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To my family

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ABSTRACT

My dissertation consists of three chapters in the field of managerial economics and experimental economics. The first chapter studies the ratchet effect and the possible ways to mitigate it. Specifically, I conduct a controlled experiment to test the effectiveness of job rotation in eliminating the ratchet effect. Additionally, I compare effort provision between the situation where agents are rotated exogenously and the situation where the principal rotates agents endogenously. The experiment shows that the ratchet effect is effectively reduced both when workers are informed that they will be rotated in the future and when a principal has a costly option of rotating agents.

The second and third chapter are based on joint work with Prof. Yaroslav Rosokha. In the second chapter, we study a single-queue system in which human servers have discretion over the effort with which to process orders that arrive stochastically. We show theoretically that the efficient outcome in the form of high effort can be sustained in the subgame perfect equilibrium if the interactions are long term (even when each server has a short-term incentive to free ride). In addition, we show that queue visibility plays an important role in the type of strategies that can sustain high-effort equilibrium. In particular, we show that limiting feedback about the current state of the queue is beneficial if servers are patient enough. We conduct a controlled lab experiment to test the theoretical predictions and find that when the queue is visible, human subjects cooperate if the queue is long, but defect if the queue is short. We also find that cooperation is hard to achieve when the queue is not visible.

In the third chapter, we report another lab experiment to test the theory developed in the second chapter. In the new experiment, we provide a more natural queueing frame for the subjects rather than the neutral language used in the second chapter. We also increase the number of matches in each treatment. We find that effort increases with the expected duration of the interaction. We also find that visibility has a strong impact on the strategies that human subjects use to provide effort. As a result, providing less visibility makes servers more willing to provide high effort if they are patient enough.

INTRODUCTION

In this thesis, I study how workers behave under different managerial mechanisms. I am interested in studying which mechanism could motivate workers to provide more effort, and thus lead to higher efficiency in a firm or organization. Throughout this thesis, I utilize both theoretical and experimental methodologies to answer my research questions. While the papers in this thesis may analyze different environments, they are connected by their attempt to provide managerial implications for managers and firms.

In the first chapter, I study the ratchet effect since there is evidence that the ratchet effect does exist in both industrial settings and laboratory settings. The ratchet effect refers to the phenomenon where an agent strategically restricts effort and output levels in order to avoid revealing private information to the principal. Since it is socially inefficient, I experimentally investigate the extent to which job rotation may help to mitigate the ratchet effect. Job rotation is theoretically possible to offset the ratchet effect. It has also been shown to improve welfare in topics such as collusion, innovation, and corruption. The novelty of this study is that I compare effort provision between the situation where agents are rotated exogenously and the situation where the principal rotates agents endogenously.

The experiment shows that the ratchet effect is significantly reduced when workers are informed that they will be rotated in the future. We also find that the ratchet effect is significantly reduced when a principal has a costly option of rotating agents, which is contrary to the prediction using Perfect Bayesian Equilibrium but consistent with the literature regarding the costly punishment. In that strand of literature, an option of costly punishment is able to promote contribution in social dilemma games. The experimental results have clear implications for managers in operating firms. Our experiment first provides additional evidence of the existence of the ratchet effect. When managers makes policies regarding efficiency improvement and effort motivation, mechanisms of eliminating the ratchet effect should not be ignored. If there is no cost of rotating workers, regularly rotating workers between jobs should be considered. When there is a cost of rotating workers, to reduce the ratchet effect, managers may also inform workers that she has an option to rotate workers.

In the second chapter, we study queueing systems that underlie many economic activities. We point out that servers usually work as a team over a long term. The long-term interactions could allow for the development of reputation and reciprocity. Therefore, we focus on a scenario where human servers work together over an indefinite horizon to repeatedly process orders from a single queue. Using the techniques of subgame perfect Nash equilibrium, dynamic programming, and some properties of Markov Chain, we first theoretically show that even when individuals face incentives to free ride, high effort can be supported if the expected length of the servers' interaction is long enough. Additionally, we investigate the role of queue visibility on servers' effort provision. We show that if the expected length of the servers' interaction is short and the queue is visible, servers are more willing to provide high effort. When the queue is less visible, sustaining high effort is still possible if the expected length of the servers' interaction is long enough.

In the experiment, we test the theoretical predictions using neutral language to achieve the experimental control. The experiment shows clear evidence that effort increases with the expected duration of the repeated interaction. Regarding the effect of queue visibility, we find that when servers can see the state of the queue, a significant proportion of subjects provide high effort when the queue is long, but to provide low effort when the queue is short. We also find that when subjects are provided less visibility of the queue, cooperation is difficult to achieve even when the discount factor is large and cooperation is theoretically possible. Lastly, we conduct an econometric estimation of strategies that subjects use. We find that when the queue is visible, a significant portion of subjects rely on state- and history-contingent strategies during the interaction with other subjects. These strategies not only respond to the current state of the queue, but also respond to the behavior observed the last time the queue was in the current state.

The third chapter presents another lab experiment to test the theory developed in the second chapter. Instead of the neutral language used in the experiment in the second chapter, we provide a context-rich framing for the participants during the new experiment. We assume servers work together to process tasks and each server's cost depends on the effort by the other server. In the experimental instructions, we also present details of the cost and compensation functions to the subjects. Lastly, we include more matches for each treatment in the new experiment.

The results of the experiment in the third chapter are consistent with the results in the second chapter. We first find evidence that average effort increases with the expected duration of repeated interaction. We also find that when the queue is visible, the average effort is higher when the queue is long than when the queue is short. The most interesting result is that we find support for the theoretical predictions regarding the effect of queue visibility. That is, when the expected duration of future interaction is short, servers provide higher effort when the queue is visible than when it is not, but when the expected duration of future interaction is long, the opposite is true.

The second and third chapters have several implications for managers who are trying to design more efficient queueing systems. First, in the presence of a group-based incentive scheme, emphasizing the long-term nature of the interaction among the servers is important. This implication also suggests that the managers should be cautious when implementing policies regarding rotating human servers among groups. Although regularly rotating workers among teams has been shown to have multiple benefits in literature (e.g., limit collusion, reduce the ratchet effect, and promote innovation), it may intensify free-riding. Second, based on the theoretical and experimental results, ensuring that the queue is visible would be useful when the expected duration of interaction is short. When the interactions are long, however, hiding information about the state of the queue, may be beneficial if the manager would like to instill fast and homogeneous processing speeds across all of the states of the queue. On the other hand, if managers value the servers' welfare, providing more visibility should be considered.

1. CAN JOB ROTATION ELIMINATE THE RATCHET EFFECT: EXPERIMENTAL EVIDENCE

1.1 Introduction

The ratchet effect refers to the phenomenon where an agent strategically restricts effort and output levels in order to avoid revealing his private information to his principal (Ickes and Samuelson [1], Laffont and Tirole [2], Charness and Kuhn [3], Cardella and Depew [4], and Charness, Kuhn, and Villeval [5]).[1] Specifically, this phenomenon arises when a principal contracts with an agent, whose effort is not enforceable, in multiple periods, and binding multi-period contracts are not feasible. In these situations, working hard to produce more output in the early periods may unintentionally reveal private information to the principal, which can then be used by the principal in the later periods to extract more surplus from the agent (ratcheting). This private information is classified in two main ways in the literature, the worker's ability or the firm's technology. If the agent is able to anticipate the principal's response, he might lower his effort and output levels to conceal his private information in early period. The ratchet effect is socially inefficient since agents strategically restrict their performance in the early periods. Consequently, principals are unable to take optimal actions which might be conditional on the private information that agents concealed.

The empirical literature indicates that the ratchet effect does exist in both industrial settings and laboratory settings. For instance, Bouwens and Kroos [6] show that store managers in a Dutch retailer reduce sales effort in the final quarter in order to mitigate the increase in their next-year sales target. Using the data from 51 local banks, Bol and Lill [7] find evidence of strategic output-restriction for a subset of general directors who do not have an implicit agreement with their principals . In an implicit agreement, general directors agree not to restrict output, and principals will not "punish" them by increasing the target in later period (ratcheting). Meanwhile, Cooper, Kagel, Lo, *et al.* [8], Charness, Kuhn, and Villeval [5] and Cardella and Depew [4] also find the existence of the ratchet effect in their experiments. In Cooper, Kagel, Lo, *et al.* [8], the contextualized instructions speed up the

[1]↑Throughout the article, when referring to the principal (agent), we use a feminine (masculine) pronoun.

learning process and promote the strategic play for the actual firm managers. So there are similarities between the real-world ratchet effect and the lab version, and the similarities are strong enough that the actual firm managers are able to use their real-world experience to improve their laboratory decision making.[2]

Both the theoretical literature and the empirical literature have proposed a variety of mechanisms that might reduce the ratchet effect. Kanemoto and MacLeod [9] theoretically show that ex-post competition among principals for agents is effective in eliminating the ratchet effect. Charness, Kuhn, and Villeval [5] support the prediction of Kanemoto and MacLeod [9] using a laboratory experiment. Their experiment also supports the effectiveness of ex-post competition among agents for jobs in eliminating the ratchet effect. Meyer and Vickers [10] present a dynamic agency model which shows that relying on peer performance information can alleviate the ratchet effect under certain conditions. Casas-Arce, Holzhacker, Mahlendorf, *et al.* [11] adapt the model of Meyer and Vickers [10] and provide evidence that incorporating past peer performance into target setting can reduce the ratchet effect. Cardella and Depew [4] find that the ratchet effect can be mitigated by evaluating agents' productivity at the group-level.

Additionally, a common assumption in the theoretical literature is that job rotation offsets the ratchet effect.[3] For example, in the work of Ickes and Samuelson [1], the authors state that "Job transfers break the link between current performance and future incentive schemes, and hence remove the incentive-stifling implications of the ratchet effect". Arya and Mittendorf [12] also state "When agents privately learn about the productivity of tasks on which they work, job rotation can be an efficient means of eliciting their information". Meanwhile, Hakenes and Katolnik [13] suggest that rotating agents to a different job creates fresh impetus for costly effort. Note that in this strand of literature, the private information possessed by the worker refers to the firm's technology. If the private information was about

[2]↑ Charness, Kuhn, and Villeval [5] conclude that the experiment conducted by Cooper, Kagel, Lo, *et al.* [8] supports the external validity of the ratchet effect found in the laboratory.
[3]↑ Job rotation also refers to "job transfers" in some literature.

the worker's ability, job rotation would not give the worker incentives to reveal the ability and would not help to combat the ratchet effect.[4]

However, it is hard to test the effectiveness of job rotation in reducing the ratchet effect using observational data: agents may have pro-social behaviors; principals might not rotate agents due to the loss of job-specific human capital; and sample sizes of studying the job rotations are sometimes small. For example, Bouwens and Kroos [6] fail to find evidence that job rotation can mitigate the ratchet effect using their data. They attribute this failure to the limited sample size. To the best of our knowledge, no empirical evidence exists to support the common assumption regarding the effectiveness of job rotation in eliminating the ratchet effect.

Therefore, our project investigates the extent to which job rotation may help to offset the ratchet effect. Specifically, we have designed a controlled lab experiment to test the impact of job rotation on the ratchet effect under different scenarios. The strong theoretical prediction and the lack of empirical evidence suggest the necessity and the importance of our study. In addition, the novelty of our project is that we compare agents' behavior between a situation in which all agents are rotated and a situation in which the principal has a costly option to rotate agents endogenously.

We implement three treatments to study the effect that job rotation has on reducing the ratchet effect: No Rotation Treatment, Exogenous Rotation Treatment, and Endogenous Rotation Treatment. For all of these three treatments, a principal, who has two new food stands, interacts with two agents over two stages. The principal hopes to hire these two agents to manage the stands separately. Each stand can be either highly productive or less productive, and the distribution of stands' type is common knowledge. An agent is informed about the productivity of the stand once he is assigned to the stand, whereas the principal does not know the exact type of each stand initially. In the first stage, the agent

[4]↑We are also aware of some qualitative and anecdotal examples that suggest an impact of job rotation on the effort/output restriction. Mathewson [14] writes that "an experienced worker came to this second plant from the first plant which had the higher rates. This new worker soon earned 50 percent more than had been customary on this type of work in the second plant." Knoeber [15] finds that the collusion of reducing effort among meat producers under a relative incentives scheme is limited since the principal regularly shuffles their competitors. Bandiera, Barankay, and Rasul [16] suggest that reallocating workers to different fields on different days is one of the reasons why the ratchet effect is unlikely in a fruit farm.

who works in a less productive stand produces low output, and the agent who works in a highly productive stand can decide to produce either high output or low output. Although providing high output is beneficial for the principal, the agent faces a trade-off between the current benefit and the long-term benefit. In the second stage, after having observed agents' first-stage outputs, the principal chooses a fixed amount of money (rental fee) for each agent. Agents can choose to not work in the second stage, but they have to pay the rental fee if they choose to work and produce goods. In the No Rotation Treatment, two agents are kept in the same stand across two stages. In the Exogenous Rotation Treatment, two agents in the same group are forced to switch between two stands before they enter into the second stage, which is the only difference between this treatment and the No Rotation Treatment. In the Endogenous Rotation Treatment, the principal can choose to either rotate agents between stands or keep them in the same stands before they enter into the second stage. The principal pays a small cost to rotate agents.

The experimental results confirm that job rotation has a significant effect on reducing the ratchet effect. In all three treatments, principals extract more surplus (i.e., choose a higher rental fee) from an agent if the stand that the agent is going to run produced more output in the first stage. In the No Rotation Treatment, a ratchet effect is observed since a large share of agents choose to provide low effort levels when they are in a high-productivity stand in the first stage. The ratchet effect is significantly reduced in the Exogenous Rotation Treatment because nearly all agents choose to provide high effort levels when they run a high-productivity stand in the first stage. Moreover, the ratchet effect in the Endogenous Rotation Treatment is less severe than the No Rotation Treatment. This is surprising since Perfect Bayesian Equilibrium predicts that an agent should shirk in the first stage when he is in a high-productivity stand both in the No Rotation Treatment and in the Endogenous Rotation Treatment. Contrary to the theory, however, we find that principals are more likely to rotate agents if they observe low output levels produced in the first stage in the Endogenous Rotation Treatment. The higher frequency that agents produce high output in the first stage is therefore attributed to the principal's out of equilibrium behavior.

The ratchet effect has been extensively studied in various theoretical contexts including environmental regulation, innovation, education, and centrally planned economies (see

Cardella and Depew [4], Charness, Kuhn, and Villeval [5], and Cooper, Kagel, Lo, *et al.* [8] for reviews). Similar to Cooper, Kagel, Lo, *et al.* [8] and Charness, Kuhn, and Villeval [5], our experiment captures the common features of the strategic interaction between principals and agents in the environment where the ratchet effect emerges. In these environments, a ratchet effect arises when agents who have favorable private information imitate agents who have inferior information, thus resulting in a pooling equilibrium. This project contributes not only to the literature regarding the existence of the ratchet effect, but also to the literature regarding the possible mechanisms that can mitigate the ratchet effect. We join Charness, Kuhn, and Villeval [5] and Cardella and Depew [4] in testing these mechanisms using a stylised laboratory experiment, but we are distinct in assuming that the private information concealed by agents is the firm's technology (rather than agent's ability). Our work also features a stated-effort/output (instead of real-effort) design of studying an endogenous mechanism that firms are able to implement. This stated-effort/output design enables us to control over the relevant aspects of the model that we studied, which makes it more feasible to identify the ratchet effect and study the effect of job rotation. We refer readers to Charness, Gneezy, and Henderson [17] for the comparison between the stated-effort design and the real-effort design.

We then provide the first empirical evidence to support the theoretical literature regarding the effectiveness of job rotation on the ratchet effect. More broadly, this project adds evidence to the welfare improvements of job rotation as job rotation has been studied in the frameworks outside labor economics. For instance, job rotation is observed to limit the collusion among agents under a relative incentives scheme (Knoeber [15] and Bandiera, Barankay, and Rasul [16]). Meanwhile, job rotation is argued to promote process (rather than product) innovation by Carmichael and MacLeod [18] and Dearden, Ickes, and Samuelson [19]. There is also a strand of literature that studies the effect of job rotation on reducing the corruption behavior (Choi and Thum [20], Abbink [21], and Fišar, Krčál, Staněk, *et al.* [22]).

In addition, we show that a costly option of job rotation can alleviate the ratchet effect, which contributes to the literature related to the option of punishment. This strand of literature finds that participants in social dilemma experiments punish free riders even though the punishment is costly (Brandts and Charness [23], Carpenter [24], Villeval and Masclet

[25], and Cason and Gangadharan [26]). This behavior is caused by multiple reasons such as the fear of being a “sucker” or the enjoyment of punishing others (Fehr and Gächter [27] and Fudenberg and Pathak [28]). Importantly, researchers observe more pro-social behaviors in the environment where the option of costly punishment is provided compared to the environment where it is not available (Bochet, Page, and Putterman [29], Casari and Luini [30], and Ambrus and Greiner [31]).

The rest of the paper is structured as follows. Section 1.2 describes the theoretical environment and the experimental design. Section 1.3 presents the experimental results and the empirical analysis. Section 1.4 concludes the paper.

1.2 Environment and Experimental Design

In this section, we first present the theoretical environment and introduce each of the parameters in section 1.2.1. Then, we outline the procedure of our experiment in section 1.2.2. Finally, we describe each of the three treatments and develop testable hypotheses in section 1.2.3 and section 1.2.4.

1.2.1 Theoretical Environment

In order to study the effect of job rotation on the ratchet effect, we implement an environment that is similar to Charness, Kuhn, and Villeval [5]. A principal, who will interact with an agent over two stages, owns a new food stand. The principal wants to make an offer to the agent at the beginning of each stage in order to have that agent run the food stand. We assume that agents are homogeneous and risk neutral, and that they attempt to maximize the sum of their profits over two stages. The principal is also risk neutral, and her objective function is the total surplus generated by the agent minus a salary that she has to pay. This form of objective function is common in the ratchet effect literature (Cooper, Kagel, Lo, *et al.* [8]).

There are two types of stands: high-productivity stand ($\overline{\theta}$) and low-productivity stand ($\underline{\theta}$), where $\overline{\theta} > \underline{\theta}$. The stand is highly productive with probability p, and less productive with probability $1 - p$. The type of the stand is determined independently and randomly according to p at the start of the first stage and is fixed across stages. The probability p is common knowledge to both the principal and the agent. We assume the principal does not know the exact productivity of the stand at the beginning of the interaction since the stand is new, but the agent learns the type of the stand once he receives the job offer. Appendix A.1 provides the specific form of both parties' utility function and the first best outcomes under this environment.

In our setting, we assume the agent is a residual claimant. That is, the agent receives all revenues from the production, whereas the principal receives a rental fee from the agent.[5] This rental fee is the only source of profit the principal can obtain. In the first stage, since

[5]↑See the discussion of the rental fee in Charness, Kuhn, and Villeval [5]

the principal does not know the productivity of the stand, she offers a fixed rental fee R for the agent. If the agent rejects the offer, both parties receive 0 as their payoffs in the first stage. If an agent is in a low-productivity stand, he can only produce Y_L units of output by exerting effort e_L. On the other hand, if an agent is in a high-productivity stand, he is able to produce Y_H by exerting effort e_H. Meanwhile, if this agent behaves as if he is in a low-productivity stand by producing Y_L, he chooses to shirk by exerting effort e_S.[6]

The second stage in our experiment is twice as long as the first stage in order to make the difference between the payoff from shirking and the payoff from working hard in the first stage more salient. This design is consistent with Charness, Kuhn, and Villeval [5].[7] For example, The first stage represents the first week of operation, and the second stage represents the following two weeks of operation. As a result, an agent can provide either $2Y_H$ or $2Y_L$ if he works in a high-productivity stand in the second stage, and can provide $2Y_L$ if he works in a low-productivity stand. At the beginning of this stage, the principal offers either R_H or R_L as the rental fee that the agent has to pay. Similar to the first stage, both parties earn 0 if the agent rejects the offer.

To increase the chance of observing the ratchet effect in our baseline treatment, the principal should incorporate the output information from the agent into setting the second-stage rental fee, and the agent should use the pooling strategy to conceal the type of a high-productivity stand. For the sake of this goal and simplicity, we set $\underline{\theta} = 10$, $\overline{\theta} = 14$ and $p = \frac{1}{3}$.[8] Based on the derivations in Appendix A.1, we get $\underline{\mathrm{e}^*} = 5$, $\overline{\mathrm{e}^*} = 7$, and $\mathrm{e}_S = \frac{25}{7}$. Accordingly, we get $Y_H = 98$ and $Y_L = 50$. We also set $R = 15$, which is small enough so that an agent is willing to accept the offer regardless of the type of stand that he will run, and hence makes it feasible to test the ratchet effect. Finally, we allow principals to choose either $R_H = 60$ or $R_L = 30$ as the rental fee. This ensures that the agent earns a positive payoff even if he reveals the type of his stand and the principal earns the larger share of the contract's surplus. Table 1.1 lists players' payoffs in different scenarios.

