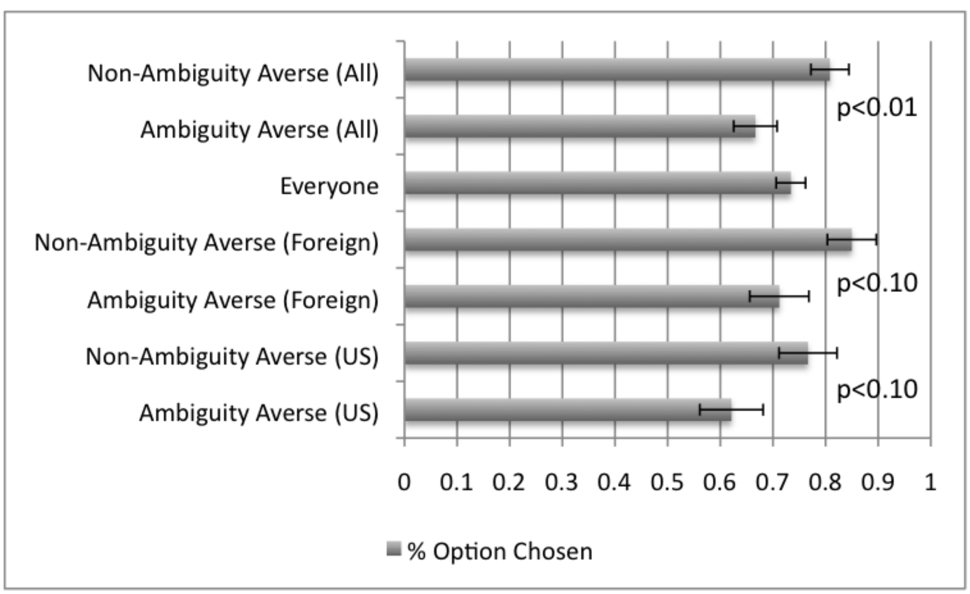


Figure 4.3: Decision Comparison: By Ambiguity and Origin of Assets

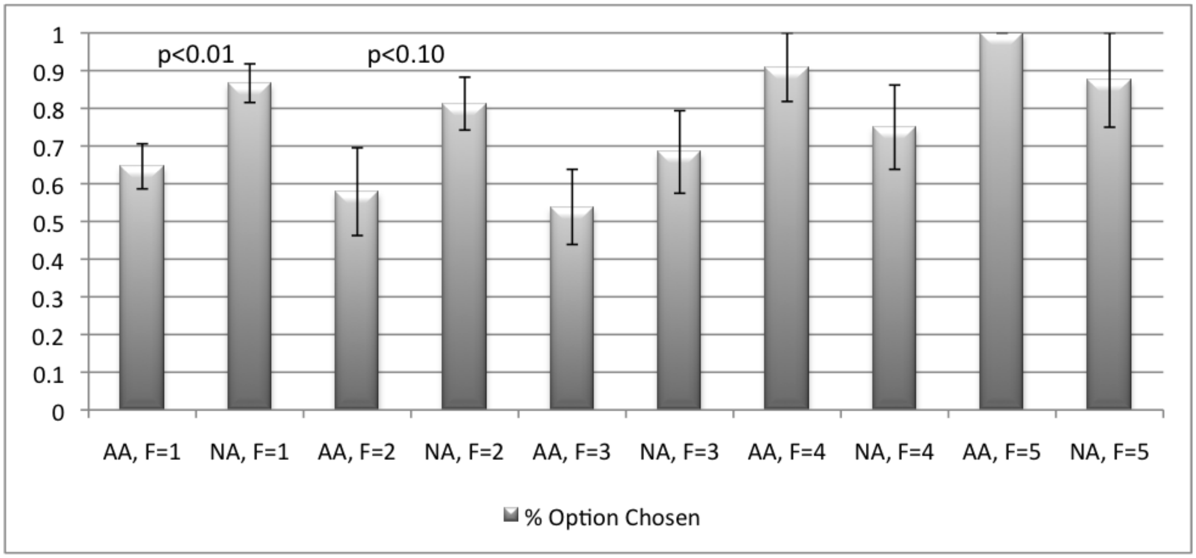


Figure 4.4: Decision Comparison: By Ambiguity and Familiarity

AA: Ambiguity Averse. NA: Not Ambiguity Averse. Fi: Familiarity level i

Dependent Variable: Decision = 1 if Option and 0 if Bond			
Ind. Variables	All Assets	Familiar Assets	Unfamiliar Assets
Constant	0.899	-4.343**	1.762*
	(0.631)	(2.201)	(0.942)
Ambiguity Averse	-1.015#	-0.112	-1.275**
	(0.679)	(0.876)	(0.621)
US Asset	-0.765**	-0.873	-0.848**
	(0.358)	(0.747)	(0.431)
High Ambiguity	1.989***	1.930**	1.544***
	(0.392)	(0.761)	(0.462)
Familiarity	0.262*	1.584**	-0.060
	(0.158)	(0.683)	(0.518)
Log likelihood	-116.919	-40.682	-77.758

All Assets: Number of Obs: 252. Number of Groups: 21
Familiar Assets: Number of Obs: 91. Number of Groups: 21
Unfamiliar Assets: Number of Obs: 161. Number of Groups: 21

#p<0.15, *p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test)
Numbers in parentheses are standard errors

Table 4.4: Random-Effects Logit Regression: Decision

Variables are defined in the same manner as Table 4.3

Familiar Assets model restricts attention to assets with familiarity level greater than 2

Unfamiliar Assets model restricts attention to assets with familiarity level less than 3

4.7 Experiment 3: Company Preference

4.7.1 Experimental Summary and Motivation

In this part of the experiment, the investors are shown two companies (A and B) and asked to choose one of the three gambles: *Gamble 1*: A outperforms B, *Gamble 2*: B outperforms A and *Gamble* 3: A equals B. The term outperform means that the percent change in the company's stock price is higher than the other companys percent change one week from the day of the experiment. For the purpose of payment, we randomly selected one of the trials the investor went through and paid \$5 if he made the correct choice.

The key to this experiment is how the two companies are populated. Recall that from experiment 1, the investor specified his portfolio. Using this portfolio, the experiment is programmed to ask for comparison between US companies with put requests and foreign companies with call requests. In addition, the experiment also asked for a comparison between US companies with call requests and foreign companies with put requests. Given that the investor requested a put option for one company and a call option for another company, he should take the gamble which states the call company will outperform the put company. If the investor selects the US company which he requested a put option for over the foreign company which he requested a call option for, by the proposition below, the investor is showing ambiguity aversion against the foreign company.

Proposition 4.7.1 *After choosing a put option for company A and a call option for company B, stating that company A will outperform company B leads to a sub-additivity in probability measure.*

Proof. Denote v as an event of increase in price and w as an event of decrease in price of the company's stock price. Having chosen a put option for company A implies that $p(w|A) > p(v|A)$. Having chosen a call option for company B implies that $p(v|B) > p(w|B)$. Stating that company A will outperform company B implies that $p(v|A) > p(v|B)$. Since p is a probability measure, highest $p(v|A)$ can be is 1/2.

Therefore, $1/2 > p(v|B) > p(w|B)$ hence $p(v|B) + p(w|B) < 1$. ∎

This design addresses the following major questions. 1. Do the investors consistently prefer the US companies over the foreign companies? 2. Are the investors who showed signs of ambiguity aversion during the Ellsberg setting (experiment 1) more likely to choose US (put) companies over foreign (call) companies?

4.7.2 Results

In short, we do not find any statistically significant results from this experimental study.

To support that there is sub-additive probability beliefs towards foreign companies, one would expect to see a higher rate of choosing US put over foreign call gambles compared to choosing foreign put over US call gambles. In our data, when investors were making a decision between US put company and foreign call company, investors preferred the US put over foreign call 22.59% (SE=4.58%) of the time (Figure 4.5). In other words, the investors exhibited sub-additivity 22.59% of the time. However, when faced with US call and foreign put, investors preferred the foreign put 25.74% (SE=3.45%) of the time. The difference is not statistically significant.

As presented below, we further divided the observation by ambiguity category (Figure 4.5), portfolio composition (Figure 4.6), and conducted various regression analyses (Table 4.5). However, we did not find any significant result to support our theory.

The two possible explanation for the results we observed are: 1. familiarity and 2. risk hedging. The result we observe here may be due to higher familiarity of foreign companies shown over the US companies. The survey of familiarity of the companies chosen during the portfolio building section was not taken and cannot be tested.

Another possible explanation which we can infer from the data is that the investors were hedging their risk. Since the mean share of US companies in the investor's portfolio is 51%, we can split the investors into two types: US-heavy investors who have over 51% of US companies in their portfolio and US-light investors who have less than 51%. Then, from Figure 4.6 we observe that among the US-heavy investors, they are much more likely to prefer foreign put over US call ($p < 0.1$). However, this difference disappears when we only consider the US-light investors. Since the investors over-invested in US assets during the portfolio building section, they may have decided to under-invest in company comparison section since these are exactly the same companies they previously invested in. This type of experimental spill-over is a potential drawback of having the same subject participate in the various treatments.

