Experimental studies of antitrust policy and portfolio selection

by

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Abstract

Antitrust and collusion have been the subjects of many economic papers since the passage of the Sherman Act in 1890. However, research in these areas faces numerous challenges. Even when real-world issues are modeled, there are limits to theoretical predictions, as well as relevant legal issues regarding the use of data on cartel firms. Moreover, antitrust policy affects both firm decision-making and social welfare, so any proposed policy changes should be carefully implemented. Comparable challenges are present in the field of research on selecting portfolios of risky assets, where limitations on theoretical predictions about human decision-making and the significant impact of decisions on investments prevail. To address these practical problems, I uses experimental methods to study firms' collusive behavior under antitrust regulation and to compare two different preference theories for portfolio selection.

In my first chapter, I explore the impact of strategic delegation between owners and managers on firms' compliance with antitrust policy. Decision-making authority is often delegated to managers in modern firms, and the salaries of executives, such as CEOs and top executives, are mainly based on profit and revenue, not solely on profit. This may result in different outcomes for firms' collusive behavior compared to what is predicted by the standard economic assumption of profit maximization. I compare the formation rates of cartels under both strategic delegation and profit maximization. The results indicate that while strategic delegation does not lead to a greater or lesser rate of cartel formation than profit maximization, it may result in a higher proportion of tacit collusion. In addition, antitrust policies have also influenced the collusive practices of firms, resulting in the formation of cartels that

circumvent regulations.

In the second chapter, the effects of leniency policies in the US and South Korea on the formation of cartels are analyzed. The US leniency policy offers complete exemption from fines to the first applicant only, while South Korea's policy allows subsequent applicants to receive partial fine exemption. This research focuses on the differences in the policies regarding (1) the size of fines imposed on cartels (High or Low) and (2) the number of applicants granted leniency (Single or Multiple (two)). According to the results, leniency policies that vary in terms of the amount of fines and number of leniency applicants do not have a significant effect on cartel formation, compared to a scenario where no leniency is granted. However, such policies increase the exposure of established cartels, leading to their eventual decline in cartel success.[1]

The third chapter compares Expected Utility Theory (EU) and Quantile preference (QP) for portfolio selection. EU, commonly used in economics, involves maximizing the average payoffs from assets, while the QP theory maximizes a specific quantile of their payoff distribution. The experiment investigates which preference theory between EU and QP describes participants' decisions more closely. The results indicate that generally, EU generally explains individuals' optimal portfolio selections well but QP is a good alternative to EU in the cases where the first stochastic dominance between two assets does not exist.[2]

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[1]The chapter has been accepted for publication in the *Review of Industrial Organization* in 2023.

[2]The chapter has been published in the *Journal of Behavioral and Experimental Economics* in 2022.

Chapter 1

Strategic Delegation and Collusion: An Experiment

The widely accepted idea in economics that firms aim to maximize their profit is often used to explain their behavior and market outcomes. However, this assumption may result in inaccurate predictions when firms engage in strategic delegation, where owners (e.g., shareholders) and managers (e.g., company executives) have differing incentives. This study explores the issue of firms' collusion under the assumption of strategic delegation versus profit maximization. The experiment is designed to align with the antitrust regime in the United States, with cartel fines imposed on both owners and managers. The study also investigates the effect of communication between firms on cartel formation under strategic delegation. The experiment highlights the following three key findings: (i) strategic delegation does not necessarily increase the overall number of cartels, but it may promote more implicit cartels; (ii) antitrust policies can affect cartel formation through two distinct pathways, either via simultaneous agreement on collusive output (low output) or periodic shifts between competitive (high) and collusive (low) outputs to avoid fines; and (iii) the likelihood of cartel formation is higher when firms have heterogeneous incentive schemes for managers, rather than identical schemes across all firms.

1.1 Introduction

The assumption of profit maximization has been a fundamental concept in economics, used to explain firm behavior and market outcomes. However, the separation of ownership and management in modern economies has resulted in owners (e.g., shareholders) and managers (e.g., company executives) having different incentives when running firms. While owners are concerned with dividends as a proportion of profit, managers' salaries are often linked to a firm's performance, which can be based on various metrics such as profitability, revenue, sales, market share, etc. This distinction can lead to different firm behavior and market outcomes that diverge from the profit maximization assumption. For instance, consider a store with one owner and one manager where the owner states that the manager's salary will be based on store revenue. In this scenario, the manager will aim to maximize revenue instead of profit, resulting in a higher output level than what would be obtained through the profit maximization assumption.[1]

The relationship between owners and managers in a firm is referred to as "strategic delegation." In this dynamic, owners decide how to incentivize managers in order to achieve their goals. The incentives given to managers can influence their behavior and decision-making. Under strategic delegation, owners determine the incentive schemes for managers, which can influence the managers' decisions to compete or collude in the market. If managers are always assumed to behave in a non-cooperative manner with other firms, strategic delegation can lead to improved competition in

[1]According to Bloomfield (2021), revenue-based payment schemes for CEOs and executives are more common in oligopolistic firms with a market share of 10% to 65%. The study provides empirical evidence that such schemes result in increased firms' outputs and more aggressive market equilibria. These findings highlight the need to consider alternative assumptions, such as strategic delegation, in order to accurately predict firm behavior and market outcomes.

the market, resulting in increased output and reduced profit compared to profit maximization. However, strategic delegation can also have an impact on managers' collusive behavior with other firms. In a symmetric market, profit maximization alone would result in a fixed value for the benefit of joining a cartel, which is the gap between competitive and collusive profit. Under strategic delegation, managers may not necessarily prioritize profit maximization as they aim to maximize their own incentives. The benefits of collusion for firms can vary depending on how the managers' incentives are determined. As a result, the rate or method of forming cartels under strategic delegation may differ from that based on the profit maximization assumption.

This experimental study examines whether strategic delegation increases or decreases collusion compared to the case in which it is assumed that firms maximize profit alone. The study uses a Cournot-type duopoly delegation game based on Fershtman (1985), Fershtman and Judd (1987), Sklivas (1987), and Vickers (1985)–collectively, FJSV). The game has two stages. Stage 1 is for the owners' decision-making, referred to as the *Strategic delegation* stage. It is assumed that owners are concerned with their firms' profit.[2] In this stage, owners choose between **P** and **R** for their managers' payoffs. Contract **P** grants a manager's payoff in proportion to profit alone, while contract **R** indicates that a manager's payoff is determined by a weighted average between profit and revenue." At the end of stage 1, the chosen contracts are announced publicly to owners and managers. Stage 2 is for the managers' production, referred to as the *Collusion* stage. In this stage, managers select

[2]To compare strategic delegation and profit maximization, "profit maximization" in this paper refers to a scenario where each owner operates their firm without delegating decision-making about collusion to managers and solely focuses on maximizing their firms' profit. This definition serves as a reference point for the concept of strategic delegation.

whether to choose low (**L**) or high output (**H**). The managers' expected payoffs differ depending on which contracts are given. Furthermore, cartel fines are adopted based on the antitrust regime of the United States to investigate how antitrust regulation affects cartel formation under either strategic delegation or profit maximization. The cartel detection rate in the experiment is defined as follows: if both managers select L, then there is a 15% chance that the collusion will be caught by the antitrust authority.[3] In this case, cartel fines are imposed on both owners and managers. The owners' and managers' payoffs including fines are determined at the end of stage 2.

This study also evaluates the effects of communication on cartel formation under strategic delegation. Previous research has explored the effect of communication between firms on cartel formation, and it has been shown that communication leads to more cartels than when there is no communication.[4] However, these studies have only examined the impact of communication under the assumption of profit maximization, without considering the effects of strategic delegation. This study fills this gap by examining the impact of communication on cartels under both profit maximization and strategic delegation. There are four treatments in the study: **SC** (strategic delegation with communication), **SN** (strategic delegation with no communication), **PC** (profit maximization with communication), and **PN** (profit maximization with no communication). The treatments of SC and PC have a *Communication* stage between the Strategic delegation and Collusion stages. Table 1.1 outlines the structure

[3]The 15% chance of cartel detection used in the study is based on empirical research. Bryant and Eckard (1991) estimates that the probability of a cartel being caught in US cases ranges from 13% to 17%. Combe et al. (2008) also estimates the probability ranges from 12.9% to 13.3% based on European Union cases.

[4]Previous studies have explored the impact of communication on cartel formation in various theoretical settings. For example, Fonseca and Normann (2012) found that communication leads to a higher number of explicit cartels in a Bertrand oligopoly model. Similarly, Fischer and Normann (2019) demonstrated that communication results in an increase in cartel formation, even in an asymmetric Cournot duopoly where two firms have differing cost efficiencies.

Table 1.1: The stages for each treatment

Treatment	Players	Stage		
		Strategic delegation	Communication	Collusion
PN	2 owners	-	-	✓
PC	2 owners	-	✓	✓
SN	2 owners + 2 managers	✓	-	✓
SC	2 owners + 2 managers	✓	✓	✓

*In the PN and PC treatments, there is no delegation. Thus, owners are players for stages. In the SN and SC treatments, owners choose managers' incentive scheme in the *Strategic delegation* stage and the managers choose whether to choose low or high output respectively. The *Communication* stage is given to players before the *Collusion* stage in the PC and SC treatments.

of the stages for each treatment.

The contributions of this paper are threefold. First, strategic delegation does not lead to an increase in the number of cartels with communication compared to profit maximization, but it may generate more implicit cartels without communication. The incentive gap between collusion and competition is a key factor in the formation of a cartel. In the experiment, the firm's profit from collusion under strategic delegation is not significantly different from that under profit maximization, but the profit in competition under strategic delegation is lower. The larger incentive gap for forming a cartel under strategic delegation may lead to more cartels being formed, but the experiment shows no difference in the rate of cartel formation between strategic delegation and profit maximization. This suggests that greater incentives to form a cartel do not necessarily result in more cartels and that cartels, both explicit and implicit, may exist in a market to some extent. This result aligns with Levenstein and Suslow's (2006) finding that the sizes of markups are associated with cartel success and stability, but not with the number of cartels formed. Therefore, it is appropriate to assume profit maximization when estimating cartel formation rates, even if strategic delegation is not considered in the estimation. However, considering strategic delegation can be valuable when studying implicit cartels.

The second contribution is that it highlights the strategic behavior of cartels in avoiding antitrust regulations. Previous research has portrayed cartel formation in a duopoly as a prisoner's dilemma, with both firms choosing low output (i.e. (L, L)). However, this study's experimental design incorporates antitrust regulations, and the results demonstrate that firms not only form "LL" cartels, as theory suggests, but they also form "switching" cartels. In these switching cartels, managers communicate with each other and alternate between choosing L and H in each round in order to avoid cartel fines. This indicates that cartels may try to evade antitrust authorities strategically to increase their stability, as noted by Harrington Jr. (2021). The experiment conducted in this study shows that firms may establish different types of cartels in the absence of antitrust laws, especially when cartel fines are involved.[5]

Third, firms are more likely to form cartels when the incentives of one firm's managers differ from those of another's. Previous research has found that firms in asymmetric markets are less cooperative and form fewer cartels compared to those in symmetric markets (Mason et al., 1992; Mason and Phillips, 1997; Fonseca et al., 2005; Fischer and Normann, 2019). For instance, suppose there are two firms where one is more cost-effective than the other. In this scenario, the incentive to deviate from collusion is greater for one firm than the other, and this difference in incentives can make it more difficult for the cartel to remain stable compared to symmetric

[5]Byrne and De Roos (2019) empirically show that cartels in the Australian gasoline market employ a strategy of alternating prices between low and high periodically to circumvent antitrust regulations.

cases. In previous studies, the asymmetric market situation was fixed, such that one firm always had a greater incentive to deviate than the other, resulting in the easy dissolution of cartels. However, in this study, the owners can vary the contracts for their managers' incentives each period, and managers cannot predict which contracts the owners will choose in the next round when deciding whether to form a cartel in the current round. This study finds that managers are more likely to form cartels in asymmetric cases when there is uncertainty about owners' objectives in the next round compared to symmetric cases.[6]

In addition, this research evaluates the effects of communication on cartel formation under both strategic delegation and profit maximization. The experimental results indicate that communication increases the number and duration of cartels, compared to scenarios without communication, under both strategic delegation and profit maximization. This finding aligns with previous studies that have shown a positive effect of communication on collusion, assuming that firms aim to maximize profit. The experiment provides evidence that communication can increase the number of cartels, even under strategic delegation.

The paper is organized as follows. Section 1.2 discusses the prior literature on strategic delegation and firms' non-profit-maximizing behaviors. Section 1.3 introduces the experimental design and treatments for the design. Section 1.4 presents the main hypotheses based on theory and previous research. Section 1.5 examines

[6]The uncertainty regarding the owners' selections in the next round can lead managers to place a higher value on the current round's payoffs. The experiment's results show that managers in asymmetric situations tend to collude more in the current round and avoid competing in the next round more frequently than those in symmetric situations. This outcome is consistent with the findings of an experiment conducted by Kreps et al. (1982), which revealed that the presence of incomplete information increases cooperation among players. Also, Byrne and De Roos (2019)'s research findings corroborate my experimental results, indicating that asymmetric environments have a higher propensity to produce cartels through empirical evidence.

market outcomes (profit and output), how and how many cartels are formed, and communication affects collusion for each treatment. Section 1.6 concludes.

1.2 Literature review

Previous studies have investigated the use of strategic delegation models and questioned the accuracy of the profit maximization assumption in describing firm behavior. Baumol (1958) argues that sales maximization, rather than profit maximization, is a more realistic explanation for how firms behave in a market when managerial incentives are based on sales instead of profit. He suggests that profit maximization may not always accurately reflect firm behavior in a market. Hall (1967), Hawkins (1970), and Amihud and Kamin (1979) provide empirical evidence that managers have incentives to maximize revenue while maintaining a positive profit, supporting the notion of non-profit-maximizing behavior of firms in agreement with Baumol's hypothesis.

FJSV investigate firms' non-profit-maximizing behavior through the use of a Cournot duopoly two-stage game, referred to as "strategic delegation." In the first stage, each firm's owner sets up an incentive scheme for their managers, with the scheme being determined by the weight given to profit and revenue in the range of 0 to 1. For instance, if an owner assigns equal weight to profit and revenue, the managers' incentives would be based on a combination of half profit and half revenue. In the second stage, each firm's managers decide on the production levels for their firms. The study finds that if owners choose a sales-focused incentive scheme for their managers, then managers will act more aggressively to maximize their incentives compared to a profit-focused incentive scheme, resulting in firms' non-profit-maximizing behavior. This highlights that strategic delegation can contribute to firms' non-profit-maximizing behavior in a market.

Many papers have extended FJSV's model by including more specific components related to the managers' incentives from the real world. Jansen et al. (2007) and Ritz (2008) add "market share" to profit and sales in FJSV's delegation game. In their models, there are three contracts that each owner can choose between as incentive schemes for the managers. Two of the three contracts are the same as the ones adopted by FJSV and address whether a manager's salary is determined by profit only or profit and weighted sales; the new contract stipulates that a manager's salary is proportional to profit and weighted market share. The papers show that when an owner selects the market-share-oriented contract for managers, the managers produce more output than when another firm chooses a profit-alone or sales-oriented contract. This illustrates that firms may choose higher output than that obtained under the profit maximization assumption, which is aligned with FJSV's result. The authors also verify that the result of a Bertrand-type strategic delegation model is consistent with the result of their Cournot-type model.

Similarly, Miller and Pazgal (2002) and Jansen et al. (2009) incorporate the relative profit between firms as a contract for managerial incentives in their strategic delegation models. They find that strategic delegation may result in higher output and lower prices compared to the predictions of the profit maximization assumption. The results of these studies are consistent with those of FJSV. Habiger and Kopel (2020) and Fang and Zhao (2021) further extend the strategic delegation model by incorporating product differentiation with asymmetric costs. In their Cournot duopoly models, they find that managers produce output more aggressively when their firms are more cost-efficient or when the products in the market are less differentiated. These findings suggest that when strategic delegation and other factors are taken into account, the market outcomes may differ from those predicted by the profit maximization assumption.

Besides studies on strategic delegation models, some papers have shed light on firms' tendency to not maximize profits. Dutta and Radner (1999) present a theoretical model in which firms typically fall short of maximizing their profits in both the short and long term. In the model, firms are motivated to attract investment funds and attain positive profits in order to survive in a competitive market. The authors find that entrepreneurs are more likely to increase their output aggressively in order to avoid bankruptcy and attain positive profits, compared to what would be expected under the profit maximization assumption. Oprea (2014) takes into account the fact that firms are concerned with their survival in the market and examines whether firms aim to maximize profits. He conducts an experiment with two hypothetical environments, where the survival rates of firms are either high or low. The author shows that firms attempt to maximize profits if they have a higher survival rate, but not otherwise. This finding implies that the profit maximization assumption may not be appropriate in analyzing firm behavior based on firm survival rates. Güth et al. (2015) design a delegation game that includes the costs and compensation of workers' efforts. In the model, the compensation for workers is based on revenue. Workers can choose their effort levels and production, taking into account their individual performance. The research finds that the effectiveness of delegating decision-making to workers depends on the level of competition in the market (interfirm competition) and the number of workers within a firm (intrafirm competition). This suggests that firms may not achieve profit maximization due to competition between managers within a firm or competition with other firms.

A few experimental studies have investigated the concept of strategic delegation. Fershtman and Gneezy (2001) examine the impact of strategic delegation on agents' behavior through an ultimatum game that involves a proposer and a responder. The proposer is tasked with dividing 100 points between themselves and the responder. In the game, either the proposer or the responder can delegate authority to an agent, and the contract determining the agent's payoff may or may not be visible. The results of the experiment show that delegation from the proposer (responder) leads to an increase in the proposer's (responder's) payoffs when the contracts for agents are visible. However, if the contracts are not visible, delegation may not serve as an effective commitment device for either the proposer or the responder. Although Fershtman and Gneezy's framework differs from the FJSV model, they demonstrate that delegation and contracts for agents can influence the outcome of the game.

Huck et al. (2004) conduct an experiment to study the impact of strategic delegation on firm behavior. Their experiment utilizes a two-stage Cournot duopoly game based on the FJSV model, with each firm consisting of one owner and one manager. The authors establish two contracts for managers' salaries: Contract A, where a manager's salary is solely proportional to profit, and Contract B, where it is proportional to profit and a sales bonus. During stage 1, owners simultaneously choose their contracts, and during stage 2, each manager decides their firm's production quantity. The theoretical model expects both firms to choose Contract B, resulting in managers producing output higher than the profit-maximizing output as a subgame perfect equilibrium. However, the experimental results indicate that both firms frequently chose Contract A, which suggests the prediction did not hold in practice.

The difference between Huck et al.'s framework and my research is that they examine if market output with strategic delegation is higher than without and analyze owner cooperation, whereas my experiment does not define owner cooperation and instead focuses on how cartels are formed through manager decisions. Additionally, Huck et al.'s experiment does not consider antitrust regimes, whereas my experiment includes the US antitrust regime to investigate cartel formation under antitrust authority.

Du et al. (2013) extend the FJSV model to a "mixed duopoly" market featuring a private firm that maximizes profit and a public firm that maximizes welfare, where managers' incentives schemes are a combination of profit and sales, as in FJSV's model. The authors find that the public firm, which prioritizes welfare, produces more output than the private firm, which prioritizes profit. The experiment's results indicate that strategic delegation leads to an increase in market output, which aligns with the results of previous theoretical and experimental studies. In another experiment, Barreda-Tarrazona et al. (2016) use a strategic delegation model with two managerial incentive contracts - one based on profit-revenue and the other based on relative firm performance, similar to Jansen et al.'s theoretical model. The experiment allows owners and managers to choose parameters within a continuous space, with owners weighing revenue or relative performance and managers determining output. The authors find that strategic delegation results in owners choosing non-profit-maximizing contracts and managers producing higher market output compared to the results predicted by the profit maximization assumption, which is consistent with the findings of this study.

Some theoretical papers have explored the impact of delegation on the stability of cartels. Lambertini and Trombetta (2002) analyze the effect of delegation between owners and managers on cartel stability in a duopoly market. In their model, each manager's compensation consists of a combination of profit and weighted sales. The owners can collude with each other in determining the weight of sales, and the managers can collude with each other in setting the production levels. The authors' results suggest that if two owners agree to set a weight for sales, delegation may destabilize the cartels formed by the managers. Otherwise, it does not impact the stability of newly formed cartels. Spagnolo (2005) examine firms' collusive behavior in a price-fixing scenario that is representative of the real world. In a two-stage oligopoly game, each owner decides whether to delegate decision-making to their manager under a long-term profit-sharing contract. In the second stage, managers set prices for each period. The author's findings indicate that when managers are risk averse and owners choose delegation, the managers tend to smooth profits, which stabilizes collusion and thus increases tacit collusion among firms. Building upon Spagnolo's work, Paha (2017) investigates the collusive behavior of managers in response to an external profit shock. They find that if a manager's utility function is concave and profit shocks persist, more cartels may be formed and sustained more easily.

In an experiment to examine the effect of communication on collusion, Fonseca and Normann (2012) compare firm behavior with and without communication. The authors design four Bertrand oligopoly markets with varying numbers of firms (2, 4, 6, and 8) and observe the firms' price decisions. The prices selected by the subjects determine the firms' profits and payoffs. The authors find that communication increases the rate of cartel formation, with the median-sized market (four firms) having the highest number of cartels among the four markets. Cooper and Kühn's (2014) experiment divides communication levels into no communication, limited messages, and free chat, and shows that while delivering an intention for collusion may not be enough to sustain cartels, rich communication increases cartel stability. Bigoni et al. (2019) investigate the impact of interaction frequency on firms' collusion in a duopoly experiment. The experiment involves two firms choosing quantities in fixed periods, with random shocks affecting their profits. The fixed period length differs across three treatments, from 1 to 3. In the game, a firm can see the prices determined by the chosen quantities but cannot know about the random shocks or the other firm's choice. The experiment supports the view that communication increases cartel formation and highlights that communication is essential to form a cartel under imperfect monitoring.

In brief, previous studies on strategic delegation demonstrate that the interests of owners who focus solely on profit are not always consistent with those of managers who are concerned with their salaries. Managers tend to produce more output to maximize their salaries, which results in firms not maximizing their profits. The previous research has also shown that communication can increase the formation of cartels, and delegating decision-making to managers can stabilize existing cartels. However, the impact of strategic delegation on cartel formation remains unclear. This paper aims to shed light on this question.

1.3 Experimental design

1.3.1 Basic setup

The present study employs a finitely repeated game in a Cournot duopoly setup. The game features a finite number of rounds, each consisting of two stages. The market comprises two firms, labeled 1 and 2, each with one owner and one manager. The study assumes a linear demand and a constant marginal cost, following the FJSV model. The inverse demand function p is

$$p(q_1, q_2) = 140 - q_1 - q_2 \tag{1.1}$$

where q_i is firm i's output, $i = 1, 2$. The marginal cost is equal to 40. The profit and revenue of each firm are represented as π_i and R_i, respectively, where i refers to the firm's number (1 or 2). The owners of each firm are assumed to be concerned with their respective firm's profit, as detailed in Appendix A.1.1. The objective function for the payoff of each firm's manager is defined as U_i, $i = 1, 2$.

$$U_i^P = \pi_i = (100 - q_1 - q_2)q_i \tag{1.2}$$

$$U_i^R = .5\pi_i + .5R_i = .5(140 - q_1 - q_2)q_i + .5(100 - q_1 - q_2)q_i \tag{1.3}$$

In stage 1 of the game, the owners of each firm make a strategic delegation decision by selecting between contracts **P** and **R**. This determines the objective function for the managers' payoffs. The manager's payoff is proportional to the firm's profit alone when contract **P** is selected, as indicated by U_i^P in Equation (1.2). On the other hand, contract **R** represents a situation where the manager's payoff is proportional to half the profit and half the revenue, as described in Equation (1.3) with U_i^R. Based on the owners' selections, there are four possible combinations for firms 1 and 2: (P, P), (P, R), (R, P), and (R, R). The symmetric cases of (P, P) and (R, R) have managers with the same objective functions for their payoffs, while the asymmetric cases of (P, R) and (R, P) result in different objective functions for the managers. The details of these objective functions can be found in Table 1.2. At the end of stage 1, the contracts chosen by the owners become common knowledge to all players in the game.[7]

Table 1.2: Managers' objective functions (U_1, U_2) after owners' selection

Managers' obj. functions		Firm 2: P	Firm 2: R
Firm 1	P	$(U_1^P, U_2^P) = (\pi_1, \pi_2)$	$(U_1^P, U_2^R) = (\pi_1, .5\pi_2 + .5R_2)$
	R	$(U_1^R, U_2^P) = (.5\pi_1 + .5R_1, \pi_2)$	$(U_1^R, U_2^R) = (.5\pi_1 + .5R_1, .5\pi_2 + .5R_2)$

In stage 2, the *Collusion* stage, each manager simultaneously chooses between **L** (low output) and **H** (high output). The payoffs of the owners correspond to their firm's profit, while the payoffs of the managers depend on both the contracts selected by the owners and the output selected by the managers. The outputs available for selection by the managers in stage 2 vary based on the contracts chosen by the owners in stage 1, and the manager's choice of L or H determines the amount of output produced.[8]

For the symmetric cases, where (P, P) or (R, R) has been selected, this study considers three types of outputs to calculate owners' and managers' payoffs: (i) (L, L)

[7]This experiment assumes that owners' contracts for management incentives are publicly announced due to the requirements of federal securities laws, which mandate the disclosure of compensation paid to CEOs and high-ranking managers. The Compensation Discussion and Analysis (CD&A) section provides comprehensive information on executive compensation programs of companies.