6↑This is a special case of the more generous continuous model studied in Appendix A.1

7↑The difference of the length between two stages is only regarding the payoff space. There is no difference between two stages regarding the actual time in the experiment.

8↑In Charness, Kuhn, and Villeval [5], there are two types of workers: low-talented workers and high-talented workers. The social optimal output levels are 50 and 100 for the low- and high-talented workers. The maximum rental fees that a firm charges each type of workers are 25 and 50.

Table 1.1. Payoff Table

Stage	Stand Type	Rental Fee	Agent's Choice	Output	Principal's Payoff	Agent's Payoff
First	$\overline{\theta}$	15	Reject	0	0	0
			High Output(Y_H)	98	15	34
			Low Output(Y_L)	50	15	22.24
	$\underline{\theta}$	15	Reject	0	0	0
			Low Output(Y_L)	50	15	10
Second	$\overline{\theta}$	30	Reject	0	0	0
			High Output($2Y_H$)	196	30	68
			Low Output($2Y_L$)	100	30	44.48
		60	Reject	0	0	0
			High Output($2Y_H$)	196	60	38
			Low Output($2Y_L$)	100	60	14.48
	$\underline{\theta}$	30	Reject	0	0	0
			Low Output($2Y_L$)	100	30	20
		60	Reject	0	0	0
			Low Output($2Y_L$)	100	60	-10

Note: In the second stage, when an agent runs a high-productivity stand, it is always optimal for him to provide high output. When a worker runs a low-productivity stand, it is optimal for him to reject to work if he is charged the high rental fee.

1.2.2 Experimental Procedures

We recruited 108 students from the ORSEE (Greiner [32]) database, and the experimental software was programmed in oTree (Chen, Schonger, and Wickens [33]). We ran nine sessions at the Vernon Smith Experimental Economics Laboratory (VSEEL) at Purdue University in August and September 2019, and each session included 12 student subjects. We used a between-subjects design where each participant took part in only one session of a given experimental treatment.

The experimental instructions (see Appendix A.4 for Exogenous Rotation Treatment) and a payoff table (see Appendix A.5) were provided to each subject in a written form and were read aloud in a neutral voice (created by Microsoft Word) by a computer speaker. Subjects completed an incentivized quiz (see Appendix A.6 for Exogenous Rotation Treatment) at the end of the instructions, which contains 10 questions to test their understanding of the instructions. We used experimental points as the currency with 100 points equal to 4 U.S. dollars. The average earnings were \$17 including a \$5 show-up fee, and the session lasted approximately 60 minutes. Subjects were paid in cash at the end of the session.

Each session consisted of 45 rounds, and these 45 rounds were broken down into nine blocks with each block consisting of five rounds. There were three roles of players: firm f, worker $w1$ and worker $w2$. Subjects were informed of their role at the beginning of each block, and kept the same role throughout these five rounds. Each firm was paired with a worker $w1$ and a worker $w2$, and they were re-matched randomly for each new round. Subjects experienced each role for three blocks, and the order was randomly determined.[9] The computer randomly selected 3 rounds (one from each role) for payment.

In each round, a firm (f), who owns two new food stands ($S1$ and $S2$), interacts with two workers ($w1$ and $w2$) over two stages.[10] In the first stage of the experiment, all workers accept the offer by default since it is always optimal for workers to accept the offer. At the end of the first stage, a results page shows on each participant's screen, from which workers

[9]↑Specifically, in each session, each subject will be assigned roles nine times according to one randomly selected order from the following three orders: (a) $f, w1, w2, f, w1, w2, f, w1, w2$; ($b$) $w1, w2, f, w1, w2, f, w1, w2, f$; and ($c$) $w2, f, w1, w2, f, w1, w2, f, w1$

[10]↑This enables us to study the effect of switching workers between stands. The analytical reasoning in the baseline treatment is identical to the single-worker environment studied in section 2.1 and Appendix A.1

can observe their actions together with their first stage payoffs and the firm is able to see each stand's output together with her first stage payoffs. It is common knowledge that a firm can see each stand's output. At the end of the second stage, a final results page is presented on each participant's screen. The final results page on a worker's screen shows both his decisions and payoffs from two stages. The final results page on a firm's screen shows both the output produced by each stand and her payoffs from two stages.

1.2.3 Treatments

This experiment has three treatments: No Rotation Treatment (Baseline), Exogenous Rotation Treatment, and Endogenous Rotation Treatment.

No Rotation Treatment (Baseline Treatment)

In this treatment, workers are kept in the same stand across two stages. That is, worker $w1$ is asked to run stand $S1$ for both the first stage and the second stage; worker $w2$ is asked to run stand $S2$ for both the first stage and the second stage. The productivity of each stand stays the same across two stages.

Exogenous Rotation Treatment

In this treatment, two workers are forced to switch between two stands before they enter into the second stage. That is, in the first stage, worker $w1$ is asked to run stand $S1$, and worker $w2$ is asked to run stand $S2$. But in the second stage, worker $w1$ is switched to run stand $S2$, and worker $w2$ is switched to run stand $S1$. The rest of this treatment is the same as the No Rotation Treatment.

Endogenous Rotation Treatment

In this treatment, after seeing the first stage output but before entering into the second stage, the firm chooses to either switch workers between two stands or keep them in the same stands. If the firm chooses to switch workers between stands, worker $w1$ will be offered to run stand $S2$, and worker $w2$ will be offered to run stand $S1$ in the second stage. If the firm chooses to keep workers in the same stands, worker $w1$ will continue running stand $S1$, and worker $w2$ will continue running stand $S2$ in the second stage.

In addition, if the firm chooses to switch workers between stands, she pays a cost $c = 1$ experimental point; if the firm chooses to keep workers in the same stands, she pays no cost. The rest of this treatment is the same as the No Rotation Treatment.

1.2.4 Theoretical Predictions and Hypotheses

This environment can be modeled as a signaling game with incomplete information. We use Perfect Bayesian Equilibrium (PBE) to obtain predictions. In particular, PBE requires each player's strategy to be optimal given her belief, and each player's belief to be updated according to Bayes Rule whenever possible.

In the No Rotation Treatment, only a pooling PBE exists (no separating PBE exist). In a separating PBE in which workers produce type-contingent first-stage outputs, the firm believes that a stand is highly productive if she sees Y_H produced, and a stand is less productive if she observes Y_L produced. Therefore, the firm should charge 60 as the rental fee in the second stage for the agent who produced Y_H in order to maximize her profit, and charge 30 for the agent who produced Y_L. Given her strategy, however, a worker who runs a high-productivity stand has an incentive to deviate since he can earn $22.24 + 68 = 90.24$ instead of $34 + 38 = 72$ if he chose to shirk in the first stage (assume he always behaves rationally by choosing the high effort in the second stage). On the other hand, in a pooling PBE, workers produce Y_L in the first stage regardless the type of a stand. Thus, a firm believes that it is $p = \frac{1}{3}$ that the stand is highly productive when she sees Y_L was produced in a stand. Therefore, if she charges 60 as the rental fee for a worker who produced Y_L, she expects to get 20 since it is only optimal for the worker who runs a high-productivity stand to accept this offer. On the contrary, she gets 30 for certain if she charges 30 as the rental fee. A worker who works in a high-productivity stand has no incentive to deviate from this equilibrium since he would be charged 60 if he produced Y_H in the first stage. This pooling PBE leads to our first testable hypothesis:

Hypothesis 1. In the No Rotation Treatment, workers in a high-productivity stand choose to shirk (produce Y_L) in the first stage.

For a worker who is in the first stage of the Exogenous Rotation Treatment, he knows for certain that he will be switched to the other stand as well as the distribution of the other stand's type. Therefore, his expected payoff in the second stage will be the same regardless of the type of the stand that he is running in the first stage. This expected payoff in the second stage should also be independent of what he did at his stand in the first stage. Meanwhile, if a worker is assigned a high-productivity stand in the first stage, his expected payoff from producing Y_H is the sum of 34 and his expected payoff in the second stage. This is larger than his expected payoff from producing Y_L, which is the sum of 22.24 and his expected payoff in the second stage. The dominant strategy of producing Y_H if he runs a high-productivity stand leads to our second hypothesis:

Hypothesis 2. In the Exogenous Rotation Treatment, workers in a high-productivity stand work hard (produce Y_H) in the first stage.

In the Endogenous Rotation Treatment, a firm will form a belief regarding the type of each stand once she observes the output produced from the two stands in the first stage. This belief is independent of her choice of switching workers in the second stage. Therefore, her expected second-stage payoff from charging rental fees are the same regardless of whether she switches workers between stands. For example, if a firm sees Y_H was produced in stand $S1$ and Y_L was produced in stand S_2, she will be sure that $S1$ is a high-productivity stand and then charge a high rental fee for the agent who will run $S1$ in the second stage. In addition, she will believe that there is a probability μ that stand $S2$ is highly productive. If $60 \times \mu > 30$, she will charge 60 as the rental fee for the worker who will run stand $S2$ in the second stage. In this case, her expected second-stage payoff from collecting rental fees is $60 + 60\mu$, and this is the same between switching workers and not switching workers. However, the firm pays a cost of one experimental point to switch workers between stands. As a result, the firm's expected second-stage payoff from switching workers is $59 + 60\mu$, which is strictly less than her expected second-stage payoff from not switching workers. Similarly, If $60 \times \mu < 30$, the firm's expected second-stage payoff from switching workers is 89, which is less than the expected second-stage payoff from not switching workers (90).

According to the above analysis, firms never find it optimal to rotate workers between stands. Knowing this, a rational worker will behave exactly the same as he would do in the No Rotation Treatment, and thus only pooling PBE exists. This pooling PBE suggests the following two hypotheses:

Hypothesis 3. In the Endogenous Rotation Treatment, firms never switch workers between stands.

Hypothesis 4. In the Endogenous Rotation Treatment, workers in a high-productivity stand choose to shirk (produce Y_L) in the first stage.

One may, however, relax some assumptions and consider job rotation as a costly option of punishment. A firm may transfer a worker who has a possibility of shirking to another workplace even if this transfer cannot increase the firm's payoff. There is a large number of experimental literature shows that subjects punish others since they dislike being the "sucker" (Fehr and Gächter [27]) or they enjoy punishment (Fudenberg and Pathak [28]). As a result, the threat of a costly punishment becomes credible, and then significantly promote pro-social behaviors (See e.g., Villeval and Masclet [25], Cason and Gangadharan [26], Ambrus and Greiner [31], and Nikiforakis [34]).

From firms' perspective, workers who produced Y_L have the possibility to shirk in the first stage. They may switch these workers as a way of punishment even it is costly. If workers can anticipate this, they will be less likely to provide Y_L if they run a high-productivity stand in the first stage. Based on the above reasoning and previous findings, we can write the following two behavioral hypotheses:

Hypothesis 3a. In the Endogenous Rotation Treatment, firms are more likely to switch workers if they observe Y_L was produced in the first stage.

Hypothesis 4a. In the Endogenous Rotation Treatment, workers in a high-productivity stand are more likely to provide Y_H compared with the No Rotation Treatment.

1.3 Results

Table 1.2 provides the summary statistics for each treatment. We proceed by first analyzing firms' behavior and then workers' behavior. In addition, we provide one result for firms' behavior in the Endogenous Rotation Treatment.

Table 1.2. Summary Statistics

Treatments	No Rotation	Exogenous Rotation	Endogenous Rotation
Frequency of a firm choosing high rental fee	Y_H is observed: 168/197 (0.853) Y_L is observed: 97/883 (0.109)	Y_H is observed: 235/312 (0.753) Y_L is observed: 87/768 (0.113)	Y_H is observed: 219/269 (0.814) Y_L is observed: 120/811 (0.148)
Frequency of a worker choosing high output in the first stage*	197/351 (0.561)	311/335 (0.928)	269/361 (0.745)
Frequency of a worker choosing high output in the second stage*	346/351 (0.986)	334/335 (0.997)	350/361 (0.969)
Frequency of choosing switch	-	-	85/540 (0.157)
Average firms' earnings	91.9 (points)	96.8	89.7
Average workers' earnings	43.9 (points)	43.4	42.2

Note: Fractions are in parentheses. * refers to the situation where a worker runs a $\overline{\theta}$ stand.

1.3.1 Firms' behavior

In all three treatments, in order to maximize her expected payoff, a firm should choose a high rental fee for a worker who will run the stand that produced Y_H in the first stage and a low rental fee otherwise. The reasoning can be found in the derivation of Hypothesis 1. Therefore, firms' strategy regarding choosing rental fees should be the same across all treatments. This prediction is supported by Figure 1.1.

Panel A shows the frequency of the high rental fee being offered by firms across all rounds. In the No Rotation Treatment, when a firm observes high output was produced in a stand, she selects a high rental fee in 168 of 197 instances (85.3%) for the worker who will run that stand in the second stage. In the Exogenous Rotation Treatment, this frequency becomes 235 of 312 instances (75.3%), and it is 219 of 269 instances (81.4%) in the

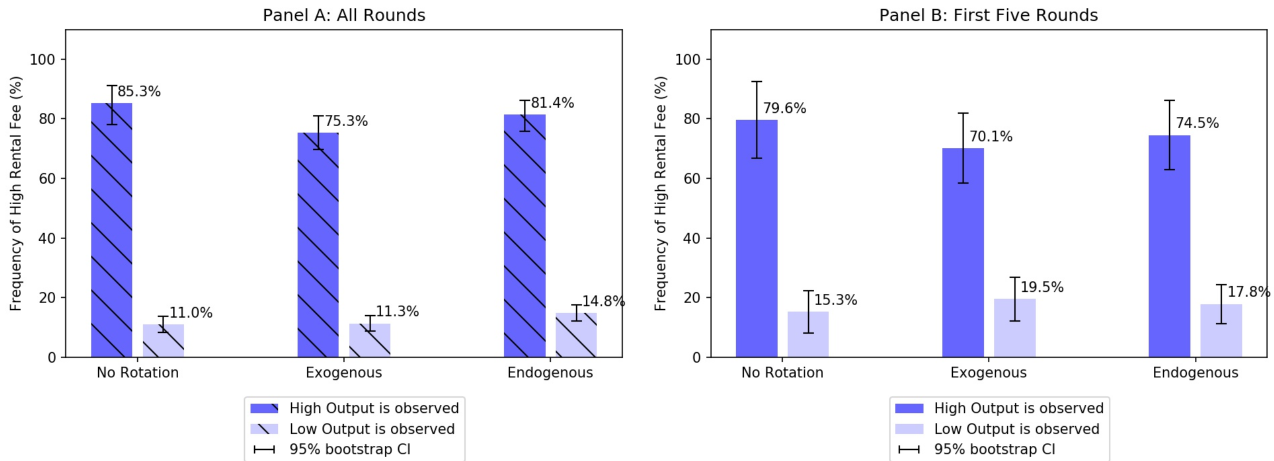


Figure 1.1. Firms' Choices in Three Treatments

Note: 95% bootstrap confidence interval is calculated by drawing 1000 random samples. For each sample, we first draw the appropriate number of subjects with replacement. For each subject, we randomly draw the appropriate number of actions with replacement.

Endogenous Rotation Treatment. Most firms offer high rental fees when workers produced high output, but a small portion of them choose the opposite – they offer low rental fees when high output was observed. These firms' behaviors are consistent with the suggestion of other-regarding preferences. Specifically, subjects are inequality averse and know that others are also inequality averse. Given the firm has selected the high rental fee and the worker is placed in the high-productivity stand, the worker earns less than the firm by providing either the high output or low output, whereas rejecting the offer results no difference between the worker's payoff and firm's payoff. The worker prefers rejecting the offer if he is inequality averse enough.[11] If a firm knows this, she is less likely to choose the high rental fee since there is a risk of receiving nothing by choosing that.

When a firm observes low output was produced, in the No Rotation Treatment, she selects a high rental fee in 97 of 883 instances (11.0%). In the Exogenous Rotation Treatment, a firm chooses a high rental fee in 87 of 768 instances (11.3%) when she observes low output was

[11] ↑Given the firm has selected the high rental fee and the worker is placed in the high-productivity stand, the rejection rate is 14 out of 180 (7.8%)/ 10 out of 236 (4.2%)/ 30 out of 232 (13.0%) in the No Rotation Treatment/ Exogenous Rotation Treatment/ Endogenous Rotation Treatment.

produced. This frequency becomes 120 of 811 instances (14.8%) in the Endogenous Rotation Treatment.[12] These rates show that a few firms offer the high rental fee after the low output was observed. These firms' choices are consistent with the risk loving behaviors, especially in the No Rotation Treatment and in the Endogenous Rotation Treatment. In these two treatments, although the pooling equilibrium suggests the expected payoff of offering the high rental fee ($20 = 1/3 \times 60$) is less than offering the low rental fee (30 for certain), a risk loving firm is more likely to take a chance and offer the high rental fee. Meanwhile, exploration could partially explain why some firms choose high rental fees after low output was observed and choose low rental fees after high output was observed. It is reasonable to conjecture that subjects might spend some time exploring and testing different options if they do not fully understand the environment. This behavior of exploration should be more frequent in the first several rounds.

Panel B shows the frequency of the high rental fee being offered by firms for the first five rounds. Firms' actions in the first several rounds are important because they imply the firms' understanding of the mechanism, from which we also see the evolution of their behaviors by comparing with Panel A. In the first five rounds, the frequency of choosing a high rental fee when a firm observes high output is a bit lower than their correspondent in Panel A.[13] The frequency of choosing a high rental fee when a firm observes low output is a bit higher than their correspondent in Panel A.[14] On the other hand, there is still a clear pattern that a firm is more likely to choose a high rental fee when she observes high output and less likely to choose a high rental fee otherwise.

In order to identify the determinants of a firm choosing a high rental fee, we estimate a random-effect Probit model using firms' choice in the second stage as the dependent variable. This dummy variable "rentalFee" is one if a firm selects the high rental fee and zero otherwise. The independent variables include a dummy variable "output" which is one if high output was observed at a stand in the first stage, and zero if low output was observed. A dummy

[12]↑A bootstrap regression, in which standard errors are clustered at individual level, indicates that these three rates are all significantly different from zero at the one percent level.

[13]↑In the first five rounds, the frequency is 39 out of 49 (79.6%)/ 47 out of 67 (70.1%)/ 38 out of 51 (74.5%) in the No Rotation Treatment/ Exogenous Rotation Treatment/ Endogenous Rotation Treatment.

[14]↑In the first five rounds, the frequency is 20 out of 131 (15.3%)/ 22 out of 113 (19.5%)/ 23 out of 129 (17.8%) in the No Rotation Treatment/ Exogenous Rotation Treatment/ Endogenous Rotation Treatment.

variable for being in the Exogenous Rotation treatment and a dummy variable for being in the Endogenous Rotation Treatment are also included. We also interact these two treatment variables with the variable "output". Since a subject acts as both a worker and a firm sequentially in the experiment, we consider a trend variable "roundFirm" which is the number of rounds an individual has spent as a firm and a trend variable "roundWorkers" which is the number of rounds an individual has spent as a worker in the regression. Tables 1.3 displays the results of the estimation for the first treatment in the first column and for pooling the three treatments in the second column.[15]

Table 1.3. Determinants of a Firm Choosing a High Rental Fee

	No Rotation	*Pooling data*
Variables	rentalFee	rentalFee
roundFirms	0.0144	-0.005
	(0.0243)[0.002]	(0.0125)[-0.001]
roundWorkers	-0.02274	-0.0110
	(0.013)[-0.004]	(0.006)[-0.002]
output	2.328***	2.29***
	(0.134)[0.438]	(0.128)[0.496]
exog	-	0.015
		(0.092)[0.003]
endo	-	0.19**
		(0.089)[0.04]
exog× output	-	-0.37**
		(0.161)[-0.081]
endo× output	-	-0.34**
		(0.165)[-0.073]
constant	-1.028***	-1.041***
	(0.113)	(0.081)
observations	1080	3240
Number of id	36	108

Note: Standard errors (clustered at individual level) are in parentheses, and marginal effects are in brackets. The first column displays the estimation for the No Rotation Treatment, and the second column displays the estimation for pooling the three treatments. "output" is 1 if a high output is observed at a stand in the first stage, and 0 if a low output is observed. "exog" is 1 if the subject is in the Exogenous Rotation Treatment, and 0 otherwise. The dummy variable "endo" is 1 if the subject is in the Endogenous Rotation treatment , and 0 otherwise. Variable "roundFirms" is the number of decisions a subject has made as a firm (from 1 to 15); variable "roundWorkers" is the number of decisions a subject has made as a worker (from 1 to 30). *** p<0.01, ** p<0.05, * p<0.1.

[15]↑ Standard errors estimated in Table 1.3 are clustered at individual level. See Table A.1 in Appendix A.2 for regression models in which standard errors are clustered at session level.