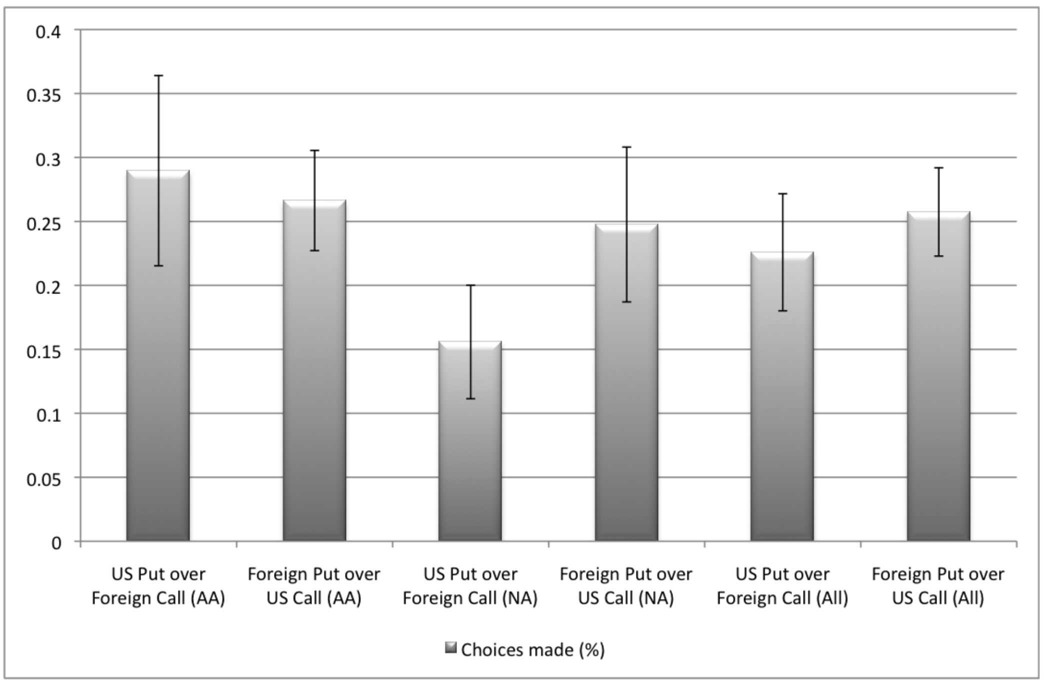


Figure 4.5: Company Comparison Choices Made: By Ambiguity

AA: Ambiguity Averse. NA: Not Ambiguity Averse

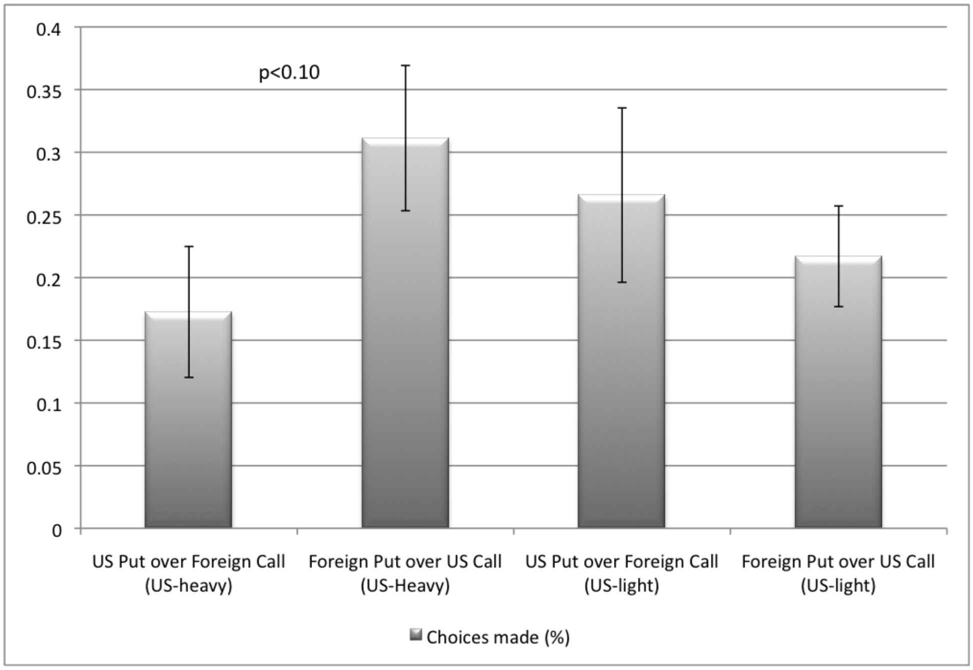


Figure 4.6: Company Comparison Choices Made: By Portfolio

US-heavy: Portfolio consists of more than 51% US companies. US-light: Portfolio consists of less than 51% US companies

	Dependent Variables	Independent Variable: Constant	Independent Variable: Ambiguity Averse
US-Heavy	US Put over Foreign Call	0.143*	0.067
		(0.077)	(0.109)
	Number of Obs: 9. R^2: 0.0507		
US-Heavy	Foreign Put over US Call	.379***	-0.153
		(0.074)	(0.110)
	Number of Obs: 9. R^2: 0.2157		
US-Light	US Put over Foreign Call	0.169	0.167
		(0.106)	(0.138)
	Number of Obs: 12. R^2: 0.1271		
US-Light	Foreign Put over US Call	0.116**	0.173**
		(0.050)	(0.065)
	Number of Obs: 12. R^2: 0.4125		
*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test) Numbers in parentheses are standard errors.			

Table 4.5: Regressions: Company Comparison Choices Made

US-heavy: Portfolio consists of more than 51% US companies. US-light: Portfolio consists of less than 51% US companies

4.8 Experiment 4: Position Holding

Definition 2 *A* ***position*** *is a vector* $\theta = (\theta_1, ..., \theta_n) \in \mathbb{R}^n$*, where* n *is the number of companies available and* θ_i *denotes the number of shares of company* i*.*

Definition 3 *Holding a* ***short*** *position means that the investor has done the following procedure. The investor borrowed the share from another investor and sold it today at today's price. Then the investor will buy back the share in the future and return the borrowed share to the original owner.*

One should short a share if he believes that the stock price will drop in the future. The payoff from short position: $price_{today} - price_{future}$.

Definition 4 *Holding a* ***long*** *position means that the investor has done the following procedure. The investor borrowed cash to buy the stock today at today's price. Then the investor will sell the stock in the future and pay back the borrowed money.*

One should long a share if he believes that the stock price will increase in the future. The payoff long position: $price_{future} - price_{today}$

Example: $\theta = (1, 2, -4, 2)$ with companies Q =(Microsoft, Dell, Shell, IBM). The holding from this position is θQ^T which indicates that the investor holds a long position on 1 share of Microsoft, 2 shares of Dell, shorted 4 shares of Shell and holds a long position on 2 shares of IBM.

Definition 5 *The preference relation* $\succeq$ *satisfies the* ***sure-thing principle*** *if for any subset* $E \subset S$*,* $(x_1, ..., x_S)$*,* $(x'_1, ..., x'_S)$*,* $(\overline{x}_1, ..., \overline{x}_S)$ *and* $(\overline{x'}_1, ..., \overline{x'}_S)$ *are such that 1. For all* $s \notin E$*:* $x_s = x'_s$ *and* $\overline{x}_s = \overline{x'}_s$ *and 2. For all* $s \in E$*:* $x_s = \overline{x}_s$ *and* $x'_s = \overline{x'}_s$ *then* $(\overline{x}_1, ..., \overline{x}_S) \succeq (\overline{x'}_1, ..., \overline{x'}_S) \iff (x_1, ..., x_S) \succeq (x'_1, ..., x'_S)$*.*

4.8.1 Experimental Summary and Motivation

This experiment provides a method for testing the behavior of the investor in the multiple companies setting. This can be seen as investing in funds (such as mutual funds). In this experiment, the investor was asked to choose between taking a position that is shown or taking a bond. We will first discuss the concept behind this experiment and then discuss the exact implementation in the experimental structure section. This experiment is structured in the following manner. The investor was given a list of domestic positions $\theta_D \neq (0, ...0) \in \mathbb{R}^n$. We then went through several iterations and determined the investor's preference between the position and bond. Then we asked for the investor's preference between $\theta = (\theta_D, \theta_F)$ and a bond, where $\theta_F \in \mathbb{R}^M$ is a position in foreign companies. Again we went through several iterations in this setting. Lastly, we asked for the investor's preference between $\theta^* = (\theta_D, -\theta_F)$ and a bond. For the purpose of payment, an investor was paid from a randomly selected trial and was paid based on the performance of the choice. If a position was selected, investor was paid based on the performance of the position. We capped the earnings at \$10 while the minimum was bounded at \$0 for the purpose of the experiment.

The data allows us to test whether the investor's preferences are consistent. In other words, if the investor preferred θ_D over the bond but preferred the bond over $\theta = (\theta_D, \theta_F)$, then he should prefer $\theta^* = (\theta_D, -\theta_F)$ over the bond. Otherwise, he is violating the *sure-thing principle* (Savage 1954).[9] Same argument applies to the setting in which the investor prefers bond over θ_D, $\theta = (\theta_D, \theta_F)$ over the bond and $\theta^* = (\theta_D, -\theta_F)$ over the bond.

4.8.2 Experimental Structure

This is divided into two phases. This section is written to provide a detailed explanation of what actually occurred during the experiment and may be skipped. The overview was explained in the previous section.

Phase 1: Single US and Single Foreign Company

1. Randomly select a US company listed under the call option from experiment 1.

[9]Note that the violation of the sure-thing principle is a necessary but not a sufficient condition for ambiguity aversion.

   (a) Ask for preference between the positive position of this company and a bond.
   (b) Repeat this procedure until "position" choice is selected.

2. Randomly select a foreign company.
   (a) Ask for preference between a positive position from the US company from 1-b and negative position from the foreign company.
   (b) Repeat this procedure until the "bond" choice is selected.

3. Reverse the position for the foreign company from 2-b and ask for preference between the bond and the position.

Phase 2: Two US and Two Foreign Companies

1. Randomly select 2 US companies (without replacement) and give one a positive and one a negative position.
   (a) Compare the position with a bond.
   (b) Repeat this 4 times.

2. Randomly select 2 foreign companies (without replacement), give one positive and one negative position, and pair this with one of the pairs from 1 (without replacement).
   (a) Compare the position with a bond.
   (b) Do this for all 4 pairs

3. Reverse the foreign company's position from 2.
   (a) Compare the position with a bond.
   (b) Do this for all 4 pairs

This section addresses the following two major questions: 1. Do investors violate the sure-thing principle in the multiple companies setting? 2. If so, who are more likely to violate the sure-thing principle?

4.8.3 Results

In this section, each investors provided 5 data points.[10] Each data point is a binary result of whether the investor violated the sure-thing principle. On average, investors violated the sure-thing principle 0.81 times (SE = 0.164), hence violated the sure thing principle approximately 1 out of 5 times. These violations of sure-thing principle supports the argument that investors are ambiguity averse towards foreign assets.

Judging by the regression in Table 4.6, investors are more likely to violate the sure-thing principle in the position experiment if they are ambiguity averse ($\beta = 4.920$, $p < 0.10$). This result again supports the theory that ambiguity aversion does play a role in home bias. However, US-heavy investors are less likely to violate the sure-thing principle if they are also ambiguity averse ($\beta = -9.367$, $p < 0.10$), which is consistent with the results from the third experimental design (company comparison).

Dependent Variable: Position (number of times sure-thing principle was violated)				
Ind. Variables	Constant	Ambiguity Averse	US Assets	AmbiguityXUS Assets
	-0.404	4.920*	2.109	-9.367*
	(1.811)	(3.303)	(3.430)	(6.516)
Number of Obs: 21. R^2: 0.1278				
*p < 0.1, **p < 0.05, ***p < 0.01. (One-tailed test) Numbers in parentheses are standard errors.				

Table 4.6: Regression: Violation of Sure-Thing Principle

US Asset: % of US companies in investor's portfolio

[10] This is because a series of choices only provides 1 observation.

4.9 Experiment 5: Portfolio Building with Indices

4.9.1 Setup for Indices

Thus far we have focused on individual companies. We will shift our focus to indices for the next two experimental designs. Both setup and the experimental designs for the indices treatment are similar to the setup and the designs for the individual companies. There are several reasons why we need to consider both indices as well as individual companies. First, average investors tend to discuss and invest at a company level for daily trading. However, when the average investors are planning a retirement plan through financial advisors, they tend to invest in indices that are provided by the holding company. Secondly, people are more familiar with the companies than indices. In other words, there is less of a company-level effect or company-level informational advantage, since indices are composed of hundreds of different companies. Therefore, showing ambiguity aversion at the indices level may provide a stronger case of home bias. We are interested to learn whether the ambiguity aversion is concentrated only at the individual company level or if it is also present at the index level.