[8]This study assumes that the owners' profit is independent of the managers' payoffs, which is consistent with previous research (FJSV; Huck et al. (2004)). If the managers' payoffs were subtracted from the owners' profit, then the prediction would be affected by the relative gap between the managers' payoffs and the profit, depending on the parameters of the demand function and marginal cost. However, this experiment focuses on the impact of strategic delegation on firm behavior and the market, not the effect of the relative gap on firm decisions. Thus, this assumption simplifies the description of firm behavior and the market under strategic delegation. The reasoning behind this assumption is further explained in Appendix A.1.1.

Table 1.3: Outputs for the two-stage strategic delegation game

			q_2					
			P			R		
			L	H		L	H
q_1	P	L	$(25, 25)$	$(25, 38)$	L	$(25, 30)$	$(\mathbf{27}, \mathbf{47})$
		H	$(38, 25)$	$(\mathbf{33}, \mathbf{33})$	H	$(35, 30)$	$(35, 47)$
			L	H		L	H
	R	L	$(30, 25)$	$(30, 35)$	L	$(30, 30)$	$(30, 45)$
		H	$(\mathbf{47}, \mathbf{27})$	$(47, 35)$	H	$(45, 30)$	$(\mathbf{40}, \mathbf{40})$

* Bold numbers mean Nash equilibrium for each subgame in the cases (P, P), (R, R), (P, R), and (R, P).

is a conventional way to form a cartel that maximizes the joint profit of the two firms. In this case, the output-maximizing joint-objective functions of the two managers are used. (ii) (H, H) represents competition between the managers, and both managers will maximize their individual objectives. Thus, in the (H, H) case, the Cournot competition output is used. Finally, (iii) (L, H) and (H, L) depict scenarios where one manager deviates from the cartel. In these cases, defection output is utilized to describe a manager's incentive to break from the collusion. For instance, in the (P, P) case, both managers have the same objective function, $U_1^P = \pi_1 = (100 - q_1 - q_2)q_1$ and $U_2^P = \pi_2 = (100 - q_1 - q_2)q_2$. Using these two equations, the output (q_1, q_2) for (L, L) is (25, 25), and the output for (H, H) is (33, 33). If firm 1 deviates from the cartel while firm 2 does not, the output for (H, L) is (38, 25). In the experiment, symmetric cases have three different outputs for collusion, competition, and one firm's defection.

For the asymmetric cases where (P, R) or (R, P) is chosen, it can be challenging to describe collusion, competition, and one firm's defection. For instance, if firm 1's owner selects P and firm 2's owner selects R in stage 1, the managers' objective functions are $U_1 = \pi_1 = (100 - q_1 - q_2)q_1$ and $U_2 = .5\pi_2 + .5R_2 = (120 - q_1 - q_2)q_2$. In this scenario, the Cournot competition output is (27, 47), but there can be multiple possible collusive outputs for (L, L) in asymmetric cases, as noted by Ivaldi et al. (2003).[9] To address this, this study adopts the "alternating monopoly output" for (L, L) in the asymmetric cases. The alternating monopoly output of each manager is defined as half of their monopoly output. For example, firm 1's monopoly output is 50, and firm 2's is 60. Thus, the alternating monopoly output for firms 1 and 2 is (25, 30).[10]

Another issue arises when determining the positions of competition and defection outputs in asymmetric cases. For instance, when (P, R) is chosen, the collusive output for (L, L) is (25, 30). If firm 1 deviates from the collusion, then the defection output is (35, 30). If firm 2 deviates, then the defection output should be (25, 47.5). When the firms compete with each other, the competitive output is (27, 47). The little difference between (25, 47.5) and (27, 47) makes it difficult to distinguish competition from deviation by firm 2. To address this issue, the competitive output (27, 47) is used for firm 2's defection output and (35, 47) is set for (H, H). This ar-

[9] The work by Ivaldi et al. (2003) highlights that it is not possible to find a unique collusive output in asymmetric situations like in symmetric situations where a joint-profit-maximizing output can be found. For instance, in the example discussed, the managers of firms 1 and 2 could maximize their joint payoff by producing zero output and 60 output, respectively, resulting in an output of (0, 60). However, it is unrealistic for one firm to produce nothing in a collusive arrangement, and this outcome cannot explain firm 2's incentive to deviate from the cartel. To address this issue, Fischer and Normann (2019) conducted an experiment to determine which of the several possible collusive outputs in an asymmetric duopoly market is closest to the actual collusive output.

[10] In Fischer and Normann's (2019) research, they showed that the alternating monopoly output, defined as the convex combination of two firms' monopoly output: $wU_i + (1-w)U_j$, where $w \in [0, 1]$, is one of the closest outputs to the collusive output in an asymmetric duopoly market. They found that the alternating monopoly output with a weight of $w = .5$ is one of the closest outputs to the collusive output. Therefore, this study adopts the alternating monopoly output with $w = .5$, which is half of each manager's monopoly output, as the collusive output in asymmetric cases.

rangement accommodates collusion, competition, and one firm's defection output.[11] The possible outputs for the two-stage game are indicated in Table 1.3.

Additionally, this experiment takes into account the possibility of cartel fines, which would be imposed by an antitrust authority in the event of a cartel being detected. If the two managers choose (L, L) in stage 2, there is a 15% chance that the cartel will be detected and fined. The fine imposed on the cartel firms is set at 10% of revenue, as per previous research (Apesteguia et al. (2007); Hinloopen and Soetevent (2008a); Bigoni et al. (2012)). If the cartel is detected, the profit of the cartel firms will decrease, resulting in a decrease in the owners' payoffs. In accordance with the US antitrust regime, the managers involved in the cartel will also be fined. Managers' fines in the experiment are set at around 20% of their payoff, aligning with the proportion of an owner's fine to their own payoff. This accounts for the impact of the cartel fine on the firm's profit, which in turn reduces the manager's payoff.

1.3.2 Treatments

This study compares two scenarios: (i) strategic delegation and (ii) profit maximization, both with and without communication. There are four treatments in total: profit maximization with no communication (**PN**), profit maximization with com-

[11] The experiment setting is designed to illustrate that competition between the two firms is close to one firm's deviation from collusion in asymmetric cases. The setup takes into account that a manager with R has a greater incentive to deviate from the cartel than a manager with P. This structure is similar to the setting used by Huck et al. (2004). However, Huck et al. only use collusive and competitive outputs and do not include defection outputs. In asymmetric cases in Huck et al.'s setting, the benefits of collusion for the firm with R (i.e., the difference in payoffs between competition and deviation) would be reduced. To address this issue, this study uses defection outputs from collusion.

Table 1.4: Owners' payoff table for the PN and PC treatments

		π_2 L	π_2 H
π_1	L	1250, 1250 (85%) or 1025, 1025 (15%)	(925, 1406)
	H	(1406, 925)	(**1111**, **1111**)

munication (**PC**), strategic delegation with no communication (**SN**), and strategic delegation with communication (**SC**).

In the PN and PC treatments, owners choose the outputs themselves, without delegating their decisions to managers, to maximize profit. In each group, there are only two owners in the PN and PC treatments. The PN treatment consists of a single stage, *Collusion*, while the PC treatment has two stages, *Communication* and *Collusion*. In the PC treatment, owners communicate with each other for one minute before choosing L or H in the *Collusion* stage. Owners can view their payoff table during communication. If both owners choose L, there is a 15% chance that the cartel will be detected and fined, with the size of the fine for each cartel firm being 10% of its revenue. For example, if the owners choose (L, L), the output for collusion is (25, 25), and using the inverse demand function $p(q_1, q_2) = 140 - q_1 - q_2$ and marginal cost $c = 40$, the cartel price is 90 and the cartel profit for each firm is 1250. The revenue of each firm is 2250, so the cartel fine is 225. This results in a cartel profit with a fine of 1025 in the 15% chance that the cartel is detected, or 1250 with no detection. At the end of each round, payoffs, including fines, are announced. Table 1.4 presents the payoff tables for owners in the PN and PC treatments.

Table 1.5: Owners' payoff table for the SN and SC treatments

			π_2			
			P		R	
			L	H	L	H
π_1	P	L	1250, 1250 (85%) or 1025, 1025 (15%)	(925, 1406)	1125, 1350 (85%) or 912, 1095 (15%)	**(702,1222)**
		H	(1406, 925)	**(1111, 1111)**	(1225, 1050)	(630, 846)
	R	L	1350, 1125 (85%) or 1095, 912 (15%)	(1050, 1225)	1200, 1200 (85%) or 960, 960 (15%)	(750, 1125)
		H	**(1222, 702)**	(846, 630)	(1125, 750)	**(800, 800)**

Table 1.6: The four possible payoff tables for managers in the SN and SC treatments

		U_2	
		L	H
U_1	L	125, 125 (85%) or 102, 102 (15%)	(93, 141)
	H	(141, 93)	(**111**, **111**)

(a) (P, P)

		U_2	
		L	H
U_1	L	138, 124 (85%) or 112, 101 (15%)	(**95**, **145**)
	H	(148, 94)	(88, 107)

(b) (P, R)

		U_2	
		L	H
U_1	L	124, 138 (85%) or 101, 112 (15%)	(94, 148)
	H	(**145**, **95**)	(107, 88)

(c) (R, P)

		U_2	
		L	H
U_1	L	128, 128 (85%) or 102, 102 (15%)	(83, 150)
	H	(150, 83)	(**108**, **108**)

(d) (R, R)

The SN and SC treatments include the *Strategic Delegation* stage, where each group consists of two owners and two managers representing two firms in a market. The SC treatment involves three stages: *Strategic Delegation*, *Communication*, and *Collusion*. In the *Strategic Delegation* stage, each owner selects P or R and can view not only their own payoff tables, but also the managers' payoff tables for all four possible outcomes. The owners' decisions determine the managers' payoff tables. In the *Communication* stage, managers communicate with each other for one minute while viewing the payoff tables determined by the owners' decisions. After the communication is finished, managers simultaneously choose L or H in the *Collusion* stage. Based on the managers' decisions, the payoffs for both owners and managers, including fines, are announced to everyone, and the round is completed. The SN treatment is similar to the SC treatment, but without the *Communication* stage. Table 1.5 presents the owners' payoff tables, while Table 1.6 displays the managers' four possible payoff tables, which vary depending on the owners' decisions.

1.3.3 The sessions

Each subject is assigned to a group before the start of a session. For the SN and SC treatments, each group comprises of four subjects. At the beginning of the session, each subject is assigned a firm designation (1 or 2) and a role (owner or manager). In the PN and PC treatments, each group consists of two subjects who are assigned to either firm 1 or 2. The session consists of sixteen rounds, describing a finitely repeated game.[12] After the completion of the sixteen rounds, cumulative payoffs from each

[12] See Normann and Wallace (2012) and Embrey et al. (2018). In the study by Normann and Wallace (2012), it was shown that the length of a game in a finitely repeated setting can increase firms' cooperation. The results of Normann and Wallace's experiment revealed that the cooperation rate for a 10-round game was 41%, while the cooperation rate for a 22-round game was 44%,

round are provided to the subjects.[13] The experiment involved 120 participants, who were divided into ten groups for each treatment, and were recruited from the Economic Science Laboratory at the University of Arizona in Tucson, Arizona, USA.

The experiment is programmed using oTree (Chen et al. (2016)). The average running time for a session is 35 to 45 minutes, depending on the treatments with different stages. An experimental currency, Point, is used to denominate payoffs. Owners receive one dollar for every 2,000 points, while managers receive one dollar for every 200 points.[14] The subjects received 18.1 dollars on average, including a show-up fee of 5 dollars.

1.4 Hypotheses

Based on the experimental design and the equilibrium of each treatment, this paper develops four hypotheses. The first two hypotheses compare the rate of cartel formation under strategic delegation to that under profit maximization. These hypotheses are based on the subgame perfect equilibria of the respective games. The game is finitely repeated, and as discussed, the stage game has a unique subgame perfect equilibrium. Therefore, the only subgame perfect equilibrium of the repeated game

providing support for the sixteen-round setting used in this study. Furthermore, in infinite repeated settings in Normann and Wallace's study, higher cooperation rates were observed, but the conclusion that the length of a game increases firms' cooperation remained unchanged. Additionally, according to the results of Embrey et al. (2018), when the length of the round is sufficient, subjects can cooperate until reaching a threshold round in a finitely repeated game that has only one non-cooperative equilibrium. This result suggests that finitely repeated games can be used to describe the rates of cartel formation among firms.

[13] Normann and Wallace (2012) show that a finite repeated game is not affected by a termination rule.

[14] See Appendix A.1.2, which includes additional assumptions to describe owners' and managers' payoff tables for the experiment.

is for all players to play the single-period subgame perfect equilibrium in each period.

In the PN and PC treatments, the two players, i.e., the owners, simultaneously choose between actions L and H, as shown in Table 1.4. Each player has a strictly dominant strategy to choose H in the stage game. Hence, the unique Nash equilibrium of the stage game is for both players to choose H, resulting in the unique subgame perfect equilibrium of the finitely repeated game.[15] In this equilibrium, players choose H in each period for each possible previous history of play, resulting in an equilibrium of (H, H) and a payoff of 1,111 to each player in each period. The cheap talk communication in the PC treatment does not affect the set of equilibrium outcomes.

In the SN and SC treatments, each period consists of two stages. During the first stage, owners determine the incentive structures for their own managers. In the second stage, managers choose their outputs. The resulting payoffs for the owners can be found in Table 1.5 and the payoffs for the managers are presented in Table 1.6. When examining the managers' decisions in the second stage, it becomes clear that the subgame influenced by the owners' choice of (P, P) or (R, R) in the first stage, each manager has a dominant strategy of choosing H. In the subgame that follows the owners' choice of (P, R), the Nash equilibrium is (L, H). In the subgame that follows the owners' choice of (R, P), the Nash equilibrium is (H, L). This means that in these subgames, the manager of the firm that selected the R incentive scheme will choose high output (H), while the manager of the firm that chose P will choose low output (L).[16]

[15]See Benoit and Krishna (1987).

[16]As discussed earlier, these Nash equilibria for the subgames capture the managers' decisions in a competitive setting. When owners select (P,R) or (R,P), the manager with the R incentive scheme chooses L, as there is more incentive to deviate from a cartel, while the manager with the

In the first stage, each owner has a higher payoff with R compared to P, regardless of the other firm's incentive scheme. This is because 1111 is less than 1222 and 702 is less than 800, as shown in Table 1.5. Therefore, the subgame perfect equilibrium in the single-period stage game is for both owners to choose R and for the managers to choose H, unless their owner has chosen P and the other owner has chosen R. In this case, the manager with the contract P will choose L and the manager with the contract R will choose H.

The finitely repeated game has a unique subgame perfect equilibrium, where both owners play strategy R, and both managers play strategy H in each period. This results in a payoff of 800 to each owner and 108 to each manager in each period. Communication in the PC treatment is cheap talk and does not affect the set of equilibrium outcomes.

Hypothesis 1.a. *With communication, the cartel formation rate under profit maximization (PC) does not differ from that under strategic delegation (SC)*

Hypothesis 1.b. *Without communication, the cartel formation rate under profit maximization (PN) does not differ from that under strategic delegation (SN)*

The remaining two hypotheses focus on the impact of communication on cartel formation in both the strategic delegation and profit maximization contexts. Previous studies have demonstrated that communication can facilitate cooperation and reduce conflict among subjects, leading to an increase in the formation of cartels (Fonseca and Normann, 2012; Awaya and Krishna, 2016; Bigoni et al., 2019). However, these studies have not considered the impact of delegation between owners and

P incentive scheme chooses H, as there is little incentive to deviate from a cartel.

managers. Therefore, this paper seeks to examine the impact of communication on cartel formation in both strategic delegation and profit maximization settings, with the formation of "implicit cartels" in the PN and SN treatments and "total cartels" in the PC and SC treatments.[17] Based on previous research, it is hypothesized that communication may increase the formation of cartels in both strategic delegation and profit maximization scenarios.

Hypothesis 2.a. *Under profit maximization, the cartel formation rate with communication (PC) is higher than that with no-communication (PN)*

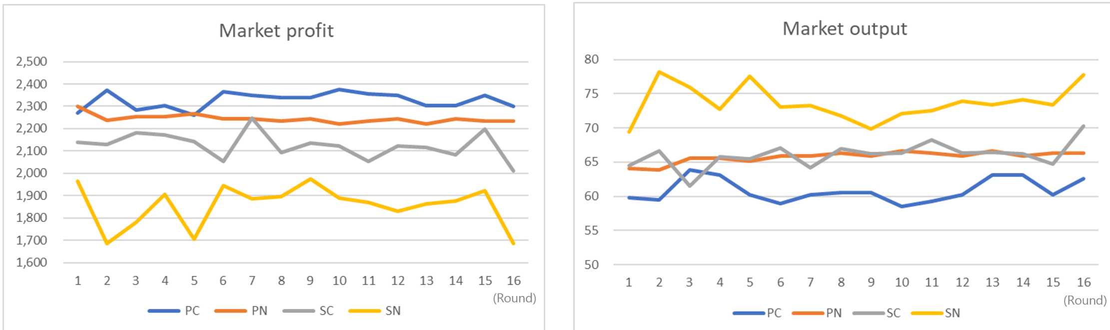
Hypothesis 2.b. *Under strategic delegation, the cartel formation rate with communication (SC) is higher than that with no-communication (SN)*

1.5 Results

1.5.1 Market outcome

This section discusses how the experiment results in terms of profit and output are determined in the four treatments. Table 1.7 shows the "market profit" and "market output" for each treatment, as depicted in Figure 1.1. The market profit for each treatment is calculated as the average profit of each group (consisting of two firms) over all sixteen rounds, and is represented as the total profit of all firms divided by 160 (16 rounds per group multiplied by 10 groups). The table indicates that the market

[17] Allowing communication does not necessarily result in the formation of explicit cartels. During the pilot test of my study, a few cartels formed without communication despite communication being allowed. This suggests that when communication is permitted, the resulting cartels may include both explicit and implicit cartels, which we can refer to as total cartels.



(a) Market profit (b) Market output

Figure 1.1: Market outcomes over the sixteen rounds for all treatments

profit under the SN treatment (1,855) is lower than that under the PN treatment (2,244), as supported by the Mann-Whitney U (MW) test result ($p = .001$) for SN and PN. On the other hand, the market profit under the SC treatment (2,125) is lower than that under the PC treatment (2,326), however, this finding is not supported by the MW test result ($p = .174$) for SC and PC.

Table 1.7: Market outcomes across treatments

	PN	PC	SN	SC
Market profit	2,244	2,326	1,855	2,125
Market output	65.8	60.9	73.7	66.1

* Market profit(output) = all firms' profit(output) divided by 160 (= 16 rounds × 10 groups)

The results of the experiment show that market output in the SN treatment (73.7) is higher than that in the PN treatment (65.8), which is supported by the MW test ($p = .001$). The market output in the SC treatment (66.1) is also higher than that in the PC treatment (60.9), but this finding is not supported by the MW test ($p = .174$). The results of market output are consistent with the findings of market profit, where the SN treatment shows lower profit but higher output compared to the

PN treatment. On the other hand, the SC treatment does not differ in a statistically significant way from the PC treatment in terms of both market output and profit.

1.5.2 Cartel formation rate

This section compares the rates of cartel formation under the PN and SN treatments, as well as under the PC and SC treatments. The rates of cartel formation are presented in Table 1.8. There is no significant difference ($p = .849$) in the cartel formation rates between PC (51.9%) and SC (48.1%), supporting Hypothesis 1.a. However, the cartel formation rate under PN (0.6%) is lower than that under SN (10%), with a MW test result of $p = .045$ which does not support Hypothesis 1.b. Table 1.9 also shows that strategic delegation leads to more cartels when communication is not allowed ($p = .046$). This implies that strategic delegation does not increase the number of cartels when communication is allowed, but without communication, it may increase cartels. This result also suggests that previous research that used the profit maximization assumption and estimated results such as the rates of cartel formation and detection by antitrust authorities remains relevant, even when it describes a market that does not consider strategic delegation.

Second, this experiment investigates how antitrust policies affect the ways in which firms form cartels. Two distinct forms of cartels are identified: "LL" cartels and "switching" cartels. LL cartels are established when both managers select "L," while switching cartels occur when the managers alternate between "L" and "H" from round to round.[18] The presence of switching cartels suggests that cartel members

[18]In the experiment, the subjects, who were acting as managers, engaged in discussions about how to collude with each other. For instance, they might say, "OK, how about this round I choose 'H' and you choose 'L'? Then we can switch the next round?" Through these interactions, I was

Table 1.8: Cartel formation rates by treatment

	PN	PC	SN			SC		
				PP/RR	PR/RP		PP/RR	PR/RP
Cartels	**1**	**83**	**16**	6	10	**77**	39	38
(%, rate)	**(0.6%)**	**(51.9%)**	**(10%)**	(6.1%)	(16.1%)	**(48.1%)**	(39.4%)	(62.3%)
LL	1	42	11	3	8	57	32	25
Switching	0	41	5	3	2	20	7	13
Sample size	160	160	160	98	62	160	99	61

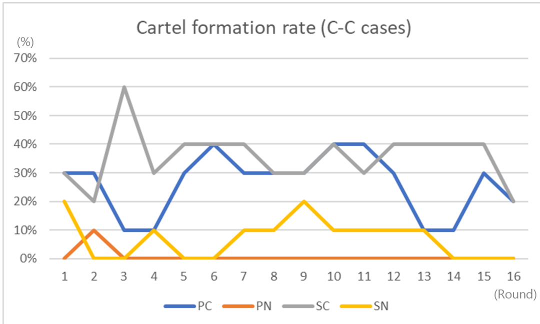
* Cartel formation rate = Cartel formed divided by 160 (16 rounds $\times$ 10 groups)
** PP(RR) means if (P,P) or (R,R) is chosen in stage 1, defined as symmetric cases. In the same manner, PR and RP are asymmetric cases.

are attempting to avoid punishment from antitrust authorities, and that they may form other types of cartels in the absence of antitrust regulations.[19] Table 1.8 and Figure 1.2 present the two forms of cartels identified in the experiment. In the PC treatment, LL cartels constitute half of all observed cartels (42 out of 83), while in the SN and SC treatments, they make up over two-thirds of the cartels (11 out of 16 and 57 out of 77, respectively). Results showed no statistically significant difference in the formation rates of LL cartels between PC and SC (p = .643), but strategic delegation was found to result in a higher rate of LL cartel formation in the absence of communication (p = .045). This suggests that under both strategic delegation and profit maximization, cartels can be formed through mutual agreement between two firms to choose (L,L), or by alternating between "L" and "H" to evade cartel fines. However, strategic delegation was found to result in a higher rate of LL cartel formation compared to profit maximization.

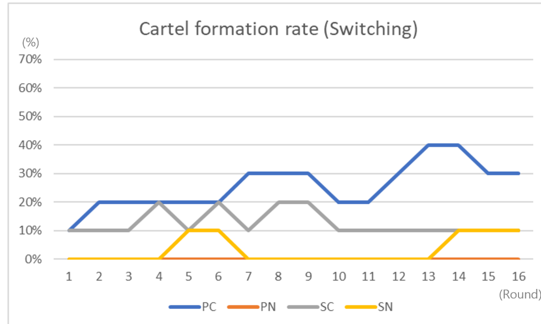
The third objective of this study is to examine the differences in cartel formation rates when owners choose the same contract versus different contracts across firms

able to observe the different ways in which firms form cartels in the experiment.

[19]Jaspers (2017) investigates the occurrence of switching cartels as a means of evading cartel regulation in a market. Switching cartels are similar to bid rotation collusions in an auction market, as demonstrated in previous studies by Aoyagi (2003) and Rachmilevitch (2013).



(a) LL cartels



(b) Switching cartels

* LL cartels are when both managers choose L.
** Switching cartels indicates alternating their choices every round, such as (L,H), (H,L), (L,H) and so on.

Figure 1.2: LL and switching cartel formation rates over the sixteen rounds for all treatments

in the SN and SC treatments. As illustrated in Table 1.8, Symmetric cases where owners choose either (P, P) or (R, R) are denoted as "PP/RR," while asymmetric cases where owners choose either (P, R) or (R, P) are denoted as "PR/RP." The results indicate that in the SN treatment, the cartel formation rate is higher in the PR/RP cases (16.1%) than in the PP/RR cases (6.1%). Similarly, in the SC treatment, the cartel formation rate is higher in the PR/RP cases (62.3%) compared to the PP/RR cases (39.4%). These comparisons suggest that under the strategic delegation scenario, managers are more likely to form cartels when owners choose different contracts for their incentives, rather than the same one. This is supported by the MW test results (p=*.041* in SN and p=*.005* in SC) and is statistically significant as seen in Panel (b) of Table A.1.