Table 1.3 suggests that firms' behavior is mainly influenced by the workers' behavior in the first stage. The probability that a firm selects the high rental fee after having observed high output increases by 43.8 percentage points compared with having observed low output in the first treatment, and by 49.6 percentage points in all three treatments. This marginal effect is significant at one percent level. Meanwhile, the probability of choosing the high rental fee in the Endogenous Rotation Treatment increases by 4 percentage points compared with the baseline treatment. Yet the effect of experience and the treatment effect of the exogenous rotation are not significant. The above observations lead to our first result:

Result 1: Most firms are rational when choosing rental fees for workers in all three treatments. They punish a worker's good behavior by extracting more surplus from him – setting a high rental fee.

1.3.2 Workers' behavior

Figure 1.2 shows the choices made by workers who work in a high-productivity stand across stages in three treatments. Panel A displays these choices across all rounds. We first notice that almost all workers behave optimally in the second stage in all three treatments. In the No Rotation Treatment, workers who work in a high-productivity stand choose the high effort (high output) 346 of 351 times (98.5%) in the second stage. Similarly, workers choose the high effort 334 of 335 times (99.7%) in the Exogenous Rotation Treatment, and 350 of 361 times (97.0%) in the Endogenous Rotation Treatment.

By contrast, workers' behavior varies across treatments regarding the effort in the first stage. In the No Rotation Treatment, workers choose the high effort in 197 out of 351 occasions (56.1%). This is in large contrast to the chance of choosing high effort in the second stage, which suggests evidence of the ratchet effect in this treatment.[16] Hypothesis 1 and 4 imply that workers should behave the same in the No Rotation Treatment and in the Endogenous Rotation Treatment. In the Endogenous Rotation Treatment, however, workers

[16]↑Among 36 participants in the No Rotation Treatment, 20 subjects choose the low output more than 50% times in the first stage when they are in a high-productivity stand as a worker. There are also 14 subjects who always choose a high output.

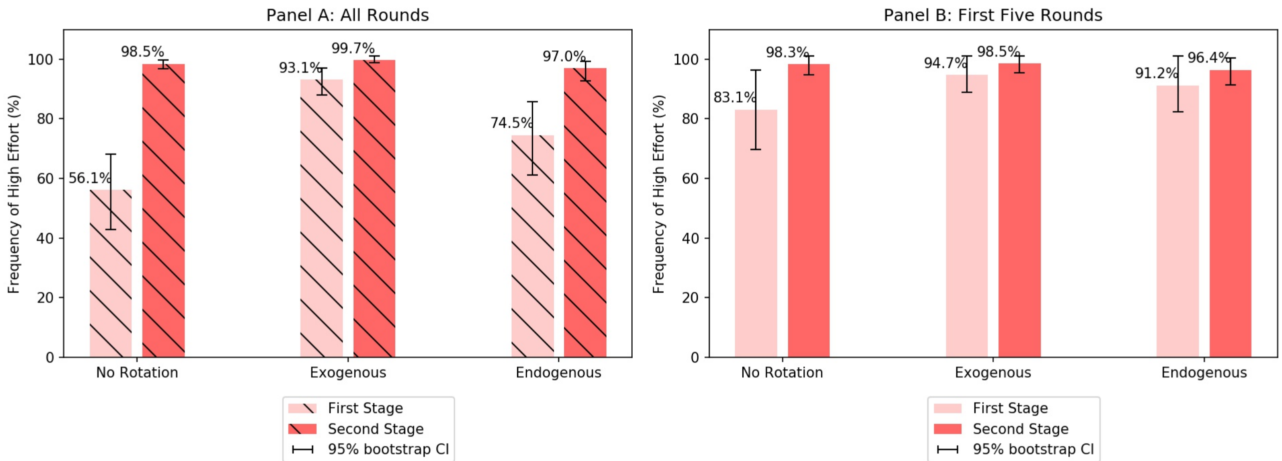


Figure 1.2. Workers' Choice When They Are in a High-productivity Stand

Note: 95% bootstrap confidence interval is calculated by drawing 1000 random samples. For each sample, we first draw the appropriate number of subjects with replacement. For each subject, we randomly draw the appropriate number of actions with replacement.

choose high effort in 269 out of 361 occasions (74.5%) in the first stage. This increase with respect to the chance of choosing high effort shows that the ratchet effect still exists but is less severe in the Endogenous Rotation Treatment. Finally, in the Exogenous Rotation Treatment, nearly all workers (93.1%) choose high effort in the first stage. The slight difference of workers' behavior across two stages in this treatment implies the elimination of the ratchet effect.

Panel B displays these choices for the first five rounds. Workers' initial decisions not only reflect their intuition of the mechanism, but also show their inclination towards output restriction. Similar to Panel A, almost all workers behave optimally and choose the high effort in the second stage of all three treatments. On the other hand, most workers choose the high effort in the first stage across three treatments. In the No Rotation Treatment, workers choose the high effort in 49 out of 59 times (83.1%) in the first stage. This frequency is 54 out of 57 times (94.7%) in the Exogenous Rotation Treatment and 52 out of 57 times (91.2%) in the Endogenous Rotation Treatment. Using the Wilcoxon signed-rank test with each individual as an observation, we find that the difference between the first stage and the second stage is not significant for each of the three treatments.[17] There are clear differences in the No Rotation Treatment and the Endogenous Rotation Treatment across Panel A and Panel B regarding the first-stage effort. These differences suggest that workers are less willing to choose low output at the beginning. Instead, they learn to restrict output in the following rounds since firms always extract more surplus from them if they produced more in the first stage.

We also use a random-effects Probit model to determine the treatment effect on workers' choice in the first stage when they are in a high-productivity stand. The dependent variable is one if a worker chooses high effort and zero otherwise. The independent variables include a dummy variable for being in the Exogenous Rotation treatment, a dummy variable for being in the Endogenous Rotation Treatment, and number of decisions as being a firm together with number of decisions as being a worker. Tables 1.4 shows the results of estimation for the No Rotation Treatment alone in the first column and for pooling the three treatments in the second column.[18]

Table 1.4 reveals that workers in the two rotation treatments are more likely to provide high effort in the first stage. In particular, the marginal effect of the Exogenous Rotation treatment compared with the No Rotation Treatment is 0.293, and it is significant at the 1 percent level. In addition, the marginal effect of the Endogenous Rotation Treatment compared with the No Rotation Treatment is 0.143, which is significant at the 5 percent level. This is surprising since theory predicts that workers, who are in the Endogenous Rotation Treatment, should not provide high effort in the first stage. However, experimental results show that rotating workers endogenously between stands is also effective in reducing the ratchet effect, which supports the hypothesis 4a. The above observations lead to our next two results:

Result 2: For each of three treatments, workers are rational since they deliver high output in the second stage if they are in a high-productivity stand.

[17]↑ $p = 0.125$ for the No Rotation Treatment, $p = 0.25$ for the Exogenous Rotation Treatment, and $p = 0.625$ for the Endogenous Rotation Treatment.

[18]↑ Standard errors estimated in Table 1.4 are clustered at individual level. See Table A.2 in Appendix A.2 for regression models in which standard errors are clustered at session level.

Table 1.4. Determinants of Choosing High Effort in the First Stage

	No Rotation	*Pooling data*
Variables	Effort	Effort
roundFirms	-0.152*	-0.207***
	(0.0841)[-0.016]	(0.0509)[-0.02]
roundWorkers	-0.0631	0.0246
	(0.0432)[-0.006]	(0.0249)[0.002]
exog	-	3.002***
		(0.663)[0.293]
endo	-	1.464**
		(.6608)[0.143]
constant	3.132***	1.970***
	(0.740)	(0.518)
observations	351	1047
Number of id	36	108

Note: Standard errors (clustered at individual level) are in parentheses, and marginal effects are in brackets. The first column displays the estimation for the No Rotation Treatment, and the second column displays the estimation for pooling the three treatment. The dependent variable is 1 if the worker picks high effort when he is in a high productivity stand and 0 otherwise. "exog" is 1 if the subject is in the Exogenous Rotation Treatment, and 0 otherwise. The dummy variable "endo" is 1 if the subject is in the Endogenous Rotation Treatment , and 0 otherwise. Variable "roundFirms" is the number of decisions a subject has made as a firm (from 1 to 15); variable "roundWorkers" is the number of decisions a subject has made as a worker (from 1 to 30). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Result 3: The ratchet effect is observed in the No Rotation treatment. It is less observed in the Endogenous Rotation Treatment. This effect is significantly reduced in the Exogenous Rotation treatment.

Moreover, in the second column, the coefficient of "roundWorkers" is not significant, but the coefficient of "roundFirms" is significant at the 1 percent level. This suggests that a subject learns to play strategically as a worker not from the experience of being a worker but from the experience of being a firm. This result relates to the recent finding by Esponda and Vespa [35]. They find that subjects behave nonstrategically due to the failure of thinking hypothetically. The previous experience as a firm could help workers to engage in hypothetical thinking, and thus better respond to a firm's strategy in later rounds.

1.3.3 Endogenous Rotation Treatment

The Endogenous Rotation Treatment and the No Rotation Treatment are predicted to result in the same workers' behavior. In addition, firms should never switch workers between stands in the Endogenous Rotation Treatment. However, we observed that workers are more likely to provide high effort in the first stage when they are in the Endogenous Rotation Treatment than in the No Rotation Treatment. Additionally, firms choose to switch workers in 85 of 540 instances (15.7%) according to Table 1.2. A bootstrap regression, in which standard errors are clustered at individual level, indicates that this switching rate is significantly different from zero ($p < 0.001$). It is reasonable to think that the decrease of the ratchet effect is related to the firms' choice in switching.

Since firms decide whether to switch workers after having observed the outputs from the two stands, it is possible that they make this decision conditional on the outputs from these two stands. Figure 1.3 shows that when firms observe two low outputs from these two stands, they switch workers in 18.7% of times (56 of 300 instances). When firms observe a high output from one stand and a low output from the other stand, they switch workers in 13.3% of times (28 of 211 instances). This rate decreases to 3.4% (1 of 29 instances) when firms observe that both stands produced a high output.

To confirm that firms make decisions based on the outputs from the two stands, we estimate three random-effect Probit models with the dummy variable "switch" as the dependent variable, which is one if firms choose to switch workers and zero otherwise. The independent variables include the number of rounds that the subject spent as a firm, the number of round the subject spent as a worker, and the combinations of outputs from two stands. Specifically, "TwoLow" is a dummy variable that is one if both stands produced a low output and zero otherwise. The dummy variable "TwoHigh" is a dummy variable that is one if both stands produced a high output and zero otherwise. The dummy variable "OneLowOneHigh" is one if one stand produced a low output and the other produced a high output, and zero otherwise. We use "TwoHigh" as the omitted (reference) variable in the first model, and "OneLowOneHigh" as the omitted (reference) variable in the second model. The third model compares firms' action when at least a low output was observed

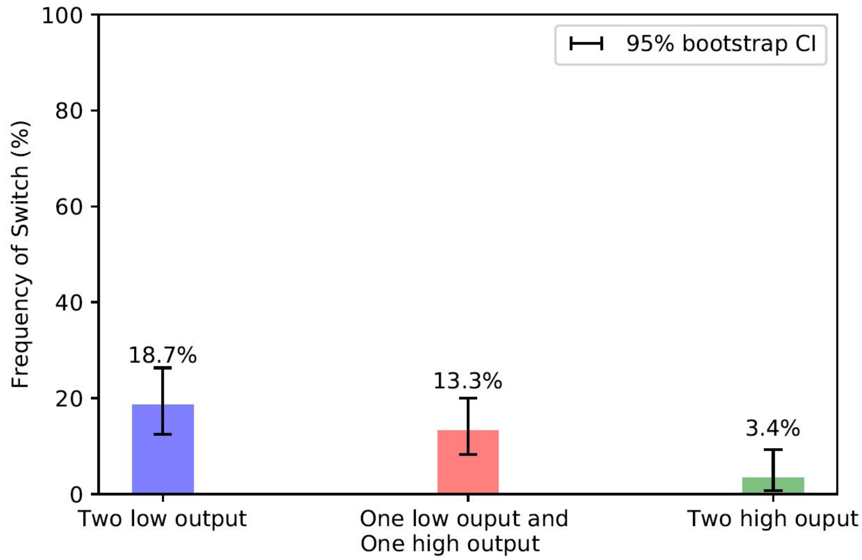


Figure 1.3. Frequency of Firms Choosing to Switch Workers

and when two high outputs were observed. Therefore, we include an independent variable "AtLeastOneLow" in the third model. The dummy variable "AtLeastOneLow" is one if both "TwoLow" and "OneLowOneHigh" are one and zero otherwise.

Table 1.5 presents the results of these regression models.[19] In the first model, the coefficient of the dummy variable "TwoLow" is significant at five percent level, and the coefficient of "oneLowOneHigh" is significant at 10 percent level. Firms are more likely to switch workers when two low outputs were observed compared with the situation when two high outputs were observed, which is also true for the case when a low output and a high output were observed. In the second model, the coefficient of the dummy variable "TwoLow" is not significant, which suggests that firms do not change their behavior from the situation where two low outputs were observed to the situation where one low output and one high output were observed. In the third model, the coefficient of variable "AtLeastOneLow" is significant at five percent level, which shows that firms are more likely to switch workers when at least one low output were observed than the case when two high outputs were observed. These results provide strong evidence that firms' behavior does not follow the PBE prediction which states

[19]↑ Standard errors estimated in Table 1.5 are clustered at individual level. See Table A.3 in Appendix A.2 for regression models in which standard errors are clustered at session level.

Table 1.5. Determinants of Switching (Random Effect Probit)

	(1)	(2)	(3)
Variables	switch	switch	switch
roungFirms	0.0015	0.0015	0.0014
	(0.0078)[0.002]	(0.0078)[0.002]	(0.0079)[0.001]
roundWorkers	-0.00399	-0.004	-0.003
	(0.0039)[-0.004]	(0.003)[-0.004]	(0.004)[-0.003]
TwoLow	0.174**	0.052	-
	(0.068)[0.174]	(0.031)[0.05]	
OneLowOneHigh	0.122*	-	-
	(0.069)[0.122]		
TwoHigh	-	-0.122*	-
		(0.0694)[-0.122]	
AtLeastOneLow	-	-	0.153**
			(0.0671)[0.152]
Constant	0.059***	0.182***	0.0584
	(0.072)	(0.0403)	(0.0726)
observations	540	540	540
Number of id	36	36	36

Note: Standard errors (clustered at individual level) are in parentheses. The dependent variable is 1 if the firm chooses to switch workers between stands and 0 otherwise. "TwoLow" is 1 if the firm observes two low outputs from two stands and 0 other wise. "OneLowOneHigh" is 1 if the firm observes a low output from one stand, and a high output from the other stand. It is 0 otherwise. "TwoHigh" is 1 if the firm observes two high outputs from two stands and 0 other wise. "AtLeastOneLow" is 1 if "TwoLow" equals 1 and "OnwLowOneHigh" equals 1, and it is 0 otherwise. *** p<0.01, ** p<0.05, * p<0.1.

that firms should never switch workers given their beliefs. We reject Hypothesis 3 in favor of Hypothesis 3a and have the next result:

Result 4: Firms are more likely to switch workers if low outputs were observed in the first stage.

It is possible that a firm wants to punish the worker whom she thinks has shirked by switching him to the other stand, even though this is costly to the firm herself. This is consistent with the result of a large number of literature that studies the effect of a costly punishment in public good games (See e.g.,Fehr and Gächter [27] and Fudenberg and Pathak [28]). There are four common explanations for subjects using a costly punishment in literature. Fehr and Gächter [27] suggest that a certain fraction of experimental subjects may strongly dislike being the "sucker", and thus they are willing to repay unkindness with costly punishment. This also relates to the reciprocity model studied by Dufwenberg and Kirchsteiger [36]. Dufwenberg and Kirchsteiger [36] show that if the principal believes the worker is unkind, she desires to be unkind and "hurt" the worker. Fudenberg and Pathak [28] discuss another three explanations: the "preference" explanation that firms act as if they enjoy punishing "shirkers" regardless of whether this has an impact on workers' subsequent behavior; the "repeated-game" explanation that firms use the punishment to try to improve their own future payoff since they mistakenly treat the one-shot interactions as if it were repeated; and the "altruism" explanation that firms punish to benefit other firms that punished workers will interact in the future. The purpose of this project is not to decompose the explanation of the costly punishment. Rather, we conjecture that it is likely the mixture of these four explanations contributes to the switching behavior. For example, the "preference" explanation can partially interpret why the switching choices are significant from zero when firms observe a high output from one stand and a low output from the other stand. Although the firm knows for certain that one of the workers took a generous action, her enjoyment of switching the other worker who has a possibility of shirking outweighs any cost of it.

Section 3.2 shows that the experiences of being a firm earlier have a significant effect on a subject's decision when she is playing as a worker. Therefore, the reason that the ratchet effect is less severe in this treatment might be the fact that a subject knows that she is more likely to switch workers if she observes a low output when she plays as a firm. As a result, when the subject plays as a worker, she might assume her opponent behaves the same as she would do as a firm. Therefore, she is less willing to provide low output in order to avoid of being switched to the other stand with an uncertain productivity.

We also test the possibility that workers are less willing to shirk in the first stage if they were switched in previous rounds. We are not able to find evidence to support this alternate explanation. The details for this result can be found in Appendix A.3.

1.3.4 Firm earnings

Finally, we compare firms' earnings between the two rotation treatments and the No Rotation Treatment. Table 1.2 shows that firms earn more points in the Exogenous Rotation Treatment compared with the No Rotation Treatment, but not in the Endogenous Rotation

Treatment. According to a Mann-Whitney test at the individual level, firms earn significant higher in the Exogenous Rotation Treatment than in the No Rotation Treatment ($p = 0.013$). The difference of firms' earnings between the Endogenous Rotation Treatment and the No Rotation Treatment is not significant ($p = 0.129$).

This is consistent with the theoretical prediction. In the Exogenous Rotation Treatment, workers who run a high-productivity stand in the first stage have no incentive to conceal the private information anymore, and thus firms are able to charge a high rental fee for a worker who will run the high-productivity stand in the second stage. However, in the No Rotation Treatment and the Endogenous Rotation Treatment, firms have no chance to charge high rental fees since all workers provide low outputs in the first stage.

1.4 Conclusion

Job Rotation is commonly assumed to reduce the ratchet effect in the literature of managerial economics and labor economics. But we cannot find any empirical evidence to support this assumption. It is also difficult and costly to test new ideas for eliminating the ratchet effect in the real world. Therefore, testing a new idea (eg., endogenous rotation) in the lab before trying to implement in the real world is reasonable and justifiable. This study is the first (to the best of our knowledge) to investigate the effectiveness of job rotation on the ratchet effect. The result of this lab experiment is not the final word on the job rotation, but it is an important and necessary first step.

We implement three treatments to study the effect of job rotation on the Ratchet Effect. In the No Rotation Treatment where workers are kept in the same workplace across stages, we observe a severe ratchet effect. In the Exogenous Rotation Treatment where all workers know that they will be switched to the other workplace in the later stage, the ratchet effect is almost eliminated. In the Endogenous Rotation Treatment where workers know that firms have an costly option to rotate them between workplaces, the ratchet effect is still reduced significantly.

Our study also serves as an experimental test of Perfect Bayesian Equilibrium (PBE). We know that the ratchet effect exists in both real–world settings and laboratory settings and PBE applies to both settings. If PBE fails in our laboratory setting, it is unlikely to be successful in the real world since the laboratory setting is much cleaner and simpler than the real world. In our setting, although exogenous rotation is supported to eliminate the ratchet effect, PBE suggests that endogenous rotation should not reduce the ratchet effect. Our lab experiment, however, demonstrates that PBE fails in this prediction. Therefore, we can conclude that endogenous rotation may actually reduce the ratchet effect in the real world and further evidence is needed.

The experimental results have clear implications for managers in operating firms. In line with previous field evidence, our experiment supports the existence of the ratchet effect. When managers making policies regarding efficiency improvement and effort motivation, mechanisms of eliminating the ratchet effect should not be ignored. Meanwhile, although job rotation is effective in eliminating the ratchet effect, managers need to identity the source of the ratchet effect and balance the cost of rotating workers with the loss from the ratchet effect. If managers are uncertain with the ability of employees, job rotation by no means helps to reduce the ratchet effect. If the uncertainty towards the job productivity is significant and there is little job-specific human capital, managers may rotate workers regularly and inform workers in advance. When there is a cost of rotating workers, to reduce the ratchet effect, managers may also inform workers that she has an option to rotate workers. Although this threat is non-credible, it might still have an effect from our experimental results. In an environment that is more complicated than ours, managers should also measure the marginal gains and the marginal disutility of the high effort when implementing the job rotation policy. Ickes and Samuelson [1] provide a condition of job-specific human capital under which job rotation is likely to be optimal. I refer readers to that paper for a comprehensive analysis regarding the trade off between the gain and the cost of job rotation.