For the indices treatment, we have selected 25 domestic and 25 foreign major indices defined by Bloomberg[11] which varied in capitalization size as well as industry focus. All the investors were initially provided with a web-based prospectus. The prospectus was created using data provided by Bloomberg which included summarization of the index, value of the index for the past three months and their trading volume. The sample instructions, screen shots, and the list of indices are provided in the appendix.

4.9.2 Experimental Summary and Motivation

A motivation for this design is to test whether there is home bias in investment behavior when dealing with indices. Investors were shown indices one by one and were asked to build their portfolio. A total of 25 domestic and 25 foreign indices were

[11] www.bloomberg.com

shown in a random order. For each of the indices, they were given 3 options: buy the index, sell the index, or receive a bond instead. The investors were paid based on the performance of their portfolio 7 days after the experiment was concluded. The payment structure was:

- If bond: \$1.00
- If buy: $\$1.00 + (20 \times r)$
- If sell: $\$1.00 - (20 \times r)$

where r is the return from the index. Although we did not use the term, they were actually going long or short on the indices. The returns were multiplied by a factor of 20 to stimulate long term investment.

This study answers the following major questions: 1. Is there home bias when investing in indices? 2. Are investors more familiar with US indices? 3. Are people more likely to buy, sell, or receive a bond with US assets? 4. Do ambiguity averse investors have different portfolio composition? Overall, what is the relationship between familiarity, ambiguity aversion, and investment choices?

4.9.3 Results

First, just as with the individual company treatment, investors are indeed more familiar with the US indices than the foreign indices. When investors were asked to rate the familiarity of each index from 1-6, 1 being least and 6 being most familiar, the average familiarity for US indices was 2.057 ($SE = 0.032$) and for foreign indices was 1.268 ($SE = 0.018$), significantly different at $p < 0.01$. In fact, the correlation of familiarity is stronger for indices ($\rho = 0.364$, $p < 0.01$) than for individual companies ($\rho = 0.24$, $p < 0.01$).

Three random-effects regressions are presented in Table 4.7 for *Bond*, *Sell* and *Buy* as the functional form in Equation (4.5):

$$choice_{ij} = \alpha + \beta_1 \text{us index}_j + \beta_2 \text{index familiarity}_{ij} + \beta_3 \text{ambiguity averse}_j \tag{4.5}$$

where i is the index for the individuals and j is the index for the indices. Bond, Sell and Buy variables take 1 if the investor chose to receive the respective choice, 0 otherwise. US index is a dummy variable taking 1 for an US index. Index familiarity ranged from 1-6 as stated above. The ambiguity averse variable takes 1 if the investor was classified as ambiguity averse via Ellsberg's experiment, 0 otherwise.

The *Bond* regression's significant coefficient is only for the index familiarity ($\beta_2 = -0.029$, $p < 0.1$), which states that investors are more likely to take the bond choice if they are less familiar with the index. This is consistent with findings from the individual company treatment. The *Sell* regression and the *Buy* regressions also have one variable that is statistically significant and it is for dummy variable US Index: $\beta_1 = -0.193$, $p < 0.01$ for *Sell* and $\beta_1 = 0.185$, $p < 0.01$ for *Buy*. This suggests that investors are much more likely to buy a US asset while less likely to sell a US asset. This is consistent with a home biased investor.

Figure 4.7 and Figure 4.8 presents the composition of investor's portfolio. Overall, we find that investors are more likely to buy than to receive a bond or sell ($p < 0.01$) although the difference in bond and selling is not significantly different. The biggest contrast appears when comparing US indices to foreign indices. There is no significant differences when comparing the ratio of selling and bond for US indices but investors are much more likely to buy US indices: composed over 50% of the portfolio ($p < 0.01$). However, the investment ratio is more evenly spread out when it comes to foreign indices. There is no significant difference when comparing buying and selling behavior for the US indices. When we divide the observation to high familiarity (familiarity level > 2) to low familiarity (familiarity level ≤ 2, investors are much more likely to choose to buy than to sell or receive a bond with in both categories ($p < 0.01$). Furthermore, investors have higher ratio of bond when it comes to low familiarity indices compared to familiar indices ($p < 0.01$). Lastly, with respect to ambiguity averse to non-ambiguity averse investors, we find that non-ambigity averse investors are much less likely to take the bond option ($p < 0.1$). However, there is no significant difference in the ratio of buying indices, but ambiguity averse investors have higher ratio of selling ($p < 0.05$).

We conclude that investors are: 1. indeed home biased (more buying and less selling in US indices), 2. more familiar with US indices, 3. more likely to buy familiar indices, 4. ambiguity averse individuals are more likely to receive a bond, and 5. more likely to receive a bond when faced with unfamiliar indices.

	Dependent Variable		
Ind. Variables	Bond	Sell	Buy
Constant	0.304***	0.394***	0.303***
	(0.065)	(0.042)	(0.059)
US Index	0.006	-0.193***	0.185***
	(0.034)	(0.036)	(0.038)
Index Familiarity	-0.029*	0.023	0.007
	(0.015)	(0.016)	(0.017)
Ambiguity Averse	0.062	-0.084	0.022
	(0.093)	(0.053)	(0.081)
Overall R^2	0.0095	0.0435	0.0389
Number of Obs: 792. Number of Groups: 16.			
*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test) Numbers in parentheses are standard errors.			

Table 4.7: Random-Effects Regression: Portfolio Composition with Indices
IV: US: 1 if true, 0 otherwise. Index Familiarity: from 1-6 least to greatest. Ambiguity Averse: 1 if true, 0 otherwise

DV: Bond: chose Bond. Sell: chose Sell. Buy: chose Buy

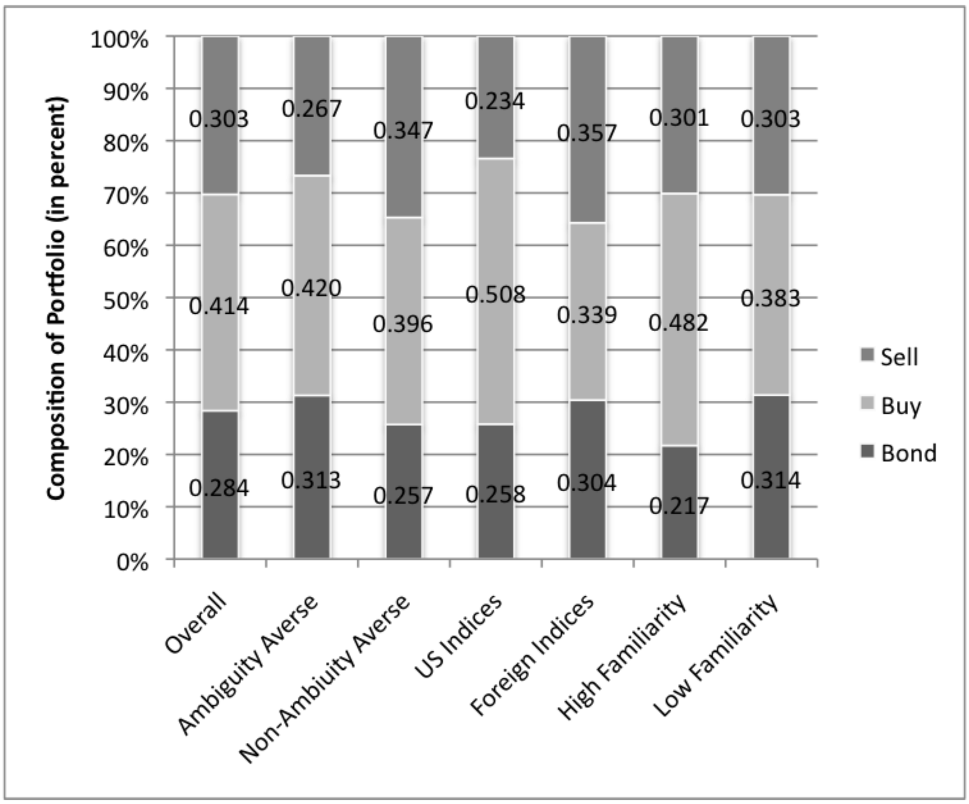


Figure 4.7: Composition of Portfolio for Indices

Average SE = 0.0178. Maximum SE = 0.0266

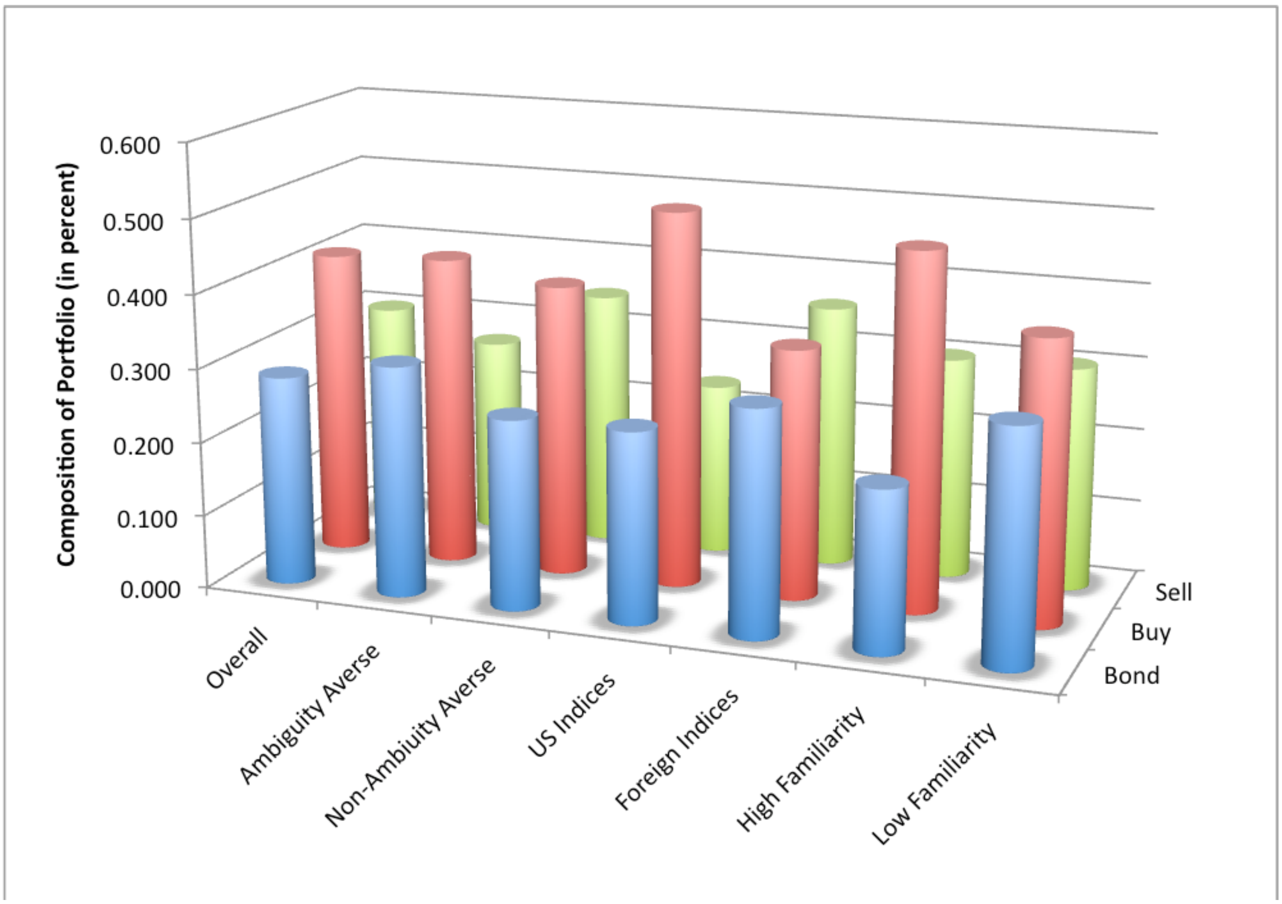


Figure 4.8: Composition of Portfolio for Indices

Average SE = 0.0178. Maximum SE = 0.0266

4.10 Experiment 6: Bond or Options with Indices

4.10.1 Experimental Summary and Motivation

The design for this experiment is similar to the *Bond or Options* experiment under the individual companies treatment. The investors were shown series of indices one at a time and were given three possible choices just as in the stock treatment:

- Receive a bond which pays \$1.00 with probability P.
- Receive a digital call option with exercise value of \$1.00 with probability $1 - P$.
- Receive a digital put option with exercise value of \$1.00 with probability $1 - P$.