The way in which asymmetry is designed in this experiment differs from previous studies, as noted in previous research (Ivaldi et al. (2003), Mason et al. (1992), Mason and Phillips (1997), and Fonseca et al. (2005)). The previous papers have established

Table 1.9: Regression result for cartel formation

	Cartel formation	
	(1)	(2)
Strategic Delegation (SD)	4.075**	0.706
	(2.041)	(2.286)
Comm.	7.996***	3.974*
	(2.335)	(2.409)
SD × Comm.	-4.371*	0.125
	(2.502)	(2.797)
Round	0.026	-0.819***
	(0.053)	(0.050)
Round × SD		0.840***
		(0.137)
Round × Comm.		0.920***
		(0.096)
Round × SD × Comm.		-0.973***
		(0.179)
Constant	-8.111***	-4.722**
	(2.227)	(2.122)
Observations (group)	40	40

a "fixed" asymmetric duopoly situation where one firm is always more cost-efficient than the other. In such a scenario, if the two firms collude, one firm always has a stronger incentive to deviate from the collusion, leading to instability in the cartel. However, this study allows owners to change their selections, resulting in changing asymmetric situations between the managers of different firms every round. The managers' recurring uncertainty about which incentive schemes are given to them in the next round may impact the current round's rate of cartel formation differently depending on whether they operate in a symmetric or asymmetric environment. As a result, the comparison of cartel formation rates between symmetric and asymmetric environments in this experiment can provide insights into cartel behavior under conditions of changing asymmetry.[20]

[20] Table 1.6 displays the differences in incentives for the two managers to defect from collusion when (P, R) or (R, P) is selected. For instance, if (P, R) is chosen, the difference in payoffs for the manager of Firm 1 between colluding and defecting is 13.9=(148-(.85×138+.15×112)). The

1.5.3 Communication's effect

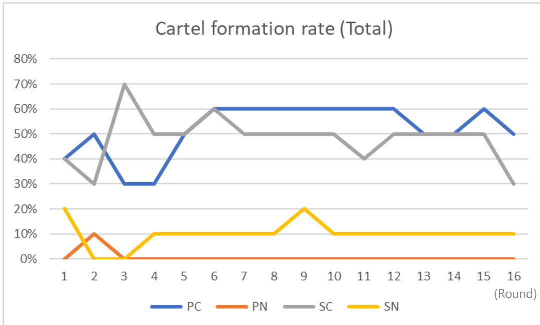
This section examines the effect of communication on the formation and duration of cartels. Figure 1.3(a) displays the rates of cartel formation (LL cartels + switching cartels) over the course of sixteen rounds. The average formation rate of cartels in the PC treatment (51.9%) is higher than in the PN treatment (.6%), and similarly, the average formation rate of cartels in the SC treatment (48.1%) is higher than in the SN treatment (10.0%). The MW test results indicate that communication treatments result in more cartel formation compared to no-communication treatments, with $p = .001$ for PC and PN, and $p = .062$ for SC and SN. This supports Hypotheses 2.a and 2.b.[21]

Figure 1.3(b) shows the average duration of a cartel.[22] The duration of a cartel is calculated as the number of rounds from its beginning to its end. On average, cartels in the PC treatment last 5.8 rounds, which is longer than those in the PN

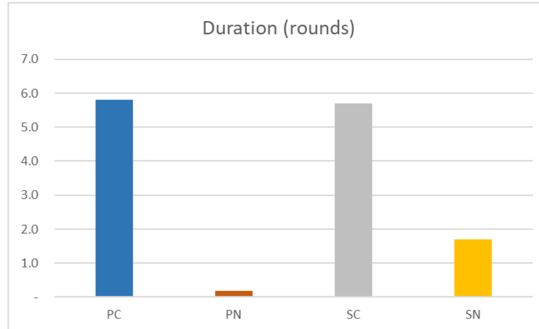
difference in payoffs for the manager of Firm 2 is 24.5=(145-(.85×124+.15×101)). This illustrates that the manager of Firm 2 has a stronger incentive (24.5) to deviate from collusion compared to the manager of Firm 1 (13.9). If (R, P) is chosen, the manager of Firm 1 is more likely to defect from collusion than the manager of Firm 2. The managers' incentives to defect from collusion will change as the owners switch between P and R in each round.

[21]This experiment compares the impact of communication on cartel formation under strategic delegation and profit maximization. The strategic delegation treatments also involve an asymmetric duopoly setting, as discussed in Section 1.5.2. The experiment observes two types of cartels: LL cartels and switching cartels. The results show that communication increases the formation of both types of cartels. There are more LL cartels in the PC treatment (26.3%) than in the PN treatment (.6%). The formation of LL cartels is also higher in the SC treatment (35.6%) compared to the SN treatment (6.9%). Additionally, communication is found to result in more switching cartels, as seen in the comparison between PC and PN (25.6% vs. 0%) and SC and SN (12.5% vs. 3.1%).

[22]Previous research aligns with the findings of this experiment. For instance, Harrington Jr. and Wei (2017) used a Bayesian approach to analyze the duration of cartels, developing a theoretical model to describe cartel duration, and comparing the results to the estimated cartel duration obtained from US cartel data from 1960 to 1985. They show that the average duration of cartels is estimated to be between 3.6 and 5.5 rounds when the cartel detection rate is .15, while US cartel data indicates that the average cartel duration is 5.8 years.



(a) Total cartels (LL + Switching)



(b) Cartel duration

* Cartel duration is the average length of rounds that a cartel last in each treatment.

Figure 1.3: The effect of communication on cartel formation

treatment that last only 0.2 rounds. Similarly, cartels in the SC treatment last 5.7 rounds, which is longer than those in the SN treatment that last 1.7 rounds. The MW test results for both comparisons are statistically significant, with $p = .001$ for PC versus PN and $p = .062$ for SC versus SN. These findings support the conclusion that communication leads to longer-lasting cartels under both strategic delegation and profit maximization settings when compared to the absence of communication.

1.6 Conclusion

This study investigates the impact of strategic delegation on cartel formation in markets subject to antitrust regulations. In modern economies, the separation of ownership and management is a common practice, with managers holding decision-making power in firms. Consequently, managers may have incentives beyond profit-maximization, with various performance indicators influencing their decision-making. Given that managers also play a crucial role in forming cartels, delegating decision-making to them may result in different collusion outcomes than under the assumption of profit maximization. This research aims to explore the effect of strategic delegation between owners and managers on cartel formation in markets.

The study employs a laboratory experiment to compare cartel formation rates under strategic delegation and profit maximization and to examine the effects of communication on cartel formation. Based on this two-by-two setting, there are four hypotheses: (1) when communication is allowed, the cartel formation rate under strategic delegation does not differ from that under profit maximization; (2) when communication is not allowed, the cartel formation rate under strategic delegation does not differ from that under profit maximization; (3) under strategic delegation, communication generates more cartels than no communication; and (4) under profit maximization, communication generates more cartels than no communication.

The experiment results show that (i) when communication is allowed, the cartel formation rate does not significantly differ between strategic delegation and profit maximization, supporting hypothesis (1); (ii) however, when communication is not permitted, strategic delegation generates more cartels compared to profit maximization, which does not support hypothesis (2); and (iii) both under strategic delegation and profit maximization, communication increases the formation rate and duration of cartels, supporting hypotheses (3) and (4).

The key conclusion of this research is that the impact of strategic delegation on cartel formation depends on the presence of communication. When communication is allowed, the number of cartels formed under strategic delegation does not differ from that under profit maximization. However, in the absence of communication, strategic delegation leads to a higher number of implicit cartels compared to profit maximization. This highlights the importance of considering both strategic delegation and communication in examining firms' behavior and the potential for collusion in a market. The results suggest that previous findings on the total number of cartels formed under a profit maximization assumption are still valid, but they may underestimate the existence of implicit cartels in a market.

The results also suggest that greater incentives for firms to collude do not necessarily lead to an increase in cartel formation rates. The study finds out that the difference in profits between collusion and competition is larger in the market under strategic delegation compared to the market under profit maximization. This implies that a market under strategic delegation may be perceived as more competitive, with a higher incentive for firms to form a cartel. Despite this, the experiment shows no statistically significant difference in the cartel formation rates between the market under strategic delegation and the market under profit maximization. These findings highlight that there may be a certain number of cartels that exist in any market and that a seemingly more competitive market does not necessarily mean fewer cartels.

In addition, this study provides a meaningful insight into how cartels can be formed to evade antitrust laws. The experiment incorporates fines for forming a cartel and a 15% chance of being detected by antitrust authorities. The results show that cartels can not only be formed through agreement to produce low output but also through alternating between low and high output every round. This second strategy, named switching cartels, reflects cartels' efforts to avoid regulation by antitrust authorities. While bid rigging in auctions has been widely discussed in previous literature, the formation of switching cartels in a market setting has received limited attention in economics. This study sheds light on the various ways in which cartels can be formed in an attempt to evade antitrust regulation using a simple experiment setting, highlighting the need to be aware of these strategies in policymaking and enforcement.

Furthermore, this study highlights the significance of asymmetry in market conditions for cartel formation. Previous research has studied the formation of cartels in asymmetric duopoly situations, where firms face a "fixed" asymmetry in every period. In such a fixed asymmetric setting, one firm always has a greater incentive to deviate from the cartel, making it easier for the cartel to break down. However, in this study, owners have the ability to change the market conditions by selecting the managers' incentive scheme in each period. Owners' selections in the present period makes it challenging that their managers cannot know whether the market would be symmetric or asymmetric in the next period. The uncertainty about the owners' selection in the future leads to an increase in cartel formation in order to maximize the current round payoffs. The study shows that managers form more cartels in asymmetric market situations compared to when the market is symmetric.

Lastly, this study investigated the impact of communication on cartel formation when decision-making is delegated to managers. Prior research has explored the effect of communication on cartels using the assumption that firms maximize profits. This study, however, takes into account the strategic delegation between owners and managers, which is common in today's economy. The results show that communication leads to more cartel formation and longer cartel duration in both strategic delegation and profit maximization, supporting the conclusion that communication plays a crucial role in the formation and longevity of cartels.

In conclusion, this study provides valuable insights into the effects of strategic delegation under antitrust policy. The results show that while communication does not increase the number of cartels formed under strategic delegation, its absence may lead to more cartels. The research also find out that higher incentives for collusion do not necessarily result in a higher rate of cartel formation, and those firms may form more cartels in asymmetric market situations. Moreover, the study demonstrates that communication plays a significant role in generating more cartels and extending their longevity under both strategic delegation and profit maximization. While this research is based on a laboratory experiment and thus has some limitations in its ability to perfectly reflect real-world situations, it still provides valuable insights into cartel formation and has important practical implications. This study can serve as a foundation for future research that more accurately reflects real-world firm behavior by incorporating fewer constraints and limitations.

Chapter 2

Leniency Policies and Cartel Success: An Experiment

Cartels are often fought by granting leniency, in the form of forgiveness of penalties, to whistle-blowers. This study employs a laboratory experiment to compare leniency programs that differ with respect to fine size and whether a second whistle-blower may apply for leniency. The results show that leniency does not affect the probability that a cartel forms, but is effective in exposing cartels and thereby inhibiting cartel success. Higher fines are more effective, but allowing leniency to a second whistle-blower is no more effective than granting leniency to only one whistle-blower.

2.1 Introduction

Economists and regulators have long been interested in the most effective policies to prevent the formation of cartels. While collusion and the formation of monopolies have generally been prohibited in the United States since the Sherman Antitrust Act of 1890, there have nevertheless been many attempts by companies to form cartels in a variety of industries. One reason that cartelization is an enduring problem is because once a cartel has formed, it can be difficult for antitrust authorities to expose it. Bryant and Eckard (1991) estimate the probability of catching a cartel at between 13% and 17% in the US. Combe et al. (2008) estimate the probability of uncovering a cartel in the EU at 12.9% to 13.3% in the period from 1969 and 2008. In addition, the costs of the investigations necessary to expose cartels can be substantial. For example, the US Department of Justice allocated $188.5 million for antitrust enforcement in 2021. The duration of investigations can also be quite long. For instance, in the EU, cases brought between 2000 and 2011 had an average length of investigation of 50.8 months (Hüschelrath et al. (2012)).

In order to make it easier to expose cartels, the US introduced a leniency program in 1978. This initial program allowed the first applicant for leniency to receive a partial exemption from the penalties and fines for collusion, including reduced criminal punishment. The hope was that by giving a partial exemption, whistle-blowing would be encouraged, leading to the breakup of existing cartels and the deterrence of future cartelization. The incentives were strengthened in 1993, with whistle-blowers receiving full immunity from any penalties. As a result, leniency applications have increased by a factor of 10, with convictions and fines skyrocketing as well.[1]

Following the success of the US policy, leniency policies were adopted by other countries. The European Union's leniency policy, instituted in 1996, guarantees the first whistle-blower a penalty exemption, but also grants fractionally reduced fines for second and third whistle blowers. South Korea introduced a leniency policy in 1997, and then in 2005 additionally guaranteed a partial penalty exemption of 50% for the second whistle-blower. Japan adopted a leniency program in 2006 that allows a partial fine exemption additionally for a third applicant. The magnitudes of the penalties for collusion differ by country. For example, the EU and South Korea impose a maximum penalty of 10% of revenue for firms that have acted as a cartel, while the US specifies a maximum penalty of 20% of "affected volume."

In this paper, using a controlled laboratory experiment, we study the effects of the two key components of leniency policies that vary internationally: the size of the penalty, and how many whistle blowers receive leniency. We consider whether, ceteris paribus, incentivizing a second whistle-blower with leniency and changing the fine size affect the rate of cartel formation, the probability of cartel exposure, the probability that an industry successfully colludes, industry profits, and the fines that the authorities collect.

The choice of experimental design and parameters was guided by a comparison of the American and South Korean leniency policies. Our research question is the following: is the system of leniency in the US more or less effective at reducing cartels than the system in place in South Korea? The policies differ in two dimensions.

[1] See https://www.justice.gov/atr/speech/detecting-and-deterring-cartel-activity-through-effective-leniency-program

First, in the US, leniency is granted to one whistle-blower and in South Korea it is granted to two whistleblowers. Second, the fine size differs in the two countries, and is higher in the US than in South Korea.[2] The two-factor, two-level design of the experiment considers which of the two dimensions might be the source of any differences in outcomes that we observe. An additional control treatment is used to establish whether some of the versions of the leniency policy might not even be better than no leniency policy at all.

Our data show that all of the leniency policies we include in our study reduce the ability of firms to successfully collude, with the exception of a policy granting leniency to two whistle blowers in conjunction with a relatively low fine. High penalties have the effect of reducing overall industry profits and increasing the fines collected by the state. The success of the leniency policies does not result from deterring the formation of cartels, but rather from increasing the rate at which they are reported and punished.

The paper is organized in the following manner. Section 2 discusses the prior experimental literature on cartel leniency. Section 3 describes the experimental design. Section 4 presents our hypotheses. Section 5 reports the results and Section 6 provides a summary of the results and a concluding discussion.

[2]In the US, the fine is 20% of "affected volume", which refers to revenue, and in South Korea it equals 10% of revenue. In December 2021, after this study was conducted, the fine size in Korea was increased to 20% of revenue, and is now comparable to that in the US.

2.2 Previous related literature

Previous research has studied the effect of leniency policies on cartel activity and has verified that they do have an effect. Motta and Polo (2003) show that leniency increases the chance that a cartel is exposed, but also note that the cartel formation rate may actually increase due to the drop in the expected cost of cartelization. Leslie (2005) finds that allowing exemptions for cartel ringleaders may promote the destabilization of cartels. Miller (2009) verifies empirically that leniency programs lead to greater levels of cartel revelation and deterrence, using cartel data in the US from 1985 to 2005. However, Brenner (2009), using data from the EU during the period of 1990 to 2003, shows that it is possible for leniency policies to actually lead to cartel stabilization. Harrington Jr (2008) studies the effect of fine reductions and finds that a full fine exemption is more effective for catching cartels than a partial fine exemption, but the increase in the number of full fine-exempt firms may make it difficult to destabilize cartels. Zhou and Gärtner (2012) confirm that higher fine reductions give rise to the faster breaking-up of cartels.

A number of experiments have investigated the effect of leniency policies. See Marvão and Spagnolo (2014) for a survey. The initial studies considered environments with Bertrand price competition. Apesteguia et al. (2007) study the effect of leniency on cartel formation in a one-shot Bertrand game with homogeneous goods. There are four treatments in their experiment. In the *Ideal* treatment, no communication among firms is permitted and there is no opportunity for whistle-blowing. *Standard* allows communication among firms but there is no fine reduction from reporting a cartel. *Leniency* awards a fine reduction to firms that report their cartel. If only one firm reports, it is fully exempt from paying the fine (which is 10% of revenue). If there are $k > 1$ whistle-blowers, each receives a $1/k$ reduction in its fine. *Bonus* transfers the fine from those cartel members that are fined to whistle-blowers as a reward.[3] The results show that the *Leniency* treatment has the lowest rate of cartelization among the treatments, and also leads to lower prices than the *Standard* or *Bonus* conditions.

Hinloopen and Soetevent (2008b) consider behavior in a repeated Bertrand game, extending the setting of Apesteguia et al. (2007) to repeated interaction. Their design has four treatments. Under *Benchmark*, no communication is permitted. Under *Communication*, firms can communicate in every period. In *Antitrust*, a 15% probability of detection is introduced, and in *Leniency*, firms in the cartel can blow the whistle and obtain an exemption from their fine. There is a full fine exemption for the first applicant and a 50% fine reduction for the second applicant, as in two of our treatments. Hinloopen and Soetevent (2008b) find that *Leniency* reduces cartel formation and destabilizes existing cartels, but fails to reduce cartel recidivism from the level observed in *Antitrust*.

Bigoni et al. (2012) compare leniency policies in a repeated Bertrand competition with two firms selling differentiated products. After deciding whether or not to communicate with the competitor, firms choose their prices. The treatments include a *L-Faire* condition, in which firms are free to collude, and a *Fine* treatment in which there is a probability of detection and penalty. In the *Leniency* treatment, if one firm reports the cartel, it receives full leniency, while if both report, each receives leniency equal to 50% of the fine. In the *Reward* treatment, if there is only one firm

[3]While prior experiments show that awarding such rewards is effective in reducing the number of cartels, we rule out the study of reward systems here. The reason is that we are also interested in achieving high revenue from fines for the regulatory authority.

reporting, it receives a reward equal to the fine paid by the other firm. There are two chances to blow the whistle, both before and after setting prices. The authors find, as in the prior studies, that *Leniency* does reduce cartel incidence compared to the *Fine* treatment. *Fine*, in turn, leads to lower cartelization than *L-Faire*. Exempting the ringleader, defined as the first firm to start communication, from leniency, and well as increasing fines in the absence of leniency, have no additional deterrent power.

Bigoni et al. (2015) study the effects of leniency, fine size, and detection probability. Their design allows some interaction effects to be studied that we cannot, such as the interaction between the fine size and the probability of detection and between leniency policy and the probability of detection. However, like the studies mentioned above, they use a Bertrand pricing paradigm, which is quite different from the Cournot setup that we employ. It differs both in underlying theoretical structure (the Bertrand game is one of strategic complements while the Cournot game is one of strategic substitutes), and in its propensity for collusive behavior (Bertrand competition leads to more collusion than Cournot competition). In Bigoni et al.'s design, there are two whistle-blowing opportunities, one before prices are set and one afterward. They find that both higher fines and leniency help deter cartels, and fines tend to be more effective under leniency. They note that low fines can be counterproductive to the deterrence of cartels, since they may be used as punishments to stabilize rather than to deter cartels.

Chowdhury and Wandschneider (2018) study conditions with (i) a low cartel detection probability and high fine size, and (ii) a high detection probability and low fine size, each in a setting with and without leniency. Detection probability and fine size are not varied independently while holding the other variable constant. Their setup is also a repeated Bertrand setting with a random ending rule. They find that under leniency, there are fewer cartels under low detection rates and high penalties, but observe the reverse pattern in the absence of leniency.

Andres et al. (2021b) observe the contrasting finding that leniency does not have an effect on cartelization. Their experimental design has the distinctive feature that a human experimental participant is placed in the role of a regulator who can award leniency at their own discretion after reviewing the content of the communication between firms. Their setup does not include a voting stage where firms choose whether or not to join a cartel, and the authors argue that not including this stage makes cartel formation more difficult. Their design also includes open communication, which they argue builds trust and reduces whistle-blowing.

Bodnar et al. (2021) are concerned with the effect of the ability to sue colluding firms for damages on the effectiveness of a leniency policy. In their leniency system, the first whistle blower receives a full fine exemption and the second receives a 50% reduction. Damages are set at 60% of the difference between the cartel and the Nash equilibrium revenues, summed over the life of the cartel. The damages are won and awarded with probability .95. All cartel members must share the costs equally. They find that private damages significantly reduce the likelihood of cartel formation. Damages also reduce the number of applications for leniency and lower prices. The study also compares structured and free-form communication, and finds that cartel stability and leniency applications are lower under chat communication, though the overall amount of collusion is higher under more restricted, structured communication.

Hamaguchi et al. (2009) study the how the effectiveness of leniency policies is affected by the number of firms in the industry, and by the percentage of the fine that is exempted to firms that report the cartel. They also compare a policy of granting leniency only to the first reporter versus to all reporters. Their experiment is framed as a prisoner's dilemma with two possible actions labeled with the abstract terms A and B. They observe that leniency does reduce the incidence of cartels, but that there is no difference between granting full or partial leniency, or between giving leniency to one or all reporters. They also find that giving a reward to reporters reduces the incidence of cartels more than merely granting exemptions from fines.

Hinloopen and Soetevent (2008a) investigate two-firm oligopolies in a setting with multiple equilibria. Like Hamaguchi et al. (2009), they use a two-action prisoner's dilemma, rather than a price setting framing. There are four treatments in the experiment. Under the *Benchmark* treatment, there is no penalty for collusion, Under *Antitrust*, there is a probability of detection of 40%. In the *Exploitable* treatment, there is full leniency for a firm who is the only one to report, and 90% leniency for the two firms if they both report. In the *Non-Exploitable* treatment, full leniency is given to the first applicant and 50% to the second, as in some of our treatments. The results show that in the *Exploitable* condition, firms learn to increase their earnings by colluding and then reporting on their cartel. In the *Non-Exploitable* treatment, many pairs of firms are able to collude by taking turns monopolizing the market in successive rounds of the interaction.

Feltovich and Hamaguchi (2018) are concerned with the relative power of the direct effect of whistle-blowing, which would serve to deter cartel formation, and the indirect effect of leniency lowering the cost of exiting the collusive agreement, which might make such agreements more likely. In their experiment, being caught in collusion by the competition authority is very costly and means that the firms are unable to charge high prices in any later periods. They found that leniency significantly lowered prices and reduced cartel stability. They conclude that leniency is a good anti-collusive policy.

Clemens and Rau (2019) investigate the behavior of leniency policies that exclude ringleaders from possible leniency. The idea is that doing so would discourage cartel formation. In their experiment, firms can choose to collude or not, and firms who do not collude receive the payoffs that they would as Cournot players. Firms engage in a finitely repeated game. Their design includes a baseline treatment, called *AA*. with No-leniency, and another called *LEN*, in which firms sequentially have the opportunity to report the cartel. Two other treatments, *RD2* and *RD4*, make either two or four ringleaders ineligible for leniency. The results show that discriminatory leniency policies are not effective in reducing the incidence of cartels, but they also confirm that non-discriminatory leniency is effective in doing so.

In summary, previous experimental research analyzing the effect of leniency programs on cartels generally find that leniency programs do reduce the likelihood that cartels are successful. Granting leniency to one or to multiple reporting firms does not seem to make a difference insofar as it has been directly compared. There is evidence that higher fines reduce cartel formation, whether or not a leniency policy is in place. Leniency policies reduce successful cartel formation both in paradigms in which prices are set from a relatively extensive menu of prices and those that are framed as two-or three-action social dilemmas.

2.3 Experiment Design

2.3.1 The basic setup

The structure of the experiment is based on that of Clemens and Rau (2019). Subjects are assigned to groups of four, representing four firms in a market with identical products to sell. Each group has no contact with or information about any other groups in their session. Thus, each group's activity can be considered an independent observation. Sessions consist of ten periods, and group assignments are fixed for the ten periods. Participants are made aware that their session payoffs are determined by their profits up until a randomly selected final period, plus a participation fee of $5.

At the beginning of each period, group members can talk each other in a chat box for one minute. All messages are seen by all members of the group, but not by any members of other groups. After the discussion period ends, each individual decides whether to join a cartel or not. In the experiment, this is referred to as choosing whether or not to "join the market agreement."[4] Firms make their decision before knowing how others decided. If two or more subjects agree to join a cartel, then a cartel is formed, with those who agreed to collude as the members. There is an exogenous probability of .15 that the cartel is discovered and that all cartel members

[4]There are advantages and disadvantages to allowing this communication. Two disadvantages are that such communication is typically illegal in the field and it is difficult to model theoretically. One advantage is that is allows inexperienced players to have a chance at establishing a cartel more readily, since it allows some players to educate others about the benefits of cartelization and build confidence in each other. We felt that cartel formation would be enhanced if communication were allowed. Otherwise, the strategic uncertainty would be too strong for players to collude. We wanted to give cartels a decent chance of occurrence. In the field cartel participants might not communicate directly, but are often quite familiar with how their competitors are thinking.

are fined.

The parameters are the same as in the study of Clemens and Rau (2019), and based on the following underlying structure. There are four identical firms that produce a homogeneous good. Market demand is given by the inverse demand function $P = 100 - Q$, where Q is the quantity produced by the industry. All firms have a constant marginal cost of 60. The monopoly quantity and price are 20 and 80, respectively. If all four firms join a cartel and share the profits equally, each firm would produce 5, and receive revenue of $5 \times 80 = 400$, making a profit of $5 \times (80 - 60) = 100$. If a fine of 10% of revenue is imposed on the cartel, the fine is 40 for each firm, and each firm would receive 60 as its net payoff. In the Cournot equilibrium, each firm produces a quantity of 8, and the resulting price is 68. This results in profits of $8 \times (68 - 60) = 64$. Cartels with two or three members result in different profit vectors.

Table 2.1 shows the net payoffs for each player, depending on how many firms join the cartel and whether or not it is exposed. The table indicates the final period payoffs in the benchmark No-leniency (*No-len*) treatment. It shows that partial cartels of two or three firms are less profitable than the Cournot equilibrium for the cartel participants, while a full cartel of four members is the most profitable arrangement for the industry.[5]

We induce time discounting with the following procedure. All groups play exactly 10 periods, but the payoffs are equivalent to those that would exist in an indefinitely repeated game with a .1 probability of termination in each period. After the 10

[5]The payoffs assume that any firms that are not members of the current cartel behave non-cooperatively, that is, as Cournot players against the cartel and other non-cartel members.