There are multiple avenues for future research that are promising. First, it would be interesting to test whether the ratchet effect will be reduced if the cost of switching workers is high in the Endogenous Rotation Treatment. Although PBE predicts that there is no difference between the situation where workers are kept in the same stand and the situation where firms have a costly option of switching workers, our experiment shows the contradiction of this prediction when the cost of switching is small. Thus, it is ambiguous if firms and workers' behaviors are affected by an option of switching workers when its cost is high. Second, it would be interesting to test whether job rotation is still effective in reducing the ratchet effect if workers are able to communicate with each other before being rotated. On the one hand, Cardella and Depew [4] show that communication between workers promotes the ratchet effect. On the other hand, the non-binding communication between workers does not change the incentive structure. Job rotation would be more robust in eliminating the ratchet effect if it is still effective when agents could communicate with each other.It is also worth to think what would happen if we add an announcement stage at the beginning of the Endogenous Rotation Treatment. This makes the environment more realistic since an employer usually announces that she has a mandatory job rotation policy in the real world, and then stick to it. It would be interesting to see if firms make such announcement at the beginning and if this announcement could reduce the ratchet effect. Finally, as suggested by Bol and Lill [7], agents and principals can form implicit agreements when they can form a long-term interaction. Studying the ratchet effect under a long-term interaction will certainly be exciting.

2. COOPERATION IN QUEUEING SYSTEMS

with Yaroslav Rosokha

2.1 Introduction

Queueing systems composed of servers that carry out a sequence of (randomly) arriving tasks underlie most economic activity. Examples abound and include the retail industry in which individuals and companies are selling products that customers demand, the manufacturing industry, in which a combination of human and non-human workers transform raw materials into finished products, and the healthcare industry, in which providers deliver services to patients. Not surprisingly then, queueing theory has had a vibrant history across many domains including mathematics (Erlang [37], Kolmogorov [38], and Kendall [39]), operations research (Cobham [40] and Little [41]), management (Kao and Tung [42] and Graves [43]), and economics (Sah [44] and Polterovich [45]). Although most of the early research assumed servers process orders at fixed rates — a reasonable assumption when one deals with machines — more recently, the field has seen a push to understand the implications of servers having discretion over work speed (George and Harrison [46] and Hopp, Iravani, and Yuen [47]), being utility maximizing (Gopalakrishnan, Doroudi, Ward, *et al.* [48]), or being susceptible to behavioral biases (Bendoly, Croson, Goncalves, *et al.* [49]).

An important but largely overlooked feature of multi-server queueing systems is that servers interact repeatedly. The repeated interaction provides room for reputation-building and reciprocity, which may result in more complex strategies on the part of the decision-makers (i.e., human servers). Although such strategies have been studied in the theoretical and experimental literature on repeated games (Dal Bó and Fréchette [50]), to the best of our knowledge, these topics have not been investigated in the context of queueing systems. What makes the queueing setting distinct is the stochastic nature of customer arrivals and the dynamic implication of servers' decisions. Specifically, when servers exert high effort, more customer orders are being processed and the length of the queue is likely to decrease. This change in the number of outstanding orders affects the servers' short-term incentives, making low effort more attractive. On the other hand, when servers exert low effort, fewer customer orders are being processed and the length of the queue is likely to increase, making the incentives to continue providing low effort less attractive.

In this paper, we consider a setting in which human servers work together over an indefinite horizon to repeatedly process orders from a single queue. In particular, we focus on a scenario in which human servers have discretion over effort, and the compensation depends on the total number of customers processed by the group, which creates an incentive to free ride. We formalize the queueing environment as a stochastic dynamic game and show theoretically that even when individuals face incentives to free ride, high effort can be supported in the subgame perfect Nash equilibrium (SPE) of the game if the expected length of the interaction is long enough. In addition, we explore the role of common knowledge about the number of customer orders in the queue (i.e., queue visibility). We show that sustaining high effort when the queue is not visible is theoretically possible. We also show that when the queue is visible, there exist equilibria in which players play a class of state- and history-contingent trigger strategies that provide high effort when the queue is long, and provide low effort when the queue is short – dynamics that have been documented in the empirical studies (e.g., Kc and Terwiesch [51]).

We use a controlled laboratory experiment to test our theoretical predictions for a simplified two-server three-state queueing system. In each state of the system, providing low effort is the Nash equilibrium, but providing high effort is socially optimal in two out of three states. In the experiment, we implement a 3×2 factorial design in which we vary the expected duration of interaction (i.e., probability of continuing interaction to the next period) and whether servers know the state of the queue (i.e., whether servers can see the number of outstanding tasks). We find clear evidence that effort increases with the expected duration of repeated interaction. Regarding the queue visibility, we find that when servers can see the state of the queue, a significant proportion of subjects provide high effort when the queue is long, but provide low effort when the queue is short. When servers cannot observe the number of arrival tasks, we find no substantial differences in effort when comparing across states of the queue. In addition to the analysis of (observable) effort, we carry out an econometric estimation of (unobservable) strategies that subjects use. When the queue is not visible, we find that subjects either play Always Defect (i.e., provide low effort in all states of the queue regardless of the actions of the other server) or play tit-for-tat. When the queue is visible, we find a significant proportion of subjects use sophisticated state- and history-contingent versions of tit-for-tat and grim-trigger strategies. These strategies respond to the behavior observed the last time the queue was in the current state.

The rest of the paper is organized as follows: In section 2.2, we review related literature in operations management and economics. In section 2.3, we develop the notation and set up theoretical characterization of an SPE. In section 2.4, we present the experimental design for a simplified environment with two servers and three states of the queue, as well as provide theoretical predictions for the chosen parameters. In section 2.5, we carry out the analysis of the data. In particular, we first analyze effort choices and then conduct econometric estimation of underlying repeated-game strategies. We conclude in section 2.6.

2.2 Related Literature

Our work contributes to four broad streams of research across operations management and economics. The first stream includes papers that investigate queueing systems with human servers.[1] Our contribution to this stream can be organized along two dimensions. The first dimension includes the theoretical analysis of the effort provision when servers are utility-maximizing (e.g.,Zhan and Ward [53], Zhan and Ward [54], and Armony, Roels, and Song [55]). Among the most relevant theoretical papers along this dimension is Gopalakrishnan, Doroudi, Ward, *et al.* [48], who study strategic servers in multi-server systems and the impact of scheduling policies on the equilibrium of the one-shot game among the servers. Our project contributes to this dimension by theoretically investigating the impact of long-term relationships and queue visibility on the servers' effort provision. In particular, we focus on the strategies that servers can use to enforce high effort in the SPE of the repeated game underlying the queueing system. The second dimension includes experimental papers on human-server behavior in queueing systems. The most relevant papers along this dimension include Schultz, Juran, Boudreau, *et al.* [56], Schultz, Juran, and Boudreau [57] and Powell and Schultz [58], who consider behavioral factors that influence effort provision in a variety of queueing systems. More recent work along this dimension also includes Buell, Kim, and Tsay [59], who find that operational transparency increases customers' perceptions of service quality and reduces throughput times; Shunko, Niederhoff, and Rosokha [60], who find that the visibility of the queue may speed up servers' service rate; and Hathaway, Kagan, and Dada [61], who find that servers incorporate the state of the queue into their decisions. Our work is distinct in that we provide a game-theoretic foundation for the servers' behavior and highlight that visibility of the queue may have different consequences on servers' effort provision depending on the expected duration of an interaction among servers.[2] In addition,

[1] ↑For a thorough discussion of issues studied within the stream of literature that considers servers as decision-makers, we refer the reader to section 9.3 of the recent review by Allon and Kremer [52]. The review also encompasses related streams that consider the effect of the customer (section 9.2) and the manager (section 9.4) having discretion over the respective decisions.

[2] ↑In this paper, we consider customers to be non-strategic agents. Previous work has shown that the visibility of the queue may influence customers' decisions to join/leave the queue (for a review of the literature that considers the impact of information about the queue on customers' decisions and the resulting system properties, see Chapter 3 of Hassin [62]). As a direction for future research, building a model that considers

although a large body of literature has considered empirical regularities associated with human-server behavior (e.g., a review by Delasay, Ingolfsson, Kolfal, *et al.* [63]), our paper is the first to conduct econometric investigation of the repeated-game strategies that human servers may use in queueing systems.

The second stream of research that we contribute to includes papers in operations and supply-chain management that investigate the impact of long-term relational incentives.[3] Papers in this stream of literature include Nosenzo, Offerman, Sefton, *et al.* [66], who investigate the threat of punishment and power of rewards in the repeated inspection game; Davis and Hyndman [67], who investigate the efficacy of relational incentives for managing the quality of a product in a two-tier supply chain; Beer, Ahn, and Leider [68], who show that the benefits of buyer-specific investments for both suppliers and buyers are strengthened when firms interact repeatedly; and Hyndman and Honhon [69], who investigate indefinitely binding and temporarily binding contracts in the repeated two-person newsvendor game. Taken together, the findings from these papers suggest that long-term relationships can be effective in enforcing more efficient outcomes. Our project contributes to this stream of research by highlighting the role of repeated interactions on the behavior of servers in the queueing setting.

The third stream of literature that we contribute to is the experimental and theoretical work in economics that investigates behavior in the indefinitely repeated Prisoners' Dilemma (henceforth PD) game (see Dal Bó and Fréchette [50] for a review). Papers in this stream of literature have shown that cooperation is sensitive to the probability of continuation and payoffs, and that cooperation may not always be sustained even if theoretically possible (e.g., Dal Bó and Fréchette [70] and Blonski, Ockenfels, and Spagnolo [71]). Regarding the strategies that human subjects use in PD experiments, recent papers, including Dal Bó and Fréchette [70], [72] and Romero and Rosokha [73], [74], show that simple strategies such as Grim Trigger, Always Defect, and Tit-for-Tat are prevalent. The extent to which these

both –strategic servers that interact repeatedly, and strategic customers that have a choice of when to join/leave the queue– would be interesting.

[3]↑In this paper, we focus on the repeated nature of interaction and abstract away from settings with end-of-shift or temporary workforce considerations, which may be better captured with a finite-horizon model. For an early discussion of finite versus indefinite horizon see Cox and Oaxaca [64]. For a recent study of finitely-repeated PD games, see Embrey, Fréchette, and Yuksel [65].

strategies will be played in a stochastic environment with a transition between the PD and non-PD games is unknown. In particular, in our setting, cooperation (i.e., high effort) in the PD game leads to a higher likelihood that the non-PD game in which low effort is both the Nash equilibrium and the socially optimal outcome will be played next. These transitions create room for spillover effects related to Knez and Camerer [75], Peysakhovich and Rand [76], and Cason, Lau, and Mui [77], and path dependence in equilibrium selection studied by Romero [78].

The fourth stream of literature that we contribute to explores dynamic and stochastic repeated games. Early papers in this literature include work by Green and Porter [79] and Rotemberg and Saloner [80], who theoretically show that collusion among firms can be supported in the presence of stochastic demand shocks that are independent of firms' decisions.[4] Recent experimental work by Rojas [84] confirms that collusion in such environments can arise in the lab.[5] In an experimental study of the dynamic oligopoly game, Salz and Vespa [85] point out that restricting attention to Markov strategies, when decision-makers can use a richer class of state- and history-contingent strategies to support cooperation in the SPE of the repeated game, may lead to systematic biases in estimation of strategies. Our work is also closely related to the dynamic Vespa and Wilson [86], [87] and stochastic Kloosterman [88] variations of the repeated PD game. Vespa and Wilson [86] find that subjects are conditionally cooperative and adjust their behavior not only in response to the state, but also to the history. Vespa and Wilson [87] test the extent to which subjects internalize the incentives of changing the transition rule from endogenous to stochastic. Kloosterman [88] focuses on the beliefs about the future in a two-state stochastic PD and finds that subjects cooperate when beliefs about the future support a large scope for punishment. Our work is distinct in that the queueing problem that we study combines both the dynamic and the

[4]↑Our work is also related to the study of dynamic common-pool resource games Walker, Gardner, and Ostrom [81] and Gardner, Ostrom, and Walker [82]. Recent papers that experimentally study common-pool resource games by Vespa [83] find that although efficiency can be supported with history-contingent strategies, in practice, subjects find it difficult to cooperate and rely on state-contingent Markov strategies.
[5]↑ In the intermediate treatment of Rojas [84], two firms play a repeated Cournot game in which the demand of each period is stochastic. Firms only know the distribution for next period's demand state, and they need to select the amount of quantities to produce in each period. In that environment, firms' choices in a certain period do not affect the demand realizations in the next period.

stochastic components.[6] In particular, the dynamic implications of decisions are different from environments studies in previous work. In addition, we focus on the common knowledge about the underlying state. We find evidence that when the queue is visible, a significant portion of subjects rely on history-contingent repeated-game strategies to sustain high-effort cooperation.

[6]↑From here on, we use the term stochastic game Shapley [89] to refer to a dynamic game with multiple states and state transition probabilities determined by the actions of the players.

2.3 Theoretical Background

Consider a single-queue system with $N = \{1, 2\}$ identical servers and a finite buffer of size B. In particular, suppose that in each time period $t \in \{1, ..., \infty\}$, λ_t customer orders arrive to the queue and servers discount the future according to the common discount factor δ. Further suppose λ_t is a random variable that is distributed according to G, where G is a distribution with integer support on $[\lambda_{min}, \lambda_{max}]$. Then, let $\Theta = \{\theta \in \mathbb{N} | \, \lambda_{min} \leq \theta \leq B\}$ denote the set of states of the queueing system. That is, $\theta_t \in \Theta$ denotes the number of customers in line in period t.

In this paper, we are interested in scenarios in which servers face a social dilemma in at least one state of the queue. To set up such a dilemma, we consider an environment in which (i) servers have discretion over effort and (ii) free-riding incentives exist for each of the servers. Regarding the discretion over effort, we assume that each server can choose among a finite number of effort levels such that the higher the effort level, the more capacity exists in a period. We further assume that the cost of processing orders, $c(.)$, is increasing in effort and is convex in the number of orders processed within a period by the server.[7] Regarding the free-riding incentives, we assume that individual effort choices are not observed by the managers and that individual payoff, $r(.)$, is a function of the total number of customers processed by the group.[8] Next, we focus on the case of a two-server queuing system in which each server has discretion over two effort levels.

2.3.1 One-Shot Game

Suppose that in each period, server $\mathrm{i} \in N$ decides whether to provide high effort or low effort, $\mathrm{e_i} \in E_\mathrm{i} := \{h, l\}$. Let $M(\mathrm{e_i}, \mathrm{e_{-i}}, \theta)$ denote the number of orders processed by the

[7]↑The convex-cost assumption is a standard component across the theoretical, empirical, and experimental streams of literature (e.g., Mas and Moretti [90], Ortega [91], Clark, Masclet, and Villeval [92], and Gill and Prowse [93]).

[8]↑Group-based payment schemes are frequently observed in the real world. For example, Ortega [91] finds that group-based performance pay is the third most frequent type of performance pay among employees according to the European Working Conditions Survey. In the queuing context, examples include Tan and Netessine [94], who document that restaurant workers face, at least in-part, team-based incentives; and Hamilton, Nickerson, and Owan [95], who document team-based incentives in the garment industry setting with a group of workers facing a queue of cloth pieces that need to be sewn together into garments (the team then receives a piece rate for the entire garment).

group within a period, and let $c(\mathrm{e_i}, \mathrm{e_{-i}}, \theta)$ denote the corresponding personal cost to server i. Next, suppose the service process is such that the manager cannot observe the effort levels contributed by each server, and can only observe the total output by the group. That is, the compensation to server i, $r(\mathrm{e_i}, \mathrm{e_{-i}}, \theta)$, is a function of the total number of customer orders processed by the group, $M(\mathrm{e_i}, \mathrm{e_{-i}}, \theta)$. Then, the net payoff within a period to server i is $u(\mathrm{e_i}, \mathrm{e_{-i}}, \theta) = r(\mathrm{e_i}, \mathrm{e_{-i}}, \theta) - c(\mathrm{e_i}, \mathrm{e_{-i}}, \theta)$.

Let $g(\theta) = \langle N, E, U(\theta)\rangle$ denote the stage game played in state θ, where the set of players is given by N, the set of strategy profiles is given by $E = \prod E_{\mathrm{i}}$, and the set of payoffs is given by $U(\theta) = \{u(\mathrm{e}, \theta) : \mathrm{e} \in E\}$. We restrict our attention to the scenario in which providing low effort is a dominant action of $g(\theta)\ \forall\ \theta \in \Theta$, but there exists $\theta \in \Theta$ for which a high effort profile is socially optimal. Formally, we restrict our attention to games in which the following two conditions hold:

$$u_{\mathrm{i}}(l, \mathrm{e_j}, \theta) > u_{\mathrm{i}}(h, \mathrm{e_j}, \theta)\ \forall\ \mathrm{e_j} \in E_{\mathrm{j}}, \theta \in \Theta, \tag{2.1}$$

$$\exists\ \theta \in \Theta : 2r(h, h, \theta) - 2c(h, h, \theta) > 2r(l, l, \theta) - 2c(l, l, \theta). \tag{2.2}$$

Inequality (2.1) means that, regardless of what the other player does, each player receives a higher payoff for providing low effort than for providing high effort. In particular, (2.1) implies that effort profile $\mathrm{e}^d = (l, l)$ is the unique Nash equilibrium of the stage game $g(\theta)\ \forall\theta \in \Theta$. Inequality (2.2) means that there exists a state θ in which both players receive a lower payoff if both provide low effort than if both provide high effort. Note that (2.1) and (2.2) imply that the game played in state θ is a 2-player PD. In practice, the two conditions are satisfied if the extra cost of providing high effort, $c_{\mathrm{i}}(h, \mathrm{e_j}, \theta) - c_{\mathrm{i}}(l, \mathrm{e_j}, \theta)$, is greater than the individual benefit of increasing the capacity by an extra order, $r(h, \mathrm{e_j}, \theta) - r(l, \mathrm{e_j}, \theta)$, but less than the total benefit to both players, $2r(h, \mathrm{e_j}, \theta) - 2r(l, \mathrm{e_j}, \theta)$.

2.3.2 Stochastic Game

Our goal is to investigate the server's behavior when interactions are long-term. In particular, from the repeated-PD literature, we know that when players face the same problem repeatedly over the time horizon $t \in \{1, 2, 3..., \infty\}$, they may be able to use trigger strategies to sustain high effort (i.e., socially efficient choices). However, the extent to which high effort can be sustained in the queueing setting with randomly arriving customer orders and the queueing dynamics that lead to transitions between PD and non-PD stage-games has been unexplored.

Let $\Gamma = \langle N, E, U, \Theta, \mathcal{P} \rangle$ denote a stochastic game implied by the queueing environment above. In particular, in addition to sets N, E, U, and Θ, let $\mathcal{P}$ denote the transition probability across the states. Specifically, let $\mathcal{P}_{\theta\theta}^{\mathrm{e_i e_j}} := \mathcal{P}(\theta|\theta, \mathrm{e})$ denote the probability that the next state is θ given the current state θ and the effort profile $\mathrm{e} \in E$. Notice that the transition probability is fully determined by the current state, the action profile by the servers, and the arrival process. Next, we formally consider some of the strategies the players may use to sustain high effort in equilibrium for the two cases – when the queue is visible and when it is not.

2.3.3 Strategies and Subgame Perfect Equilibrium When Queue Is Visible

When the queue is visible, players may utilize three types of repeated-game strategies. The first are the state-contingent *Markov strategies*. These strategies condition only on the realization of θ. For example, a player may always provide high effort in one particular state θ and always provide low effort in all other states. We refer to this strategy as AC^{θ}. The second are the *history-contingent strategies*. These strategies condition only on the realized history of actions but not on the current state or the history of states. An example of this type of strategy is the well-known *Grim trigger* strategy (henceforth GT), which begins by providing high effort in the first period and continues to provide high effort until one of the players provides low effort. The third are *state- and history-contingent strategies*. These strategies condition on both the state realization and the history of actions. An example of this type of strategy is a strategy that plays GT in a particular state θ but always provides low effort in all states $\theta \neq \theta$. We refer to such a strategy as GT^{θ}.