However, there are two differences. First, we used indices instead of companies: 25 domestic and 25 foreign, which were presented in random order. Second, we varied the value of P, the known risk of receiving the actual derivative. Instead of focusing only on $P = 33\%$ or $P = 29\%$ as in the individual companies treatment, we varied the $P \in \{30, 32, 34, 36\}$ for the indices treatment. Note that we are in a super-additive subjective probability measure once $P \geq 34\%$.

This study answers the following major questions. What is the relationship between familiarity, ambiguity aversion, and investment choice?

4.10.2 Results

Table 4.8 presents several random-effects logistical regression models. We regress sub-additive cases, super-additive cases, and all cases with the following two functional forms:

$$decision_{ij} = \alpha + \beta_1 \text{us index}_j + \beta_2 \text{familiarity}_{ij} + \beta_3 \text{P-level} \tag{4.6}$$

and

$$decision_{ij} = \alpha + \beta_2 \text{familiarity}_{ij} \tag{4.7}$$

Table 4.8 details the dependent variables. Consistent with our findings thus far, we find that people are more likely to take the option with more familiar indices (see model (1), (2), (4), and (5)). The significance disappears once we focus only on the super-additive cases and this is expected (see model (3) and (6) in Table 4.8). Furthermore, model (1) shows that people are also more likely to take the option with a US index compared to foreign index.

Unlike the case with the individual companies, we do not get a strong result when analyzing the data by ambiguity and origin of indices (see Figure 4.9). The difference in rate of choosing an option is not statistically different when we divide our observation by US indices only and foreign indices only. Furthermore, even in the aggregate level, the difference is only marginally significant ($\mu_{non-ambiguity\ averse} = 0.89 \neq 0.84 = \mu_{ambiguity\ averse}$, $p < 0.15$, two-tailed t-test).

Figure 4.10 compares the decisions divided by ambiguity classification of the investors and their familiarity level for the indices. Consistent with the results from the individual companies, we do find that investors are more likely to take the bond (in turn, showing sub-addivity in subjective probability), when it comes to unfamiliar assets compared to non-ambiguity averse investors. This difference, again disappears appropriately when we focus the observation to familiar indices.

In summary, although not as strong as the individual company treatment, we find that subjects show ambiguity aversion when it comes to investing in unfamiliar indices.

Dependent Variable: Decision = 1 if Option and 0 if Bond						
Ind. Variables	All P-level (1)	$P \in \{30, 32\}$ (2)	$P \in \{34, 36\}$(3)	All P-level (4)	$P \in \{30, 32\}$(5)	$P \in \{34, 36\}$(6)
Constant	13.045***	4.983	24.582***	1.674 ***	2.225***	0.802*
	(1.734)	(5.110)	(5.074)	(0.295)	(0.262)	(0.488)
US Index	0.277*	0.196	0.405			
	(0.168)	(0.195)	(0.507)			
Familiarity	0.202**	0.171*	0.085	0.355***	0.198**	0.192
	(0.085)	(0.100)	(0.191)	(0.080)	(0.098)	0.164
P-level	-0.348***	-0.089	-0.677***			
	(0.052)	(0.160)	(0.143)			
Log likelihood	-627.066	-420.044	-184.201	-659.718	-420.661	-196.493
All P-level: Number of Obs: 1,692. Number of Groups: 34						
$P \in \{30, 32\}$: Number of Obs: 1,296. Number of Groups: 34						
$P \in \{34, 36\}$: Number of Obs: 396. Number of Groups: 16						
*p < 0.1, **p < 0.05, ***p < 0.01. (Two-tailed test)						
Numbers in parentheses are standard errors.						

Table 4.8: Random-Effects Logit Regression: Decision for Indices
IV: US Index: 1 if true, 0 otherwise. Familiarity: from 1-6 least to greatest. P-level: 30, 32, 34, or 36

DV: Restrict sample to their respective variables

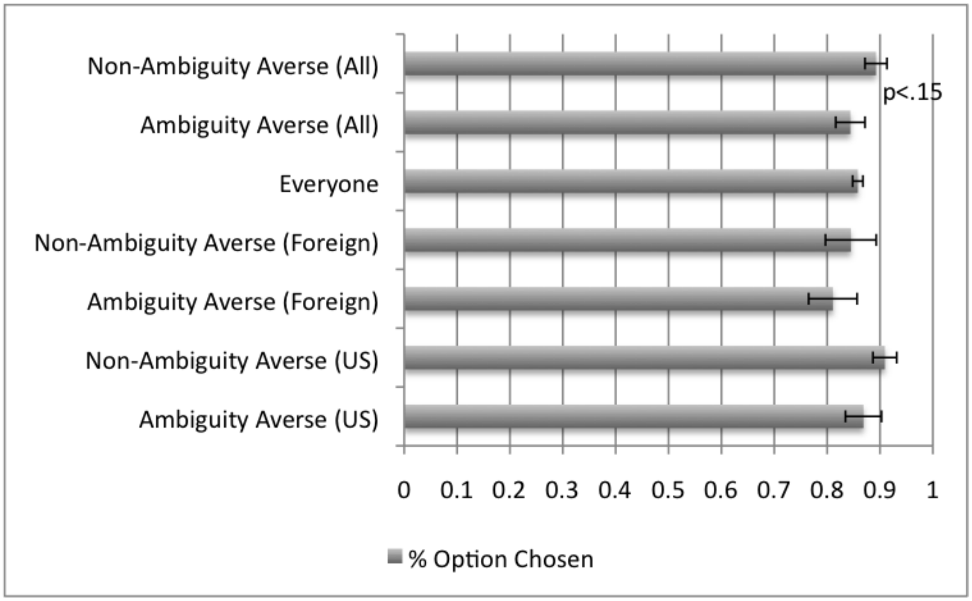


Figure 4.9: Decision Comparison: By Ambiguity and Origin of Indices

Sub-addivity cases only: $P \in \{30, 32\}$

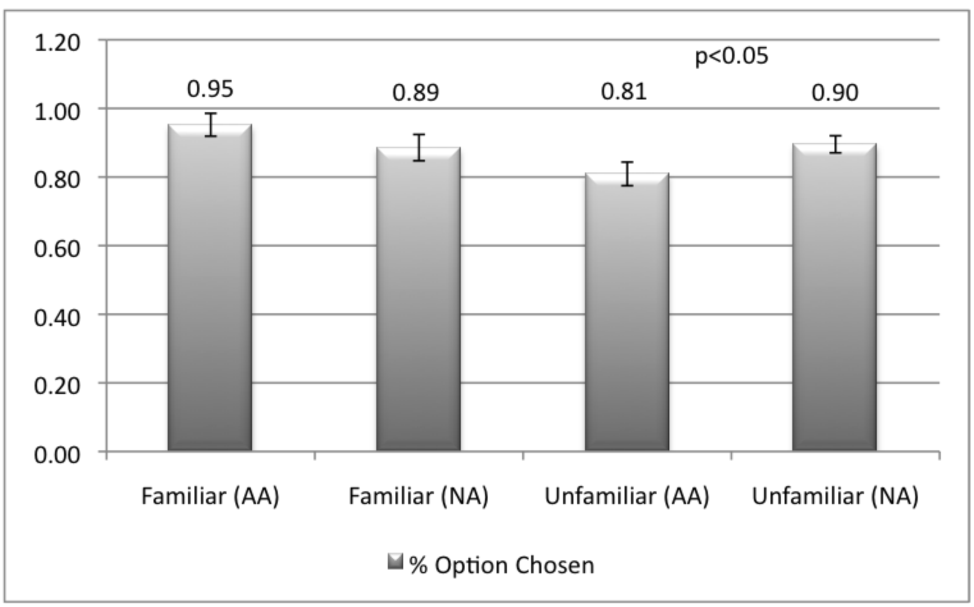


Figure 4.10: Decision Comparison: By Ambiguity and Familiarity for Indices

AA: Ambiguity Averse. NA: Not Ambiguity Averse

Familiar if familiarity level > 2. Otherwise, Unfamiliar. Sub-addivity cases only: $P \in \{30, 32\}$

4.11 Conclusion

We started out this research to show that ambiguity aversion is a possible candidate for explaining home bias paradox despite what the rational choice model suggests. We designed experiments that used real world assets and prices. We then used the concept of sub-addivity to show whether an investor's choices expressed ambiguity aversion. Our experimental data supports the theory that ambiguity aversion partly explains home bias phenomena.

Overall, experiment 5 (*Portfolio Building with Indices*) provided the strongest support for home bias in our lab environment and experiment 2 (*Bond or Options* with individual companies) provided the strongest support that ambiguity aversion helps to explain some part of home bias behavior.

In quick summary, we classified about 50% of the participants as ambiguity averse by using the Ellsberg's urn experiment. Portfolio building with individual companies showed a modest size in home bias. Bond or Options with individual companies experiment showed that investors do show higher rate of ambiguity aversion (sub-additivity in probability) when it comes to unfamiliar assets, and the investors are more familiar with US assets. The company preference experiment failed to show significant results which we contribute to spill-over effect from the portfolio building experiment. The position holding experiment demonstrated that investors do violate the sure-thing principle approximately 20% of the time, and ambiguity averse investors are even more likely to violate the principle. Portfolio building with indices provided evidence that there is home bias in our laboratory setting; investors prefer to buy familiar indices and are more familiar with US indices. Lastly, Bond or Options with Indices experiment also showed that, even with indices, investors exhibit higher rate of ambiguity aversion when investing with unfamiliar indices.

Overall, the results provided here show positive support that ambiguity aversion as a partial explanation of home bias phenomenon. As Camerer and Karjalainen (1994) stated, methodologically, "this kind of work is difficult" and that even these modest size (sub-addivity of less than 5%) in ambiguity aversion "could have important economic consequences" (pp. 348 - 349). Therefore, we are quite content with our modest result provided through our experiment, and hopeful for future research.