Number of firms entering cartel	Payoff of each cartel member		Payoff of each non-member
	If cartel is not exposed	If cartel is exposed	
0	-	-	64
1	-	-	64
2	50	15	100
3	59	25	178
4	100	60	

Table 2.1: Period payoffs of cartel members and non-members based on size of cartel

Note: Payoffs are denominated in terms of experimental currency. 200 ECU = 1 US dollar. If all of the four firms join a cartel, the revenue of each firm is 400. If the cartel is exposed, each cartel member is fined 10% of its revenue, 40. Thus, each firm's payoff becomes $100 - 40 = 60$. Similarly, 10% of revenue is considered as the fine level for cases in which two or three firms form a cartel.

periods of the session are completed, we generate a sequence of random numbers which determines the probability that a given period already played would continue to count. For example, a random number is drawn for period 1 from a uniform distribution on $[0, 1]$. If the number drawn is in the interval $(.1, 1]$, periods 1 and 2 both count. Then, a random number is drawn for period 2. If this number is in $[0, .1]$, only periods 1 and 2 count. If the draw is $> .1$, period 3 also counts, and so on. If a number in $(.1, 1]$ is drawn in period 10, and the game is thus slated to continue to count, then each individual is paid an additional amount equal to the amount that they have earned in the 10 periods that have already been played. This additional payment is equal to their expected additional payment were the game to continue under the same 10% probability of ending after each period (the expected number of future periods would be 10) and assuming the same average-per-period payoffs as in the 10 periods played. Therefore, in this case, participants' total earnings for the session equal the show-up fee of \$5, plus double the amount of money that they earned in periods 1 to 10.

Though there is discounting of the future at a constant discount factor of $\delta = .9$, there is a unique subgame perfect equilibrium. This is because period 10 is certain to be the last period, and thus the game is finitely repeated. The only Nash equilibrium in period 10 is the Cournot equilibrium. Thus, the only subgame perfect equilibrium in the finitely repeated 10 period game is to play the Cournot equilibrium in each period regardless of past history. In any subgame where a cartel forms, all players blow the whistle on the cartel.

2.3.2 Treatments

Our design consists of a total of five treatments. The differences among the five treatments are summarized in Table 2.2. The benchmark treatment is called *No-len*. In this treatment, there are no leniency policies in effect, but rather an exogenous 15% probability that a cartel is discovered and fined. If exposed, the cartel is fined 10% of revenue. The *High1* treatment has two key features of the current US leniency system. (1) The treatment has a relatively high fine and (2) the first applicant for leniency is given a 100% fine exemption, with no other whistle-blowers receiving any reduction in their fines. Under the *High2* treatment, a second applicant also receives a 50% reduction in her fine, but the condition is otherwise identical to High1. Under *Low1*, only the first applicant receives a 100% fine reduction, but the fine size is only 5% of revenue. Finally, the *Low2* treatment has two features of the leniency program of South Korea. (1) The fine size is relatively low, and (2) there is a 50% fine exemption to the second applicant, in addition to 100% forgiveness to the first reporter.

In all treatments other than No-len, the game has a second decision stage after the choice of whether or not to join a cartel. In this second stage, the subjects who have joined the cartel choose whether or not to to blow the whistle on the cartel. Blowing the whistle is described to the participants as "reporting the market agreement." Firms who do not join a cartel skip this stage. If only one or none of the participants chose to join a market agreement, then this stage is also skipped, as there are no cartels that can be reported.

Under the High1 and Low1 treatments, if there is one whistle-blower, she receives full leniency and pays no fine. Thus, she receives the cartel payoff for the period. The remaining cartel members pay the fine (10% of revenue in High and 5% of revenue in Low). If there is more than one whistle-blower, only one among them, chosen randomly, receives full leniency. In High2 and Low2, two whistle-blowers, randomly chosen if there are more than two, receive leniency. One receives full leniency and pays no fine, and the second pays only 50% of his allotted fine. If there is only one whistle-blower, she receives 100% leniency.

Each firm's earnings are equal to its profits in the market minus any fines levied for participation in a cartel. After each period, each participant receives some information about activity in the period, consisting of how many firms agreed to join the cartel, how many applied for leniency, and one's own earnings.

2.3.3 The sessions

Each treatment is in effect for ten groups. As indicted earlier, each group has four members. Thus, in total, there are 50 groups and 200 participants in the study. The experiments are implemented via Zoom using Qualtrics. We employ an experimental

Treatment	Existence of leniency program	Fine size (% of revenue)	Fine reduction	
			First applicant	Second applicant
No-len	No	10%	-	-
High1	Yes	10%	100%	-
High2	Yes	10%	100%	50%
Low1	Yes	5%	100%	-
Low2	Yes	5%	100%	50%

Table 2.2: Differences among the Treatments

currency (ECU) to denominate earnings, with each 200 ECUs exchangeable for 1 US dollar at the end of the session. The show-up fee is $5 dollars, and participants earn $12 on average. The subjects are recruited from the subject pool maintained by the Economic Science Laboratory (ESL) at the University of Arizona, located in Tucson, Arizona, USA.

A session takes on average 45 minutes. Each session has two or three groups participating simultaneously. Subjects join a Zoom meeting room at the scheduled starting time of the session. They then receive a link to the experiment and are told that they would earn a show-up fee of 5 dollars and additional money depending on their decisions during the experiment. They read the instructions and are then randomly assigned to groups of four. They then proceed through the experiment.

2.4 Hypotheses

We rely on previously obtained experimental results to formulate hypotheses. The available previous work on cartel leniency is in near-complete agreement that leniency reduces the incidence of cartels. The variable that we use as a measure of the performance of an antitrust regime is the rate of successful cartel formation. This is defined as the percentage of periods in which a cartel is formed and not exposed, either through antitrust enforcement or whistle-blowing. We view the objective of antitrust policy to minimize this percentage of these "successful" cartels. We first hypothesize that the result obtained in prior studies would also be observed here, and that the rate of successful cartel formation would be reduced by leniency. This is tested by comparing the rate of successful cartel formation in the No-Len treatment with those in the High1 and High2 treatments, which have the same fine size in place.

Hypothesis 3. *The leniency treatments High1 and High2 have fewer successful cartels than No-Len.*

Our treatments vary whether a second whistle-blower can receive partial leniency or not. As discussed in Section 2.2, the available evidence is mixed regarding whether granting leniency to one or to multiple whistle-blowers is more effective in preventing cartels. The evidence is also inconclusive as to whether granting full or partial leniency makes cartels less likely. Moreover, there is no direct previous comparison between awarding full leniency to the first party to report the cartel, and awarding full leniency to the first and partial leniency to a second whistle-blower as well. Thus, in the absence of prior evidence, we hypothesize that:

Hypothesis 4. *A leniency program that allows a second applicant a partial fine exemption leads to a similar likelihood of successful cartel formation as a program that does not. Thus, the rate of successful cartel formation is not different between High1 and High2, and not different between Low1 and Low2.*

Bigoni et al. (2015) observe that, under Bertrand competition, stronger penalties are more likely to deter cartels in the absence of leniency. They also find that the deterrent power of high penalties is magnified under leniency, since the benefits of leniency to the whistle blower increase as the fine avoided becomes larger. We thus hypothesize that higher fines lead to fewer successful cartels.

Hypothesis 5. *Under a leniency program, the rate of successful cartel formation is higher under Low1 than in High1, and higher under Low2 than in High2.*

2.5 Results

2.5.1 Leniency and Cartel Formation

We begin our reporting of the data by considering the frequency with which cartels form and how the likelihood of their formation is affected by leniency policy. Table 2.3 indicates the cartel formation rate, the percentage of periods in which a cartel is formed (this occurs if two or more individuals agree to join a cartel). For each treatment, the cartel formation rate is the total number of periods in which a cartel was formed, divided by 100, the total number of periods played under each treatment (10 groups times 10 periods per group in each treatment). We define a *Full Cartel* as a cartel including all four firms and a *Partial Cartel* as a cartel with two or three members. The term *All Cartels* encompasses both full and partial cartels. Table 2.3(a) shows the percentage of possible instances in which a cartel, either full or partial, is formed in each of the five treatments. Figure 2.1(a) illustrates how the cartel formation rate changes over time, by tracking the percentage of groups that form cartels in each period.

The table shows that the cartel formation rates under High2 (84%), High1 (83%),

	No-len	High1	High2	Low1	Low2
Cartel formation rate*	85%	83%	84%	81%	95%

(a) All cartels

	No-len	High1	High2	Low1	Low2
Full cartel formation rate**	49%	32%	27%	33%	45%

(b) Full cartels

Table 2.3: Cartel formation rate, by treatment

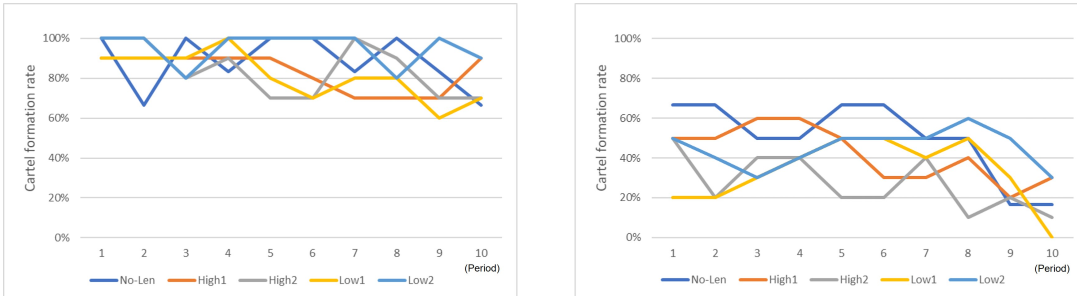
*Cartel formation rate = Number of Cartels formed/100 periods (= 10 periods × 10 groups per treatment)

**Full cartel formation rate = Number of full cartels formed/100 periods

and Low1 (81%) are similar to that under No-len (85%). Low2 (95%), however has an even higher cartel formation rate than No-len. However, Mann-Whitney U tests for pairwise treatment differences between No-len and each of the other treatments are not significant. This means that the various leniency policies do not change the likelihood of cartel formation from that in No-len.[6] Indeed Figure 2.1 confirms that there are no obvious differences among treatments.

The data for full cartels only are shown in Table 2.3(b) and Figure 2.1(b). The full cartel formation rate in a treatment is the number of periods in which full cartels

[6]In this paper, all comparisons between No-len and High1, as well as between No-len and High2, are one-sided, since we have a hypothesis (1) regarding the sign of the differences between these treatment pairs. Furthermore, all comparisons between Low2 and High2, and between Low1 and High1 are also one-sided since we also have a hypothesis (3) about differences between these two treatments. Though the hypotheses refer to the cartel success rate, the primary measure of policy effectiveness, we also use one-sided tests for the cartel formation rate, cartel exposure rate, industry profit, and fine revenue, since these are all measures that are related to the cartel success rate. Thus, we test one-sided hypotheses that High1 and High2 lead to lower cartel formation rates, higher exposure rates, lower industry profit, and greater fine revenue than No-Len. High1 exhibits the same differences relative to Low1 and High2 the same relationships with Low2. All other p-values are based on two-sided tests. In all tests, each group's activity over the 10 periods they played is taken as one observation, so that we have ten observations under each treatment. For example, in testing whether the cartel formation rate differs between two treatments, we have ten observations in each treatment, where each observation is the percentage of periods in which a group has formed a cartel in the ten periods that the group interacted.



(a) All cartels (b) Full cartels

Figure 2.1: Cartel formation rate over the 10 periods, each treatment

form, divided by the total number of periods. Full cartel formation rates are highest under No-len (49%), followed by Low2 (45%), and then in turn by Low1 (33%), High1 (32%), and High2 (27%). Figure 2.1 (b) shows some tendency for the incidence of full cartels to decrease in the later periods of a session. MW tests, conducted between pairs of treatments, do not show any significant differences between treatments in the percentage of instances that a full cartel forms. Thus, none of our leniency policies has an effect on the incidence of cartel formation relative to a regime of No-leniency.

2.5.2 The effect of leniency programs on cartel exposure and cartel success

We have seen that the leniency policies do not significantly affect the likelihood that a cartel forms. We now consider whether the leniency policies expose more of the cartels that do form. Table 2.4 presents the data on the *Cartel Exposure Rate*. A cartel is exposed when it is either detected by an antitrust regulator or it is revealed by a whistle-blowing action on the part of a cartel member. The cartel exposure rate is defined as the number of cartels exposed divided by the total number of cartel

	No-len	High1	High2	Low1	Low2
Exposed cartels	10	53	44	49	41
by whistleblowing	-	44	36	42	33
by investigation (15% chance)	10	9	8	7	8
Cartels formed	85	83	84	81	95
Cartel exposure rate*	12%	64%	52%	60%	43%

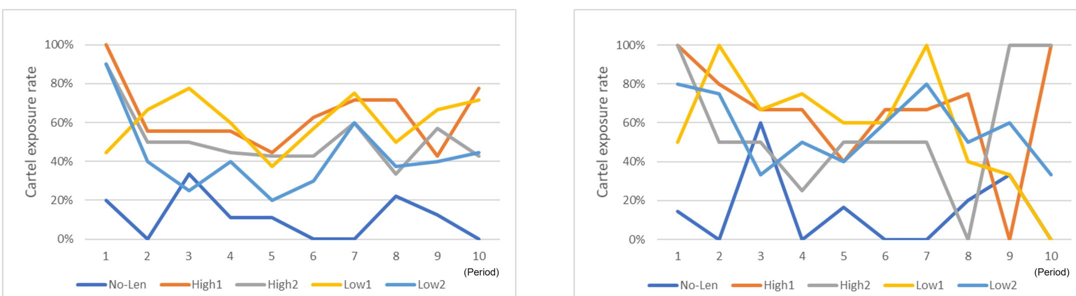
(a) All cartels

	No-len	High1	High2	Low1	Low2
Exposed Full cartels	7	29	16	21	26
by whistleblowing	-	22	13	19	20
by investigation (15% chance)	7	7	3	2	6
Full cartels formed	49	32	27	33	45
Full cartel exposure rate**	14%	91%	59%	64%	58%

(b) Full cartels

*Cartel exposure rate = Exposed cartels / Cartels formed
**Full Cartel exposure rate = Exposed Full cartels / Full cartels formed

Table 2.4: Cartel exposure rate



(a) All cartels (b) Full cartels

Figure 2.2: Cartel exposure rate over the 10 periods, each treatment

that are formed.

Panel (a) in the table shows that each of the four leniency treatments has a much higher cartel exposure rate than that under No-len. The cartel exposure rate is greatest under High1 (64%), followed by Low1 (60%), High2 (52%), Low2 (43%) and

	No-len	High1	High2	Low1	Low2
Cartels formed	85	83	84	81	95
Exposed cartels	10	53	44	49	41
Unexposed cartels	75	30	40	32	54
Cartel success rate*	75%	30%	40%	32%	54%

(a) All cartels

	No-len	High1	High2	Low1	Low2
Full cartels formed	49	32	27	33	45
Exposed Full cartels	7	29	16	21	26
Unexposed Full cartels	42	3	11	12	19
Full Cartel success rate**	42%	3%	11%	12%	19%

(b) Full cartels

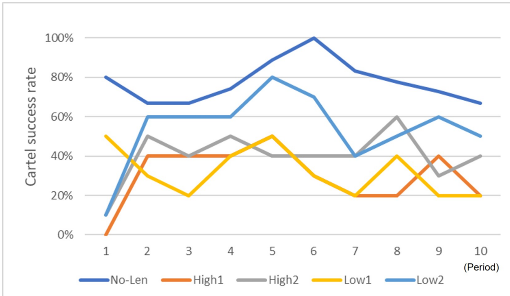
*Cartel success rate = Number of unexposed cartels divided by 100 (= 10 periods × 10 groups per treatment)
**Full cartel success rate = Number of unexposed full cartels divided by 100

Table 2.5: Cartel success rate, by treatment

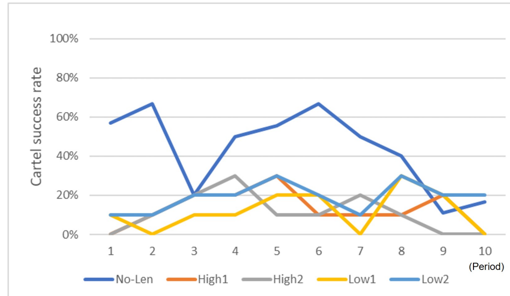
finally No-len (12%). MW test results, taking each group as the unit of observation, indicate that each of the four leniency programs reveals significantly more cartels than No-len (No-len vs. High1, $p = .001$; No-len vs. High2, $p = .001$; No-len vs. Low1, $p < .001$; and No-len vs. Low2, $p = .007$). However, there are no statistically significant MW test results between any pair among the four leniency treatments.[7]

Table 2.4(b) and Figure 2.2(b) include the data for full cartels only. All leniency treatments expose many more full cartels than No-len, Full cartels are exposed at the highest rate under High1 (91%), followed by Low1 (64%), High2 (59%), and Low2 (58%). Under No-len, only 14% of full cartels are exposed.

[7]For this test, the cartel exposure rate is calculated as the (number of cartels a group makes that are exposed)/(the number of cartels a group forms). Thus, for groups that do not form cartels, the variable is not defined and groups for which this is the case are not included the test. This particularly affects the comparisons of the exposure rate of full cartels, which form relatively infrequently.



(a) All cartels



(b) Full cartels

Figure 2.3: Cartel success rate over the ten periods, all treatments

MW test results show that High1 and Low2 break more full cartels than No-len (No-len vs. High1, $p = .003$; No-len vs. Low2, $p = .032$), but other treatments are not statistically different from No-len (No-len vs. There are no statistically significant differences among the remaining treatment pairs. Thus, some leniency policies expose more cartels than No-leniency, with High1 the most effective among the policies.

A more complete measure of the performance of a cartel mitigation policy is the *Cartel Success Rate*. This is calculated as the probability that both a cartel forms and is not exposed. In such a situation, the cartel can be said to be successful since it was able to avoid detection. The rate of cartel success is thus a variable that a regulator seeks to minimize since it is a measure of undetected cartels. Table 2.5 and Figure 2.3 show the rate of cartel success in the different treatments, for all cartels as well as for full cartels only. The hypothesis presented in Section 2.4 were formulated in terms of this variable.

The data in the table show that the cartel success rate is higher under No-len (75%) than under any of the leniency policies. The lowest success rate occurs under

High1 (30%), followed by Low1 (32%), High2 (40%) and Low2 (54%). As can be seen in Table B.3 of Appendix B.1, Hypothesis 3 is supported in that the differences between No-len and the two High fine conditions are significant (No-len vs. High1 $p = .001$, No-len vs High2 $p = .004$). It is also the case that there are significantly fewer successful cartels under Low1 than in No-len. Low2 is not as effective in reducing cartel success as Low1 ($p = .036$).

High1 and High2 also lead to significantly fewer successful full cartels than No-len. This supports Hypothesis 3. There are no significant differences among the leniency policies in the full cartel success rate. All four policies yield a full cartel success rate of between 3% and 19%, compared to 42% without leniency.

2.5.3 Profits and fines

We now consider the overall payoffs to firms. These are increased by the successful formation of full cartels, reduced by the fines that are paid when the cartel is exposed, and increased by leniency awarded to reporters. The average profits, fines paid, and resulting payoffs to the industry, summed over the 10-periods played, by treatment, are shown in Table 2.6. In the table, the industry's payoff is defined as its profit minus the fines it pays. These payoffs to firms differ considerably among treatments. The highest industry payoffs are obtained in Low2, with No-len second highest. These treatments are followed by High1, Low1, and High2.

MW tests show that there are no significant pairwise differences in industry profit among No-len, Low1, and Low2. (No-len vs. Low1, $p = .131$; No-len vs. Low2 $p = .880$). However, High1 and High2 do lead to significantly lower firm payoffs than

	No-len	High1	High2	Low1	Low2
Industry Profit	3,524	3,488	3,365	3,373	3,599
Fines	136	533	346	219	200
Industry Payoff (= Profit − Fine)	3,388	2,956	3,019	3,154	3,392

Table 2.6: Average industry profits, fine, and payoff, each treatment

No-len. (No-len vs. High1. $p = .010$; No-len vs. High2, $p = .021$). Low2 leads to greater industry payoffs than High1 ($p = .008$) or High2 ($p = .004$). Firms earn greater profit under Low1 than High1 ($p = .048$) Thus, a leniency policy lowers firms' payoffs relative to a No-leniency regime when the fine is sufficiently high. High fines reduce industry profit. Granting leniency for two whistle-blowers raises industry profit when the fine level is low.

Table 2.6 also indicates the average take from fines over the ten periods in each treatment. The fine revenue is greatest in High1 (533), followed by High2 (346), Low1 (219), Low2 (200) and finally by No-len (136). As can be seen in Table B.4 in Appendix B.1, MW tests reject the hypothesis that fines are the same under No-len and High1 ($p = .001$), as well as between No-len and High2 ($p = .012$). Thus, both High1 and High2 lead to greater fines than No-len, indicating that despite the forgiveness of fines through leniency, the revenue to the authority is greater under leniency. Whether leniency is granted to one or two whistle blowers has no impact on fine revenue. Revenue under High1 is not statistically different than under High2 ($p = .112$). Low1 and Low2 also do not generate different revenue from each other ($p = .762$). Both High conditions generate greater fines than Low2 at $p < .05$, and High1 leads to more revenue than Low1 ($p = .008$).

2.6 Discussion

In this paper, we compare different cartel whistle-blower leniency programs. We vary the size of the fine for being caught participating in a cartel and whether one or two whistle-blowers receive leniency from penalties. We advanced three hypotheses: (i) that leniency would reduce the likelihood that firms would successfully collude, (ii) that it would make no difference whether leniency was offered to one or to two whistle-blowers, and (iii) that the larger the fine size, the fewer cartels that would be successful. The first hypothesis was strongly supported and the other two received qualified support.

In our experiment, we observe that: (1) Leniency policies do not reduce cartel formation. (2) However, they tend to expose more cartels, and thus do reduce the probability that firms successfully collude. (3) Higher fines reduce firm profits and increase the fine take to the state. (4) There is no consistent difference between the effects of awarding leniency to one or to two whistle-blowers.

Our results show that cartel formation rates are not significantly affected by leniency policies. However, leniency policies do increase cartel exposure rates through whistle-blowing. The cartel success rate, an overall measure of effectiveness in reducing cartels, refers to the likelihood that a cartel is both formed and unexposed. This is a measure that is unobservable in the field, but straightforward to measure in laboratory experiments. In the experiment, the data from High1 and High2 show that both leniency policies reduce full cartel success rates, lower firms' payoffs and increase the state's fine revenue. Hypothesis 1 is supported in the data.

Why does a leniency policy not reduce the incidence of cartels? There appear to be offsetting effects of leniency on the rate of cartel formation. Leniency reduces the incentive to form a cartel, since others may report on the collusive agreement, lowering a potential cartel member's payoffs compared to under a policy of no leniency. However, it makes a strategy of joining a cartel and subsequently blowing the whistle more attractive as well. It appears that in our data, these effects offset, and the result is that a leniency policy does not, on balance, deter attempts to form cartels. Rather than deterring cartels, a leniency policy merely causes more cartels to be exposed, and that is why they are effective in reducing cartel success.

The cartel success rates, which depend directly on how much whistle blowing occurs, are not different when leniency is granted to one or to two whistle blowers when penalties are high. While cartels enjoy a higher rate of success with two whistle-blowers when fines are low, there is no difference for the full cartels, which are the ones that are profitable. Hypothesis 2 is therefore mostly supported. It appears that a marginal incentive of a 50% reduction in the second whistle blower's fine is not a strong enough incentive to alter collusive behavior. It is rather small difference in the overall incentive to report on the cartel since it only applies if a firm one is the second whistle-blower, an event which is not very likely, and the fine reduction is only partial.

Hypothesis 3, which stated that higher fines would reduce the cartel success rate compared to lower fines, was not supported at conventional levels of statistical significance. Higher fines do reduce the incidence of successful full cartels, from 12% under a low fine to 3% under a high fine, when there is leniency for one whistle blower. If there is leniency for two whistle blowers going from a Low to a High fine reduces the cartel success rate from 19% to 11%. Similar relationships are observed for cartels overall. The effect of higher fines goes in the hypothesized direction, but does not rise to the level of statistical significance.

Our results suggest that two features of the leniency policy of South Korea, (i) its relatively low fines and (ii) leniency for two whistle-blowers rather than one, when applied together, serve to preserve industry profits and reduce fine revenue. The system may also may be ineffective in reducing the number of unexposed profitable cartels from the level that would exist under a No-Leniency policy. The Low2 treatment is the only one that does not improve upon the cartel success rate from the level in No-len. In December 2021, South Korea doubled its fine level for cartels from 10% of revenue to 20%. Our results suggest that this decision will have a positive impact on the state budget and reduce industry profit.

Chapter 3

Experiments on portfolio selection: A comparison between quantile preferences and expected utility decision models

This paper conducts a laboratory experiment to assess the optimal portfolio allocation under quantile preferences (QP) and compares the model predictions with those of a mean-variance (MV) utility function. We estimate the risk aversion coefficients associated to the individuals' empirical portfolio choices under the QP and MV theories, and evaluate the relative predictive performance of each theory. The experiment assesses individuals' preferences through a portfolio choice experiment constructed from two assets that may include a risk-free asset. The results of the experiment confirm the suitability of both theories to predict individuals' optimal choices. Furthermore, the aggregation of results by individual choices offers support to the MV theory. However, the aggregation of results by task, which is more informative, provides more support to the QP theory. The overall message that emerges from this experiment is that individuals' behavior is better predicted by the MV model when it is difficult to assess the differences in the lotteries' payoff distributions but better described as QP maximizers, otherwise.