To check whether a strategy profile s is an SPE, we have to check whether, for each player i and each subgame, no single deviation would increase player i's payoff in the subgame. For example, to find conditions under which strategy profile $s^{GT} = (GT, GT)$ is an SPE, we have to check single deviations in two kinds of contingencies: (i) after histories in which all players provided high effort and (ii) after histories in which at least one of the players provided low effort at some point. To evaluate whether a player has a profitable deviation in state θ for the first type of contingency, we need to compare the total value from continuing to provide high effort, which we denote as V_{θ}^{c}, and the total value of deviating, which we denote as V_{θ}^{dev}. Formally,

$$V_{\theta}^{c} = u(\mathrm{e}^{c}, \theta) + \delta \sum_{\theta} \mathcal{P}_{\theta\theta}^{hh} V_{\theta}^{c} \tag{2.3}$$

$$V_{\theta}^{dev} = u(\mathrm{e}^{dev}, \theta) + \delta \sum_{\theta} \mathcal{P}_{\theta\theta}^{lh} V_{\theta}^{d} \tag{2.4}$$

$$V_{\theta}^{d} = u(\mathrm{e}^{d}, \theta) + \delta \sum_{\theta} \mathcal{P}_{\theta\theta}^{ll} V_{\theta}^{d}. \tag{2.5}$$

The second type of contingency in which one of the players has deviated is satisfied because the best course of action given that the other is going to provide low effort is to provide low effort oneself. Thus, a strategy profile s^{GT} is an SPE of Γ if

$$V_{\theta}^{c} - V_{\theta}^{dev} \geq 0 \ \forall \ \theta. \tag{2.6}$$

2.3.4 Strategies and Subgame Perfect Equilibrium When Queue Is Not Visible

When the queue is not visible, the state of the game is not known with certainty. Therefore, to enforce high effort in equilibrium, the servers cannot condition on the current state

θ, but instead are limited to history-contingent strategies. For example, when the queue is not visible, a strategy profile s^{GT} is a subgame perfect Nash equilibrium if

$$\mathbf{E}_\theta \left[V_\theta^c - V_\theta^{dev} \right] \geq 0. \tag{2.7}$$

Note the difference between (2.6) and (2.7) is that the former has to hold for each state (including states with high incentives to deviate), whereas the latter has to hold in expectation. In section 2.4.1 we show that this feature means that not knowing the state of the queue may lead to higher effort provision among the servers. On the flip side, knowing the queue length means that servers may more easily sustain high effort in a subset of states.

2.4 Experimental Design and Theoretical Predictions

In this section, we describe the environment, provide the theoretical predictions, and formulate the hypotheses for the first set of experiments. In particular, we set $B = 4$, G uniform, $\lambda_{min} = 2$, $\lambda_{max} = 4$, and $\Theta = \{2, 3, 4\}$. We chose these parameters so that the number of states is small (so can be reasonably implemented in the lab) yet provides room for queueing dynamics with the queue being shorter or longer than the average arrival rate. In terms of the payoffs, we picked the parameters of the convex cost function, $c(.)$, and the parameters of the compensation function, $r(.)$, so that in addition to creating an environment with desired features, the payoffs in certain states match stage-game parameters from the existing papers in the literature that have been shown to yield a range of cooperative behavior (e.g., Dal Bó and Fréchette [70]).

We assume that with low effort each server will always process one task, but with high effort each can process up to two tasks, if available. We further assume that the cost of processing $m_{\text{i}}(.)$ tasks with low effort is $c(l, \text{e}_{\text{j}}, \theta) = am_{\text{i}}(l, \text{e}_{\text{j}}, \theta)^2 + bm_{\text{i}}(l, \text{e}_{\text{j}}, \theta) + c$ with $a = 22$, $b = -37$, and $c = 40$. The cost of processing $m_{\text{i}}(.)$ tasks with high effort is $c(h, \text{e}_{\text{j}}, \theta) = xm_{\text{i}}(h, \text{e}_{\text{j}}, \theta)^2 + ym_{\text{i}}(h, \text{e}_{\text{j}}, \theta) + z$ with $x = 22, y = -37$ and $z = 49$.[9] Note that *ceteris paribus*, providing high effort is more costly. Also note that the cost function depends on the effort by the other server, because when work is available (e.g., $\theta = 3$) a server would rather split the workload than do the majority of it alone.

Regarding the compensation function, we assume that the compensation to the individual server depends on the number of total tasks, $M(.)$, processed by the group: $r(\text{e}_{\text{i}}, \text{e}_{\text{j}}, \theta) = kM(\text{e}_{\text{i}}, \text{e}_{\text{j}}, \theta) + \mathbf{1}_{M(\text{e}_{\text{i}}, \text{e}_{\text{j}}, \theta)=4} bonus$ with $k = 25$, and $bonus = 11$. The interpretation is that the server is compensated based on the total number of units processed by the group in two ways. The first is per-unit compensation that depends on $M(.)$, with $M(l, l, \theta) = 2 \forall \theta$, $M(l, h, \theta) = min(3, \theta)$, $M(h, h, \theta) = min(4, \theta)$. This means that the server's compensation is naturally influenced by the queue length and the chosen effort (i.e., when the queue is shorter–fewer customers can be processed; when servers reduce effort–fewer customers can be processed). The second is a bonus that is paid when the favorable output is observed.

[9]↑We provide a visual representation of the cost function in Figure B.1 of Appendix B.1.

Note that four orders are processed only if both servers provide high effort. Bonus payment based on the observable outcomes is a common feature of many compensation structures (e.g.,Hathaway, Kagan, and Dada [61], Hashimoto [96], Blakemore, Low, and Ormiston [97], and Bell and Reenen [98]).

The resulting payoffs for each combination of effort choices are presented in Figure 2.1.[10]

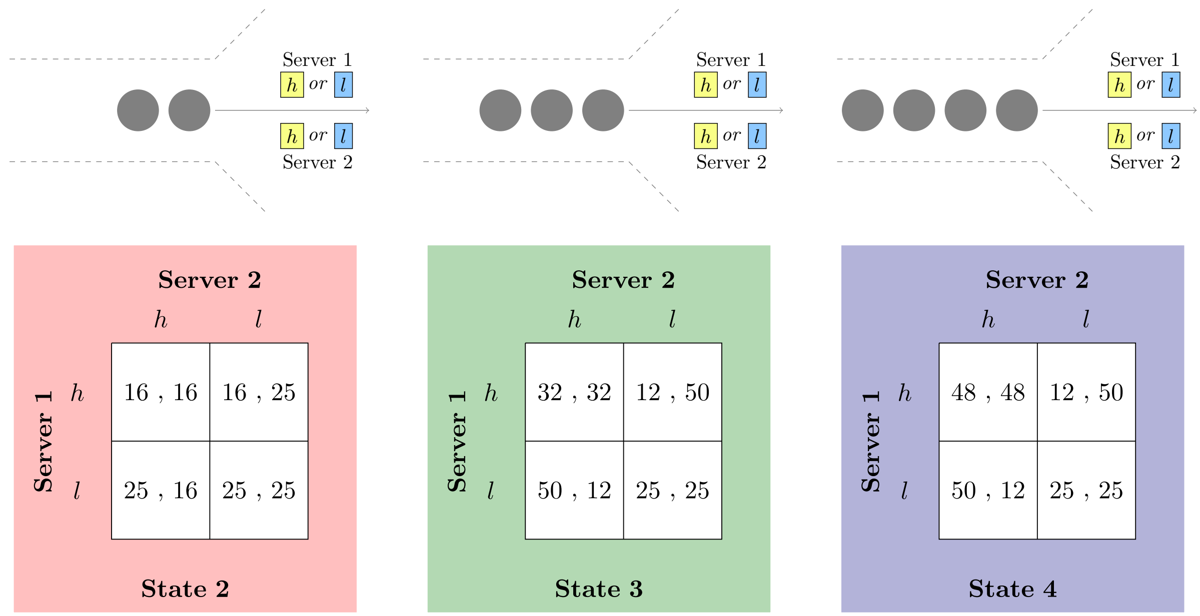


Figure 2.1. Stage-Game Payoffs in Each State

Notes: The three columns present stage games played in the three possible states. State $\theta \in \{2, 3, 4\}$ corresponds to θ customer orders in line. Each player chooses low effort (l) or high effort (h) to process customer orders. With low effort, each player can process up to one order; with high effort, each player can process up to two orders. Matrices present normal form representation of the stage game played in each state. Note that stage games played in states 3 and 4 are PD games studied in Dal Bó and Fréchette [99]. The stage game played in state 2 is non-PD.

The consequence of the payoffs presented in Figure 2.1 is that when two customer orders are available, the dominant action –to provide low effort– is also the socially optimal in that state. However, when three or four customer orders are available, the socially optimal outcome is for both servers to provide high effort even though, individually, each would prefer

[10]↑In Appendix B.1.3, we provide examples of calculating entries in the payoff tables presented in Figure 2.1

to provide low effort. In a repeated-interaction context, when three or four customers are in line, there exist short-term incentives to free ride but long-term incentives to cooperate. In terms of the difference between states 3 and 4, the free-riding incentives are larger when three customer orders are in line, because each player would prefer that the other provide high effort and process two of the three customer orders.

Figure 2.2 presents example dynamics in our experimental environment. In particular, panel (a) presents an example in which three customer orders in line, and both servers select low effort. In such a case, one order will be left over for the next period. Panel (b) presents an example in which four new customer orders arrive. In this case, the total number of customer orders will exceed the buffer size, and as a result, one order will be lost. Then, panel (c) presents the outcome if one server provides high effort and the other server provides low effort. Note that the state of the queue is partly endogenous (via effort choices) and partly exogenous (via stochastic arrivals). If, for example, three customers arrived every period and the buffer size was limited to three, we would have a non-stochastic version of the indefinitely repeated PD, with payoffs identical to the $R = 32$ treatment studied in Dal Bó and Fréchette [70].

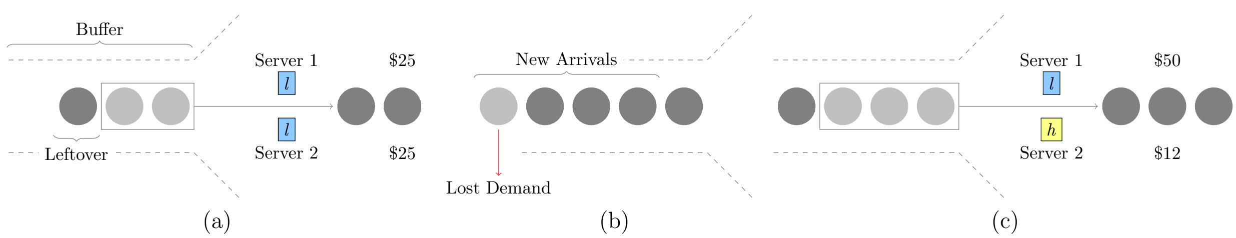


Figure 2.2. Example Dynamics

Notes: Panel (a) presents an example decision in period t. In particular, suppose three customer orders are in the queue and each server selects low effort; then, two orders are processed in period t and each server earns 25 points. The payoffs are determined from the stage-game payoff matrix in Figure 2.1 corresponding to state 3. Panel (b) presents example arrivals in period $t + 1$. For this example, four orders are arriving in period $t + 1$, and because the new orders together with the leftover orders from period t exceed the buffer size, one order is considered lost demand. Panel (c) presents an example decision in period $t + 1$ whereby server 1 chooses l and server 2 chooses h. The payoffs are determined from the stage-game payoff matrix in Figure 2.1 corresponding to state 4.

2.4.1 Theoretical Predictions

In this section, we derive conditions under which cooperation in the form of high effort may arise in the stochastic game specified above. In particular, the game has a nice feature that both the Nash equilibrium of all stage games and the Markov perfect equilibrium of the overall stochastic game is to provide low effort in all three states. Thus, high effort can *only* be sustained using strategies that condition on the past history of play. We first begin by deriving the condition on the discount factor that would ensure that high effort could be supported in equilibrium of the infinitely repeated game. In particular, we follow the typical approach in the theoretical literature and focus on trigger strategies.[11]

Queue Is Visible

To determine whether GT is an equilibrium strategy, we first find the transition probability matrix implied by the strategy profile s^{GT}. In particular, if both players provide high effort, the transition probabilities are given by $\mathcal{P}^{hh}$; if one player deviates from high effort, the transition probabilities are given by $\mathcal{P}^{lh}$; and if both players provide low effort, the transition probabilities are given by $\mathcal{P}^{ll}$:

$$\mathcal{P}^{hh} = \begin{array}{c c} & \begin{array}{ccc} \scriptstyle\theta\; 2 & 3 & 4 \end{array} \\ \begin{array}{c} 2 \\ 3 \\ 4 \end{array} & \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{pmatrix} \end{array} \quad \mathcal{P}^{lh} = \begin{array}{c c} & \begin{array}{ccc} \scriptstyle\theta\; 2 & 3 & 4 \end{array} \\ \begin{array}{c} 2 \\ 3 \\ 4 \end{array} & \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \end{pmatrix} \end{array} \quad \mathcal{P}^{ll} = \begin{array}{c c} & \begin{array}{ccc} \scriptstyle\theta\; 2 & 3 & 4 \end{array} \\ \begin{array}{c} 2 \\ 3 \\ 4 \end{array} & \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 0 & 0 & 1 \end{pmatrix} \end{array}. \quad (2.8)$$

Thus, if both players provide high effort, they process all of the customer orders, and therefore, the transition probability is determined by the arrival process (i.e., uniform distribution). However, if one or both players provide low effort, then some of the states will have

[11]↑Although the reliance on GT-type strategies is in part due their simplicity, which allows for analytical tractability, it is important to note that unforgiving trigger strategies like this allow us to find the minimal discount factor (i.e., continuation probability) that supports cooperation. In addition, recent experimental studies (Fréchette and Yuksel [100]) show that GT is one of the five most popular strategies used by the human subjects.

leftover customer orders, which, together with the arrival process, implies that transition to states with more customers is more likely. Vectors u^c, u^{dev}, and u^d specify payoffs obtained in each of the states:

$$u^c = \begin{pmatrix} u_2^c \\ u_3^c \\ u_4^c \end{pmatrix} = \begin{pmatrix} 16 \\ 32 \\ 48 \end{pmatrix} \qquad u^{dev} = \begin{pmatrix} u_2^{dev} \\ u_3^{dev} \\ u_4^{dev} \end{pmatrix} = \begin{pmatrix} 25 \\ 50 \\ 50 \end{pmatrix} \qquad u^d = \begin{pmatrix} u_2^d \\ u_3^d \\ u_4^d \end{pmatrix} = \begin{pmatrix} 25 \\ 25 \\ 25 \end{pmatrix}. \tag{2.9}$$

Lastly, the total values for the three cases in matrix notation are

$$V^c = [I - \delta\mathcal{P}^{hh}]^{-1}u^c, \qquad V^{dev} = u^{dev} + \delta\mathcal{P}^{lh}V^d, and \qquad V^d = [I - \delta\mathcal{P}^{ll}]^{-1}u^d, \tag{2.10}$$

where $V^c = \begin{pmatrix} V_2^c \\ V_3^c \\ V_4^c \end{pmatrix}$, $V^d = \begin{pmatrix} V_2^d \\ V_3^d \\ V_4^d \end{pmatrix}$, and I is the identity matrix. To show that s^{GT} is an SPE when the queue is visible, we need to find δ so that each element of V^c is at least as large as the corresponding element of V^{dev}. We find that s^{GT} is an SPE when δ is at least 0.72. We denote this critical threshold as $\delta_v^*(GT)$.

Note GT does not distinguish among the states. However, we expect that a human participant would. Therefore, we consider two trigger strategies that do. In particular, the first strategy, which we term GT^{34}, plays GT across states 3 and 4 and always provides low effort in state 2. The only difference in the analysis above is that $u^c = \begin{pmatrix} 25 \\ 32 \\ 48 \end{pmatrix}$, which leads to $\delta_v^*(GT^{34}) = 0.64$. The second state- and history-contingent strategy, which we term

GT^4, plays GT in state 4 only and provides low effort in both states 2 and 3. The implied transition-probability matrices and the payoff vectors for this strategy are

$$\mathcal{P}^c = \begin{array}{c} \theta \\ 2 \\ 3 \\ 4 \end{array}\!\!\begin{array}{c} \begin{array}{ccc} 2 & 3 & 4 \end{array} \\ \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 1/3 & 1/3 & 1/3 \end{pmatrix} \end{array} \quad \mathcal{P}^{dev} = \begin{array}{c} \theta \\ 2 \\ 3 \\ 4 \end{array}\!\!\begin{array}{c} \begin{array}{ccc} 2 & 3 & 4 \end{array} \\ \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 0 & 1/3 & 2/3 \end{pmatrix} \end{array} \quad \mathcal{P}^{ll} = \begin{array}{c} \theta \\ 2 \\ 3 \\ 4 \end{array}\!\!\begin{array}{c} \begin{array}{ccc} 2 & 3 & 4 \end{array} \\ \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 0 & 0 & 1 \end{pmatrix} \end{array} \tag{2.11}$$

$$u^c = \begin{pmatrix} 25 \\ 25 \\ 48 \end{pmatrix} \qquad u^{dev} = \begin{pmatrix} 25 \\ 25 \\ 50 \end{pmatrix} \qquad u^d = \begin{pmatrix} 25 \\ 25 \\ 25 \end{pmatrix}. \tag{2.12}$$

Note that we chose to label the transition probabilities as $\mathcal{P}^c$ instead of $\mathcal{P}^{hh}$ and $\mathcal{P}^{dev}$ instead of $\mathcal{P}^{lh}$, because the cooperative path of s^{GT^4} involves low effort in states 2 and 3. Solving for $\delta_v^*(GT^4)$, we get 0.19. One way to interpret these results is that GT^4 is the easiest to sustain, followed by GT^{34}, and GT is the most difficult to sustain when the queue is visible. In other words, cooperating is easier when the queue is long than when it is short.

Queue Is Not Visible

When the queue is not visible, we solve (2.7) and find that $\delta_{nv}^*(GT)$ is 0.58, which means that full effort can be supported at a lower discount factor when the queue is not visible ($\delta_{nv}^*(GT) < \delta_v^*(GT)$). The reason is that when the queue is visible, players know the exact state they are in, so they know the exact benefit of providing high or low effort in the current period. However, if players do not know the exact state, they can only consider the expected benefit. Thus, we have theoretical evidence that if the goal is to achieve high effort in all states of the queue, reducing visibility may be beneficial.[12]

[12]↑In Appendix B.1.4 we investigate how these results depend on the parameters of the cost and compensation functions.

Lastly, we would like to note that sustaining some amount of high effort in equilibrium is possible even when the discount factor is low and the queue is not visible. In particular, players can infer the probability of being in a state given a sequence of action profiles. For instance, if players observe a long sequence of defections, then even without knowing the history of states, the probability of the queue being long is high. If, in addition, players can observe (or infer) partial history of states, they can reach this conclusion with greater certainty. For example, for our parameter combination, if players have observed that $\theta_{t-1} = 4$ and $\mathrm{e}_{t-1} = (l, l)$, then even without observing the current state, the players should conclude that $Pr(\theta_t = 4) = 1$. We define a trigger strategy $D.AlT^4$ that defects until mutual defection has been observed in state 4 and then cooperates in the subsequent period. Then, after one period of high effort, this strategy immediately reverts back to defection until another mutual defection is observed in state 4 in the past. The strategy is also a trigger strategy in that it prescribes low effort forever if one of the players did not cooperate after mutual defection has been observed in state 4. We calculate that $\delta^*_{nv}(D.AlT^4)$ is 0.40.

2.4.2 Treatments and Hypotheses

For the first study, we implement a 3×2 factorial design in which we vary the expected length of the interaction and queue visibility. To induce long-term relationships, we implemented a random termination protocol of Roth and Murnighan [101]. In particular, we described this protocol to subjects as the computer rolling a 12-sided die each period of the match, with the match continued if the number was below 7 (9; 11) for the $\delta = \frac{3}{6}$ ($\delta = \frac{4}{6}$; $\delta = \frac{5}{6}$) treatment. To ensure that subjects were comfortable with this procedure, we included a testing phase in which we required them to roll the computerized dice to simulate a duration of 10 matches. The rolls in the actual experiment were pre-drawn so that different visibility treatments had the same supergame-length realizations. The supergame-length realizations for each treatment are presented in Figure B.1 in the Appendix B.2.

To vary the queue visibility, we modified the timing of when the number of new order arrivals was revealed within the decision period. In particular, for the treatments in which the queue was visible, the number of new orders was revealed *before* subjects made their decisions for that period. Thus, in the visible treatment, subjects knew the number of outstanding orders and the stage-game payoff matrix at the time of making their decision. For the treatments in which the queue was not visible, the number of new orders was revealed *after* subjects made their decisions for that period. Thus, at the time of their decision, subjects did not know the exact number of outstanding orders nor the exact stage-game payoff matrix. In both cases, subjects had access to the history of states and actions from all of the previous periods of the match.[13] Other than the timing of the new orders, the instructions for different visibility treatments were the same.

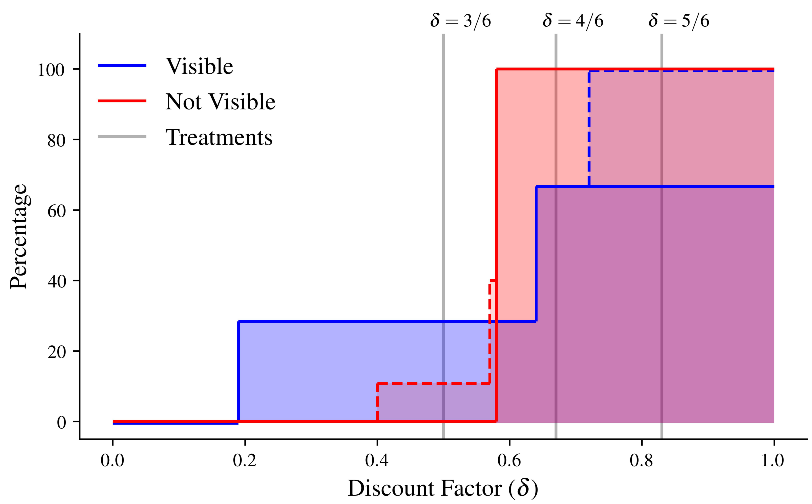


Figure 2.3. Average Effort Supported in an SPE

Notes: $\delta^*_v(GT^4) = 0.19$; $\delta^*_v(GT^{34}) = 0.64$; and $\delta^*_v(GT) = 0.72$; $\delta^*_{nv}(D.AlT^4) = 0.40$; $\delta^*_{nv}(D.AlT^{34}) = 0.56$; $\delta^*_{nv}(GT) = 0.58$. **Solid blue:** maximum average effort that can be sustained in an efficient SPE. **Dashed blue:** maximum average effort in an SPE. **Solid red:** maximum average effort sustained via history-contingent strategies (e.g., GT). **Dashed red:** maximum average effort sustained in SPE that requires inference of the state (e.g., $D.AlT^4$).