4.12 Appendix

4.12.1 Instructions for Individual Companies

The following 4 pages are sample instructions used in the experiment.

Instruction provided to the students.

These instructions were handed out one section at a time

Experiment Overview

You are about to participate in an experiment in the economics of decision making. If you listen carefully and make good decisions, you could earn a considerable amount of money that will be paid to you in cash or check at the end of the experiment (7 days from today).

You will not be paired with any other individual. In addition, no other person's decision will influence your outcome. All your choices will be recorded today and your outcome will be realized one week from today.

The rules for the experiment are as follows. Do not talk or communicate with other participants. If you are using a computer, do not use any software other than that is explicitly required by the experiment. You are not allowed to browse the internet or check emails, etc. If you are violate these rules, you'll be asked to leave without pay. Feel free to ask questions by raising your hand or signaling to the experimenter.

Payment: You will receive a show-up fee of $10 today. At the end of today's session, you can arrange to either pick up the additional earnings in cash in person at Baxter Hall, Room 6 or have a check mailed to you.

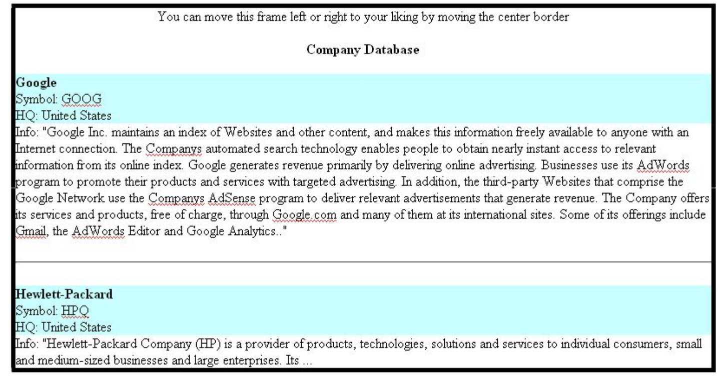
The Process will now be explained in detail.

The Process

This experiment is divided into four parts plus a survey section.

Part 1. Portfolio Building

In this part of the experiment, you will be shown a list of companies and be asked to build a portfolio. All the companies are from the technology or semiconductor industry and are considered to be one of the top 50 biggest companies in the world with respect to their industry by Forbes. Included in the company list are the company name, company ticker symbol, location of the headquarters and a brief information about the company provided by finance.google.com. In this particular portfolio, you'll be asked to choose **15** companies in which you wish to receive call options and **15** companies in which you wish to receive put options. Details about these options will be explained below. You will receive one call option per company you list under the call option box. You will receive one put option per company you list under the put option box. You cannot use the same company twice (meaning, if you requested a call option on Microsoft, you cannot request a put option on it as well). When inserting the companies, please insert the company **symbol** separated by **comma**. Do **not** place a comma after the last symbol. See screen show below for an example.

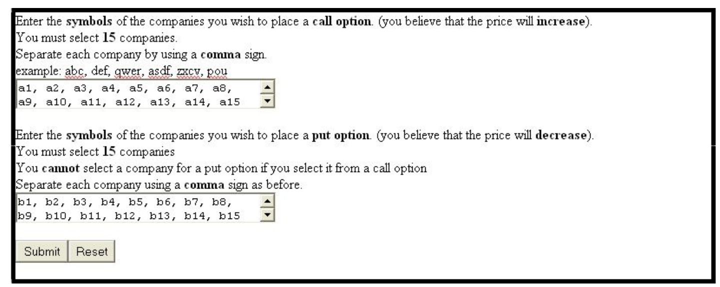

You can move this frame left or right to your liking by moving the center border

Company Database

Google
Symbol: GOOG
HQ: United States
Info: "Google Inc. maintains an index of Websites and other content, and makes this information freely available to anyone with an Internet connection. The Companys automated search technology enables people to obtain nearly instant access to relevant information from its online index. Google generates revenue primarily by delivering online advertising. Businesses use its AdWords program to promote their products and services with targeted advertising. In addition, the third-party Websites that comprise the Google Network use the Companys AdSense program to deliver relevant advertisements that generate revenue. The Company offers its services and products, free of charge, through Google.com and many of them at its international sites. Some of its offerings include Gmail, the AdWords Editor and Google Analytics.."

Hewlett-Packard
Symbol: HPQ
HQ: United States
Info: "Hewlett-Packard Company (HP) is a provider of products, technologies, solutions and services to individual consumers, small and medium-sized businesses and large enterprises. Its ...

Above is the sample of the company list. Below is the sample of portfolio building section.


Enter the **symbols** of the companies you wish to place a **call option**. (you believe that the price will **increase**).
You must select **15** companies.
Separate each company by using a **comma** sign.
example: abc, def, qwer, asdf, zxcv, pou
a1, a2, a3, a4, a5, a6, a7, a8, a9, a10, a11, a12, a13, a14, a15

Enter the **symbols** of the companies you wish to place a **put option**. (you believe that the price will **decrease**).
You must select **15** companies
You **cannot** select a company for a put option if you select it from a call option
Separate each company using a **comma** sign as before.
b1, b2, b3, b4, b5, b6, b7, b8, b9, b10, b11, b12, b13, b14, b15

Submit Reset

Options: Put option will give you $0.50 if the stock price of the company one week from today is lower than the stock price today. Call option will give you $0.50 if the stock price of the company one week from today is higher than the stock price today. You will be paid $0.50 regardless of the type of option you hold if the stock price one week from today is the same as today's price. Otherwise, you will receive nothing.

Payoff: You will be paid based on how your entire portfolio performs one week from today.

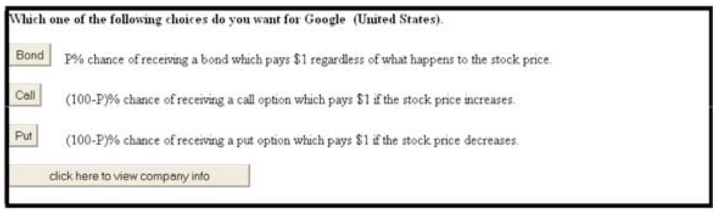
The term "today's stock price" is the last trading price of the company stock collected from finance.yahoo.com and www.tse.or.jp. This price was recorded at noon today (PST). "Price one week from today" is the last trading price of the company stock collected from finance.yahoo.com and www.tse.or.jp 7 days from today, 12:00PM (PST). Please note that finance.yahoo.com has a 10-20 minute delay on the quotes. Hence, at noon, if the last trade posted is 11:45AM, that is the price we will be using. www.tse.or.jp will be used for companies that are not listed with the exchanges from finance.yahoo.com and it also has 10-20 minute delay.

Example: Suppose you are participating on the experiment on Oct 1st. You chose a put option for Google. The last trading price posted on finance.yahoo.com at noon for Google is $400. Seven days from now, Oct 8th, 12:00PM, the last trading price posted on finance.yahoo.com for Google is $401 which is greater than $400. Since you chose a put option, you will not be paid. However, if the last trading price posted on finance.yahoo.com for Google is $400 or below, then you will be able to exercise your option and receive $0.50.

Any questions?

Part 2. Bond or Options?

In this part of the experiment, you will be shown one company name at a time and be asked whether you wish to take the bond (which pays $1), put option or a call option. These options are identical to the options in part 1 and will pay **$1** if exercised. A bond is a risk free asset which will pay you $1 independent of the stock price. In this section, you are also given a button "click here to view company info". Press this button and you will be given the company info for these specific companies. See the screen show below for an example.



Payoff: You will be paid based on the outcome of every trial in this section.

However, in this section, you are not guaranteed to receive a bond or an option. You will be given the **probability** of receiving the choice you select. In the above example, if you choose to receive a bond, you have 33% chance of actually receiving it. If you do receive it, you'll be paid $1 regardless of what happens to the company's stock price. Otherwise, you will receive $0. If you choose to receive a call option, then you have a 67% chance of receiving it and 33% chance of receiving nothing. Note that when you do actually receive a put option, you are not guaranteed to be paid $1 unless the stock price one week from today is less than today's price. See the table below to get a better understanding of the payoff.

If you select a Bond	Today's stock price is less than next week's stock price	Today's stock price is greater than next week's stock price
33% chance	$1	$1
67% chance	$0	$0

If you select a Call option	Today's stock price is less than next week's stock price	Today's stock price is greater than next week's stock price
33% chance	$0	$0
67% chance	$0	$1

If you select a Put option	Today's stock price is less than next week's stock price	Today's stock price is greater than next week's stock price
33% chance	$0	$0
67% chance	$1	$0

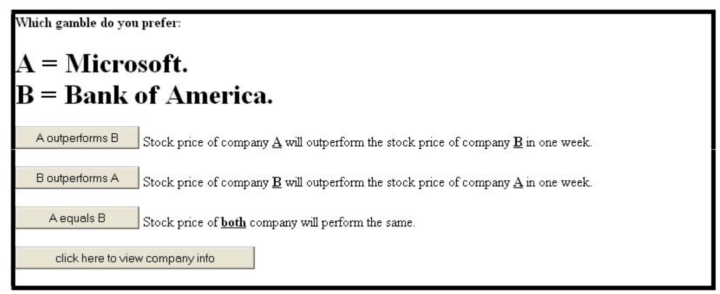
This is how the "chance" is determined in this section. If it states that there is a 45% chance of receiving a bond, it means the following: we will use a random number generator which gives a number from 1 - 100. If the number given is from 1 - 45, you will receive the bond. Otherwise, you will not. Again, if it states that there is a 55% chance of receiving an option, it means the following: we will use a random number generator which give a number from 1 - 100. If the number is from 46 - 100, you will receive the option. Each trials are independent of each other. This means that we will run the random number generator each time for each trial you have in this section.

Any questions?

Part 3. Company Preference

In this part of the experiment, you'll be shown two company names (A and B) and will be given three gambles to choose from (see screen shot below). First choice is a bet that company A will out perform company B in one week from now. Next choice is a bet that company B will outperform company A in one week from now. Last choice is a bet that company A and B will perform the same. You are also given a button "click here to view company info". Press this button and you will be given the company info for these specific companies.

Payoff: Using a random number generator, we will randomly select one of the trials. You will be paid based on the performance of the trial selected: if the gamble you chose is the winner, you will receive $5. Otherwise, you'll receive nothing.



The term "outperform" is defined as follows: company A out performs company B if and only if the increase in percentage of the dollar value of company A's stock price is higher than the percentage increase of the dollar value of company B's stock price. The time in which the stock prices are taken will be the same as in part 1.

Example1 : A = Intel and B = IBM.

	Today's price	Next week's price	Percentage change
A	$100	$101	**1%**
B	$50	$51	**2%**

In the table above, you would have made the correct choice if you chose "B outperforms A".