3.1 Introduction

Portfolio selection is a fundamental topic in economics and finance and one of the leading applications of decision theory under uncertainty. Modern portfolio theory derives its main results on diversification and risk under the important paradigm of the expected utility (EU) theory; see, for instance, Cochrane (2005a) and Campbell (2017). Nevertheless, the EU framework has been subjected to a number of criticisms, mostly arising from experimental evidence.[1] Investors may also exhibit a preference for positive skewness of returns that is not captured by EU. In response to these and other critiques, the EU model has been successfully generalized to accommodate a variety of behavioral phenomena. Two of the more well-known generalizations are the inclusion of regret (Bell, 1982a) and ambiguity in beliefs about probabilities (Gilboa and Schmeidler, 1989). Garlappi et al. (2007) develop a portfolio selection model for an investor with multiple priors and aversion to ambiguity.

Recently, de Castro et al. (2021a) studied the portfolio selection problem in a model with individuals exhibiting quantile preferences (QP). This alternative specification of individuals' preferences has been characterized in early work by Manski (1988), who studied properties of a quantile model for individual's behavior. More recently, QP have been formally axiomatized by Chambers (2009a), Rostek (2010), and de Castro and Galvao (2020). Mendelson (1987a) introduced the concept of quantile-preserving spread, which is a notion of risk aversion for the quantile

[1]Rabin (2000) criticized EU theory arguing that EU would require unreasonably large levels of risk aversion to explain the data from some small-stakes laboratory experiments. See also Simon (1979), Tversky and Kahneman (1981), Payne et al. (1992) and Baltussen and Post (2011) as examples providing experimental evidence on the failure of the EU paradigm. Some studies suggesting that individuals do not always employ objective probabilities resulted in, among others, Prospect Theory (Kahneman and Tversky, 1979), Rank-Dependent Expected Utility Theory (Quiggin, 1982), and Cumulative Prospect Theory (Tversky and Kahneman, 1992).

model that establishes a parallelism with mean-preserving spreads in the standard EU framework. Giovannetti (2013a) modeled a two-period economy with one risky and one risk-free asset, where the agent has QP. de Castro and Galvao (2019a) developed a dynamic model of rational behavior under uncertainty, in which the agent maximizes a stream of the future quantile utilities. de Castro et al. (2021b) is one of the few studies that employ an experimental study in which individuals make pairwise choices between risky lotteries to assess the importance of QP and find evidence of behavior compatible with the presence of QP for a share of the population between 30 and 50%.

There exists a literature on optimal portfolio allocation using laboratory experiments. Bossaerts et al. (2007) and Gubaydullina and Spiwoks (2009) study portfolio choices allowing for individuals' heterogeneity with EU. Charness and Gneezy (2010) and Baltussen and Post (2011) investigate diversification in portfolio choice decisions through an experiment. Ahn et al. (2014) show through experiments how individuals have heterogeneity and different risk aversion attitudes but also have pessimism or optimism when selecting a portfolio using EU. Most of the experimental evidence on portfolio allocation has considered the conventional EU framework as the baseline model. Within this framework, studies such as Andreoni and Sprenger (2012), Brandtner (2013) and Gardner (2019), used the mean-variance (MV) utility function for analyzing individuals' rationality. However, we are not aware of experimental studies on optimal portfolio allocation focusing specifically on the role of QP and comparing its predictive ability against other competing behavioral models such as the EU framework.

In this paper we depart from the EU framework and investigate through an experimental exercise the optimal portfolio allocation of individuals endowed with QP. We build on the theoretical results on optimal portfolio allocation under QP derived in de Castro et al. (2021a). These authors explore general conditions under which diversification is optimal, and also provide results for specific families of distribution functions such as the Normal, the Uniform and Chi-square distributions. In contrast to the EU framework, the portfolio allocation with QP is usually characterized by two differentiated regimes. The risk aversion regime given by values of τ smaller than a threshold τ_0 entails diversification between the lotteries comprising the portfolio. On the other hand, the optimal allocation for large values of τ is usually characterized by a corner solution that entails full allocation into one of the assets in the portfolio, usually the asset with highest risk and payoff. This unique feature of the portfolio allocation problem under QP can be used to motivate the presence of under-diversification found in many portfolio choice problems, see Mitton and Vorkink (2007) and references therein.

A second feature of the portfolio selection problem under QP that differs from the standard EU framework is the optimal allocation under the presence of a risk-free asset. Whereas the mutual fund separation theorem of Tobin (1958) obtained under a MV utility function and, more generally the EU framework, predicts a convex combination of the risk-free and the risky asset, the optimal allocation under QP predicts full allocation to the risk-free asset for high levels of risk aversion and full allocation to the risky asset for low levels of risk aversion. This theoretical result confirms the lack of diversification predicted by the QP model.

The main objective of the current study is to assess through a laboratory experiment the portfolio selection insights from the viewpoint of the QP model relative to the MV. In particular, we study the similarities and differences between the optimal portfolio choices of MV and QP individuals. We consider the MV utility function, but comparisons developed in this paper could be extended to other utility functions within the EU framework and beyond, as for example, the prospect theory. Nevertheless, for simplicity and ease of tractability we restrict to the MV utility function that summarizes individuals' utility as a linear function of mean and variance. To compare the optimal portfolio choices across theories, we estimate risk aversion coefficients associated with the individuals' empirical portfolio choices under the QP and MV theories using minimum distance estimators. We employ these methods to construct statistics for model classification, and also adapt the Diebold and Mariano (2002) test – originally introduced for evaluating predictive accuracy – to our setting for statistically comparing the suitability of the QP and MV models.[2]

Our experiment simulates a simple portfolio decision exercise and is formed of 90 tasks. These tasks were answered by 71 subjects. Each task has two assets, either two risky assets or one risk-free and one risky asset, that comprise an investment portfolio. The experiment requires individuals to assign weights $w_1, w_2 \in [0, 1]$ to these assets, with $w_1 + w_2 = 1$, to optimize their investment strategy. This strategy is not reported by participants as part of the experiment. The investment strategy may imply maximizing the expected value of their utility function, the expected portfolio payoff or some other moment of its distribution. One of the objectives of the experimental study is to infer which theory (i.e. QP vs. MV) predicts better individuals' responses. Subjects for the experiment were recruited from undergrads and graduates belonging to the Experiment Science Laboratory (ESL) at the University

[2]In contrast to the original work of Diebold and Mariano (2002), we use the test as a model selection mechanism rather than as a test of predictive accuracy.

of Arizona. Due to ongoing Covid-19 pandemic, the experiments were implemented online using Qualtrics over the period December 2020 to February 2021. The actual payment to participants is the sum of the payoff of one of the 90 tasks plus a show-up fee, $5, for participating in the experiment. The choice of the actual task for payment is done randomly as in similar experiments, see Gubaydullina and Spiwoks (2009), Ahn et al. (2014), and Gardner (2019).

Another important aspect of the experimental exercise is the choice of the distribution function for the risky assets. Previous experiments have relied on binary lotteries characterized by Bernoulli distributions to model the distribution of the payoffs, see Andreoni and Sprenger (2012) and Brandtner (2013). Ahn et al. (2014) is one of the few experimental papers that go beyond the Bernoulli distribution to characterize the payoffs. In this paper, we explore the Uniform distribution function for several reasons. First, it is very intuitive and easy to understand by individuals not familiar with advanced probability theory concepts. Second, it is analytically tractable. In particular, we derive the optimal allocation to each asset under both QP and MV theories under the assumption that both lotteries follow independent Uniform distributions. Third, we avoid the presence of unbounded tails that yield infinite payoffs with some strictly positive probability. Fourth, we can easily consider the whole spectrum of combinations between pairs of lotteries. These combinations reflect first and second order stochastic dominance as particular examples but can also accommodate distributions with overlapping payoffs and no stochastic dominance order.

The data gathered by this experiment are individuals' portfolio weights under a variety of portfolio combinations within the family of Uniform distributions. These data allow us to identify and estimate the QP and MV parameters for each individual and also to implement the Diebold and Mariano (2002) test as a model selection mechanism. The first important finding of our experimental study is the suitability of both theories to predict individuals' choices. There are differences across individuals and tasks but, in general, both models accurately predict the optimal responses of individuals to the tasks. We obtain two different conclusions depending on whether we aggregate the results by individual or by task. The aggregation of results by individual offers support to the MV theory suggesting that the overall behavior of the individuals participating in the experiment is more aligned with the MV than with the QP portfolio theory. The aggregation of results by task provides richer information on the behavior of individuals when confronted with specific portfolio problems. The evaluation of the results by task shows, in general, more support to the QP theory than the MV theory although the results depend on the specific task under study.

The main message that emerges from this experimental study is that individuals' behavior is better predicted by the MV model when it is difficult to assess the differences in the lotteries' payoff distributions. Diversification may act as a decision mechanism that individuals use when it is not clear how to assess the relative gains/losses of one strategy over the other as, for example, when the lotteries' payoff distributions overlap. In these cases, MV preferences seem a safer choice as the optimal outcome of these policies usually yield to diversification. In contrast, when individuals are able to clearly assess the differences in the lotteries' payoff distributions their portfolio choices are closer to the optimal decision of a QP maximizer than of a MV maximizer. Individuals are able to maximize over the distribution of the portfolio rather than trading expected return for variance.

The empirical results show evidence that, for pairs of lotteries with very different supports and entailing a first order stochastic dominance relationship between them, individuals' portfolio choices are closer to the predictions of the QP model (full allocation to the dominant lottery) than the MV model. In contrast, when the supports of the lotteries are similar but the stochastic dominance relationship still holds, individuals' choices are closer to the MV strategy, that usually corresponds to a diversified portfolio. Illustrative examples of this scenario are $A : U(0, 2)$ vs. $B : U(0, 20)$ and $A : U(2, 20)$ vs. $B : U(0, 20)$ for the former case, with U denoting the Uniform distribution, and $A : U(0, 16)$ vs. $B : U(0, 20)$ and $A : U(12, 20)$ vs. $B : U(0, 20)$ for the latter case. These tasks exercises reveal that individuals' choices cannot be fully rationalized by a single theory. Instead, QP predictions are better suited to explain individuals' decisions when the differences in support suggest a clear stochastic dominance relationship between lotteries. In contrast, as these *distributional* differences vanish, individuals smoothly change their objective function and trade expected return for variance despite the fact the stochastic dominance relationship between the lotteries still holds.

We also consider portfolios of lotteries with overlapping supports, such as $A : U(2, 22)$ vs. $B : U(0, 20)$ and $A : U(18, 38)$ vs. $B : U(0, 20)$. Lottery A stochastically dominates lottery B in first order in both cases, which corresponds to the optimal portfolio decision under QP and moderate levels of risk aversion. The MV theory predicts more diversification than what we observe in the realized individuals' choices. The distribution of the empirical weights seems more in line with the optimal portfolio allocation obtained under the QP theory. On the other hand, whereas the QP theory predicts full allocation to lottery A the empirical weights show some non-negligible allocation to lottery B too. This phenomenon is more apparent as the supports of the Uniform distributions corresponding to each lottery are more separated, as in the second example above.

The last set of experiments considers combinations of a risk-free and a risky asset. In this case both theories predict full allocation to the risk-free asset for high levels of risk aversion, however, as the payoff of the risk-free asset and the degree of risk aversion decrease, the MV theory predicts full diversification whereas the QP theory predicts a complete shift to the risky asset (full under-diversification). These differences are reflected in individuals' responses across tasks in this category. For example, for $A : 2$ vs. $B : U[0, 20]$, we find that most individuals allocate some weight to the risk-free asset in the range $(0, 0.25)$, which is more in line with the QP theory than with the MV theory. However, as the payoff of the risk-free asset increases, the predictions of the QP model imply full allocation to the risk-free asset, which may be too drastic from an investor's point of view. In these cases, we do observe a positive shift of the empirical distribution of weights towards the risk-free asset but this increase is smoother than under the QP theory. MV predictions are better able to explain individuals' choices than QP predictions.

Given these empirical results, the overall message that emerges from this analysis is that individuals' behavior is better predicted by the MV model when it is difficult to assess the differences in the payoff distribution of the lotteries comprising the portfolio. Individuals behave as QP maximizers, otherwise. This result suggests that diversification may act sometimes as a decision mechanism that individuals use when it is not clear how to assess the relative gains/losses of one strategy over the other as, for example, when the lotteries' payoff distributions overlap. In these cases, MV preferences seem a safer choice as the optimal outcome of these policies usually yield to diversification. This outcome involves fewer exposures to single assets than the QP theory even if the latter might lead to superior monetary rewards. In contrast, when individuals are able to clearly assess the differences in the distribution of payoffs between lotteries their portfolio choices are closer to the optimal decision of a QP maximizer than of a MV maximizer. In these (simpler) cases, individuals are able to maximize over the distribution of the portfolio rather than trading expected return for variance.

The remainder of the paper is laid out as follows. Section 3.2 illustrates the portfolio selection problem under QP and shows how individuals can optimize portfolio allocations under this theory. Section 3.3 sets up our experiment design to obtain individuals' portfolio allocations. Section 3.4 develops the econometric methodology necessary to estimate the risk aversion coefficients and test the underlying theories explaining individuals' behavior. Section 3.5 discusses the empirical results of the experiment and explains the results of the tests across individuals and tasks. Section 3.6 concludes. A separate Online Appendix presents the instructions of the experiment, detailed summary statistics of the experiments, and the payoffs of all the portfolio combinations under QP and MV.

3.2 Optimal portfolio choice problem

This section studies theoretically the optimal portfolio allocation problem for individuals with quantile preferences under different assumptions on the distribution of the assets' payoffs. We start by formally describing the portfolio selection problem under QP. Let

$$S_w = \sum_{i=1}^{n} w_i r_i,$$

be an investment portfolio comprised by n assets with payoffs (returns) given by r_i. The fraction of wealth allocated to each asset in the portfolio is denoted by $w \equiv (w_1, ..., w_n)$, with $\sum_{i=1}^{n} w_i = 1$. For illustration purposes, we consider portfolios that do not allow short-selling, that is, we further assume $w \in [0,1]^n$, but the model can be extended to relax this restriction.

To be consistent with the literature on optimal portfolio theory under EU preferences, we assume that individuals are endowed with a utility function $u(S_w)$, where $u : \mathbb{R} \to \mathbb{R}$, for describing individual's preferences on wealth. Then, for a given risk attitude $\tau \in (0,1)$, the portfolio choice problem under QP is

$$\max_{w\in[0,1]^n} \mathrm{Q}_\tau \left[u\left(S_w\right)\right], \text{ s.t. } \sum_{i=1}^{n} w_i = 1. \tag{3.1}$$

A well-known and important property of quantiles is its invariance with respect to monotonic transformations. More formally, if $u : \mathbb{R} \to \mathbb{R}$ is continuous and strictly increasing, then

$$\mathrm{Q}_\tau[u(S_w)] = u\left(\mathrm{Q}_\tau[S_w]\right). \tag{3.2}$$

It is also important to notice that quantile preferences are in fact independent of the utility function. Indeed, for any continuous and strictly increasing $u : \mathbb{R} \to \mathbb{R}$, from (3.2),

$$X \succeq Y \iff \mathrm{Q}_\tau[u(X)] \geq \mathrm{Q}_\tau[u(Y)] \iff \mathrm{Q}_\tau[X] \geq \mathrm{Q}_\tau[Y]. \tag{3.3}$$

with $\succeq$ denoting a τ-quantile preference. This result shows that the utility function plays absolutely no role in defining the preference. We can use (3.2) to make any transformation of u; therefore, we could transform a concave utility function into a convex one without changing the preference. Hence the quantile optimization problem (3.1) using a given utility is equivalent to maximizing the quantile obtained directly from the distribution of the random variable such that the problem of interest becomes

$$\max_{w\in[0,1]^n} \mathrm{Q}_\tau\left[S_w\right], \text{ s.t. } \sum_{i=1}^{n} w_i = 1. \tag{3.4}$$

Our aim is to uncover the optimal portfolio choices under QP and assess the similarities and differences with those under the MV paradigm. To illustrate these differences, and for simplicity, in what follows, we restrict the analysis to a portfolio of two assets. First, we consider the case of two risky assets and, second, we study the optimal allocation between a risk-free and a risky asset. Let the portfolio be defined as

$$S_w \equiv wX + (1-w)Y, \tag{3.5}$$

with X and Y continuous random variables, and $0 \leq w \leq 1$ the portfolio weight. First, we present the optimal allocation between X and Y for the case of two Uniform random variables.

3.2.1 S_w is a mixture of two Uniform random variables

The case of two Uniform distribution functions is analytically more cumbersome than the choice of lotteries with discrete payoff distributions or following a Normal distribution. However, this choice may be more intuitive for describing the probability law of the payoffs of each random variable for someone without knowledge on financial markets. Second, it is analytically tractable. In particular, we present the optimal allocation to each asset under both QP and MV theories under the assumption that both lotteries follow independent Uniform distributions. Third, we consider lotteries defined by continuous random variables. In this way, we extend most of the literature on portfolio choice experiments that considers lotteries with binary payoffs. Fourth, we avoid the presence of unbounded tails that yield infinite payoffs with strictly positive probability. Finally, we can easily entertain a large spectrum of investment scenarios by considering different combinations of pairs of Uniform random variables.

For each lottery the experimenter induces a monetary payoff associated with the probability of the outcome. Hence, for each quantile τ, we can calculate the optimal theoretical portfolio allocation as

$$w^*(\tau) = \underset{w \in [0,1]}{\arg\max}\ Q_\tau\left(S_w\right).$$

Consider now the MV case. The optimization problem also has a single preference parameter $\gamma \in \Gamma \subset \mathbb{R}_+$. Then,

$$w^\dagger(\gamma) = \underset{w \in [0,1]}{\arg\max}\, \mathcal{U}_\gamma(S_w) = \underset{w \in [0,1]}{\arg\max}\ \left(E\left(S_w\right) - \frac{\gamma}{2} Var\left(S_w\right)\right),$$

where $\mathcal{U}_\gamma$ is the mean-variance representation with parameter γ.[3] The optimal portfolio allocation for $X : U[a,b]$ and $Y : U[c,d]$ two independent random lotteries with Uniform distributions is given by

$$w^\dagger(\gamma) = \begin{cases} \widetilde{w}(\gamma) & \text{when } 0 < \widetilde{w}(\gamma) < 1, \\ 0 & \text{when } \widetilde{w}(\gamma) \leq 0, \\ 1 & \text{when } \widetilde{w}(\gamma) \geq 1. \end{cases} \tag{3.6}$$

[3] For a CARA utility function, and normally distributed assets, MV is a special case of expected utility preference. See, for example, Sargent (1987, p.154-155).

where

$$\widetilde{w}(\gamma) = \frac{6[(a+b)-(c+d)] + \gamma(d-c)^2}{\gamma[(b-a)^2 + (d-c)^2]}.$$

The following paragraphs illustrate these theoretical results on optimal portfolio allocation for Uniform distributions with different examples. Thus the case of two standard uniform distributions, $X : U(0,1)$ and $Y : U(0,1)$, is reported in Example 3.2.1.[4]

Example 3.2.1. *Consider* $X : U(0,1)$ *and* $Y : U(0,1)$*, independent. The optimal allocation to* X *under QP is*

$$w^*(\tau) = \begin{cases} 0.5, & \textit{if } \tau \in \left(0, \frac{1}{2}\right] \\ 1, & \textit{if } \tau \in \left(\frac{1}{2}, 1\right). \end{cases}$$

In contrast, the optimal portfolio allocation to X *under MV is* $w^\dagger$ *in* (3.6) *with* $\widetilde{w}(\gamma) = 0.5$*, for all* $\gamma \in \Gamma$.

Example 3.2.2. *Consider* $X : U(0,2)$ *and* $Y : U(0,1)$ *independent. The optimal allocation to* X *under QP is*

$$w^*(\tau) = \begin{cases} 0.5, & \textit{if } \tau \in (0, 0.25] \\ 1, & \textit{if } \tau \in (0.25, 1). \end{cases}$$

In contrast, the optimal portfolio allocation to X *under MV is* $w^\dagger$ *in* (3.6) *with* $\widetilde{w}(\gamma) = \frac{6+\gamma}{5\gamma}$*, for all* $\gamma \in \Gamma$.

In this case, even though $U(0,2)$ stochastically dominates $U(0,1)$, the optimal portfolio weight w is interior, $w^* = 0.5$, implying that diversification under quantile

[4]The numerical methods to solve Examples 3.2.1–3.2.5 are described in de Castro et al. (2021a).

preferences is optimal for $\tau \leqslant 1/4$. This is an interesting result, because despite the fact that X first order stochastically dominates Y, there exists a convex combination S_w that dominates both random variables X and Y for low quantiles. Notice, however, that this feature is desirable, because the independence of X and Y makes a convex combination of the two less risky than any of them. For the MV case, the optimal portfolio allocation is a function of γ such that for large levels of risk aversion ($\gamma \to \infty$), the optimal allocation to X is 0.2.

Another interesting scenario is the absence of diversification with different lower ends of the distributions of X and Y. For the QP case, de Castro et al. (2021a) show that the optimal choice is $w^* = 1$ for all τ, provided that the difference between the two distributions at the left end point is sufficiently large. Example 3.2.3 illustrates this result for the pair $X : U(0.5, 1)$ and $Y : U(0, 1)$.

Example 3.2.3. *Consider* $X : U(0.5, 1)$ *and* $Y : U(0, 1)$ *independent. Then, the optimal allocation to* X *under QP is* $w^* = 1$ *for all* $\tau \in (0, 1)$*. In contrast, the optimal portfolio allocation to* X *under MV is* $w^\dagger$ *in* (3.6) *with* $\widetilde{w}(\gamma) = \frac{3+\gamma}{1.25\gamma}$*, for all* $\gamma \in \Gamma$*.*

The optimal portfolio allocation under the MV case is similar to the QP case. Thus, for large levels of risk aversion ($\gamma \to \infty$), we obtain $\widetilde{w}(\gamma) = 0.8$. Similarly, for low levels of risk aversion ($\gamma \to 0$), the MV theory predicts $\widetilde{w}(\gamma) = 1$.

Nevertheless, the behavior with different lower end points can be complex under the QP theory. For instance, it may be the case that the optimal choice is $w^* \in \{0, 1\}$ for small τ, it becomes interior for intermediate values of τ and then becomes $w^* \in \{0, 1\}$ again for large τ's. The following example illustrates this scenario further.

Example 3.2.4. *Consider $X : U(0.25, 1.25)$ and $Y : U(0, 1)$ independent. The optimal allocation to X under QP is $w^* \in (0, 1)$ for $\tau \in (0, 0.25)$ and $w^* = 1$ for $\tau > 0.25$. In contrast, the optimal portfolio allocation under MV is $w^\dagger$ in (3.6) with $\widetilde{w}(\gamma) = \frac{3+\gamma}{2\gamma}$, for all $\gamma \in \Gamma$.*

The last example considers the remaining possible combination between X and Y. In this case, the support of the random variable X is inside the support of Y. Whereas the previous examples represent lotteries exhibiting first order stochastic dominance, the latter example does not.

Example 3.2.5. *Consider $X : U(0.25, 0.75)$ and $Y : U(0, 1)$ independent. The optimal allocation to X under QP is $w^* \in (0, 1)$ for $\tau \in \left(0, \frac{1}{2}\right)$ and $w^* = 0$ for $\tau \in \left(\frac{1}{2}, 1\right)$. In contrast, the optimal portfolio allocation under MV is $w^\dagger$ in (3.6) with $\widetilde{w}(\gamma) = 0.8$, for all $\gamma \in \Gamma$.*

Figure 3.1 plots $w^*(\tau)$ under the QP paradigm for different examples.

3.2.2 Optimal portfolio allocation when there is a risk-free asset

Manski (1988) derives the preferences of a quantile maximizer between two outcomes X and Y when one of the outcome measures is degenerate, and finds a complete separation in preferences between the degenerate and risky outcome. The deterministic

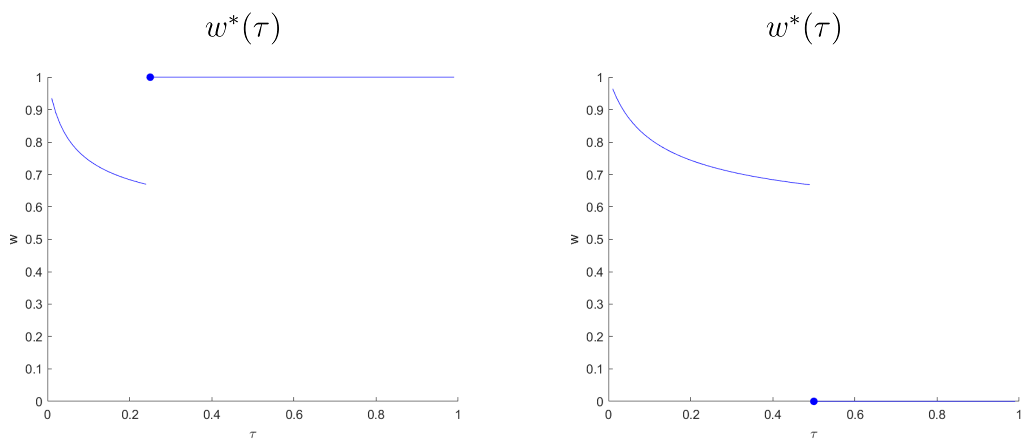


Figure 3.1: Illustration of Example 3.2.4 (left panel) and Example 3.2.5 (right panel).

choice is the preferred strategy for low quantiles. In contrast, for high quantiles, the risky outcome is the preferred strategy.