Figure 2.3 provides a visual summary of the theory calculations for the two visibility treatments. In particular, the figure presents the maximum proportion of high effort sus-

[13]↑When the queue is truly non-visible, servers see neither the arrivals nor the leftovers. For our experiments, we made the decision to show the previous period's outcomes for several reasons. First, it allowed for minimal change between the treatments (i.e., the only difference in the instructions was regarding the timing of arrivals). Second, by providing the outcome of the previous period, we removed any uncertainty about the payoffs obtained in the previous period. Third, we gave the state-contingent strategies the best chance. That is, if the state was truly non-visible, the amount of state-contingent strategies would go down.

tained in SPE as a function of the continuation probability (δ). The case of the queue being visible is blue and not visible in red. A few points that we would like to re-iterate follow. First, providing low effort is always an SPE. Furthermore, when cooperation is supported, infinitely many SPEs exist, so the analysis of GT-type strategies is useful to identify the maximum amount of high effort that could be sustained. Whether and to what extent subjects actually use these strategies and provide high effort is an empirical question we address with behavioral experiments. Second, for the case of a visible queue, we distinguish between the maximum efficient (solid blue) and maximum absolute (dashed blue) proportions of high effort that can be sustained in SPE. We do so because even though, theoretically, 100% of high effort can be sustained in SPE, we can reasonably expect that subjects will recognize that this sustained effort is not efficient, as they can be better of limiting their effort when the queue is short. As such, we expect them to cooperate up to the solid blue threshold. Third, for the case of a queue that is not visible, we delineate cooperation that relies on inference of the state (e.g., $D.AlT^4$ and $D.AlT^{34}$ in dashed red) from cooperation sustained via history-contingent strategies (e.g., GT in solid red).

We chose the three values of δ so that, in combination with the variation in visibility, we obtain distinct predictions regarding the maximum high effort sustained in an SPE across the three states of the visible treatment. Table 2.1 presents the summary of the six treatments of our experiment. For each treatment, we list some of the SPE strategies as well as the maximum amount of high effort, the waiting time, and the throughput losses of the queuing system if subjects are using those strategies.[14]

Next, we provide three general hypotheses based on the theoretical predictions based on Table 2.1 and Figure 2.3 . Our first hypothesis deals with the effect of the expected duration of the interactions:

Hypothesis 1. *Effort is increasing in the expected duration of an interaction.*

We expect that in both the visible and the not-visible treatments, a longer expected duration of an interaction would lead to higher effort. This hypothesis is consistent with the

[14]↑Recall that strategies that can be sustained in SPE at lower discount factors (e.g., GT^4 and $D.AlT^4$) can also be sustained at higher discount factors.

Table 2.1. Summary of Theoretical Predictions

Treatment			Performance in the Efficient SPE		
Visibility	δ	SPE Strategies	High Effort (%)	Waiting Time	Throughput Losses
Yes	$\frac{3}{6}$	AD, $\mathbf{GT^4}$	28.4	0.999	3.4
Yes	$\frac{4}{6}$	AD, GT^4, $\mathbf{GT^{34}}$	66.7	0.806	0.0
Yes	$\frac{5}{6}$	AD, GT^4, $\mathbf{GT^{34}}$, GT	66.7	0.806	0.0
No	$\frac{3}{6}$	AD, $\mathbf{D.AlT^4}$	10.8	1.154	10.2
No	$\frac{4}{6}$	AD, $D.AlT^4$, $\mathbf{GT}$	100.0	0.639	0.0
No	$\frac{5}{6}$	AD, $D.AlT^4$, $\mathbf{GT}$	100.0	0.639	0.0

Notes: Notable strategies that are supported as an SPE. The performance calculations are carried out for the efficient SPE (in bold). Waiting times (in periods) are calculated assuming all orders arrive at the beginning of the period and the order is processed in 0.5 periods if the server chose high effort and 1.0 periods if the server chose low effort. Waiting times include processing times. GT^θ denotes a trigger strategy that plays GT in states θ and plays Always Defect (AD) across all other states. $D.AlT^\theta$ denotes a trigger strategy that provides high effort immediately after observing mutual defection in state θ.

existing experimental evidence on the effect of an increase in the probability of future interactions on cooperation in repeated-game settings (e.g., see Result 1 inDal Bó and Fréchette [50]). Our second hypothesis deals with the effect of queue visibility on effort provision:

Hypothesis 2.

(a) *For low δ, effort is higher when the queue is visible.*

(b) *For high δ, effort is higher when the queue is not visible.*

Given our theoretical results, we expect that when the discount factor is low ($\delta = \frac{3}{6}$), some amount of high effort can be sustained if the queue is visible, because subjects should be able to sustain high effort when the queue is long. However, if the state of the queue is not known, none of the state-contingent GT-like strategies can be supported in SPE. Although strategy $D.AlT^4$ can be supported when the queue is not visible, we expect the percentage of high effort will be lower compared to the scenario when the queue is visible. Therefore, we expect longer average waiting times and greater throughput losses when the queue is not visible.

When $\delta = \frac{4}{6}$, the prediction flips and we expect higher effort if the queue is not visible than if it is. Lastly, when $\delta = \frac{5}{6}$, full effort can be supported in equilibrium in both settings. Nevertheless, we expect that when the queue is visible, subjects will learn to coordinate on an efficient outcome, which is to provide low effort when the queue is short and high effort when the queue is long. These predictions suggest that shorter average waiting time will be observed when the queue is not visible when δ is $\frac{4}{6}$ and $\frac{5}{6}$. In Appendix B.1.4, we conduct robustness checks to ensure that these theoretical results are robust to parameters of the cost and revenue functions chosen for the experiment.

The third hypothesis deals with the type of strategies that we should observe across the treatments.

Hypothesis 3. *When the queue is visible, subjects use state-contingent strategies.*

We expect that subjects will use state- and history-contingent strategies when the queue is visible, but use only history-contingent strategies when the queue is not visible. Although, this may seem trivial, the multiplicity of equilibria in repeated-game settings like the ones studied in this paper means the theory does not provide a sharp prediction. In fact, subjects could rely only on history-contingent strategies or could provide low effort across all states in both visible and non-visible treatments. Thus, without conducting lab experiments, whether subjects will learn to play strategies that differ in effort provision across different states and whether there will be any differences among the visibility treatments is not clear.

Hypothesis 3 is important because it provides an insight regarding the mechanism behind the main hypothesis of the paper (Hypothesis 2). In particular, Hypothesis 3 highlights the reason why visibility matters. Namely, by changing the visiblity of the queue, a manager can influence the type of strategies that servers use to support high effort in equilibrium.

2.4.3 Experiment Details and Administration

For study 1, we used ORSEE software Greiner [102] to recruit 280 students on the campus of a large public US university between January and February of 2020. We ran 24 sessions with the experimental interface programmed in oTree (Chen, Schonger, and Wickens [33]).[15] For each session, we invited 14 subjects; however, because of the no-shows, the actual number of participants in each session varied between 10 and 14. Instructions used in the experiment consisted of a set of interactive screens that explained all aspects of the experiment, and we provided a printed copy that subjects could use for reference during the experiment (see Appendix B.2.3). At the end of the instructions, subjects completed a 10-question quiz (see Appendix B.2.4). Subjects were asked to describe their strategies in a survey right after the experiment. They were also asked if their decisions in a period depended on what happened in the previous periods and if their strategy was different between the initial matches and the later matches. We report their answers in Table B.2 in Appendix B.3.

We used a between-subjects design whereby each participant took part in only one experimental treatment. Table 2.2 presents a summary of the six treatments. Each treatment consisted of four sessions, and each session consisted of either 80, 50, or 25 matches depending on the probability of continuation. At the beginning of each match, subjects were randomly paired with one other subject and remained paired with that subject for the duration of the match. Subjects remained anonymous throughout the session. Throughout the experiment, we used experimental points as the currency, with 250 points equaling $1. Subjects were paid in cash at the end of the experiment. The average earning in our experiment was $22.60 (including the $5 show-up fee).

[15]↑ see Appendix B.2.2 for screenshots of the interface.

Table 2.2. Summary of Experiment Administration

Treatment		Administration				Demographics		
Visibility	δ	Sessions	Subjects	Matches	Earnings	% Male	% STEM	% US HS
Yes	$\frac{3}{6}$	4	42	80	22.6	50.0	61.9	69.0
					(0.3)	(7.9)	(7.5)	(7.4)
Yes	$\frac{4}{6}$	4	46	50	22.9	56.5	65.2	56.5
					(0.3)	(7.2)	(7.0)	(7.5)
Yes	$\frac{5}{6}$	4	48	25	24.1	54.2	64.6	75.0
					(0.2)	(7.2)	(7.0)	(6.0)
No	$\frac{3}{6}$	4	48	80	22.2	66.7	62.5	68.8
					(0.2)	(6.8)	(6.9)	(6.9)
No	$\frac{4}{6}$	4	48	50	20.8	50.0	68.8	72.9
					(0.2)	(7.0)	(6.6)	(6.5)
No	$\frac{5}{6}$	4	48	25	22.8	60.4	60.4	66.7
					(0.1)	(7.4)	(7.0)	(6.7)

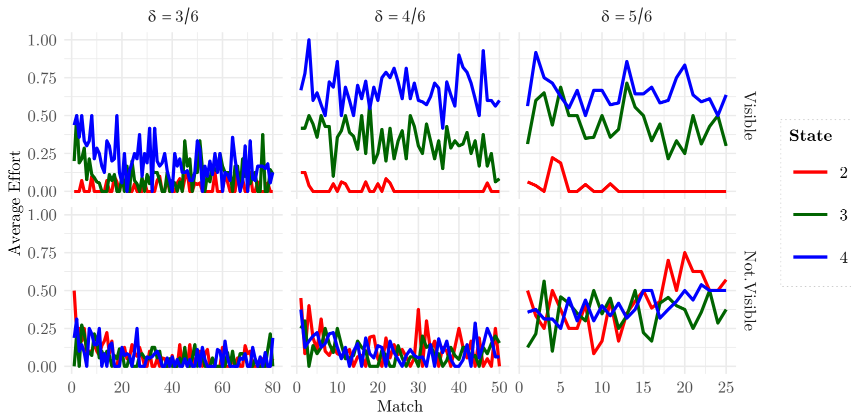
Notes: Earnings are reported in USD and include a $5 show-up fee. Standard errors are in parentheses.

2.5 Results

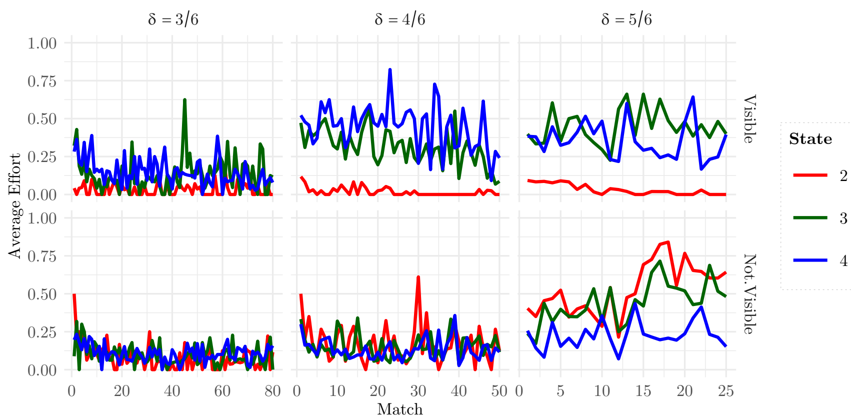
Figure 2.4 presents the evolution of effort across all matches in our experiment. Panel (a) shows the average effort by treatment for the first period, and panel (b) shows the average effort for all periods. Several clear patterns emerge. First, the average effort was higher for higher values of δ. Second, when the queue was visible, the average effort across the states are different, indicating that subjects made choices contingent on states. As expected, this pattern is more salient for the high δ treatments. Finally, in the treatment in which the queue was not visible and $\delta = \frac{5}{6}$, the average effort is increased as subjects gained experience.[16]

Figure 2.4 also shows that some subjects provided high effort in state 2 when the queue was not visible. This finding is more salient in the second half of matches of the $\delta = \frac{5}{6}$ treatment. Although, this is good news for a manager who wants servers to exert a

[16]↑In figure B.4 of Appendix B.3, we show that subjects' choices have a time trend effect.



(a) First Period



(b) All Periods

Figure 2.4. Evolution of Effort

Notes: High effort is coded as 1, and low effort is coded as 0.

homogeneous and fast processing speed, this is inefficient from the subjects' perspective because in state 2 both the Pareto-optimal and the Nash-equilibrium was for both to provide low effort. In fact, the efficiency was higher when the queue was visible than when the queue was not visible across all three δ values.

Table 2.3 presents the efficiency of outcomes for each of the six treatments. Efficiency is defined as the ratio of both subjects' earnings to their maximum possible earnings in a period. We observe that queue visibility has an significant effect on efficiency. For example, The effect of visibility on efficiency is significant at 0.05 level when $\delta = \frac{4}{6}$ and $\delta = \frac{5}{6}$ (p-values of 0.01 and 0.03, respectively), but not significant when $\delta = \frac{3}{6}$ (p-value of 0.45). This observation suggests that managers should consider providing more visibility of the queue if servers' efficiency is valued.

Table 2.3. Efficiency

Treatment		First Period			All Periods			
Visibility	δ	State 2	State 3	State 4	State 2	State 3	State 4	All States
Yes	$\frac{3}{6}$	98.7 (1.0)	82.2 (2.1)	56.5 (1.4)	98.6 (0.8)	83.4 (1.7)	55.6 (0.8)	66.1 (0.8)
Yes	$\frac{4}{6}$	99.9 (0.1)	87.2 (3.2)	80.4 (2.7)	99.8 (0.1)	85.2 (1.8)	66.5 (1.8)	74.9 (1.5)
Yes	$\frac{5}{6}$	100.0 (0.0)	91.5 (4.3)	79.2 (2.8)	99.6 (0.1)	91.5 (2.1)	64.6 (1.6)	73.3 (1.8)
No	$\frac{3}{6}$	98.7 (0.4)	79.4 (1.2)	53.0 (0.6)	97.8 (0.6)	81.2 (1.1)	55.0 (0.4)	65.0 (0.5)
No	$\frac{4}{6}$	96.5 (1.4)	81.2 (2.1)	55.2 (0.9)	94.4 (1.1)	83.0 (1.5)	56.4 (0.7)	64.7 (0.8)
No	$\frac{5}{6}$	81.8 (2.3)	90.0 (4.1)	68.0 (2.4)	75.8 (1.9)	92.0 (1.7)	61.2 (1.2)	67.7 (1.2)

Table 2.4 presents the percentage of high effort observed in the second half of our experiment.[17] The table breaks down actions by effort in the first period and effort across all periods. The first-period effort is important because it provides clear evidence of the subject's intention for the match. In addition, first-period effort choices provide an unbiased view of the decisions across the three states. Finally, combined with effort across all periods, the first-period effort provides indirect evidence on the dynamics within the interaction. For example, the fact that for $\delta = \frac{5}{6}$ and queue visible, effort in state 4 across all periods was approximately half the effort in state 4 in the first period (29.0% vs. 65.0%), suggests that

[17]↑In the repeated-games literature, it is common to focus on the second half of the experiment, because at that point subjects have become familiar with the strategic environment. In addition, after the initial learning phase, it is reasonable to assume that strategies that subjects are using do not change much.

subjects have used strategies that punished deviation from high effort. An end-of-experiment survey also reveals this dynamic (Table B.2 of Appendix B.3).

Table 2.4. Percentage of High Effort

Treatment		First Period			All Periods			
Visibility	δ	State 2	State 3	State 4	State 2	State 3	State 4	All States
Yes	$\frac{3}{6}$	3.7	11.4	15.0	3.9	17.0	10.7	10.9
		(2.6)	(4.0)	(4.2)	(2.2)	(5.0)	(2.9)	(2.8)
Yes	$\frac{4}{6}$	0.3	28.6	66.5	0.7	23.8	34.8	25.0
		(0.3)	(5.4)	(6.0)	(0.3)	(4.7)	(4.4)	(2.6)
Yes	$\frac{5}{6}$	0.0	41.3	65.0	1.1	50.5	29.0	28.4
		(0.0)	(6.2)	(6.5)	(0.4)	(5.7)	(4.1)	(3.0)
No	$\frac{3}{6}$	3.6	3.5	3.8	6.1	8.9	9.8	8.9
		(1.2)	(1.8)	(1.4)	(1.7)	(2.3)	(1.8)	(1.7)
No	$\frac{4}{6}$	9.7	8.7	8.9	15.5	16.0	12.9	14.0
		(4.0)	(3.5)	(3.9)	(3.3)	(3.5)	(2.3)	(2.4)
No	$\frac{5}{6}$	50.5	36.7	44.3	64.7	54.2	23.5	36.8
		(6.3)	(6.2)	(5.5)	(4.8)	(4.9)	(3.1)	(4.3)

Notes: Standard errors (in parentheses) are calculated by taking one subject as a unit of observation.

Several observations from Table 2.4 are noteworthy. The first observation concerns effort provision in the first period of interaction in each treatment. As expected, no difference exists across the three states when the queue is not visible.[18] This finding is reassuring in that subjects could not distinguish among the states in the first period. When the queue is visible, however, we find a clear trend – higher effort in the states with more customer orders in line. Specifically, when the discount factor is $\frac{3}{6}$, the percentage of high effort increases from 3.7% in state 2, to 11.4% in state 3, to 15.0% in state 4. When the discount factor is $\frac{4}{6}$, the percentage of high effort increases from 0.3% in state 2, to 28.6% in state 3, to 66.5% in state 4. When the discount factor is $\frac{5}{6}$, the percentage of high effort increases from 0.0%

[18]↑The p-value for a matched-pairs t-test of choosing high effort between state 2 and state 3 when the discount factor is $\delta = \frac{3}{6}(\frac{4}{6}, \frac{5}{6})$ is 0.97 (0.68, 0.61). The p-value for a matched-pairs t-test of choosing high effort between state 3 and state 4 when the discount factor is $\delta = \frac{3}{6}(\frac{4}{6}, \frac{5}{6})$ is 0.34 (0.65, 0.58).

in state 2, to 41.3% in state 3, to 65.0% in state 4. All of the increases from state 2 to state 4 are significant at the 0.01 level using a matched-pairs t-test.[19]

Table 2.4 shows that the percentage of high effort is increasing in δ. The difference is present across all states when the queue is not visible and across states 3 and 4 when the queue is visible. The difference is particularly noticeable in the first-period outcomes, because outcomes after the first period largely depended on what happened initially.[20] To formally test whether this difference is significant, we focus on the comparison between $\delta = \frac{3}{6}$ and $\delta = \frac{5}{6}$ and we run a multilevel mixed-effects probit regression of the choice of high effort in the first period on the dummy for whether the discount factor is high ($\delta = \frac{5}{6}$), including the subject-specific random effect and the session-specific random effect. We find a significant difference (p-value < 0.01) both when the queue is visible and when it is not. We summarize these observations as Result 1.

Result 1. *Servers provide higher effort when the expected duration of future interaction is longer.*

Next, Table 2.4 shows that servers provide higher effort when the queue is visible than when it is not, if the discount factor is low ($\delta = \frac{3}{6}$). To formally test whether the difference is significant, we run a multilevel mixed-effects probit regression of high effort in the first period on the dummy for whether the state is visible, including the subject-specific random effect and the session-specific random effect. We find that the difference is significant at the 0.10 level (p-value 0.05). When the discount factor is medium ($\delta = \frac{4}{6}$), the theory suggested that more cooperation is possible when the queue is not visible, however, in the data, we find that cooperation is significantly higher when the queue is visible (p-value< 0.01). One reason for this might be that although GT is an SPE strategy when the queue is not visible, it is not risk dominant when $\delta = \frac{4}{6}$.[21] Taken together, the two treatments provide evidence

[19]↑As a robustness check, we run a multilevel mixed-effects probit regression of the choice of high effort in the first period on the dummy for whether the state is 2 or 4 (with the subject-specific random effect and the session-specific random effect), we find that the increase from state 2 to state 4 are significant at 0.01 level for all values of δ.