	Today's price	Next week's price	Percentage change
A	$100	$101	**1%**
B	$50	$49	**- 2%**

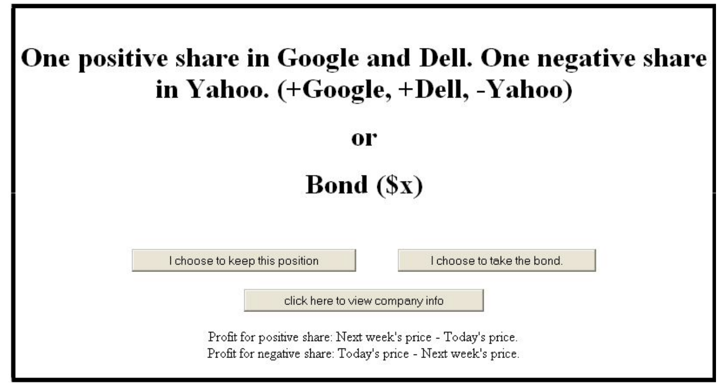
In the table above, you would have made the correct choice if you chose "A outperforms B".

Any questions?

Part 4. Position Holdings.

In this part of the experiment, you will be shown a list of companies and a position held. You will be asked if you prefer to keep the current position or a bond. See screen shot for an example. A position is a portfolio constructed with both positive and negative shares of the company stock. When you have a positive share, it means that you have borrowed money today to buy the stock (at today's price) and will sell it in the future to pay back the loan. Negative share means you have borrowed the stock to sell it today (at today's price) and will buy it back in the future (at the future price) to return the stock to the owner. See example below to see how these will actually work. A bond is a risk free asset, meaning, it will pay $x in one week regardless of the outcome of the position. In this setting, you will only work with one share per company. In summary, you want to have a negative share if you believe that the price will drop and a positive share if you believe that the price will increase. If you believe that the total return from your position is going to be less than $x, when you should choose the bond.

Again, you are also given a button "click here to view company info". Press this button and you will be given the company info for these specific companies.



How to Calculate your payoffs by holding your position:

To calculate your profit with positive share: Next week's price - Today's price = profit.

To calculate your profit with negative share: Today's price - Next week's price = profit.

Payoff: Using a random number generator, we will select one of the trials. In one week, you will be paid based on the performance of the selected position. The Bond will pay $x dollars in one week, regardless of the outcome of the position. $x differs between trial and will be specified accordingly during the trials. Since this is an experiment, you will not have to pay anything back if you end up owing money by holding your position. Therefore, the worse you can do with a position holding is zero which is still strictly less than what you will receive with by holding the bond. In addition, the maximum that a position can pay off will be limited at $10.

The time in which the stock prices are taken will be the same as in part 1.

Example of what a positive share means:

Today: Price of Toyota share is $50.	Next week: Price of Toyota share is $40
Your profit = $40 - $50 = - $10	

Example of what a negative share means:

Today: Price of Toyota share is $50.	Next week: Price of Toyota share is $40
Your profit = $50 - $40 = $10	

Example: (- Microsoft, + Intel, - IBM, + Toyota)

Position	Company	Today's price	Next week's price	Payoff
-	Microsoft	$50	$55	-$5
+	Intel	$40	$41	$1
-	IBM	$100	$50	$50
+	Toyota	$102	$50	-$52

Adding up the results in the payoff column, this position has paid off **-$6**. This will provide you with return of zero. However, if you chose the bond instead, you would have received $x regardless of what happen to the position.

In summary, take the bond if you believe that the sum of the payoff by holding the position is going to be less than $x. Otherwise, take the position.

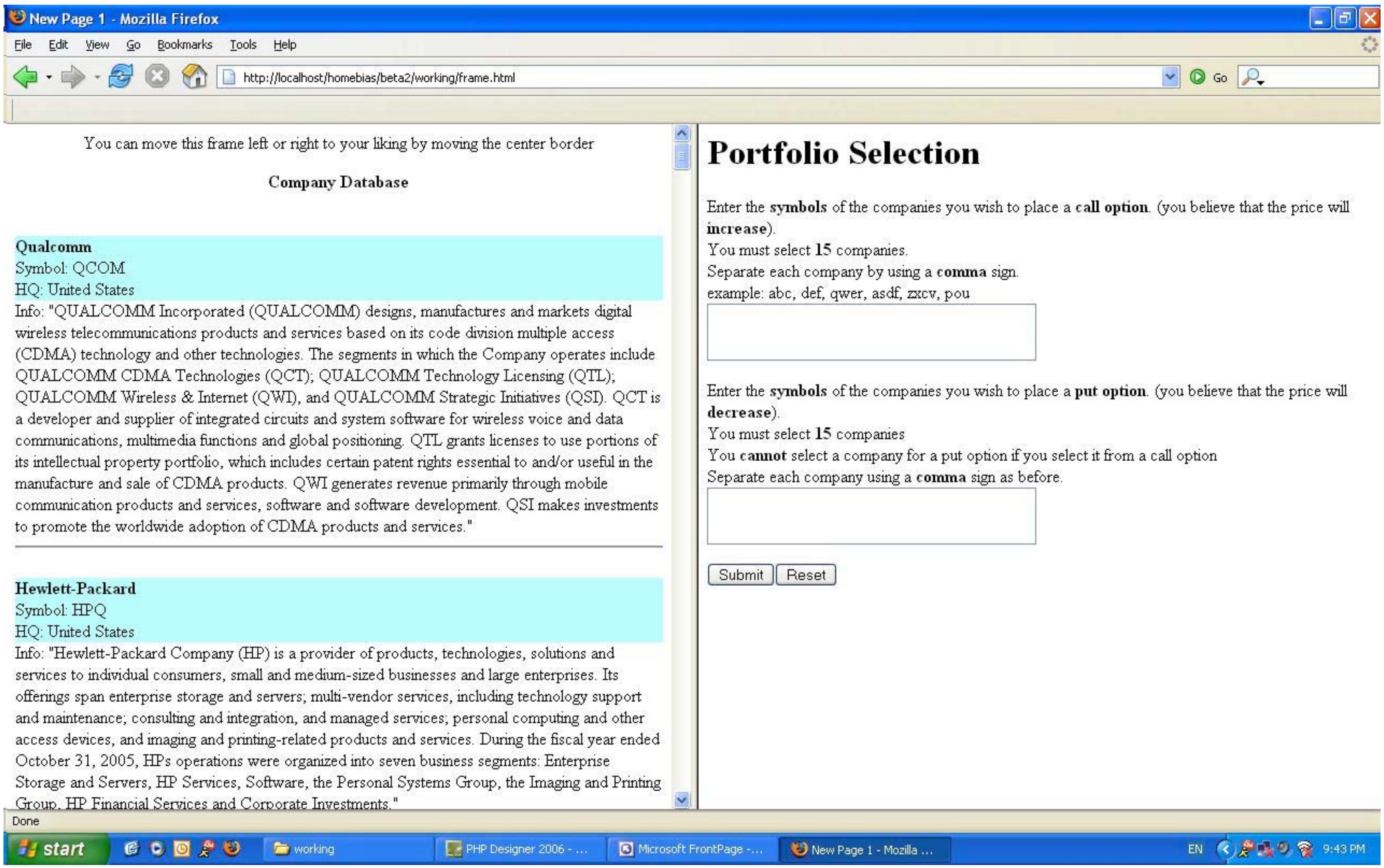
Any questions?

Click here when instructed to do so by the experimenter.

4.12.2 Screenshot for Individual Companies

The following page is a sample screenshot from the experiment.

Sample Screen Shot



4.12.3 Instructions for Indices

The following 5 pages are sample instructions and screenshots used in the experiment.

Instructions for the Financial Decision Making Experiment

Welcome to the Financial Decision Making Experiment. So far, you had a chance to look over the prospectus. Now you will be explained the details of the experiment. If you listen carefully and make good decisions, you could earn a considerable amount of money that will be paid to you in cash or check at the end of the experiment (7 days from today).

You will not be paired with any other individual. In addition, no other person's decision will influence your outcome. All your choices will be recorded today and your outcome will be realized one week from today.

The rules for the experiment are as follows. Do not talk or communicate with other participants. If you are using a computer, do not use any software other than that is explicitly required by the experiment. You are not allowed to browse the internet or check emails, etc. If you violate any of these rules, you will be asked to leave without pay. Feel free to ask questions by raising your hand or signaling to the experimenter.

Payment

You will receive a show-up fee of $10 today. You will be told in detail of how you can arrange to pickup the additional earnings at the end of the experiment.

All accounting from here on out are done in a fictitious currency called *Francs*. Exchange rate: 200 francs = 1 USD. At the end of the experiment, all your earnings will be converted back to USD.

The experiment is divided into two parts plus a survey section.

Part 1. Portfolio Building

In this part of the experiment, you will construct your portfolio over a series of rounds. In each round, you will be presented with a stock index. These indices are the indices you had a chance to look over during the prospectus section. Your decisions will be whether you want to buy a share of the index, sell a share of the index or buy a bond. (See example below).

Keys: Press 1 for Buy. Press 2 for Bond. Press 3 for Sell.

Figure 1: Portfolio building example screen

Each index will cost 100 francs. To calculate your payoff from your investments on the indices, we will pay you the original investment plus your percent return multiplied by 20. This is done to increase the range of possible returns and to simulate longer-term investments.

To summarize, the payoffs for the three possible choices are:
Bond: 100
Buy: 100(1+20*r) You buy if you want to bet that the index value will increase.
Sell: 100(1-20*r) You sell if you want to bet that the index value will decrease.

For example, suppose you invested in XYZ Index at 50. One week later, XYZ is at 52. We will calculate the % return as (52 - 50) / 50 = 0.04. Your initial investment of 1 share of XYZ will then be worth 1 + (20 * 0.04) = 1.8 times as much, or 180 francs.

If you buy the bond, you will be paid a fixed sum of 100 francs.

One More Example

To make sure you understand the payoffs, we will now go through an example showing all the possible outcomes.

Suppose that there are three rounds. You are asked to invest in Indices ABC, OPQ, and XYZ. You choose to buy ABC, sell OPQ, and took the bond on XYZ. Suppose one week from now, ABC gained 5%, OPQ gains 3%, and XYZ loses 10%.

Your return would then be $1+(20\times 0.05)=2$ for ABC (you bought ABC and it gained), $1+(20\times -0.03)=0.4$ for OPQ (you bought OPQ and it lost), and 1 for XYZ (you took the bond).

Finally, because everything costs 100 francs, you will make 100(2 + 0.4 + 1) = 340 francs. Table 1 summarizes the above.

	ABC	*OPQ*	*XYZ*
Your choice	Buy	Sell	Bond
Initial investment	100f	100f	100f
Outcome	+5%	+3%	-10%
Your return (20x)	100%	-60%	0%
Your payoff	200f	40f	100f

Table 1: Sample payoff table

Thus, your total payment for Part I will be the aggregate return from your entire portfolio.

The term "today's value" is the last trading price of the index collected from finance.yahoo.com and Bloomberg. This price was recorded at noon today (PST). "Value one week from today" is the last trading price of the index collected from the same websites 7 days from today, 12:00PM (PST). Please note that these websites have a 10-20 minute delay on the quotes. Hence, at noon, if the last trade posted is 11:45AM, that is the price we will be using. Bloomberg will be used for companies that are not listed with the exchanges from finance.yahoo.com and it also has 10-20 minute delay.