In this section, we provide further formality to the example in Manski (1988) and frame it in an optimal asset allocation context. We assume there is a riskless security that pays a rate of return equal to $R_f = \bar{r}$, and just one risky security that pays a stochastic rate of return equal to R with distribution function F_R. The portfolio return is defined by the convex combination

$$R_p = w\bar{r} + (1-w)R = \bar{r} + (1-w)(R-\bar{r}),$$

and the investor's maximization problem (3.4) for τ is $\arg\max_w \mathrm{Q}_\tau[u(\bar{r}+(1-w)(R-\bar{r}))]$. Using the monotonicity of the quantile process, for a continuous and increasing utility function, the investor's problem simplifies to

$$\arg\max_w (1-w)\mathrm{Q}_\tau[R] + w\bar{r}.$$

Simple algebra shows that the individual portfolio choice w is then given by the following:

$$w^* = \begin{cases} 1 & \text{when } \mathrm{Q}_\tau[R] < \bar{r} \\ 0 & \text{when } \mathrm{Q}_\tau[R] > \bar{r} \\ \text{any } w \in [0,1] & \text{when } \mathrm{Q}_\tau[R] = \bar{r}. \end{cases}$$

The intuition of this solution is simple. For small values of τ the individual's optimal portfolio choice is $w^* = 1$ and corresponds to full investment on the risk-free asset. This is so because $\bar{r} > \mathrm{Q}_\tau[R]$ for any combination R_p characterized by $0 < w < 1$. For larger values of τ, such that $\mathrm{Q}_\tau[R] > \bar{r}$, the optimal portfolio decision reverses and yields $w^* = 0$. For $\mathrm{Q}_\tau[R] = \bar{r}$, the QP maximizer is indifferent between the risk-free and the risky asset for any $w \in [0,1]$ defining the portfolio return.

In particular, for the example of Uniform distributions discussed above, we can consider $X = a$, with a a fixed payoff, and $Y : U(c,d)$, where $c \leq a$. The optimal portfolio allocation under QP is

$$w^* = \begin{cases} 1 & \text{when } \mathrm{Q}_\tau[R] < \frac{a-c}{d-c} \\ 0 & \text{when } \mathrm{Q}_\tau[R] > \frac{a-c}{d-c} \\ \text{any } w \in [0,1] & \text{when } \mathrm{Q}_\tau[R] = \frac{a-c}{d-c}. \end{cases}$$

The corresponding optimal portfolio allocation for mean-variance investors yields

$$w^\dagger(\gamma) = \begin{cases} \widetilde{w}(\gamma) & \text{when } 0 < \widetilde{w}(\gamma) < 1, \\ 0 & \text{when } \widetilde{w}(\gamma) \leq 0, \\ 1 & \text{when } \widetilde{w}(\gamma) \geq 1, \end{cases} \tag{3.7}$$

where

$$\widetilde{w}(\gamma) = 1 - \frac{6(c+d-2a)}{\gamma(d-c)^2}.$$

The outcome of the latter optimal asset allocation problem is known in the literature as the mutual fund separation theorem, see Tobin (1958).

In this setting, there is an interior solution to the portfolio allocation problem that is given by a convex combination of a risk-free and a risky asset. The allocation to the risky asset depends on the degree of risk aversion γ. In contrast, under quantile preferences, the investor does not diversify at all. The optimal portfolio specializes in the risk-free asset for quantiles below the magnitude of the standarized risk-free rate and on the risky asset, otherwise.

3.3 Experiment design

In Section 3.2, we discussed analytically the optimal allocation between two assets in a portfolio under QP preferences and provide illustrative examples. In the following sections, we present an experiment to assess with real data individuals' optimal portfolio choices, and compare those choices with the predictions of the QP and MV models. This section explains the experiment design. Each experiment session has 90 independent decision-making tasks. Each of these 90 tasks corresponds to an optimal allocation of tokens between two lotteries. The list of tasks is explained in detail in Appendix C.1. Tasks are divided into five categories and each category considers a different type of relationship between two independent Uniform distributions, each corresponding to a different lottery A and B. Section 3 in the Online Appendix also presents graphs with the optimal portfolio allocation w^* to lottery A. Left panels plot the optimal allocation under the MV framework and the right panels plot the optimal allocation under the QP framework. For the MV case, the x-axis is given by $1/\gamma$, with γ the risk aversion coefficient, and for the QP case ,the x-axis is given by τ.

Table 3.1 summarizes the composition of the lotteries, stochastic dominance relationship between them, and the optimal allocation to lottery A under quantile preferences. The optimal allocation under MV is given in expression (3.6). The

Table 3.1: The 90 tasks in our experiment

Tasks	Composition of lotteries	Stochastic dominance	$w^*(\tau)$ by QP (w^*: optimal allocation)
1 to 20	$A : U(a, b)$ and $B : U(a, d)$ with $b < d$.	B FSD A	0.5 if $\tau \leqq \tau_0$ 0, otherwise
21 to 35	$A : U(a, b)$ and $B : U(0, b)$ with $a > 0$	A FSD B	1 if $a > b/2$ $w^* \in (0.5, 1)$, otherwise
36 to 55	$A : U(a, b)$ and $B : U(c, d)$ with $a > c$ and $b > d$	A FSD B	0.5 if $\tau \leqq \tau_0$ 1, otherwise
56 to 69	$A : U(a, b)$ and $B : U(c, d)$ with $a > c$ and $b < d$	There is no FSD between A and B	$w^* \in (0, 1)$ if $\tau \leqq \tau_0$ 0, otherwise
70 to 90	A: a (constant number) and B: U(c,d)	-	1 if $\tau \leqq \tau_0$ 0, otherwise

following paragraphs summarize the cases under investigation.

The first class of experiments in tasks 1 to 20 presents lotteries A and B. These lotteries share the same left end point of the distribution. In this scenario, lottery B first order stochastically dominates lottery A. Example 3.2.2 above is in this family of lotteries. The optimal allocation to A is given by full diversification for risk averse individuals (characterized by a small τ). For individuals with higher tolerance to risk, the optimal allocation under QP is determined by the FSD relationship.

The second class of experiments in tasks 21 to 35 considers lotteries that share the same right end point of the Uniform distributions. In this scenario, lottery A first order stochastically dominates lottery B. Example 3.2.3 above is in this family of lotteries. The optimal allocation to A is determined by the FSD relationship if $a < b/2$, otherwise, the QP optimal portfolio decision differs from the FSD relationship and implies an interior solution given by a convex combination of the two lotteries.

The third class of experiments in tasks 36 to 55 considers two lotteries with over-

Table 3.2: Descriptive data

	Total	Male	Female	Non-binary
Subjects	71	35	35	1
Earnings ($)	21.16	22.62	19.93	13.27
	(5.94)	(6.19)	(5.27)	(-)
Duration of time for experiment (min)	34.00	33.51	33.80	58.46
	(9.34)	(8.59)	(9.25)	(-)
Quiz score (out of 3)	2.54	2.8	2.26	3
	(0.84)	(0.40)	(1.05)	(-)

*Numbers in parentheses indicate standard deviation.

lapping supports. In these examples, lottery A first order stochastically dominates lottery B. Example 3.2.4 above is in this family of lotteries. The optimal allocation to A is given by full diversification for risk averse individuals (characterized by a small τ). For individuals with higher tolerance to risk, the optimal allocation under QP is determined by the FSD relationship.

In the fourth class represented by tasks 56 to 69, there is no stochastic dominance relationship between the variables. Example 3.2.5 above is in this family of lotteries. The optimal allocation to A is given by an interior solution for risk averse individuals (characterized by values of $\tau \leq 0.5$). For individuals with higher risk tolerance ($\tau > 0.5$), the optimal allocation under QP is lottery B.

The last class given by tasks 70 to 90 is given by different combinations of a risk-free asset, represented by a fixed deterministic payoff a, and a risky asset given by a Uniform distribution. In this case, full allocation to the risk-free asset is optimal for values of τ below τ_0, with $\tau_0 = \frac{a-c}{d-c}$. Otherwise, the optimal allocation is the risky asset with payoffs driven by the Uniform distribution.

Our online experiments were programmed in Qualtrics. To create a setting similar to that of a lab-experiment, we used a Zoom meeting room with cameras and informed students they were being observed. We did this because student concentration dropped drastically in the pilot tests when cameras were off. In addition to observing concentration levels, we used the Zoom setting to give students instructions regarding the rules of the experiment. The currency used in the experiment was USD, and subject earnings were paid after each experiment by Venmo or online transfer. We obtained 71 subjects for the experiment. Individuals were a mix of undergraduate and graduate students recruited from the Experiment Science Laboratory (ESL) at the University of Arizona. Due to Covid 19, the experiments were implemented online from December 2020 to February 2021. The experiment consisted of the consent of participating in the experiment (3-5min), introduction for uniform distributions (5-10 min), quiz (5-10min), reading instruction (5-10 min), the main experiment (average of 34min), and payment (3-5min). Because some of the subjects did not have much background in probability theory or mathematics, we explained the basic concept of Uniform distributions and then checked subjects' understanding with three simple questions. This was done prior to the experiment and took about 15 minutes. The instructions shown to subjects in the experiment are found in Section 1 of the Online Appendix. Each session of our experiments lasted about one hour and fifteen minutes on average, and the main experiment took an average of 34 minutes. There was no time limit to complete the experiment; a few individuals took almost an hour to complete it. The standard deviation of the time for the experiment, shown in Table 3.2, was 8.59 minutes for males and 9.25 minutes for females.

The experiment proceeded as follows: students were asked three questions before the experiment to demonstrate their understanding of Uniform distributions.

Subjects then received a bonus depending on how many of these questions they got correct. If they got 3 out of 3, then \$2 were offered. If 2 out of 3, then \$1 was offered, otherwise they received no bonus. The average overall score for these questions was 2.54 out of 3 (84%). See Table 3.2 for summary statistics on earnings, duration of experiment, and quiz score. After the quiz, subjects started the main experiment. The investigator gave a short instruction about the experiment, and then subjects reread the instructions to reinforce their understanding about the lotteries in each task, how to assign the 100 tokens, and how their own earnings would be decided as a result of the experiment. As mentioned earlier, subjects completed 90 tasks during the experiment. These tasks are randomly shown in the screen to avoid distractions or a monotonic choice such as (100,0) or (0,100) across tasks. The questions are presented on 6 pages with 15 tasks per page. In each task, 100 tokens are given to the subject. These tokens can be viewed as the weights that subjects allocate to each lottery. They assign between 0 to 100 tokens to each lottery such that the sum of the weights allocated to the two lotteries is 100. If the sum of weights between lotteries within a task is different from 100, the system reports an error message and the subject has to reintroduce the allocation of weights to the lotteries.

Individuals' earnings from taking part in the experiment are given by the sum of the bonus from taking the initial quiz, the fixed show-up fee of \$5, and the earnings from one randomly selected task out of the 90 tasks completed as part of the experiment. Including the show-up fee of \$5, subjects obtained an average of \$21.16. As an illustrative example, suppose the payment-determining task for a subject has two lotteries, where lottery $A = \$6$ and lottery $B = U[\$0, \$20]$. Assume the subject assigns 40 tokens to A and 60 tokens to B. Then, the computer picks a random number in the interval $[0, 20]$ (for the sake of example, let this number be 11). Then, the subject's payoff will be $\$6 \times 0.4 + \$11 \times 0.6 = \$9$. Table 3.2 includes subject earnings and consumed time for the main experiment by gender.

3.4 Econometric methodology

In this section we describe the econometric methods to estimate the parameter of interest – risk attitude – for both the QP and MV cases, as well as the procedure used to compare the fit of these models.

3.4.1 Identification

The identification of the parameters of interest, for both QP and MV cases, is achieved by varying the shape and support of the lotteries presented to the subjects. Consider the QP case. As discussed in Section 3.2, for a given quantile τ and lotteries X and Y, the economic agent chooses the weight w. Hence, we are able to identify the τ by using different Uniform distribution across tasks, and varying their associated support – see, e.g., Examples 3.2.1–3.2.5 above. Thus, for a given preference parameter τ, we induce different choices of portfolio, and identify the parameter from the data. In other words, identification is attained by assuming that individuals are endowed with the same quantile independently of the magnitude of the payoffs involved, and by varying the support of the Uniform distributions in the lotteries. This variation induces different choices for different tasks. An analogous argument is valid for the MV case.[5] The previous section and Appendix C.1 discuss

[5] We are assuming that there is no measurement error in the data, as for example, systematic rounding errors.

the different combinations of supports used to elicit the parameters of interest.

3.4.2 Estimation methods

We use minimum distance (MD) estimators to estimate the parameters of interest.[6] The MD estimator is very simple to implement in practice. In particular, it is computed by minimizing the quadratic distance of an observed variable and its theoretical counterpart. In particular, we will minimize the distance using either the quantile or the expected value, for QP and MV respectively.

Consider individuals $i = 1, 2, ..., I$. Let $j = 1, 2, ..., J$ index the J tasks each individual face in the experiment. For the experiments in this empirical exercise we have $I = 71$ and $J = 90$. First, from the experiments, we observe data for the choices $w_{ij} \in (0, 1)$, the portfolio selection each individual i make for task j. Second, from the theoretical results for the portfolio section discussed in Section 3.2, for each fixed parameter, we are able to calculate the optimal choices. Of course, this optimal choice depends on the underlying preference risk parameter, which is the parameter to be estimated by the MD method. We propose estimators based on MD to estimate τ_i and γ_i for each individual i. For the latter, we will assume that it lies on a compact set Γ, which is assumed the same for all individuals. We consider a mean-squared loss function estimator. For any portfolio w and task j, we can compute the implied

[6] The minimum distance (MD) estimator dates back to Berkson (1944a), Neyman (1949), Taylor (1953), and Ferguson (1958a), whose among others, aimed to produce statistically efficient and computationally tractable alternatives to maximum likelihood estimators. Although very simple conceptually, MD estimation has been used by many scholars in statistics and econometrics since Malinvaud (1970a) and Rothenberg (1973). The literature on MD is vast, hence we only list a limited set of examples: Amemiya (1976, 1978), Nagaraj and Fuller (1991a), Lee (1992), Koenker et al. (1994a), Newey and McFadden (1994), Lehmann and Casella (1998), Moon and Schorfheide (2002a), and Lee (2010a).

objective function, $Q_\tau(S_w^j)$ for QP and $\mathcal{U}_\gamma(S_w^j)$ for MV. Moreover, we can compute the optimal value of the objective function, $Q_\tau\left[S^j_{w_j^*(\tau)}\right]$ for QP and $\mathcal{U}_\gamma\left[S^j_{w_j^\dagger(\gamma)}\right]$ for MV. Thus, for each individual, we define

$$\widehat{\tau}_i = \underset{\tau\in(0,1)}{\arg\min} \sum_{j=1}^{J} \left(Q_\tau\left[S^j_{w_{ij}}\right] - Q_\tau\left[S^j_{w_j^*(\tau)}\right]\right)^2, \tag{3.8}$$

$$\widehat{\gamma}_i = \underset{\gamma\in\Gamma}{\arg\min} \sum_{j=1}^{J} \left(\mathcal{U}_\gamma\left[S^j_{w_{ij}}\right] - \mathcal{U}_\gamma\left[S^j_{w_j^\dagger(\gamma)}\right]\right)^2, \tag{3.9}$$

for QP and MV, respectively.

The standard asymptotic properties of MD estimators are established in Newey and McFadden (1994). We omit the details for brevity, but notice that, for these estimators, the validity of asymptotic results assume that $J \to \infty$ and independence across tasks.

To implement the estimators we use a grid search where we consider $\tau \in (0,1)$ and $\gamma \in [0,20]$ with a grid size of 2000.

3.4.3 Explaining individuals' preferences using experimental data

We divide the exercise into classification and testing of individuals' portfolio choices.

Classification We consider the following strategy to compare and classify both preferences. The estimators can be compared on the same decision choice, i.e. w. We define a minimum distance indicator using

$$\widehat{d}_{ij} = \mathbf{1}\left[|w_{ij} - w_j^*(\widehat{\tau}_i)| < |w_{ij} - w_j^\dagger(\widehat{\gamma}_i)|\right]. \tag{3.10}$$

Equation (3.10) defines an indicator function that, for each individual i and task j, compares the distance of the observed choices w_{ij} to the theoretical choices using the estimated quantile, $w_j^*(\widehat{\tau}_i)$, with the corresponding distance for the MV case. Therefore, the statistic $\widehat{d}_{ij}$ provides a notion of whether the optimal QP weight is closer to the individual's portfolio choice than the MV weight counterpart.

We then define the following statistics for the indicator. For each task j we can compute the proportion of cases where the QP provides a better fit than MV,

$$\bar{d}_j = \frac{1}{I} \sum_{i=1}^{I} \widehat{d}_{ij}. \tag{3.11}$$

Similarly, for each individual i, we can compute the proportion over the tasks as

$$\bar{d}_i = \frac{1}{J} \sum_{j=1}^{J} \widehat{d}_{ij}. \tag{3.12}$$

Intuitively, the statistic in (3.11) provides the proportion of subjects such that the decisions are a better fit for the QP for each task j. Moreover, the statistic in (3.12) shows the proportion of tasks that are better explained for QP for each individual.

Testing We also formally test which model has a better fit for the observed choices. To do so, we use a Diebold-Mariano (DM) testing strategy (Diebold and Mariano, 2002). Provided that both estimators can be compared on the same loss function, i.e. comparing actual choice and optimal choice, then we can evaluate goodness-of-fit measures between QP and MV. Define

$$\phi_{ij}(\widehat{\tau}_i) = \left[w_{ij} - w_j^*(\widehat{\tau}_i)\right]^2$$

and

$$\psi_{ij}(\widehat{\gamma}_i) = \left[w_{ij} - w_j^{\dagger}(\widehat{\gamma}_i)\right]^2,$$

the value of the loss function for QP and MV, respectively.

Consider now the null hypothesis that for a given task $j = 1, ..., J$ and for a sequence of independent individuals $i = 1, 2, ...$, both models have the same loss

$$H_0^j : E\left[\phi_{ij}(\tau_i) - \psi_{ij}(\gamma_i)\right] = 0,$$

against one-sided and two-sided alternative hypotheses. The null hypothesis states that both preferences representations give the same expected loss, while the alternatives look for systematic differences across representations. A positive (negative) sign indicates that MV (QP) is better than QP (MV), i.e. QP (MV) has a higher value of the loss function than MV (QP).

Then, define the following test statistic

$$DM_j := I^{1/2} \frac{\frac{1}{I}\sum_{i=1}^{I}\left[\phi_{ij}(\widehat{\tau}_i) - \psi_{ij}(\widehat{\gamma}_i)\right]}{\sqrt{V_j}}, \tag{3.13}$$

where $V_j = \frac{1}{I}\sum_{i=1}^{I} Var\left[\phi_{ij}(\widehat{\tau}_i) - \psi_{ij}(\widehat{\gamma}_i)\right]$. One can show that under the null hypothesis H_0^j,

$$DM_j \xrightarrow{d} N(0,1), \quad \text{as} \quad I \to \infty,$$

and hence the critical values are taken from a simple standard normal distribution.

In order to implement the test in (3.13) one needs a consistent estimator of the variance V_j. We consider the following estimator

$$\widehat{V}_j = \hat{V}_{\phi j} + \hat{V}_{\psi j} - 2\hat{C}_{\phi\psi j}, \tag{3.14}$$

with

$$\widehat{V}_{\phi j} = \frac{1}{I}\sum_{i=1}^{I}\left(\phi_{ij}(\widehat{\tau}_i) - \bar{\phi}_j\right)^2,$$

$$\widehat{V}_{\psi j} = \frac{1}{I}\sum_{i=1}^{I}\left(\psi_{ij}(\widehat{\gamma}_i) - \bar{\psi}_j\right)^2,$$

$$\widehat{C}_{\phi\psi j} = \frac{1}{I}\sum_{i=1}^{I}\left(\phi_{ij}(\widehat{\tau}_i) - \bar{\phi}_j\right)\left(\psi_{ij}(\widehat{\gamma}_i) - \bar{\psi}_j\right),$$

where $\bar{\phi}_j = \frac{1}{I}\sum_{i=1}^{I}\phi_{ij}(\widehat{\tau}_i)$ and $\bar{\psi}_j = \frac{1}{I}\sum_{i=1}^{I}\psi_{ij}(\widehat{\gamma}_i)$.

In a similar fashion one can produce DM statistics for a given individual $i = 1, ..., I$ for a sequence of independent tasks $j = 1, 2...$, using the number of tasks to compute the asymptotic results. Under $H_0^i : E\left[\phi_{ij}(\tau_i) - \psi_{ij}(\gamma_i)\right] = 0$, it follows that

$$DM_i := J^{1/2}\frac{\frac{1}{J}\sum_{j=1}^{J}\left[\phi_{ij}(\widehat{\tau}_i) - \psi_{ij}(\widehat{\gamma}_i)\right]}{\sqrt{V_i}} \xrightarrow{d} N(0,1), \quad \text{as} \quad J \to \infty, \tag{3.15}$$

where $V_i = \frac{1}{J}\sum_{j=1}^{J} Var\left[\phi_{ij}(\widehat{\tau}_i) - \psi_{ij}(\widehat{\gamma}_i)\right]$.

3.5 Empirical results

3.5.1 Data description

We have 90 tasks per individual and 71 individuals. The total is thus 6390 selections. Figure 3.2 reports the selected weights by task and individual, respectively. These scatter plots provide a rough description of the heterogeneity across tasks and individuals. All answers are in the graphs, albeit some are repeated (i.e.one task could have more than one w value or one individual could have selected the same w in different tasks). In both cases we observe that choices are not systematically

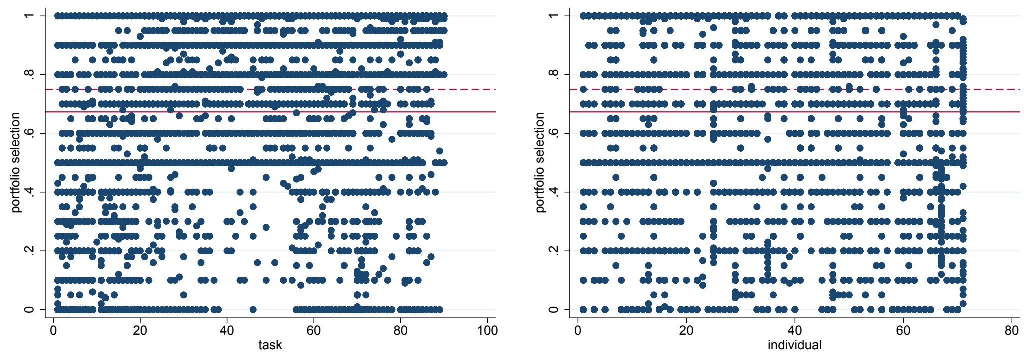


Figure 3.2: The left panel reports the selected portfolio weights by task, and the right panel the selected portfolio weights by individual. The solid and dashed horizontal lines are the overall mean and median values, respectively.

fixed on a given value of w, but that there is heterogeneity on individuals' and tasks' responses.

Now, we discuss the parameter estimates associated to individuals' preferences. For QP we consider the estimated individual-specific quantile indexes $\{\hat{\tau}_i\}_{i=1}^{71}$ in equation (3.8). The left panel of Figure 3.3 presents the histogram of estimated τs. The average $\hat{\tau}$ is about 0.32 while the median is 0.33, and the standard deviation is 0.15. For the MV approach, we consider the estimated individual-specific gamma estimates $\{\hat{\gamma}_i\}_{i=1}^{71}$ obtained from expression (3.9) in the right panel of Figure 3.3. The average $\hat{\gamma}$ is about 4.74 while the median is 4.43, and the standard deviation is 3.06.

The next exercise compares the estimates of individuals' risk aversion across theories. For each individual i, we report in Figure 3.4 the pair $(\hat{\gamma}_i, \hat{\tau}_i)$. These estimates are obtained from minimizing the distance between the implied quantiles, for $\hat{\tau}$, and the expected values, for $\hat{\gamma}$. The results show a negative relationship between the two. This result shows that both theories (QP and MV) capture individuals' underlying risk attitude. A high risk aversion given by a large value of γ for the MV model

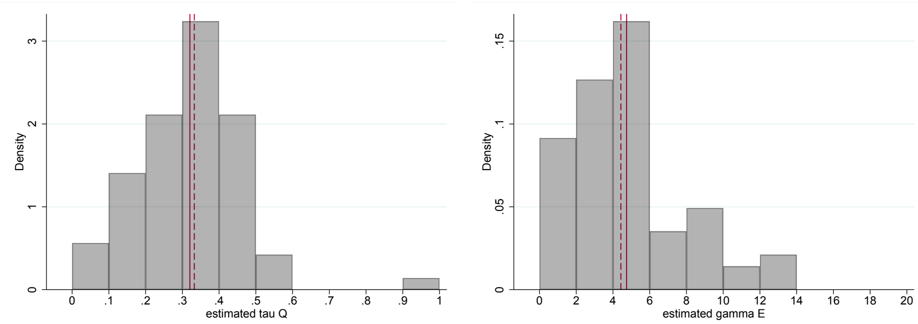


Figure 3.3: Left panel histogram of the estimated τ for QP preferences by individual. Right panel for the histogram of the estimated γ for MV preferences by individual. The solid and dashed vertical lines are the mean and median values, respectively.

is corresponded by a low τ, the parameter that reflects risk aversion under the QP model. In general, individuals exhibit a risk-averse behavior with just a few individuals characterized by values of τ greater than 0.5 and values of γ smaller than one.

3.5.2 Discussion of results per individual

In this subsection, we study the allocation to each lottery per individual. To do this, we aggregate by task. The left panel of Figure 3.5 reports the pairs $\{\bar{d}_i, DM_i\}_{i=1}^{71}$, which corresponds to the estimates of the proportion of tasks that are closer to the QP than to the MV model ($\bar{d}_i$) and the DM statistics.