[20]↑For example, if half of subjects play AD strategy and the other half of subjects play GT strategy, we would observe cooperation rate close to 25%, even though 50% of subjects play cooperative strategies.

[21]↑To check whether a strategy is risk dominant, we convert the indefinitely repeated PD game into a coordination game Dal Bó and Fréchette [99] and Blonski and Spagnolo [103]. When the queue is not visible,

that servers choose significantly higher effort when the queue is visible (p-value of 0.03).[22] When the discount factor is high ($\delta = \frac{5}{6}$), the overall effort is higher when the queue is not visible, which is consistent with the theoretical prediction of the impact of queue visibility. However, the difference is not significant (p-value 0.30). We summarize these findings as Result 2.

Result 2.

(a) *When the expected duration of future interaction is short, servers provide higher effort when the queue is visible.*

(b) *When the expected duration of future interaction is long, servers provide higher effort when the queue is not visible, but the difference is not significant.*

The fact that effort provision depends on the state realization when the queue is visible leads us to believe that subjects used state-contingent strategies. The fact that effort in the first period was greater than the effort across all periods leads us to believe that subjects used history-contingent strategies. Next, we use a finite-mixture estimation approach to formally estimate the strategies underlying choices in our experiment. This approach has advantages over other estimation methods, and evidence shows that it performs well (Dal Bó and Fréchette [50], [72] and Romero and Rosokha [73]).[23] The finite-mixture models have also been widely used in economics (e.g.,Dal Bó and Fréchette [70] and Haruvy, Stahl, and Wilson [104]) to estimate the proportion of subjects who follow a particular strategy. The method works by first specifying the set of K strategies considered by the modeler. Then, for each subject $n \in N$, and each strategy $k \in K$, the method prescribes comparing subject n's actual play with how strategy k would have played in her place. Let $X(k, n)$ denote the number of periods in which subject n's play correctly matches the play of strategy k. Then, let X denote a $K \times N$ matrix of the number of correct matches for all combinations of

GT is a risk dominant strategy when $\delta = \frac{5}{6}$, but not when $\delta = \frac{4}{6}$ or $\delta = \frac{3}{6}$. To apply this approach to the case when the queue is visible, we do this exercise for GT^{34}. We find that GT^{34} is risk dominant when $\delta = \frac{5}{6}$ and $\delta = \frac{4}{6}$, and it is not risk dominant when $\delta = \frac{3}{6}$.

[22]↑A multilevel mixed-effects probit regression regression of high effort in the first period on two dummy variables – visibility and discount factor – yields p-values of 0.02 and less than 0.01 when clustering standard errors at the session level.

[23]↑The finite-mixture approach

subjects and strategies. Similarly, let Y denote a $K \times N$ matrix of the number of mismatches when comparing subjects' play with what the strategies would do in their place. Then, define a Hadamard-product P:

$$P = \beta^X \circ (1-\beta)^Y, \tag{2.13}$$

where β is the probability that a subject plays according to a strategy and $(1-\beta)$ is the probability that the subject deviates from that strategy. Thus, each entry $P(k,n)$ is the likelihood that strategy k generated the observed choices by subject n. Then, using the matrix dot product, we define the log-likelihood function $\mathcal{L}$:

$$\mathcal{L}(\beta,\phi) = ln\Big(\phi \cdot P\Big) \cdot \mathbf{1}, \tag{2.14}$$

where ϕ is a vector of strategy frequencies.

For our estimation, the set of strategies encompasses the five most common strategies found in the literature on repeated games as well as state-contingent variations of those strategies. In particular, we include Always Cooperate (AC), Always Defect (AD), Grim Trigger (GT), Tit-for-Tat (TFT), and Suspicious Tit-for-Tat ($D.TFT$) – the five memory-1 strategies that account for the majority of the strategies in 16 out of 17 treatments reviewed by Dal Bó and Fréchette [50]. We also include modified versions of these strategies that condition on either state 4 or both states 3 and 4. Notably, we include GT^{34} and GT^4, which were analyzed theoretically. In addition, we include the $D.AlT^4$ strategy that could sustain some amount of high effort when the queue is not visible (as well as the corresponding $D.AlT^{34}$ and $D.AlT$ strategies).

Table 2.5 presents the estimation results for the second half of matches.[24,25] We find that the most common strategy across all four treatments was the AD strategy. This finding is not surprising given the prevalence of the AD strategy in the literature on the indefinitely

24↑Table B.3 of the Appendix reports the estimation results for the first half of matches.

25↑The value of $(1-\beta)$ can be interpreted as the amount of noise not captured by the specified strategies. When the queue is visible, our estimates of $(1-\beta)$ are similar to the estimates in Romero and Rosokha [73] and Romero and Rosokha [105]. However, when the queue is not visible, the values are somewhat lower, suggesting that the set of strategies may be missing relevant strategies. Table B.4 of the Appendix presents the estimates when using an expanded set of strategies. In particular, we use 20 commonly studied strategies in the indefinitely repeated PD literature Fudenberg, Rand, and Dreber [106] and Cason and Mui [107].

Table 2.5. Estimated Percentage of Strategies

Visibility	δ	AD	AC	TFT	GT	$D.TFT$	$D.AlT$	AC^{34}	TFT^{34}	GT^{34}	$D.TFT^{34}$	$D.AlT^{34}$	AC^{4}	TFT^{4}	GT^{4}	$D.TFT^{4}$	$D.AlT^{4}$	β (%)	$\mathcal{L}$
Yes	$\frac{3}{6}$	59.4 (9.9)				6.5 (5.4)		2.4 (2.5)			22.5 (9.0)		2.4 (2.3)	2.4 (2.6)		4.3 (5.8)		93.7 (1.7)	-895.9
Yes	$\frac{4}{6}$	37.9 (7.5)							11.2 (4.6)	14.2 (6.3)	2.5 (2.2)			15.6 (12.8)	18.6 (12.9)			92.0 (0.9)	-1053.6
Yes	$\frac{5}{6}$	32.7 (7.1)							32.1 (7.5)	13.7 (6.4)	4.5 (2.8)		5.5 (3.6)	5.4 (4.4)	6.2 (5.2)			93.7 (0.7)	-904.9
No	$\frac{3}{6}$	65.8 (7.2)	2.1 (2.2)			17.0 (6.9)	4.1 (3.0)					2.1 (2.3)				6.8 (4.4)	2.1 (2.1)	93.1 (1.3)	-1096.1
No	$\frac{4}{6}$	56.7 (8.6)		6.3 (3.5)	2.1 (2.2)	21.4 (6.4)						4.1 (3.4)				3.2 (3.1)	6.3 (3.9)	92.2 (1.4)	-1082.3
No	$\frac{5}{6}$	36.6 (7.1)	2.1 (2.0)	37.2 (7.7)	6.2 (3.5)	15.8 (5.5)											2.1 (2.2)	89.5 (1.3)	-1244.4

Notes: For ease of reading, estimated percentages < 0.1 are not displayed. Strategy superscripts denote states in which this strategy is played; in states that are not included in the superscripts, the strategy specifies to play AD. The first five strategies are viewed as history-contingent strategies; AC^{34} and AC^{4} are state-contingent strategies; and the rest are state- an history-contingent strategies. Bootstrap standard errors are in parentheses. The unit of observation is one subject.

repeated PD with parameters similar to ours (e.g.,Dal Bó and Fréchette [70]). Even so, we find a clear pattern in the type of other strategies used across the treatments. In particular, When the queue is visible, the frequency of state- and history-contingent strategies is 29.2%($\delta = \frac{3}{6}$), 62.1% ($\delta = \frac{4}{6}$), and 61.9% ($\delta = \frac{5}{6}$). Whereas when the queue is not visible, the frequency of state- and history-contingent strategies is 11%($\delta = \frac{3}{6}$), 13.6% ($\delta = \frac{4}{6}$), and 2.1% ($\delta = \frac{5}{6}$).[26] The difference for $\delta = \frac{3}{6}$ ($\delta = \frac{4}{6}$, $\delta = \frac{5}{6}$) treatment is significant at the .05

[26]↑The low proportion of state-contingent $D.AlT$-type strategies is supported from a reduced-form data and end-of-experiment unincentivized survey. In particular, in the period following both subjects choosing low effort in state 4, the probability of being in state 4 is 100%, but we only observe 1.0% (2.0%, 1.0%) of mutual high effort when $\delta = \frac{3}{6}$ ($\delta = \frac{4}{6}$, $\delta = \frac{5}{6}$). Regarding the end-of-experiment survey, we asked subjects to describe strategies that they used. We find that 0.0% (8.0%, and 2.0%) of subjects described strategies close to $D.AlT$ when $\delta = \frac{3}{6}$ ($\delta = \frac{4}{6}$, $\delta = \frac{5}{6}$). And among those that did describe $D.AlT$ strategy, several mentioned difficulty getting others to play this strategy. The end-of-experiment survey results pare summarized in Table B.2 of Appendix B.3

(.01, .01) level using a non-parametric permutation test.[27] We summarize this finding as Result 3.

Result 3. *When the queue is visible, servers use state-contingent strategies.*

In terms of the particular strategies played, we find that when the queue was visible, subjects played sophisticated TFT- and GT-like strategies that provided high effort when the queue was long but low effort when the queue was short. These strategies are different from the TFT and GT strategies studied in the repeated-game literature in that they respond to the opponent's behavior conditional on the state of the queue. Importantly, the proportion of these strategies observed in the data predictably varied by treatment and is comparable to the existing literature on repeated games. In particular, we observe an initial increase and then decrease of the proportion of strategies that cooperate in state 4 but not in state 3 (TFT^4 and GT^4 accounted for 2.4% when $\delta = \frac{3}{6}$; 34.1% when $\delta = \frac{4}{6}$; and, 11.6% when $\delta = \frac{5}{6}$).[28] The decrease was due to the switch to strategies that cooperated across more states (e.g., TFT^{34} and GT^{34}). For example, when $\delta = \frac{5}{6}$, 45.8% of subjects used cooperative strategies that provided high effort in states 3 and 4 as opposed to 25.4% when $\delta = \frac{4}{6}$, and 0.0% when $\delta = \frac{3}{6}$. When the queue was not visible, subjects could not play any of these strategies; as a result, when δ increased we observed a switch from non-cooperative strategies (AD and DTFT accounted for 82.8% when $\delta = \frac{3}{6}$) to cooperative strategies (TFT and GT comprised 43.4% when $\delta = \frac{5}{6}$).

Regarding the comparison to the existing literature, consider the non-stochastic version of our study with $\theta = 3$ every period (i.e., servers always face three customers in every period) studied in Dal Bo and Frechette (2011). In particular, the authors find the proportion of TFT in $\delta = \frac{3}{4}$ treatment to be 35.2%. Thus, our estimation of 37.2% of TFT in the not visible treatment and 37.5% of state-contingent TFT-like strategies is very much in line with the existing literature.

[27]↑For the permutation test Good [108], the null hypothesis is that there is no difference between the proportion of strategies across the visibility treatments for a fixed value of δ. Given the null hypothesis, the distribution of the test statistic is obtained by randomly permuting the treatment labels among subjects (unit of observation).

[28]↑The high standard errors of the estimates for TFT^4 and GT^4 are the results of these two strategies being very similar in behavior for the considered duration of interactions. When we estimate the joint proportion, we obtain 34.1 with a standard error of 6.8.

2.6 Discussion

In this paper, we theoretically and experimentally investigated the effort provision in a single-queue two-server system when compensation is based on the group performance. To the best of our knowledge, we are the first to focus on the repeated nature of interaction among servers in queueing systems and show theoretically that high effort can be sustained in equilibrium even when short-term incentives to free-ride are present for each server in each of the possible states of the queue (i.e., number of customers in line). Furthermore, if servers' interactions are long term, high effort can be sustained regardless of whether the queue is visible. However, as interactions get shorter, visibility becomes an important determinant of the types of strategies that can support high effort in equilibrium. In particular, we theoretically show that providing less visibility of the queue may be better because players will average incentives across multiple states, which will lead them to provide high effort even in states corresponding to the short queue. We also show that if the queue is visible, sustaining high effort when the queue is long is much easier than when the queue is short.

We conduct a controlled laboratory experiment to test the theoretical predictions. In particular, we implement a 3×2 factorial design in which we vary the expected length of interaction among the servers and the visibility of the queue. We find that longer expected interactions leads to higher effort. We find a modest impact of queue visibility on the overall effort. However, we find strong evidence that the underlying strategies that human servers in the two visibility treatments are different. Specifically, following the repeated-game literature we carry out finite-mixture model estimation of the strategies. When the queue is not visible, we find that subjects primarily rely on always defect, tit-for-tat and suspicious tit-for-tat. When the queue is visible, a significant proportion of subjects rely on state-contingent versions of tit-for-tat and grim trigger strategies. These strategies are sophisticated in that they remember the last time both players were in the current state and act accordingly.

Our results have several implications for managers who are trying to design more efficient queueing systems. First, in the presence of a group-based incentive scheme, emphasizing the long-term nature of the interaction among the servers is important. The emphasis on repeated interaction should encourage reputation building and provide room for the threat of future punishment. This implication also suggests that the managers should be cautious when implementing policies regarding rotating human servers among groups. Although regularly rotating workers among teams could limit collusion (Bandiera, Barankay, and Rasul [16]), reduce the ratchet effect (Wei [109]), and promote innovation (Dearden, Ickes, and Samuelson [19]), it may intensify free-riding.

Second, based on our theoretical and experimental results, ensuring that the queue is visible would be useful when the expected duration of interaction is short.[29] When the interactions are long, hiding information about the state of the queue, may be beneficial if the manager would like to instill homogeneous and fast processing speeds across all of the states of the queue, which is desired in service industries such as fast-food industries and banking where, service speed plays an important role in a customer's satisfaction (Davis and Maggard [113], Kara, Kaynak, and Kucukemiroglu [114], and Mathe-Soulek, Slevitch, and Dallinger [115]). There is plethora evidence that customers' satisfaction is positively related to a company's sales and customers' loyalty (Gómez, McLaughlin, and Wittink [116], Han and Ryu [117], and Pont and McQuilken [118]). Therefore, managers may take a homogeneous service speed into consideration when designing a queueing system. In particular, it is possible to sustain a homogeneously high processing speed when the queue is not visible. On the other hand, if managers value the servers' welfare, providing more visibility should be considered.

Finally, our theory and experiments suggest that when the queue is visible, servers may provide low effort when the queue is short and higher effort when the queue is long. This strategic adjustment not only affects their own welfare, but also the particular dynamics of the queue. Managers should take this endogenous variability into account if the service is multi-stage.

[29]↑ In other words, managers should make the queue more visible when servers have a smaller discount factor. Randomly terminated repeated games without payoff discounting is theoretically same as the infinitely repeated games with payoff discounting (Fréchette and Yuksel [100]). Empirical evidence shows that people discount their future payoffs (Dasgupta and Maskin [110], Olivola, Olivola, Wang, *et al.* [111], and Ainslie [112]).

3. COOPERATION IN QUEUEING SYSTEMS: A REVISIT

with Yaroslav Rosokha

3.1 Introduction

In this chapter, we report another experiment to test the theory of Chapter 2.3 for three objectives. The first is to provide a more natural queueing frame for the participants (instead of context-neutral presentation in the first study), including details of the cost and revenue functions. The second is to explore a wider parameter space with a streamlined microfoundation. In particular, we explicitly assume that servers work together to process tasks (e.g., a team of nurses/doctors treating a patient in healthcare setting) and the cost incurred by each server depends on her utilization, which in turn depends on the effort by the other server(s). The last objective is to include more matches for each treatments.

Chapter 2.3 presents the theoretical analysis of servers' behavior when they are working in a group for a long time. We show that it is possible to sustain high effort if servers' interactions are long enough. We also show that queue visibility plays an important role in determining the strategies that can support high effort in equilibrium. Specifically, when the expected duration of the interaction is short, providing more visibility is beneficial. When the expected duration of the interaction is long, servers are more likely to provide high effort when the queue is not visible.

The experiment in Chapter 2.5 provides evidence that longer expected interactions lead to higher effort. We also find a modest impact of queue visibility on the overall effort. There are three observations that we need to note for the experiment in Chapter 2.5. First of all, we used the abstract context in both the instructions and computer screens to achieve experimental control. Alekseev, Charness, and Gneezy [119] compare the literature with an abstract context and the literature with context-rich language and find that meaningful language is either useful or produces no changes in subjects' behavior in most cases. They also suggest that context-rich language can enhance understanding of an environment and reduce participants' confusion. Given that our environment is fairly complicated (stochastic and dynamic), it would be useful to check if a meaningful context can be helpful for subjects.

Second, we tested our theory using one set of parameter values. There is a risk that the documented effects are specific to these values. Additional sets of values would provide generalizable insights of our theory. Third, we observe that match numbers play a role in subjects' behavior in Figure B.4. The question of whether subjects' behavior will reach an equilibrium if there are more matches arises. In summary, we believe there is a need to conduct additional experiments to provide further evidence of our theory.

Similar to the experiment in Chapter 2, the new experiment tests our theoretical predictions under a simplified two-server three-state queueing system. We vary two factors – the expected duration of interaction (i.e., probability of continuing the interaction to the next period) and queue visibility (i.e., whether servers know the state of the queue). In the new experiment, we find clear evidence that the average effort increases with the expected duration of repeated interactions. We also find that when the queue is visible, the average effort is higher when the queue is long than when the queue is short. Arguably, the most interesting result is that we find support for the theoretical predictions regarding the effect of queue visibility – namely, when the expected duration of future interaction is short, on average, servers provide higher effort when the queue is visible than when it is not, but when the expected duration of future interaction is long, the opposite is true. Lastly, like the experiment in Chapter 2, we carry out econometric estimation of (unobservable) strategies that subjects use. The result of the estimation in the new experiment is consistent with that in Chapter 2.

The rest of the paper is organized as follows: In section 3.2, we present the details of the second study, with the results presented in section 3.3. We conclude in section 3.4.

3.2 Experimental Design and Theoretical Predictions

Appendix C.2.3 presents instructions that were used for the second study. To highlight some of the details, we told the subjects, "You and the participant you are paired with will work together to process the task queue. Specifically, in each round, you will choose how much capacity to allocate (either 1 or 2 units). The participant you are paired with will also choose how much capacity to allocate (either 1 or 2 units)." We chose to present the decision as the choice of capacity rather than effort or speed of processing to minimize any negative associations with "low effort" or "slow speed." We then went on to describe the implications of the capacity choices on the dynamics (i.e., leftover tasks) and how payoffs are determined. In terms of the payoffs, we explicitly provided the cost function, the revenue function, and the payoff calculations associated with the capacity choices. Finally, the decision screen was different from the one in Study 1, in that we presented the state of the queue in text, and we provided a button for decision support that, when clicked, presented the summary of the payoffs similar to how the payoff tables were presented in study 1.

In terms of the payoffs, we picked another cost function, $c(.)$ and different parameters for the compensation function, $r(.)$. Specifically, for study 2, the cost is a function of server's capacity choice and the realized utilization (i.e., the fraction of the time that server ends up working in a period), $T = min(1, \frac{\theta}{total\ capacity})$. We set the cost of choosing one unit of capacity $c(1,T) = aT^2 + bT + c$ with $a = 2$, $b = 18$, and $c = 20$; and the cost of choosing two units of capacity $c(2,T) = xT^2 + yT + z$ with $x = 6$, $y = 54$, and $z = 20$. In Appendix C.1, we provide more details on the cost function, including the visual representation (Figure C.1) and comparative statics regarding theoretical calculations (Figure C.2). Regarding the compensation, we simplify the function and only include the per-unit compensation. Specifically, when the group processed $M(.)$ tasks, $r(\mathrm{e_i}, \mathrm{e_j}, \theta) = kM(\mathrm{e_i}, \mathrm{e_j}, \theta) + \mathbf{1}_{M(\mathrm{e_i},\mathrm{e_j},\theta)=4} bonus$ with $k = 36$, and $bonus = 0$. The resulting payoffs for each combination of choices are presented in Figure 3.1.[1]

[1]↑In Appendix C.1.3, we provide examples of calculating entries in the payoff tables presented in Figure 3.1

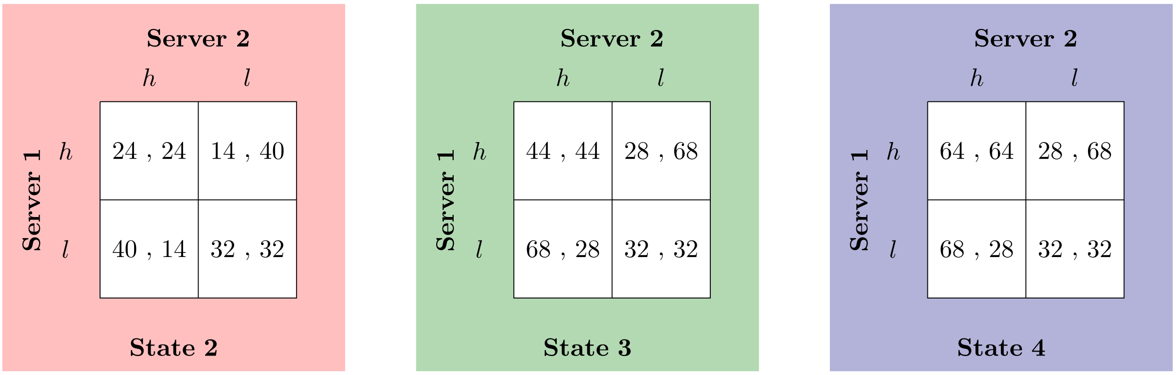


Figure 3.1. Stage-Game Payoffs in Each State

Notes: The three columns present stage-games played in the three possible states. State $\theta \in \{2, 3, 4\}$ corresponds to θ customer orders in line. Each player chooses low capacity (l) or high capacity (h) to process customer orders. Matrices present normal form representation of the stage game played in each state.