Any questions?

Part 2: Bond or Options?

In this part of the experiment, you will be shown one index at a time and be asked whether you wish to receive, with some probability, a bond (which pays 300 Francs), a digital put option or a digital call option.

Digital Options:

- *Digital put option* pays 300 francs if the index value one week from today is lower than the index value today, 0 otherwise. (You buy a put if you want to bet that the price will decrease).

- *Digital call option* pays 300 francs if the index value one week from today is higher than the index value today, 0 otherwise. (You buy a call if you want to bet that the price will increase).

Bond:

- *Bond* is a risk-free asset that pays 300 francs regardless of what happens to the value of the index.

The choice that you will have to make in this portion of the experiment is shown in the example screen below.

Keys: Press 1 for Bond, 2 for Up and 3 for Down.

Figure 2: Digital options example screen

As you can see, you are not guaranteed to receive a bond or an option. You will be given the **probability** of receiving the choice you select.

In the above example, if you choose to receive a bond, you have 30% chance of actually receiving it. If you do receive it, you will be paid 100 francs regardless of what happens to the value of the index. Otherwise, you will receive 0 francs.

	Today's Index value is less than next week's Index Value	Today's Index value is greater than next week's index value
30% chance	300 Francs	300 Francs
70% chance	0	0

Table 2: Payoff structure for the Bond

If you choose to receive a put option, then you have a 70% chance of receiving the option and 30% chance of receiving nothing. Note that when you do actually receive a put option, you are not guaranteed to be paid 100 francs unless the Index value one week from today is less than the value today. See the table below to get a better understanding of the payoff.

	Today's Index value is less than next week's Index Value	Today's Index value is greater than next week's index value
30% chance	0	0
70% chance	0	300 francs

Table 3: Payoff structure for the Put option

If you select a Put option	Today's Index value is less than next week's Index Value	Today's Index value is greater than next week's index value
30% chance	0	0
70% chance	300 francs	0

Table 4: Payoff structure for the Call option

This is how the "chance" is determined in this section. If it states that there is a 30% chance of receiving a bond, it means the following: we will use a random number generator which gives a number from 1 - 100. If the number given is between 1 to 30 (inclusive), you will receive the bond. Otherwise, you will not. Again, if it states that there is a 70% chance of receiving an option, it means the following: we will use a random number generator which gives a number from 1 - 100. If the number is between 31 to 100 (inclusive), you will receive the option. Each of the trials is independent of each other. This means that we will run the random number generator each time for each trial you have in this section.

Payment: Your total payment from part 2 will be based on the outcome of every trial in this section.

Financial Decision Making Experiment

California Institute of Technology

Introduction

Welcome to the Financial Decision Making Experiment website's Prospectus section. This prospectus contains information about the investment decisions that you will make during the actual experiment.

You are not required to memorize information from this prospectus, but familiarity with the materials in it can help you make more informed investment decisions.

To the left of you is a window with list of major stock indices throughout the world sorted alphabetically.

A stock market index is a listing of stocks and a statistic reflecting the composite value of its components. Most indices pertain to a specific country; the underlying stocks generally bear some commonality such as trading on the same stock market exchange, belonging to the same industry, or having similar market capitalizations.

Navigate the Prospectus

The prospectus is divided into two frames. The frame on the left of the screen contains a list of the major stock indices throughout the world in alphabetical order. For each of the indices, the index's country of origin is listed in the prentices.

To find out more detailed information about the index, click on its name. The information will appear in the current frame.

Example:

X
XYZ Index (Country)

Detailed Indices Information

Each index is divided into 3 sections. First section will provide you with the name, symbol and the country origin for the index. The number of stocks in the index is also included in a prentices unless it already is a part of the name of the index (example: S&P 100).

Next, you will be provided with a graph of the historical prices and trading volume of the index for the past 3 months (Mid May until end of July).

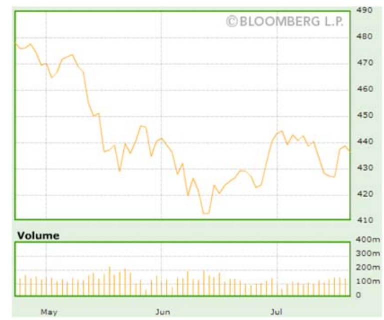
Lastly, you'll be provided with a brief description of the index itself.

Example:

Name: Name of the Index (Number of companies included in this index)

Symbol: Symbol of the Index

Country: Country where the index represents



The upper portion of the graph represents the historical performance. It's vertical axis depicts the value.

The bottom portion represents the Volume (number of trades that occurred for the underlying companies) as a bar graph.

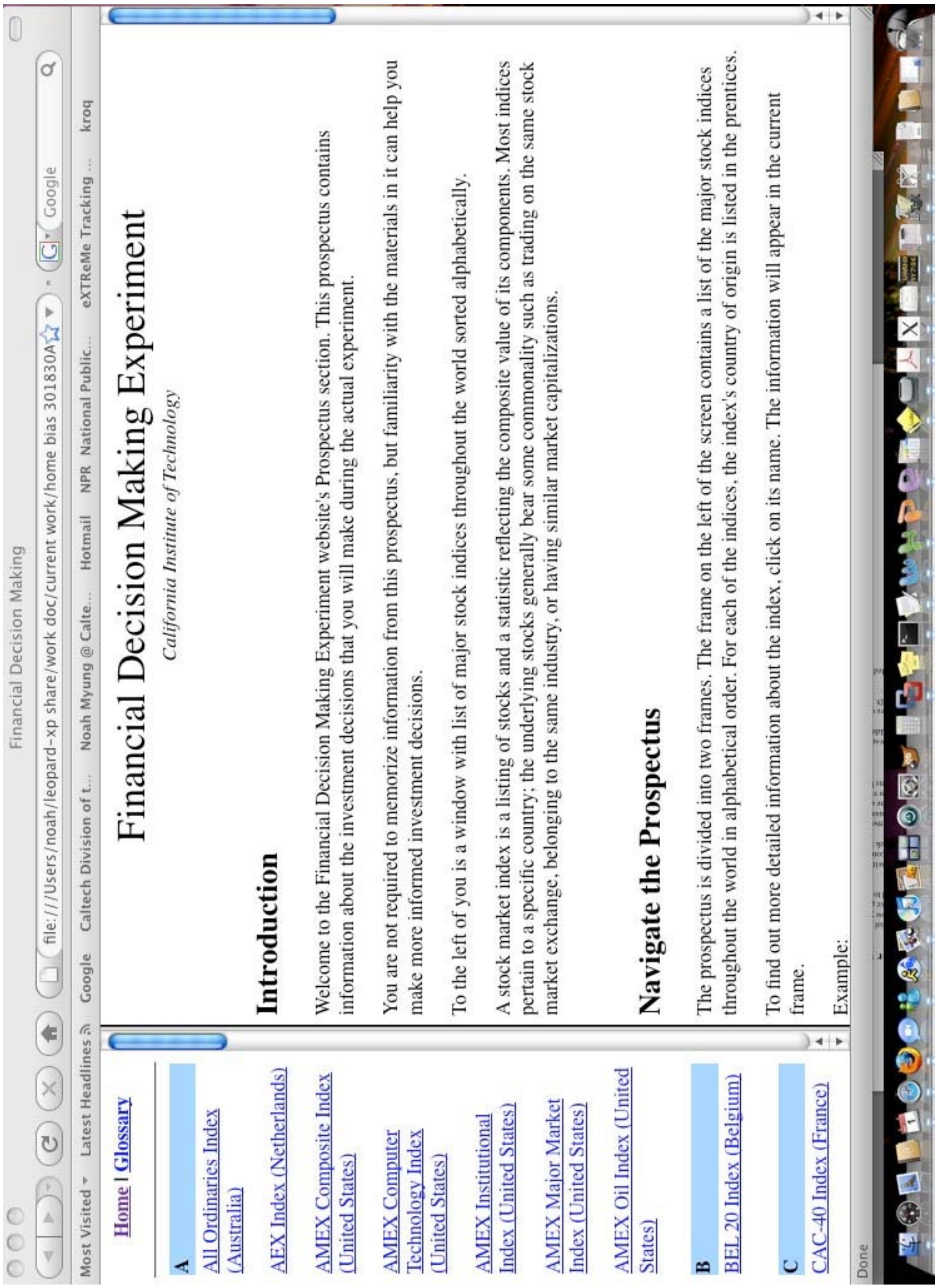
For both portion of the graph, the horizontal axis represents time, starting from mid-May 2006 until end of July 2006.

The XYZ index, derived from country ABC is a stock market index composed of Technology companies that trade on ABC exchange market. It is a capitalization-weighted index that consists of the 25 largest funds that trade on the exchange.

Glossary

Some of the references in this prospectus may be unfamiliar to you. We have included a glossary of terms that is intended to aid you in comprehension. The *glossary* link at the top of the left frame will take you to the glossary.

To return to the current page, click on the *home* link at the top of the menu.


Financial Decision Making
file:///Users/noah/leopard-xp share/work doc/current work/home bias 301830A
Google
Most Visited
Latest Headlines
Google
Caltech Division of t...
Noah Myung @ Calte...
Hotmail
NPR
National Public...
eXTReMe Tracking ...
kroq
Home | Glossary
A
All Ordinaries Index (Australia)
AEX Index (Netherlands)
AMEX Composite Index (United States)
AMEX Computer Technology Index (United States)
AMEX Institutional Index (United States)
AMEX Major Market Index (United States)
AMEX Oil Index (United States)
B
BEL 20 Index (Belgium)
C
CAC-40 Index (France)
Financial Decision Making Experiment
California Institute of Technology
Introduction
Welcome to the Financial Decision Making Experiment website's Prospectus section. This prospectus contains information about the investment decisions that you will make during the actual experiment.
You are not required to memorize information from this prospectus, but familiarity with the materials in it can help you make more informed investment decisions.
To the left of you is a window with list of major stock indices throughout the world sorted alphabetically.
A stock market index is a listing of stocks and a statistic reflecting the composite value of its components. Most indices pertain to a specific country; the underlying stocks generally bear some commonality such as trading on the same stock market exchange, belonging to the same industry, or having similar market capitalizations.
Navigate the Prospectus
The prospectus is divided into two frames. The frame on the left of the screen contains a list of the major stock indices throughout the world in alphabetical order. For each of the indices, the index's country of origin is listed in the prentices.
To find out more detailed information about the index, click on its name. The information will appear in the current frame.
Example:
Done

Bibliography

Ahearne, A. G., W. L. Griever, and F. E. Warnock (2003): "Information Costs and Home Bias: An Analysis of US Holdings of Foreign Equities," *Journal of International Economics*, 62(2), 313–336.

Arifovic, J., and J. O. Ledyard (2005 Working Paper): "Computer Testbeds for Mechanism Design," *Caltech Working Paper*.

Baker, G., R. Gibbons, and K. J. Murphy (2002): "Relational Contracts and the Theory of the Firm," *The Quarterly Journal of Economics*, 117(1), 39–84.