The overall analysis of the results suggests that the MV utility function is better able to describe individuals' behavior than the QP approach. This is so because most of the observations are above zero in the x-axis, reflecting a positive DM statistic, and are below 0.5 in the y-axis, reflecting a proportion smaller than 0.5 for the QP theory. The graph also reveals the presence of individuals that can be clearly categorized as

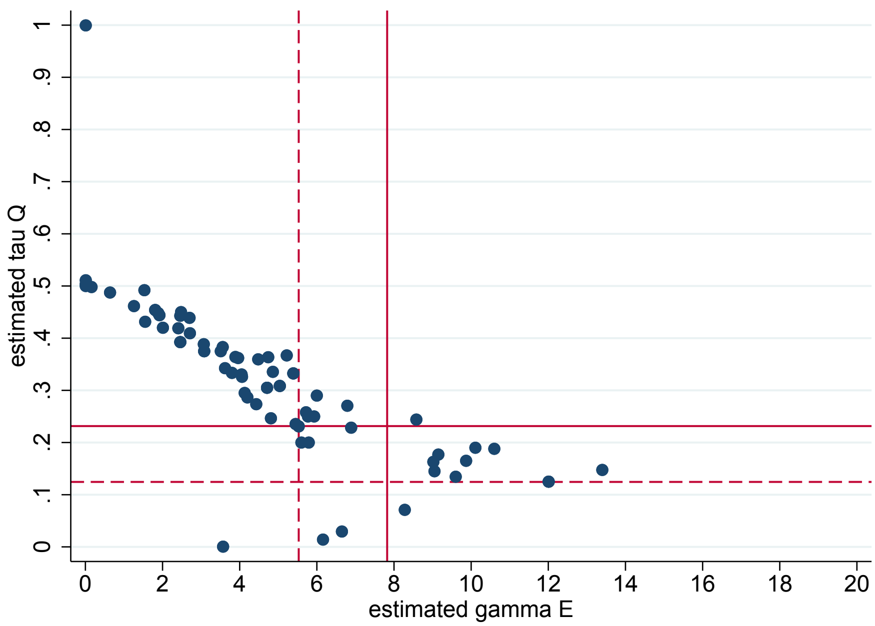


Figure 3.4: Scatter plot of $(\hat{\gamma}_i, \hat{\tau}_i)$. The solid and dashed vertical and horizontal lines are the mean and median values, respectively.

QP maximizers using one or the other metric. Note also that in order to gain a better understanding into individuals' behavior we need to study the individuals' choices by task. This is done in the next subsection.

3.5.3 Discussion of results per task

The right panel of Figure 3.5 reports the pairs $\{\bar{d}_j, DM_j\}_{j=1}^{90}$ by task. These statistics allow us to classify the tasks as MV and QP driven. The scatter plot shows a negative correlation between the statistics $\bar{d}_j$ and DM_j, across tasks. This negative correlation shows that large values of the statistic $\bar{d}_j$ are corresponded by small (or negative) values of the DM statistic. The interpretation of this scatter plot is as follows. For a given task, a large value of $\bar{d}_j$ implies that the proportion of individuals with portfolio allocations closer to the quantile model is higher than with the MV theory. This is reflected in the DM statistic, such that if this value is smaller than -1.96, we obtain statistical evidence favoring the model driven by QP. In contrast, for low values of $\bar{d}_j$, the DM statistic usually takes positive values such that if the statistic is greater than 1.96, we obtain statistical evidence favoring the MV model with respect to the QP model. Visual inspection of the graph suggests that there is evidence of both types of results across tasks. In contrast to the analysis per individual, we find a negative DM statistic for many tasks, which suggests that the QP model is better able to explain individuals' choices than the MV counterpart. In some cases, these values are also statistically significant at 5% significance level.

To obtain further insights into the relationship between the tasks and the type of preferences that drive the optimal portfolio choices, we explore these choices for each task separately. Table 3 in Section 2 of the Online Appendix presents summary

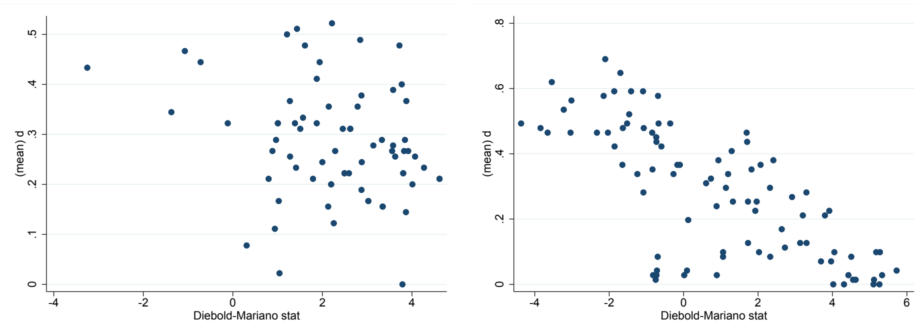


Figure 3.5: Left panel for the scatter plot for the pairs $\{\bar{d}_i, DM_i\}_{i=1}^{71}$, by individual. Right panel for the scatter plot of pairs $\{\bar{d}_j, DM_j\}_{j=1}^{90}$, by task.

statistics on portfolio weights by task. These statistics reflect the empirical distribution of weights across individuals and illustrate the heterogeneity in individuals' responses per task. We compare the empirical results in this table with the optimal allocation to lotteries A and B for each task under the QP and MV theories derived above. To illustrate the optimal portfolio choice under each theory and for all tasks, Figures 1-90 in Section 3 of the Online Appendix report the optimal values of the portfolio weight as the risk aversion coefficient (τ or γ) varies in the intervals $(0, 1)$ and $(0, 4)$, respectively. These graphs show the optimal allocation to lottery A as the risk aversion coefficient decreases.

Tasks 1 - 20:

The specific tasks within this group are found in Appendix C.1.1. A canonical example of this class of experiments is reported in Example 3.2.2. This class is characterized by $A : U(a, b)$ vs. $B : U(a, d)$, with $b < d$. Lottery B first order stochastically dominates (FSD) lottery A. Figures 1-20 in the Online Appendix show a decrease in the optimal allocation to lottery A as the risk aversion coefficient decreases. This decrease is more pronounced under QP and depends on the specific value of b. Similarly, for high levels of risk aversion, individuals with MV preferences allocate more wealth to lottery A than QP individuals. The latter type allocates a maximum weight of 0.5 to lottery A. These differences in portfolio allocations are more important for tasks that involve lotteries where b is much smaller than d. More formally, the theoretical optimal weight allocation under QP preferences is $w^*(\tau) = 0.5$ for values of τ below some threshold τ_0 and $w^*(\tau) = 0$, otherwise. The specific value of τ_0 depends on the choice of the payoff b in lottery A.

We compare these theoretical allocations with the distribution of weights across individuals per task reported in Table 3 in the Online Appendix. The empirical weights oscillate between 0 and 0.5 for most tasks in this group, with a median between 0.1 and 0.5 and a 90% percentile in the range $(0.5, 0.8)$. These weights are in line with the optimal allocations obtained under both QP and MV theories. For those tasks that involve significant differences between the supports of lotteries A and B (b is much smaller than d) the empirical weights are closer to the QP theory than to the MV theory. However, for the other tasks, the empirical weights take large values being more in line with the predictions of the MV theory. To provide statistical support to these findings, Table 4 in the Online Appendix reports the values of the pairs $\{\bar{d}_j, DM_j\}_{j=1}^{20}$ computed using the mean square distance and the quantile implied measures developed above. The results confirm the findings described above and uncover those tasks for which individuals behave as QP maximizers and those tasks for which they behave as MV maximizers.

Tasks 21 - 35:

The specific tasks within this group are found in Appendix C.1.2. These portfolio experiments are represented by lotteries $A : U(a, b)$ vs. $B : U(0, b)$, with $a > 0$ and different values of b. A canonical example is $A : U(0.5, 1)$ vs. $B : U(0, 1)$ in Example 3.2.3. This family of tasks satisfies that A FSD B and the optimal allocation under QP theory depends on the value of a. Figures 21-35 in Section 3 of the Online Appendix report the optimal allocations to lottery A under QP and MV theories as the risk aversion coefficient decreases. For Lotteries A with large a (beyond the mean of lottery B), we find that $w^*(\tau) = 1$ for all $\tau \in (0, 1)$, however, if a is small then the optimal QP allocation is between 0.5 and 1. Similar results are found for the MV theory. In this case, the optimal allocation under MV theory converges to $w^* = 1$ when a is greater than the average of lottery B. Diversification is only present in this group under high levels of risk aversion and for tasks where the support of A is large enough (small a).

The analysis of the distribution of the weights provides interesting insights, though. The 10^{th} quantile for these tasks is around 0.50, the average oscillates between 0.70 and 0.868, and the median is even higher, which suggests that individuals behave according to these theories. The DM statistic driven by the squared distance between the weights does not yield conclusive evidence and in some cases the DM statistic is NA. This is because the two proportions are exactly the same and it is not possible to calculate the variance and covariance for the DM statistic. In contrast, the statistics based on the implied quantiles provide very informative results. The corresponding DM statistic is negative and statistically significant giving support to the QP theory compared to the MV theory. Individuals when confronted with these tasks seem to follow the first order stochastic dominance rule and diversify less than under the MV theory.

Tasks 36 - 55:

The specific tasks within this group are found in Appendix C.1.3. These portfolio experiments are represented by overlapping lotteries such that $A : U(a, b)$ vs. $B : U(c, d)$, with $a > c$ and $b > d$. A canonical example is $A : U(0.25, 1.25)$ vs. $B : U(0, 1)$ in Example 3.2.4. This family of tasks satisfies that A FSD B and the optimal allocation under QP theory is $w^* \in (0, 1)$ for $\tau \leq \tau_0$ and $w^* = 1$, otherwise. In contrast, the optimal allocation under MV theory starts at $w^* = 0.5$ for all tasks for high levels of risk aversion and increases towards one as the risk aversion coefficient decreases. These allocations are reported in Figures 36-55 of the Online Appendix.

In contrast to the preceding example, the analysis of the theoretical weights in expression (3.6) and visual inspection of Figures 36-55, allow us to clearly discriminate between MV and QP. Thus, the empirical distribution of weights in Table 3 (Online Appendix) provides results that align very well with the theoretical predictions of both QP and MV theories. More specifically, the 10^{th} quantile for these tasks is around 0.50 in most cases, the average oscillates between 0.70 and 0.878, and the median is usually higher than the mean. A closer look to the summary statistics suggests, however, that these values are only consistent with the MV case for $\gamma < 1$, otherwise, the MV theory predicts more diversification than what we observe in individuals' choices. The distribution of the empirical weights seems to be more in line with the optimal portfolio allocation obtained under the QP theory. On the other hand, whereas the QP theory predicts full allocation to lottery A, the empirical weights show some non-negligible allocation to lottery B too. These empirical findings are inconclusive so the inspection of the statistics $\{\bar{d}_j, DM_j\}_{j=36}^{55}$ in Table 4 (Online Appendix) may be useful in this case to discriminate between theories. The

$\bar{d}_j$ statistic yields values greater than 0.5 for several tasks but values close to zero for many other tasks in this group. In general, the DM statistic under both estimation methods is very positive providing statistical support to the MV case. The overall analysis of the empirical results for this group suggests that the observed weights are closer to the predictions of the MV model for individuals with low levels of risk aversion.

Tasks 56 - 69:

The specific tasks within this group are found in Appendix C.1.4 and the optimal allocations are reported in Figures 56-69 of the Online Appendix. These portfolio experiments are represented by lotteries such as $A : U(a, b)$ vs. $B : U(c, d)$, with $a > c$ and $b < d$. The support of A is strictly included in the support of B, implying that the variance of the latter lottery is larger than the former. A canonical example is $A : U(0.25, 0.75)$ vs. $B : U(0, 1)$ in Example 3.2.5. The optimal portfolio allocation is an interior solution for $\tau \leq \tau_0$ and $w^* = 0$, otherwise. In contrast, the optimal allocation to lottery A under the MV theory oscillates between 0.5 and 1. It approaches $w^* = 1$ as the variance of lottery A compared to lottery B decreases (the support of A decreases with respect to the support of B). For many of the tasks in this class (those with same mean) this scenario corresponds to A that stochastically dominates lottery B in second order.

The analysis of the distribution of the weights in Table 3 (Online Appendix) provides interesting findings that align very well with both theories. The empirical distribution of weights seems to be in the range $(0.5, 1)$ and the median is also quite high. It is difficult to discriminate between both theories using the empirical weight distribution. However, inspection of the statistics $\{\bar{d}_j, DM_j\}_{j=56}^{69}$ in Table 4 (Online Appendix) sheds further light on the empirical results. This table provides strong statistical support on the superiority of the QP theory compared to MV for this class of tasks. The $\bar{d}_j$ statistic yields values greater than 0.5 for several tasks, which indicates that there is a larger proportion of individuals that can be classified as QP maximizers compared to MV maximizers. Similarly, the DM_j statistic is negative in many cases and provides statistically significant results.

Tasks 70 - 90:

Tasks in this experiment include a risk-free asset. The specific tasks within this group are found in Appendix C.1.5 and the optimal allocations are reported in Figures 70-90 of the Online Appendix. Both theories predict similar optimal portfolio allocations. The MV allocation is smoother than the QP allocation, nevertheless, both allocations predict full investment on the risk-free asset for high levels of risk aversion. As the level of risk aversion decreases, the QP theory predicts a complete shift to the risky asset. In contrast, the MV theory predicts some diversification. This is only the case if the payoff of the risk-free asset is lower than the mean of the risky asset, otherwise, the optimal allocation is full investment on the risk-free asset independently of the risk aversion coefficient.

The distribution of weights in Table 3 (Online Appendix) exhibits some heterogeneity across individuals for some tasks. For example, for Task 70 given by $A:2$ vs. $B:U[0,20]$, we find that most individuals allocate a weight to the risk-free asset in the range $(0,0.25)$, which is more in line with the QP theory than with the MV theory. For the latter theory to be consistent with the observed empirical distribution of weights, γ needs to be smaller than 1/3, which corresponds to very low levels of risk aversion. Similar findings are obtained for the analysis of Task 71. However, as the payoff of the risk-free asset increases, we observe a positive shift of the empirical distribution of weights. In these cases, the MV predictions are better able to explain individuals' choices than the QP predictions. This is mainly due to the additional flexibility of the MV case that accommodates some diversification for moderate values of the risk aversion coefficient, in contrast to the QP case. Finally, for those cases when the payoff of the risk-free asset is high both theories yield the same optimal portfolios given by full allocation into the risk-free asset.

The comparison of the theories using the statistics $\{\bar{d}_j, DM_j\}_{j=71}^{90}$ in Table 4 (Online Appendix) also present mixed results. There are, however, more tasks that are better represented by the MV theory than by the QP theory.

3.6 Conclusion

This paper has studied optimal portfolio allocation under quantile preferences using a laboratory experiment with 71 undergraduate and graduate students from University of Arizona. The experiment simulates a simple portfolio decision exercise and is formed of 90 tasks. Each task has two assets, either two risky assets or one risk-free and one risky asset, with the risky assets following a Uniform distribution function. We have used this experiment to assess the insights of the quantile preference model with real data. We have studied the suitability of the predictions of the MV and QP theories to explain the data on portfolio weights collected from the experiment. The results of the experiment confirm that both theories help to predict individuals' optimal choices. Subjects in the experiment are clearly risk averse under both specifications of individuals' preferences. The aggregation of results by individual offers partial support to the MV theory whereas the aggregation of results by task is more supportive of the QP theory.

The overall message that emerges from this analysis is that individuals' behavior is better predicted by the MV model when it is difficult to assess the differences in the payoff distribution of the lotteries comprising the portfolio. Individuals behave as QP maximizers, otherwise. This result suggests that diversification may act sometimes as a decision mechanism that individuals use when it is not clear how to assess the relative gains/losses of one strategy over the other as, for example, when the lotteries' payoff distributions overlap. In these cases, MV preferences seem a safer choice as the optimal outcome of these policies usually yield to diversification. This outcome involves fewer exposures to single assets than the QP theory even if the latter might lead to superior monetary rewards. In contrast, when individuals are able to clearly assess the differences in the distribution of payoffs between lotteries their portfolio choices are closer to the optimal decision of a QP maximizer than of a MV maximizer. In these (simpler) cases, individuals are able to maximize over the distribution of the portfolio rather than trading expected return for variance.

Appendix A
Chapter 1 Appendix

A.1 Strategic delegation game for the experiment

This chapter introduces (i) assumptions for owners in the experiment and (ii) some issues about a manager's payoffs if **R** is chosen.

A.1.1 Assumptions for owners

The game presented in this paper is based on the two-stage duopoly game described in the FJSV papers. The game features two firms in a market, each consisting of one owner and one manager. The inverse demand function is $P(q_1, q_2) = a - q_1 - q_2$, and the marginal cost is c. The game is divided into two stages.

In stage 1, each owner selects a contract to incentivize their manager, choosing between either **P** or **R**. In stage 2, each manager selects an output level to maximize their payoff. If **P** is chosen in stage 1, the payoff for firm i's manager is determined by $\pi_i = (a - q_1 - q_2 - c)q_i$ for $i = 1, 2$. If **R** is chosen in stage 1, the payoff for firm i's manager is given by $\lambda_i \pi_i + (1 - \lambda_i)R_i$, where $R_i = (a - q_1 - q_2)q_i$ for $i = 1, 2$. Here, the values of (λ_1, λ_2) depend on the owners' expectations about whether the managers will collude or compete.[1] If owners expect that the managers will collude

[1]See Lambertini and Trombetta (2002).

with each other, then $\lambda_1 > 1$ and $\lambda_2 > 1$. To ensure that $0 \leq \lambda_i \leq 1$ for $i = 1, 2$, the experimental framework imposes the following restrictions on owners' expectations:

Assumption 1. *Owners expect that managers compete with each other.*

To describe contract **R** in the experiment, this paper uses subgame perfect equilibrium weighted values $(\lambda_1^*, \lambda_2^*)$ from the case where both owners select contract **R**. To calculate the values $(\lambda_1^*, \lambda_2^*)$, we can use each firm's manager's objective function, such as Equation (2) or (3) from Section 1.3.1's basic setup. By backward induction, in stage 2, q_1 and q_2 are decided to maximize the managers' incentives. Thus, the managers' objective functions, U_1 and U_2, should satisfy the first-order conditions with respect to q_1 and q_2, which are denoted as F_1 and F_2, respectively:

$$\begin{aligned} F_1 &= \frac{\partial U_1}{\partial q_1} = a - 2q_1 - q_2 - c\lambda_1 &= 0 \\ F_2 &= \frac{\partial U_2}{\partial q_2} = a - 2q_2 - q_1 - c\lambda_2 &= 0 \end{aligned} \tag{A.1}$$

In stage 1, the owners of firms 1 and 2 individually determine λ_1 and λ_2 to maximize π_1 and π_2 simultaneously. The first-order conditions can be obtained by using the differentiability of the best response curves q_1 and q_2 with respect to λ_1 and λ_2, and are given as follows:

$$\begin{aligned} \frac{\partial \pi_1}{\partial \lambda_1} &= (a - c - 2q_1 - q_2)\frac{\partial q_1}{\partial \lambda_1} - q_1\frac{\partial q_2}{\partial \lambda_1} &= 0 \\ \frac{\partial \pi_2}{\partial \lambda_2} &= (a - c - 2q_2 - q_1)\frac{\partial q_2}{\partial \lambda_2} - q_2\frac{\partial q_1}{\partial \lambda_2} &= 0 \end{aligned} \tag{A.2}$$

A Jacobian matrix, $\begin{bmatrix} \frac{\partial F_1}{\partial q_1} & \frac{\partial F_1}{\partial q_2} \\ \frac{\partial F_2}{\partial q_1} & \frac{\partial F_2}{\partial q_2} \end{bmatrix}$, and its determinant can be derived by the implicit function theorem. Define the determinant as J. By Cramer's rule, $\frac{\partial q_1}{\partial \lambda_1}$ and $\frac{\partial q_2}{\partial \lambda_1}$ are obtained:

$$\begin{aligned}\frac{\partial q_1}{\partial \lambda_1} &= -\frac{1}{J} det \begin{bmatrix} \frac{\partial F_1}{\partial \lambda_1} & \frac{\partial F_1}{\partial q_2} \\ \frac{\partial F_2}{\partial \lambda_1} & \frac{\partial F_2}{\partial q_2} \end{bmatrix} &= \frac{2}{J} \\ \frac{\partial q_2}{\partial \lambda_1} &= -\frac{1}{J} det \begin{bmatrix} \frac{\partial F_1}{\partial q_1} & \frac{\partial F_1}{\partial \lambda_1} \\ \frac{\partial F_2}{\partial q_1} & \frac{\partial F_2}{\partial \lambda_1} \end{bmatrix} &= -\frac{1}{J}\end{aligned} \tag{A.3}$$

Similarly, we can obtain the expressions for $\frac{\partial q_2}{\partial \lambda_2}$ and $\frac{\partial q_1}{\partial \lambda_2}$. By solving equations (4), (5), and (6), we obtain $\lambda_1^* = \lambda_2^* = \frac{6c-a}{5c}$. However, to ensure that λ_1 and λ_2 are non-negative, an additional assumption is introduced.

Assumption 2. *a is satisfied with $6c > a > c$ where $c > 0$.*

Therefore, in the experiment, contract **P** indicates that $U_i^P = \pi_i$, while contract **R** represents $U_i^R = 0.5\pi_i + 0.5R_i$ for $i = 1, 2$. By using $a = 140$ and $c = 40$, $\lambda_1^* = \lambda_2^* = 0.5$ can be obtained. This value is consistent with the weighted values used to describe real-world compensation schemes in Bloomfield (2021).

A.1.2 Assumptions for managers

There are two additional assumptions related to managers' payoffs. The third assumption is that owners' profits are independent of managers' payoffs. Otherwise, the proportion of managers' payoffs to owners' profits would affect owners' decisions and the model parameters would vary depending on how a and c are chosen. In the real world, a manager's payoff is typically much smaller than the profits of firms. To focus on the behavior of the firms described by the owners' and managers' selections, and to ensure that there is no change in these selections due to changes in the model parameters, this study makes the following assumption:

Assumption 3. *Each owner's payoff is independent of their manager's payoff.*

The fourth assumption pertains to the size of managers' payoffs. When an owner selects strategy R, their manager's payoff is determined by profit and revenue. Since revenue is larger than profit unless cost is zero, a manager's payoff under R is always larger than those under P. This can affect owners' decisions in stage 1. To account for this, a negative fixed payment is applied to managers' payoffs, as adopted by Huck et al. (2004). The negative fixed payment is equal to the gap in the average of managers' payoffs when an owner chooses R versus when both owners choose P. For instance, if (R, R) is chosen, then $U_1^R = 0.5\pi_1 + 0.5R_1 = (120 - q_1 - q_2)q1$ and $U_2^R = 0.5\pi_2 + 0.5R_2 = (120 - q_1 - q_2)q2$. Table 1.3 shows the possible outputs that managers of firms 1 and 2 can choose, which are (30, 30), (30, 45), (45, 30), and (40, 40). Half of the profit plus half of the revenue from these four outputs are calculated to be 1800, 1350, 2025, and 1600. The average of these numbers is 1694. Similarly, the average profit in the (P, P) case is 1173. Therefore, the gap between (R, R) and (P, P) is $1694 - 1173 = 521$, which is used as a negative fixed payment for adjustment. The *adjusted calculations* are 1279, 829, 1504, and 1079. The negative payment does not affect equilibria for subgames. To ensure that an owner's profit is never smaller than a manager's payoff, the adjusted values are multiplied by 0.1 in the experiment. As a result, the adjusted payoffs for managers are 128, 83, 150, and 108, which are displayed in Table 1.6.

Assumption 4. *Managers' expected payoffs for each case are constant regardless of owners' selections.*

A.2 Regression (LL cartels and Asymmetric cases)

This section presents the regression results that support Section 1.5.2. Specifically, Table A.1 (a) displays the results of a logit regression examining the formation rates of LL cartels. The regression results indicate that both strategic delegation and communication have a positive effect on the formation of LL cartels. In addition, Panel (b) of the table examines the effect of "asymmetric cases" on cartel formation rates. Asymmetric cases are defined as situations where owners choose (P, R) or (R, P) in stage 1 in the SN and SC treatments. The results show that more cartels are formed in asymmetric cases than in symmetric cases.

	LL cartels	
	(1)	(2)
Strategic Delegation (SD)	3.591*	0.786
	(1.853)	(1.970)
Comm.	5.595***	2.559
	(2.108)	(2.232)
SD × Comm.	-2.945	-0.194
	(2.335)	(2.509)
Round	-0.028	-0.807***
	(0.040)	(0.052)
Round × SD		0.761***
		(0.099)
Round × Comm.		0.790***
		(0.074)
Round × SD × Comm.		-0.755***
		(0.134)
Constant	-7.389***	-4.447**
	(2.016)	(1.975)
Observations (group)	40	40

(a) Cartel formation rates and LL cartels

	Cartel formation (Asymmetric cases)	
	(1)	(2)
asym	1.601***	2.697**
	(0.541)	(1.224)
Comm.	3.860**	4.550**
	(1.572)	(1.871)
Round	0.010	0.129
	(0.074)	(0.174)
Round × asym		-0.168
		(0.138)
Round × Comm.		-0.107
		(0.163)
Round × asym × Comm.		0.076
		(0.094)
Constant	-4.742***	-5.677***
	(1.176)	(1.742)
Observations (group)	20	20

(b) Cartels in asymmetric cases

Table A.1: Cartel formation

A.3 Instructions (SC treatment)

General instruction

This is an experiment in economic decision-making in a market. In the experiment, you will be grouped with three other participants. Each group corresponds to a market consisting of two firms, 1 and 2. Each firm has one owner and one manager. You will have a role of either an owner or a manager in a firm. Your role is kept until the end of this experiment. The experiment consists of 16 rounds in total.

Your earnings today will be determined by your and others' choices. If you follow the instructions carefully and make good decisions, you can earn a considerable amount of money. The currency used in the experiment is the 'Point.' If your role is an owner, 2,000 points are worth 1 dollar. If your role is a manager, 200 points are worth 1 dollar. You can see how much you earn at the end of each round, and then points will be converted to dollars after all 16 rounds are completed. In addition, you receive a show-up fee for completing the experiment.

Each round consists of two stages. The table below describes what each role should do in stages.

Stage	**A Participant's Role**	**Each Participant's Selection**	**What impact do the decisions made in each stage have?**
1	Owner	P or R	Earnings
2	Manager	A or B	Earnings and fine (Fine is imposed with a 15% chance if both managers choose A.)

In the first stage of each round, the participants who have a role of an owner select one between two strategies P and R. Your selection affects not only your earnings, but also your manager's earnings. At the end of the first stage in each round, there is an announcement to all participants about what strategies owners select in stage 1. Managers wait for owners' decisions during stage 1.

After the first stage is completed, managers chat with each other for one minute. A payoff table depending on the owners' selection in stage 1 will be given to managers. During a chat, managers can talk with each other freely, but managers must not share personal information with others. No one who violates the rule will get any points.

In the second stage, managers choose (i) to join a market agreement (A) or (ii) not to join it (B). If both managers choose A, there is a 15% chance that owners and managers will pay a fine. Otherwise, no fine is imposed on anyone. Owners wait for managers' chat and decisions during stage 2. After stage 2, earnings and fines for participants are decided, and then a round is completed.

Instructions for each stage

Stage 1 - Owners' decisions

In stage 1 of each round, owners choose P or R. The table below indicates the owners' earnings. P and R in gray cells mean owners' possible choices. A and B in blue cells mean managers' possible choices. Owners' choices in stage 1 decide one among four cases, P and P, P and R, R and P, and R and R. Then, owners' earnings will be one of the black numbers in boldface type in the table case by case.

Suppose you are an owner. Then, earnings in the four possible cases are as follows;
- If you select P and the other owner selects P, then your earnings will be 1250 or 925 or 1406 or 1111.
- If you select P and the other owner selects R, then your earnings will be 1125 or 702 or 1225 or 630.
- If you select R and the other owner selects P, then your earnings will be 1350 or 1050 or 1222 or 846.
- If you select R and the other owner selects R, then your earnings will be 1200 or 750 or 1125 or 800.

Owners' earnings		**The opposite firm**					
		P			R		
Your firm	P		A	B		A	B
		A	**1250**, 1250	**925**, 1406	A	**1125**, 1350	**702**, 1222
		B	**1406**, 925	**1111**, 1111	B	**1225**, 1050	**630**, 846
	R		A	B		A	B
		A	**1350**, 1125	**1050**, 1225	A	**1200**, 1200	**750**, 1125
		B	**1222**, 702	**846**, 630	B	**1125**, 750	**800**, 800

Stage 2 - Managers' decisions

In stage 2, managers choose A or B, which decides earnings and fines for owners and managers. A different table for earnings is given to managers in stage 2, depending on owners' selections in stage 1. Blue numbers in the tables below indicate managers' earnings. Fines are already reflected on each table. Thus, all you have to do is to care about your earnings in the table given to you in each case.

Suppose you are a manager. First, let's look at the case that both owners choose P in stage 1.
- If you and the other manager select A, then you and the other manager get 125, respectively. With a 15% chance, you have to pay a fine, 23, and the other manager has to pay a fine, 23. With the other 85% chance, there are no fines.
- If you select A and the other manager selects B, then you get 93 and the other manager gets 141.
- If you select B and the other manager selects A, then you get 141and the other manager gets 93.
- If you select B and the other manager selects B, then you get 111and the other manager gets 111.

Managers' earnings		**P**	
P		A	B
	A	**125**, 125 with 85% or **102**, 102 with 15%	**93**, 141
	B	**141**, 93	**111**, 111

The second case is that your firm's owner chooses P and the other firm's owner chooses R in stage 1.
- If you and the other manager select A, then you get 138 and the other manager gets 124. With a 15% chance, you have to pay a fine, 26, and the other manager has to pay a fine, 23. With the other 85% chance, there are no fines.
- If you select A and the other manager selects B, then you get 95 and the other manager gets 145.
- If you select B and the other manager selects A, then you get 148 and the other manager gets 94.
- If you select B and the other manager selects B, then you get 88 and the other manager gets 107.

The third case is that your firm's owner chooses R and the other firm's owner chooses P in stage 1.
- If you and the other manager select A, then you get 124 and the other manager gets 138. With a 15% chance, you have to pay a fine, 23, and the other manager has to pay a fine, 26. With the other 85% chance, there are no fines.
- If you select A and the other manager selects B, then you get 94 and the other manager

Managers' earnings		U_2	
U_1		A	B
	A	**138**, 124 with 85% or **112**, 101 with 15%	**95**, 145
	B	**148**, 94	**88**, 107

gets 148.
- If you select B and the other manager selects A, then you get 145 and the other manager gets 95.
- If you select B and the other manager selects B, then you get 107 and the other manager gets 88.

Managers' earnings		U_2	
U_1		A	B
	A	**124**, 138 with 85% or **101**, 112 with 15%	**94**, 148
	B	**145**, 95	**107**, 88

The fourth case is that your firm's owner chooses R and the other firm's owner chooses R in stage 1.
- If you and the other manager select A, then you and the other manager get 128 respectively. With a 15% chance, you have to pay a fine, 26, and the other manager has to pay a fine, 26. With the other 85% chance, there are no fines.
- If you select A and the other manager selects B, then you get 83 and the other manager gets 150.
- If you select B and the other manager selects A, then you get 150 and the other manager gets 83.
- If you select B and the other manager selects B, then you get 108 and the other manager gets 108.

Managers' earnings		R	
R		A	B
	A	**128**, 128 with 85% or **102**, 102 with 15%	**83**, 150
	B	**150**, 83	**108**, 108

In addition, fines are imposed on owners with a 15% chance if both managers choose

A. The table below indicates each of the cases where both managers choose A, and fines are imposed on owners, depending on owners' selections. If you are an owner, the table will be given to you in your decision.

Owners' earnings			**The opposite firm**				
			P			R	
Your firm	P		A	B		A	B
		A	**1250**, 1250 with 85% or **1025**, 1025 with 15%	**925**, 1406	A	**1125**, 1350 with 85% or **912**, 1095 with 15%	**702**, 1222
		B	**1406**, 925	**1111**, 1111	B	**1225**, 1050	**630**, 846
	R		A	B		A	B
		A	**1350**, 1125 with 85% or **1095,** 912 with 15%	**1050**, 1225	A	**1200**, 1200 with 85% or **960**, 960 with 15%	**750**, 1125
		B	**1222,** 702	**846**, 630	B	**1125**, 750	**800**, 800

In brief, your total earnings rely on 1) whether owners select P or R, 2) whether managers select A or B. Please click the next button to go to stage 1 in round 1.

Appendix B

Chapter 2 Appendix

We include three Appendices. The first reports a number of Mann-Whitney tests of differences of key variables between treatments. The second contains the instructions for one treatment (High1) of the experiment. The instructions for the other treatments involve only minor or obvious departures from those of High1. Appendix C consists of the payoff tables for each treatment.

B.1 Mann-Whitney U test results for treatment differences

This section contains the MW test results reported in Section 2.5. Each cell in the tables below shows the p-value resulting from a MW test between a treatment indicated in one of the columns and a treatment listed in one of the rows. For example, the significance level of the test of a difference between No-len and High1 in the left panel of Table B.1 is .329. Because the sample size in each treatment is small, exact p-values are used. In comparisons between No-len and one of the high fine leniency treatments, High1 or HIgh2, we use one-sided MW p-values because we hypothesize a specific difference in one direction. Similarly, we employ one-sided p-values when comparing Low1 with High1 and Low2 with High2. While some of these are unstated in Section 4, the one-sided p-values are for tests that there is lower cartel formation, higher cartel exposure, and lower cartel success in High1 and High2 than under No-len, in High1 than under Low1, and in High2 compared to Low2. We use two-sided MW test results for differences among other treatment pairs, because we do not have hypotheses about directional differences in outcome variables.

	High1	High2	Low1	Low2
No-len	0.329	0.452	0.386	0.528
High1	-	1.000	0.229	0.251
High2		-	0.610	0.159
Low1			-	0.060

(a) All cartels

	High1	High2	Low1	Low2
No-len	0.500	0.132	0.300	1.000
High1	-	0.237	0.324	0.909
High2		-	0.758	0.085
Low1			-	0.425

(b) Full cartels

Table B.1: p-values from Mann-Whitney U tests of treatment differences in cartel formation rate

	High1	High2	Low1	Low2
No-len	0.001	0.001	0.000	0.007
High1	-	0.647	0.351	0.270
High2		-	0.878	0.201
Low1			-	0.543

(a) All cartels

	High1	High2	Low1	Low2
No-len	0.003	0.065	0.312	0.032
High1	-	0.205	0.075	0.105
High2		-	0.778	0.500
Low1			-	0.694

(b) Full cartels

Table B.2: p-values of Mann-Whitney U tests of pairwise treatment differences in cartel exposure rate

	High1	High2	Low1	Low2
No-len	0.001	0.004	0.003	0.099
High1	-	0.445	0.439	0.054
High2		-	0.467	0.131
Low1			-	0.036

(a) All cartels

	High1	High2	Low1	Low2
No-len	0.031	0.028	0.062	0.301
High1	-	0.932	0.483	0.207
High2		-	0.966	0.084
Low1			-	0.192

(b) Full cartels

Table B.3: p-values of Mann-Whitney U tests of pairwise treatment differences in cartel success rate

	High1	High2	Low1	Low2
No-len	0.010	0.021	0.131	0.880
High1	-	0.496	0.048	0.008
High2		-	0.364	0.004
Low1			-	0.131

(a) Industry Profit

	High1	High2	Low1	Low2
No-len	0.001	0.012	0.197	0.172
High1	-	0.112	0.008	0.004
High2		-	0.199	0.048
Low1			-	0.762

(b) Fine

Table B.4: p-values of Mann-Whitney U tests of pairwise treatment differences in industry payoffs and fines paid

B.2 Payoff tables of the treatments

The payoff tables below were those used in the experiment. All payoffs in the tables are firms' "Payoffs" calculated as "individual firm profits minus fines paid" for each case. For example, in Figure B.2, suppose three firms join a cartel and one firm does not. Then, the one who does not join a cartel obtains 178 and three firms in the cartel will get either 59 or 25. If no firms blow the whistle the cartel members each obtain 59. If one of them becomes the first or only whistle-blower, they also obtain 59. If another firm blows the whistle first or the cartel is uncovered by a regulator's monitoring, then the firms in the cartel get 25. The other situations and the other tables are read and interpreted similarly.

Number of Companies entering market agreement	**If you enter the market agreement**		**If you do not enter the market agreement**
	Participation stage earnings are (in ECU)	If the agreement is discovered by a market monitor with 15% chance, your final earnings for the round are	Final earnings for the round are (in ECU)
0	-	-	64
1	-	-	64
2	50	15	100
3	59	25	178
4	100	60	-

Figure B.1: The payoff table for the No-len treatment

Number of Companies entering market agreement	**If you enter the market agreement**			**If you do not enter the market agreement**
	Phase 1 earnings (in ECU)	Final earnings for the round (in ECU)		Final earnings for the round (in ECU)
(Column 1)	(Column 2)	If no company reports or if you are first to report the agreement (Column 3)	If another company is the first to report the agreement OR If the agreement is discovered by a market monitor with 15% chance, (Column 4)	(Column 5)
0	-	-	-	64
1	-	-	-	64
2	50	50	15	100
3	59	59	25	178
4	100	100	60	-

Figure B.2: The payoff table for the High1 treatment

Number of Companies entering market agreement	**If you enter the market agreement**				**If you do not enter the market agreement**
	Phase 1 earnings (in ECU)	Final earnings for the round (in ECU)			Final earnings for the round (in ECU)
(Column 1)	(Column 2)	If no company reports OR If you are first to report the agreement (Column 3)	If you are second to report the agreement (Column 4)	If you are not the first or second to report and any company reports the agreement OR If the agreement is discovered by a market monitor with 15% chance, (Column 5)	(Column 6)
0	-	-	-	-	64
1	-	-	-	-	64
2	50	50	15	15	100
3	59	59	42	25	178
4	100	100	80	60	-

Figure B.3: The payoff table for the High2 treatment

Number of Companies entering market agreement	**If you enter the market agreement**			**If you do not enter the market agreement**
	Phase 1 earnings (in ECU)	Final earnings for the round (in ECU)		Final earnings for the round (in ECU)
(Column 1)	(Column 2)	If no company reports or if you are first to report the agreement (Column 3)	If another company is the first to report the agreement OR If the agreement is discovered by a market monitor with 15% chance, (Column 4)	(Column 5)
0	-	-	-	64
1	-	-	-	64
2	50	50	32.5	100
3	59	59	42	178
4	100	100	80	-

Figure B.4: The payoff table for the Low1 treatment

Number of Companies entering market agreement	**If you enter the market agreement**				**If you do not enter the market agreement**
	Phase 1 earnings (in ECU)	Final earnings for the round (in ECU)			Final earnings for the round (in ECU)
(Column 1)	(Column 2)	If no company reports OR If you are first to report the agreement (Column 3)	If you are second to report the agreement (Column 4)	If you are not the first or second to report and any company reports the agreement OR If the agreement is discovered by a market monitor with 15% chance, (Column 5)	(Column 6)
0	-	-	-	-	64
1	-	-	-	-	64
2	50	50	32.5	32.5	100
3	59	59	51.5	42	178
4	100	100	90	80	-

Figure B.5: The payoff table for the Low2 treatment

B.3 Instructions (High1 Treatment)

General instructions

This is an experiment in economic decision making. The instructions are simple and if you follow them carefully and make good decisions, you can earn a considerable amount of money. In this experiment, your earnings will be determined by your choices, others' choices, and chance. The currency used in the experiment is the ECU, Experimental Currency Unit. The ECU that you have at the end of the experiment will be converted to dollars at a rate of 200 ECU to 1 dollar and paid to you as a bonus. In addition, you receive a show-up fee for completing the experiment. From now on until the end of the experiment, you may not communicate with any other participants outside the chatroom that we will organize.

In the experiment, you will be grouped with three other participants in a group of four people. You will remain grouped with the same three other people for the entire experiment. Each of you has the role of a company in the same four-company market. The experiment consists of 10 rounds in total, and the companies in your market will stay the same for the 10 rounds. During the experiment, you will not be able to know what person is in the role of each of the other companies. The other companies will also be unable to gain this information about you.

Each round consists of two phases. In the first phase of each round, all companies within a market can communicate with each other using a chat window. Afterward, each company announces whether it wishes to take part in the market agreement. In the second phase, each company that has joined the market agreement may choose to report the agreement.

Your earnings will depend on whether or not you choose to join the market agreement and on how many others join the agreement. Your earnings will also depend on whether or not you and other companies report the market agreement. Each round will proceed in the following manner.

Phase 1

In this first phase of each round, a chat window will appear for 60 seconds. You are able to communicate with the three other companies in your market using this chat window. You only need to type in the text that you wish to communicate. Your own text, as well as the text that other members of your group type in, will appear and can always be seen by all members of your group. It cannot be seen by any members of other groups. You can see how much time remains for the chat by looking at the top of your chat window. After 60 seconds, the chat window will disappear.

After the chat ends, a new screen will appear in which you must indicate whether or not you would like to join the market agreement. A market agreement is made if two or more companies choose to join it. Your current earnings at this point depend on how many people chose to join the market agreement.

∗ If all four companies join the market agreement: All four companies receive 100 ECU.
∗ If three companies join the market agreement and one company does not: Those who joined each receive 59 ECU. Those who do not join receive 178 ECU.
∗ If two companies join the market agreement and two companies do not: Those who joined receive 50 ECU. Those who do not join receive 100 ECU.
∗ If one company tries to join the market agreement and three companies do not: All four companies receive 64 ECU
∗ If no companies try to join the market agreement: All four companies receive 64 ECU.

Phase 2

If at least two companies have chosen to join the market agreement, an agreement is made and the round moves on to phase 2. Only those who have entered the market agreement participate in phase 2. In phase 2, each company that has entered the market agreement can choose whether or not to report the agreement. Based on whether or not you and others have reported the agreement, you may lose some of the earnings that you had at the end of phase 1.

∗ If you choose to report the agreement and you are the first to report, then you do not lose any earnings.
∗ If you choose to report the agreement but are not the first to report, then you will lose some of your phase 1 earnings. The amount you lose can be calculated using the table below.
∗ If you choose not to report the agreement but one of the other companies in the agreement reports, then you will lose some of your phase 1 earnings. The amount you lose can be calculated using the table below.
∗ If no companies in the agreement report, then there is an 85% chance that none of them will lose any earnings. However, there is a 15% chance that the agreement is discovered by a market monitor and then all of them including you lose some of your phase 1 earnings. The amount you lose can be calculated using the table below.

Those companies that have not entered the market agreement cannot report the agreement, and cannot lose any of their phase 1 earnings. If fewer than two companies join the market agreement, there is no phase 2 for the round.

How to calculate your earnings for each round

You can use the following table to help you make your decisions. The rows in the table correspond to the number of companies in your market that have chosen to enter the market agreement. The first column shows the number of companies that have entered the market agreement. Column 2 shows the phase one payoff if you enter the market agreement and how it depends on how many other companies have also entered the agreement. Column 3 contains your final earnings for the round if no company reports the agreement or if you are the first to report the agreement. In these cases, your final earnings for the round are equal to your phase 1 earnings. In the fourth column, you can see what you earn if another company is the first to report or if the agreement is discovered by a market monitor. Finally, column 5 shows your earnings if you do not enter the agreement.

How many rounds count toward your 'final earnings'

In the experiment, you will participate in 10 rounds. However, they may not all count toward your earnings. Imagine that a 10-sided die, with each number 1 to 10 on exactly one side, is rolled after each round. If it comes up 1, the round that has just finished becomes the last round that counts toward your earnings. If the die comes up 2, 3,..., 10, the next round also counts. Therefore, there is always a 90% chance that the next round counts, no matter what round you are currently playing. This means that there is a 100% chance that round 1 will count, a 90% chance that round 2 will count, a $0.9 \times 0.9 = 81\%$ chance that round 3 will count, a $(0.9)^3 = 73\%$ chance that round three will count, etc.

You do not see these die rolls, and you will not know which round is the last one that counts until the experiment ends. If the die does not come up 1 for 10 rounds, then you will receive the earnings from all 10 rounds you play, as well as an additional amount equal to your earnings for the 10 rounds. So in that case, you get 2 times your earnings over the 10 rounds. There is a 35% chance of this occurring.

Let's wait for other players by clicking "Next" and start the game!

Appendix C

Chapter 3 Appendix

C.1 Tasks for experiment

Here we show the optimal portfolio MV allocations and the optimal portfolio QP allocations from all of the tasks. These 90 tasks are divided in five categories from C.1.1 to C.1.5. Each category considers a different type of relationship between two Uniform distributions, each corresponding to a different lottery A and B. The section also presents figures with the optimal portfolio allocation w^*, that corresponds to lottery A. Left panels plot the optimal allocation under the MV framework and the right panel plot the optimal allocation under the QP framework. The x-axis captures risk aversion. For the MV case, we report w^* as a function of $1/\gamma$, and for the QP case, we report w^* as a function of τ.

C.1.1 Experiments replicating Example 3.2.2:

In these examples, B first order stochastically dominates A. Note that the options in this experiment, described as lotteries, are reversed compared to the example.

[1] $A: U[0,2]$ $B: U[0,20]$	[2] $A: U[0,4]$ $B: U[0,20]$	[3] $A: U[0,6]$ $B: U[0,20]$
[4] $A: U[0,8]$ $B: U[0,20]$	[5] $A: U[0,10]$ $B: U[0,20]$	[6] $A: U[0,12]$ $B: U[0,20]$
[7] $A: U[0,14]$ $B: U[0,20]$	[8] $A: U[0,16]$ $B: U[0,20]$	[9] $A: U[0,18]$ $B: U[0,20]$
[10] $A: U[0,20]$ $B: U[0,20]$	[11] $A: U[4,10]$ $B: U[4,20]$	[12] $A: U[4,12]$ $B: U[4,20]$
[13] $A: U[4,14]$ $B: U[4,20]$	[14] $A: U[4,16]$ $B: U[4,20]$	[15] $A: U[4,18]$ $B: U[4,20]$
[16] $A: U[10,16]$ $B: U[10,25]$	[17] $A: U[10,18]$ $B: U[10,25]$	[18] $A: U[10,20]$ $B: U[10,25]$
[19] $A: U[10,22]$ $B: U[10,25]$	[20] $A: U[10,24]$ $B: U[10,25]$	

C.1.2 Experiments replicating Example 3.2.3:

In these examples, lottery A first order stochastically dominates lottery B. Note that there are different lower ends of the distributions.

[21] $A : U[2, 20]$ $B : U[0, 20]$	[22] $A : U[4, 20]$ $B : U[0, 20]$	[23] $A : U[8, 20]$ $B : U[0, 20]$
[24] $A : U[12, 20]$ $B : U[0, 20]$	[25] $A : U[16, 20]$ $B : U[0, 20]$	[26] $A : U[4, 25]$ $B : U[0, 25]$
[27] $A : U[8, 25]$ $B : U[0, 25]$	[28] $A : U[12, 25]$ $B : U[0, 25]$	[29] $A : U[16, 25]$ $B : U[0, 25]$
[30] $A : U[20, 25]$ $B : U[0, 25]$	[31] $A : U[2, 10]$ $B : U[0, 10]$	[32] $A : U[4, 10]$ $B : U[0, 10]$
[33] $A : U[6, 10]$ $B : U[0, 10]$	[34] $A : U[8, 10]$ $B : U[0, 10]$	[35] $A : U[10, 15]$ $B : U[0, 15]$

C.1.3 Experiments replicating Example 3.2.4:

In these examples, lottery A stochastically dominates lottery B. The support of the random variables overlaps.

[36] $A : U[2, 22]$ $B : U[0, 20]$	[37] $A : U[4, 24]$ $B : U[0, 20]$	[38] $A : U[6, 26]$ $B : U[0, 20]$
[39] $A : U[8, 28]$ $B : U[0, 20]$	[40] $A : U[10, 30]$ $B : U[0, 20]$	[41] $A : U[12, 32]$ $B : U[0, 20]$
[42] $A : U[14, 34]$ $B : U[0, 20]$	[43] $A : U[16, 36]$ $B : U[0, 20]$	[44] $A : U[18, 38]$ $B : U[0, 20]$
[45] $A : U[16, 26]$ $B : U[10, 20]$	[46] $A : U[2, 12]$ $B : U[0, 10]$	[47] $A : U[14, 30]$ $B : U[0, 16]$
[48] $A : U[12, 28]$ $B : U[0, 16]$	[49] $A : U[10, 26]$ $B : U[0, 16]$	[50] $A : U[8, 24]$ $B : U[0, 16]$
[51] $A : U[6, 22]$ $B : U[0, 16]$	[52] $A : U[4, 20]$ $B : U[0, 16]$	[53] $A : U[2, 18]$ $B : U[0, 16]$
[54] $A : U[2, 16]$ $B : U[0, 14]$	[55] $A : U[4, 18]$ $B : U[0, 14]$	

C.1.4 Experiments replicating Example 3.2.5:

In these examples, there is no stochastic dominance on either side.

[56] $A : U[2, 18]$ $B : U[0, 20]$	[57] $A : U[4, 16]$ $B : U[0, 20]$	[58] $A : U[6, 14]$ $B : U[0, 20]$
[59] $A : U[8, 12]$ $B : U[0, 20]$	[60] $A : U[6, 22]$ $B : U[4, 24]$	[61] $A : U[8, 22]$ $B : U[4, 24]$
[62]$A : U[6, 20]$ $B : U[4, 24]$	[63]$A : U[8, 20]$ $B : U[4, 24]$	[64]$A : U[12, 18]$ $B : U[10, 20]$
[65]$A : U[14, 18]$ $B : U[10, 20]$	[66]$A : U[16, 18]$ $B : U[10, 20]$	[67]$A : U[14, 16]$ $B : U[12, 20]$
[68]$A : U[13, 17]$ $B : U[12, 18]$	[69]$A : U[14, 16]$ $B : U[12, 18]$	

C.1.5 Example with risk-free asset:

In these examples, there is no stochastic dominance on either side. Lottery A corresponds to a risk-free asset with fixed payoff.

[70] $A:2$ $B:U[0,20]$	[71] $A:4$ $B:U[0,20]$	[72] $A:6$ $B:U[0,20]$
[73] $A:8$ $B:U[0,20]$	[74] $A:10$ $B:U[0,20]$	[75] $A:12$ $B:U[0,20]$
[76] $A:14$ $B:U[0,20]$	[77] $A:16$ $B:U[0,20]$	[78] $A:18$ $B:U[0,20]$
[79] $A:20$ $B:U[0,20]$	[80] $A:12$ $B:U[8,16]$	[81] $A:9$ $B:U[8,20]$
[82] $A:8$ $B:U[4,24]$	[83] $A:10$ $B:U[8,12]$	[84] $A:6$ $B:U[2,10]$
[85] $A:14$ $B:U[4,24]$	[86] $A:16$ $B:U[4,24]$	[87] $A:18$ $B:U[4,24]$
[88] $A:20$ $B:U[4,24]$	[89] $A:22$ $B:U[4,24]$	[90] $A:24$ $B:U[4,24]$

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