Ball, S., and P. Cech (1996): "Subject Pool Choice and Treatment Effects in Economic Laboratory Research," in *Research in Experimental Economics*, ed. by R. M. Isaac, vol. 6, pp. 239–292. JAI Press.

Bekaert, G., and C. R. Harvey (1995): "Time-varying World Market Integration," *The Journal of Finance*, 50, 403–444.

Bettenhausen, K. L., and K. J. Murnighan (1985): "The Emergence of Norms in Competitive Decision-Making Groups," *Administrative Science Quarterly*, 30, 350–372.

——— (1991): "The Development of an Intragroup Norm and the Effects of Interpersonal and Structural Challenges," *Administrative Science Quarterly*, 36, 20–35.

Bloom, N., and J. van Reenen (2007): "Measuring and Explaining Management Practices Across Firms and Countries," *The Quarterly Journal of Economics*, CXXII(4), 1351–1408.

Bornstein, G., U. Gneezy, and R. Nagel (2002): "The Effect of Intergroup Competition on Group Coordination: An Experimental Study," *Games and Economic Behavior*, 41, 1–25.

Bossaerts, P., P. Ghirardato, S. Guanaschelli, and W. Zame (2005): "Ambiguity and Asset Prices: An Experimental Perspective," *Caltech Working Paper*.

Brandts, J., and D. J. Cooper (2006): "A Change Would Do You Good ... An Experimental Study on How to Overcome Coordination Failure in Organizations," *The American Economic Review*, 96(3), 669–693.

Brush, T. H., P. Bromiley, and M. Hendrickx (1999): "The Relative Influence of Industry and Corporation on Business Segment Performance: An Alternative Estimate," *Strategic Management Journal*, 20, 519–547.

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.

Camerer, C. F. (2003): *Behavioral Game Theory: Experiments in Strategic Interactions*. Princeton University Press.

Camerer, C. F., T.-H. Ho, and J.-K. Chong (2004): "A Cognitive Hierarchy Model of Games," *The Quarterly Journal of Economics*, 119(3), 861–898.

Camerer, C. F., and R. Karjalainen (1994): "Ambiguity-Aversion and Non-Additive Beliefs in Non-Cooperative Games: Experimental Evidence," in *Models and Experiments in Risk and Rationality*, ed. by M. J. Machina, and B. Munier, pp. 325–358. Kluwer Academic Publishers.

Camerer, C. F., and U. Malmendier (2007): "Behavioral Economics of Organization," in *Behavioral Economics and Its Applications*, ed. by P. Diamond, and H. Vartiainen. Princeton University Press.

Camerer, C. F., and M. Weber (1992): "Recent Developments in Modeling Preferences: Uncertainty and Ambiguity," *Journal of Risk and Uncertainty*, 5, 325–370.

Cameron, K. S., and R. E. Quinn (2005): *Diagnosing and Changing Organizational Culture: Based on the Competing Values Framework*. Jossey-Bass.

Choquet, G. (1953-1954): "Theory of Capacities," *Annales de l'Institut Fourier*, 5, 131–295.

Coase, R. (1937): "The Nature of the Firm," *Economica*, 4, 386–405.

Cooper, I., and E. Kaplanis (1994): "Home Bias in Equity Portfolios, Inflation Hedging, and International Capital Market Equilibrium," *The Review of Financial Studies*, 7(1), 45–60.

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.

Crawford, V. P. (1995): "Adaptive Dynamics in Coordination Games," *Econometrica*, 63(1), 103–143.

Cremer, J. (1986): "Cooperation in Ongoing Organizations," *The Quarterly Journal of Economics*, 101(1), 33–50.

——— (1993): "Corporate Culture and Shared Knowledge," *Industrial and Corporate Change*, 2(3), 351–386.

Dasarathy, B. (1991): *Nearest neighbor (NN) norms: NN pattern classification techniques*. Los Alamitos, CA: IEEE Computer Society Press.

Disney, R., J. Haskel, and Y. Heden (2003): "Restructuring and Productivity Growth in UK Manufacturing," *The Economic Journal*, 113, 666–694.

Einhorn, H. J., and R. M. Hogarth (1985): "Ambiguity and Uncertainty in Probabilistic Inference," *Psychological Review*, 92, 433–461.

Ellsberg, D. (1961): "Risk, Ambiguity, and the Savage Axioms," *Quarterly Journal of Economics*, 75, 643–669.

Epstein, L. G. (1999): "A Definiton of Uncertainty Aversion," *Review of Economic Studies*, 66, 579–608.

Errunza, V., K. Hogan, and M. W. Hung (1999): "Can The Gains From International Diversification Be Achieved Without Trading Abroad," *The Journal of Finance*, 54, 2075–2107.

Fama, E. F. (1970): "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance*, 25(2), 383–417.

Feiler, L., and C. F. Camerer (In Press): "Code Creation in Endogenous Merger Experiments," *Economic Inquiry*.

Fischbacher, U. (2007): "z-Tree: Zurich Toolbox for Readymade Economic Experiments," *Experimental Economics*, 10(2), 171–178.

French, K. R., and J. M. Poterba (1991): "Investor Diversification and International Equity Markets," *The American Economic Review*, 81(2), 222–226.

Gibbons, R., R. Henderson, N. Repenning, and J. Sterman (In Press): "What Do Managers Do? Suggestive Evidence and Potential Theories About Building Relationships," in *Handbook of Organizational Economics*, ed. by R. Gibbons, and J. Roberts. Princeton University Press.

Gilboa, I., and D. Schmeidler (1989): "Maxmin Expected Utility with A Non-Unique Prior," *Journal of Mathematical Economics*, 18, 141–153.

Glassman, D. A., and L. A. Riddick (2001): "What Causes Home Asset Bias and How Should It be Measured?," *Journal of Empirical Finance*, 8(1), 35–54.

Goeree, J. K., and C. A. Holt (2005): "An Experimental Study of Costly Coordination," *Games and Economic Behavior*, 51(2), 349–364.

Hamman, J., S. Rick, and R. A. Weber (2007): "Solving Coordination Failure with "All-or-None" Group-Level Incentives," *Experimental Economics*, 10, 285–303.

Harsanyi, J. C., and R. Selton (1988): *A General Theory of Equilibrium Selection in Games*. MIT Press.

Hermalin, B. E. (2001): "Economics and Corporate Culture," in *The International Handbook of Organizational Culture and Climate*, ed. by C. L. Cooper, S. Cartwright, and P. C. Earley. Wiley Press.

——— (In Press): "Chapter on Leadership and Corporate Culture," in *Handbook of Organizational Economics*, ed. by R. Gibbons, and J. Roberts. Princeton University Press.

Hill, C. W. L., and G. R. Jones (2001): *Strategic Management*. Houghton Mifflin.

Karolyi, G. A., and R. M. Stulz (2003): "Are Financial Assets Priced Locally or Globally?," in *Handbook of the Economics of Finance*, ed. by G. M. Constantinides, M. Harris, and R. M. Stulz, vol. 1, pp. 975–1014. Elsevier North Holland.

Kilka, M., and M. Weber (2002): "Home Bias in International Stock Return Expectations," *The Journal of Psychology and Financial Markets*, pp. 176–192.

Knez, M., and C. F. Camerer (2000): "Increasing Cooperation in Prisoner's Dilemmas by Establishing a Precedent of Efficiency in Coordination Game," *Organizational Behavior and Human Decision Processes*, 82(2), 194–216.

Knight, F. (1921): *Risk, Uncertainty and Profit*. Houghton Mifflin.

Kotter, J. P., and J. L. Haskett (1992): *Corporate Culture and Performance*. Free Press.

Kreps, D. M. (1990): "Corporate Culture and Economic Theory," in *Perspectives on Positive Political Economy*, ed. by J. E. Alt, and K. A. Shepsle. Cambridge University Press.

Lazear, E. P., and S. Rosen (1981): "Rank-Order Tournaments as Optimum Labor Contracts," *The Journal of Political Economy*, 89(5), 841–864.

Lewis, K. K. (1999): "Trying to Explain Home Bias in Equities and Consumption," *Journal of Economic Literature*, XXXVII, 571–608.

Macher, J. T., and D. C. Mowery (2003): "Managing' Learning By Doing: An Empirical Study in Semiconductor Manufacturing," *Journal of Product Innovation Management*, 20, 391–410.

McKelvey, R., and T. R. Palfrey (1995): "Quantal Response Equilibrium for Normal Form Games," *Games and Economic Behavior*, 10, 6–38.

Myung, N. (2008 Working Paper): "Improving Coordination and Cooperation Through Competition," *Caltech Working Paper*.

Nieuwerburgh, S. V., and L. Veldkamp (In Press): "Information Immobility and the Home Bias Puzzle," *The Journal of Finance*.

Romero, J. (2008 Working Paper): "Computational Testbeds for Coordination Games," *Caltech Working Paper*.

Roquebert, J., R. L. Phillips, and P. A. Westfall (1996): "Markets VS. Management: What 'Drives' Profitability?," *Strategic Management Journal*, 17, 653–664.

Sarin, R., and R. L. Winkler (1992): "Ambiguity and Decision MOdeling: A Preference-based Approach," *Journal of Risk and Uncertainty*, 5, 389–407.

Savage, L. J. (1954): *The Foundations of Statistics*. Wiley.

Schelling, T. C. (1960): *The Strategy of Conflict*. Harvard University Press.

Schmeidler, D. (1989): "Subjective Probability and Expected Utility Without Additivity," *Econometrica*, 57, 571–587.

Schmidt, D., R. Shupp, J. M. Walker, and E. Ostrom (2003): "Playing Safe in Coordination Games: The Role of Risk Dominance, Payoff Dominance and History of Play," *Games and Economic Behavior*, 42, 281–299.

Segal, U. (1987): "The Ellsberg Paradox and Risk-Aversion: An Anticipated Utility Approach," *International Economic Review*, 28, 175–202.

Smith, V. L. (1969): "Measuring Nonmonetary Utilities in Uncertain Choices: The Ellsberg Urn," *Quarterly Journal of Economics*, 83, 324–329.

Sonsino, D., and J. Sirota (2003): "Strategic Pattern Recognition - Experimental Evidence," *Games and Economic Behavior*, 44, 390–411.

Sorensen, J. (2002): "The Strength of Corporate Culture and the Reliability of Firm Performance," *Administrative Science Quarterly*, 47, 70–91.

van Huyck, J. B., R. C. Battalio, and R. O. Beil (1990): "Tacit Coordination Games, Strategic Uncertainty, and Coordination Failure," *The American Economic Review*, 80(1), 234–248.

Weber, R. A. (2006): "Managing Growth to Achieve Efficient Coordination in Large Groups," *The American Economic Review*, 96(1), 114–126.

Weber, R. A., and C. F. Camerer (2003): "Cultural Conflict and Merger Failure: An Experimental Approach," *Management Science*, 49(4), 400–415.

Williamson, O. (1975): *Markets and Hierarchies: Analysis and Antitrust Implications*. Free Press, New York.