3.2.1 Hypotheses and Treatments

Using the techniques described in sections 2.3 and 2.4.1, we find that when the queue is visible, $\delta^*_v(GT) = 0.67$, $\delta^*_v(GT^{34}) = 0.62$, and $\delta^*_v(GT^4) = 0.26$. When the queue is not visible, $\delta^*_{nv}(GT) = 0.55$ and $\delta^*_{nv}(D.AlT^4) = 0.46$. Figure 3.2 provides a visual summary of the theory calculations. As can be seen in the figure, the patterns are the same as in study 1, meaning that our theoretical results from section 2.4.2 are robust to the alternative specification of the compensation and cost functions.

In terms the experiment, we implement a 2×2 factorial between-subjects design in which we vary the expected duration of interaction (i.e., $\delta = \frac{3}{6}$ and $\delta = \frac{5}{6}$) and whether servers know the state of the queue. Based on the theoretical predictions we keep the same three hypotheses:

Hypothesis 1. *Effort is increasing in the expected duration of an interaction.*

Hypothesis 2.

(a) *For low δ, effort is higher when the queue is visible.*

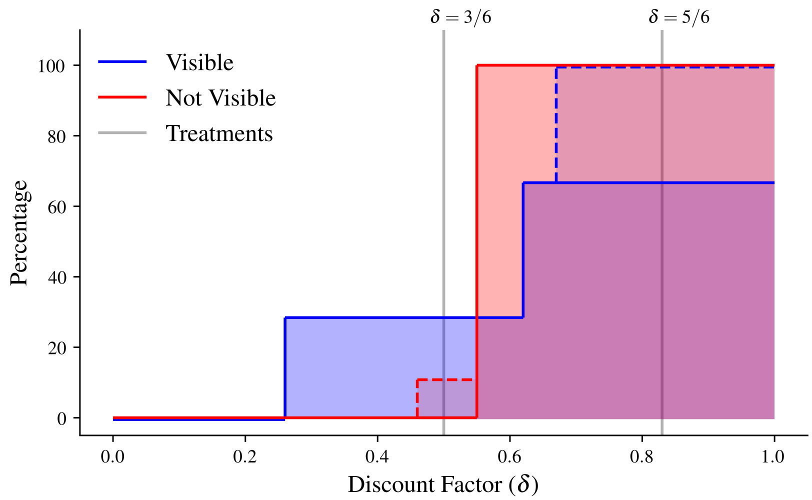


Figure 3.2. Average Effort Supported in an SPE

Notes: $\delta_v^*(GT^4) = 0.19$; $\delta_v^*(GT^{34}) = 0.64$; $\delta_v^*(GT) = 0.72$; $\delta_{nv}^*(D.AlT^4) = 0.46$; $\delta_{nv}^*(GT) = 0.58$. **Solid blue:** maximum average effort that can be sustained in an efficient SPE. **Dashed blue:** maximum average effort in an SPE. **Solid red:** maximum average effort sustained via history-contingent strategies (e.g., GT). **Dashed red:** maximum average effort sustained in SPE that requires inference of the state (e.g., $D.AlT^4$).

(b) *For high δ, effort is higher when the queue is not visible.*

Hypothesis 3. *When the queue is visible subjects use state-contingent strategies.*

3.2.2 Experiment Details and Administration

Regarding the experimental administration, we used ORSEE software (Greiner [102]) to recruit 142 students in April of 2021. We ran 12 sessions with the experimental interface programmed in oTree (Chen, Schonger, and Wickens [33]) (see Appendix C.2.2 for screenshots of the interface and Appendix C.2.4 for the quiz). Each treatment consisted of three sessions, and each session consisted of either 100 matches (for $\delta = \frac{3}{6}$) or 40 matches (for $\delta = \frac{5}{6}$). We also used a between-subjects design where each participant took part in only one experimental treatment. Table 3.1 presents a summary of the four treatments.

Note that we increased the number of matches to ensure that subjects had enough time to learn.[2] At the beginning of each match, subjects were randomly paired with one other subject and remained paired with that subject for the duration of the match. Subjects remained anonymous throughout the session. Throughout the experiment, we used experimental points as the currency, with 400 points equaling \$1. Subjects were paid in cash at the end of the experiment. The average earning in our experiment was \$27.67 (including the \$5 show-up fee).

[2]↑Figure 3.3 in Appendix B.3 presents the learning trends in the first set of experiments.

Table 3.1. Summary of Experiment Administration for the Second Study

Treatment		Administration				Demographics		
Visibility	δ	Sessions	Subjects	Matches	Earnings	% Male	% STEM	% US HS
Yes	$\frac{3}{6}$	3	36	100	22.7	56.5	60.9	73.9
					(0.2)	(10.5)	(10.3)	(9.4)
Yes	$\frac{5}{6}$	3	36	40	33.0	38.9	61.1	72.2
					(0.6)	(8.3)	(8.2)	(7.2)
No	$\frac{3}{6}$	3	36	100	22.4	61.9	61.9	66.7
					(0.1)	(10.5)	(10.7)	(10.4)
No	$\frac{5}{6}$	3	34	40	32.8	55.9	55.9	70.6
					(0.5)	(8.7)	(9.0)	(7.8)

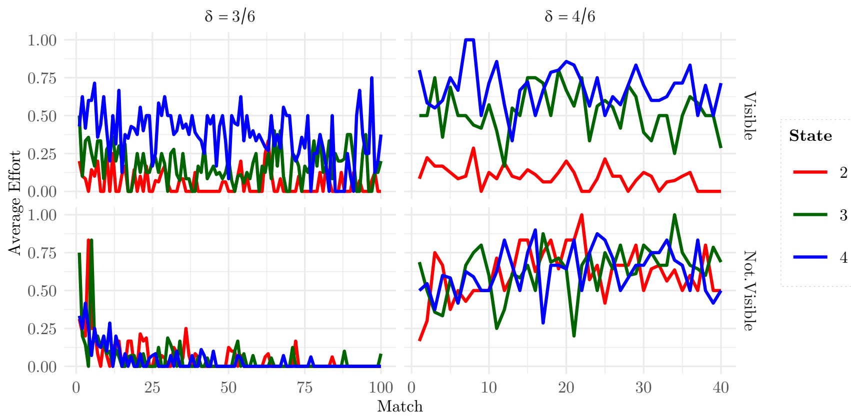
Notes: Earnings are reported in USD and include a $5 show-up fee. Standard errors are in parentheses. One session in (Yes,$\frac{3}{6}$) and one session in (No,$\frac{3}{6}$) treatments were stopped before match 100 due to time constraints. The demographics data for these two sessions are missing.

3.3 Results

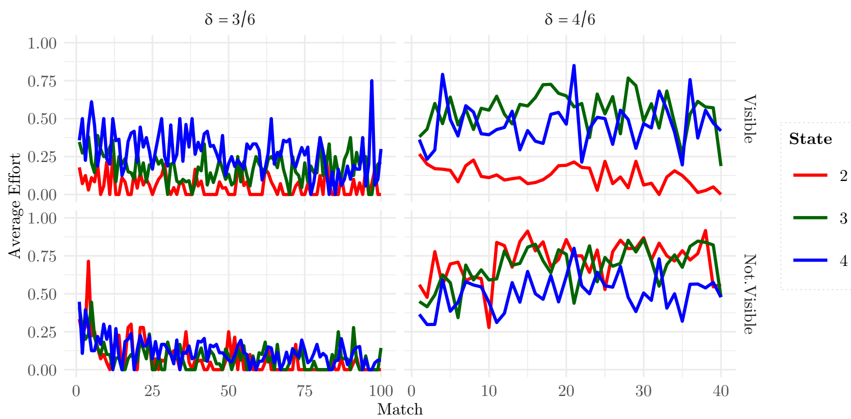
Figure 3.3 presents the evolution of effort across matches in the second study. Panel (a) shows the average effort by treatment for the first period, and panel (b) shows the average effort for all periods. As in the previous study, we first find that the average effort was higher for higher value of δ. Second, the average effort across states are separated when the queue is visible. Finally, we observe a high percentage of subjects were willing to provide high effort in the treatment where the queue was not visible and $\delta = \frac{5}{6}$.

Table 3.2 presents the efficiency of outcomes for each of the four treatments (See chapter 2.5 for the definition of efficiency). We find that when $\delta = \frac{3}{6}$, efficiency is higher if the queue is visible (p-value < 0.05). When $\delta = \frac{5}{6}$, visibility does not play a role on the efficiency (p-value 0.884).

Table 3.3 provides more details on the average percentage of high effort observed in the second half of the study. Similar to study 1, we find that high effort is increasing in δ. In particular, we run a a multilevel mixed-effects probit regression of the choice of high effort in



(a) First Period



(b) All Periods

Figure 3.3. Evolution of Effort

Notes: High effort is coded as 1, and low effort is coded as 0.

the first period on the dummy for whether the discount factor is high ($\delta = 0.83$), including subject-specific random effect and session-specific random effect. We find the difference is significant (p-value<0.01) both when the queue is visible and when it is not.

Result 1. *Servers provide higher effort when the expected duration of future interaction is longer.*

Regarding part (a) of the second hypothesis, we find that when $\delta = \frac{3}{6}$ servers provided significantly more effort when the queue is visible than when it is not (p-value<0.01). Regarding

Table 3.2. Efficiency

Treatment		First Period			All Periods			
Visibility	δ	State 2	State 3	State 4	State 2	State 3	State 4	All States
Yes	$\frac{3}{6}$	98.8 (1.6)	76.9 (1.9)	67.1 (1.6)	98.6 (1.8)	76.2 (1.3)	60.8 (1.3)	69.8 (1.2)
Yes	$\frac{5}{6}$	97.9 (2.3)	89.8 (3.1)	83.0 (2.4)	97.3 (1.7)	86.8 (0.9)	70.8 (2.1)	78.0 (1.7)
No	$\frac{3}{6}$	99.6 (0.5)	67.6 (0.3)	50.2 (0.2)	99.1 (0.5)	70.4 (0.5)	55.2 (0.5)	63.5 (0.5)
No	$\frac{5}{6}$	82.6 (4.6)	93.2 (3.5)	82.8 (2.3)	80.3 (1.6)	91.4 (1.1)	74.5 (2.1)	79.8 (1.3)

part (b) of the second hypothesis, we find that when $\delta = \frac{5}{6}$ servers provided significantly less effort when the queue is visible than when it is not. However, unlike study 1, this difference is now significant (p-value<0.01). There are two explanations for the difference becoming significant. The first is that for study 2 we increased the number of matches. This meant that subjects had more opportunities to learn and the trend noted in Figure 2.4 (and Figure B.4 in the Appendix) led to the difference becoming more pronounced. The second is that the parameters chosen for the second study were more favorable to cooperation, which led to an increase in the proportion of high effort.[3] However, while the increase occurred for all three states in the not visible treatment, the increase was minimal in state 2 of the visible treatment (in which we did not expect any cooperation). These results are consistent with our second hypothesis.

Result 2.

(a) *When the expected duration of future interaction is short, servers provide higher effort when the queue is visible.*

(b) *When the expected duration of future interaction is long, servers provide higher effort when the queue is not visible.*

[3]↑One way to compare the extent to which cooperation is favorable is using the size of the basin of attraction AD against $GT - SizeBAD$ (Dal Bó and Fréchette [70]). For $\delta = \frac{5}{6}$, in study 1 $SizeBAD = 0.32$, in study 2 $SizeBAD = 0.16$.

Table 3.3. Percentage of High Effort for the Second Study

Treatment		First Period			All Periods			
Visibility	δ	State 2	State 3	State 4	State 2	State 3	State 4	All States
Yes	$\frac{3}{6}$	3.8	16.3	34.1	4.4	16.8	21.6	16.5
		(2.8)	(5.2)	(7.6)	(2.9)	(4.6)	(5.0)	(3.4)
Yes	$\frac{5}{6}$	6.8	50.4	66.1	9.2	54.7	41.6	38.5
		(3.7)	(7.1)	(7.8)	(3.5)	(4.6)	(5.1)	(3.2)
No	$\frac{3}{6}$	1.4	1.4	0.6	2.9	6.7	10.4	8.1
		(0.8)	(1.0)	(0.4)	(1.0)	(1.9)	(2.3)	(1.8)
No	$\frac{5}{6}$	63.2	66.4	65.6	75.6	73.9	49.0	62.4
		(8.3)	(8.0)	(7.7)	(3.7)	(3.6)	(4.6)	(4.1)

Notes: The table presents the data in the second half of the experiment: 50-100 matches for $\delta = 0.5$ and 20-40 matches for $\delta = 0.83$. Standard errors (in parentheses) are calculated by taking one subject as a unit of observation.

Lastly, we conduct the finite-mixture estimation to uncover the strategies used by subjects in the second study. Table 3.4 presents the results for the second half of matches. We find that when the queue was visible, 44.1% (72.3%) of subjects relied on state-contingent strategies for $\delta = \frac{3}{6}$ ($\delta = \frac{5}{6}$), which was greater than 28.2% (5.9%) observed when the queue was not visible.[4]

Result 3. *When the queue is visible, servers use state-contingent strategies.*

Comparing the strategies used across the two studies, we find many similarities. For example, when $\delta = \frac{3}{6}$, subjects primarily relied on uncooperative strategies (AD and versions of $D.TFT$), whereas when $\delta = \frac{5}{6}$ the most popular strategies included the TFT-like strategies. One notable difference is that for $\delta = \frac{5}{6}$ the proportion of AD was smaller in study 2 (13.9 and 5.9 in study 2 versus 32.7 and 36.6 in study 1. This difference is consistent with overall higher levels of cooperation in the second study noted above.

[4]↑The p-value for the non-parametric randomization test for $\delta = \frac{3}{6}$ is .22. The p-value for the non-parametric randomization test for $\delta = \frac{5}{6}$ is $< .01$

Table 3.4. Estimated Percentage of Strategies for the Second Study

Visibility	δ	AD	AC	TFT	GT	$D.TFT$	$D.AlT$	AC^{34}	TFT^{34}	GT^{34}	$D.TFT^{34}$	$D.AlT^{34}$	AC^{4}	TFT^{4}	GT^{4}	$D.TFT^{4}$	$D.AlT^{4}$	β (%)	$\mathcal{L}$
Yes	$\frac{3}{6}$	53.1	2.8					2.8	3.3	7.8			8.4	8.3	4.5	9.0		93.7	-755.2
		(8.7)	(3.0)					(3.0)	(3.2)	(4.9)			(4.6)	(4.8)	(4.7)	(5.3)		(1.1)	
Yes	$\frac{5}{6}$	13.9		2.8		11.1		9.2	22.2	16.8	5.6		2.5		16.0			89.6	-1640.4
		(6.1)		(2.5)		(5.2)		(4.8)	(7.1)	(6.7)	(3.7)		(2.2)		(7.5)			(1.1)	
No	$\frac{3}{6}$	56.3				12.7	2.8				4.5	8.4				4.1	11.2	95.1	-708.7
		(7.4)				(6.8)	(2.8)				(4.9)	(3.9)				(3.9)	(4.4)	(1.2)	
No	$\frac{5}{6}$	5.9	14.6	37.1	16.0	20.6											5.9	89.1	-1578.2
		(3.8)	(5.7)	(7.7)	(7.1)	(6.8)											(3.9)	(1.1)	

Notes: For ease of reading, estimated percentages < 0.1 are not displayed. Strategy superscripts denote states in which this strategy is played; in states that are not included in the superscripts, the strategy specifies to play Always Defect (AD). The first five strategies are viewed as history-contingent strategies; AC^{34} and AC^{4} are state-contingent Markov strategies; and the rest are state- an history-contingent strategies. Bootstrap standard errors are in parentheses. The unit of observation is one subject.

To summarize, we find that results of the second set of experiments provide clear support for the three hypotheses derived from theoretical predictions. The results also complement findings from the first set of experiments by establishing the robustness to the decision-making context and functional specification of individual cost and compensation functions.

3.4 Conclusion

This chapter presents another experiment for testing the theory developed in chapter 2.3. There are three new features in this experiment. First of all, we provide a more natural queueing frame for the participants during the experiment. Then, we assume that servers work together to process tasks and also implement another set of parameter values in the experiment. Lastly, we include more matches for each treatment during the experiment.

Similar to the experiment in chapter 2, in this new experiment, we vary the expected length of interaction among the servers and the visibility of the queue. The results are generally consistent with the results in chapter 2. Specifically, we show longer expected interactions lead to higher effort. For subjects' strategies, we carry out finite-mixture model estimation of the strategies. We find that when the queue is not visible, subjects primarily rely on history-contingent strategies. Among them the most common ones are tit-for-tat and suspicious tit-for-tat. When the queue is visible, however, a significant proportion of subjects rely on state- and history-contingent versions of these strategies. The most interesting finding is that queue visibility may have a different impact depending on the expected duration of the interaction. In particular, if the expected duration of the interaction is short, subjects provided higher effort when the queue is visible than when it is not. However, if the expected duration of the interaction is long, subjects provided lower effort when the queue is visible than when it is not.

Taking chapter 2 and chapter 3 into together, the whole project opens many exciting avenues for future research on understating the behavior of servers and customers on both the theoretical and experimental fronts. First and foremost, in this paper, we focus on the strategic implications of repeated interactions among servers. Extending the equilibrium analysis to include strategic customers and scheduling policies would be of great importance. Second, we analyze the case of discrete effort levels, discrete states, and discrete timelines. Given recent advances in running (near-) continuous-time experiments (e.g., Friedman and Oprea [120]), considering a similar setting with continuous variables along each of those dimensions would be interesting. Third, we consider a case of identical customers and servers, introducing heterogeneity in worker ability and customer orders (and thus an asymmetry in the dynamic game) would add more realism to the environment. Fourth, we focus on the case of indefinite duration of interaction. Understanding the implications of the finite horizon in this setting would be important. Lastly, the extent to which communication among servers and different matching mechanisms (such as the one in Honhon and Hyndman [121]) can improve effort provision in the queueing setting would be of great interest.

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A. APPENDIX FOR: CAN JOB ROTATION ELIMINATE THE RATCHET EFFECT: EXPERIMENTAL EVIDENCE

A.1 Theoretical Derivations

An agent has a utility $U_A = w - c(\mathrm{e})$, where w is the wage that the agent receives if he accepts the job offer and $c(\mathrm{e})$ is the cost function of effort e. The agent receives 0 if he rejects the job offer. We use $c(\mathrm{e}) = \mathrm{e}^2$ in our environment, which satisfies the assumptions of increasing and convex. The wage w offered by the principal takes the form $w = \alpha + \beta Y(\mathrm{e})$, where β is the piece rate, α is the fixed payment to the agent and $Y(\mathrm{e})$ is the production function. The production function is $Y(\mathrm{e}) = \theta \mathrm{e}$, where θ is the productivity of the food stand. The principal observes $Y(\mathrm{e})$ instead of e at the end of the production process. We assume the principal is also risk neutral, and her utility is $U_P = Y(\mathrm{e}) - w = Y(\mathrm{e}) - \alpha - \beta Y(\mathrm{e})$.

The principal's objective is to look for contracts such as $(\overline{\alpha}, \overline{\beta})$ and $(\underline{\alpha}, \underline{\beta})$ that maximize his expected profit, $I(stand = \overline{\theta}) \times [Y(\overline{\mathrm{e}}) - \overline{w}] + I(stand = \underline{\theta}) \times [Y(\underline{\mathrm{e}}) - \underline{w}]$. $I(\cdot)$ is an indicator function, which is one if the statement in the parenthesis is true and zero otherwise. The agent's individual rationality (IR) constraints are: $\overline{U_A} = \overline{w} - \overline{\mathrm{e}}^2 \geq 0$ and $\underline{U_A} = \underline{w} - \underline{\mathrm{e}}^2 \geq 0$. In order to get the first best effort levels, we set $\overline{U_A} = 0$ and $\underline{U_A} = 0$ and then plug $\overline{w} = \overline{\mathrm{e}}^2$ and $\underline{w} = \underline{\mathrm{e}}^2$ into the principal's objective function. The principal's objective function becomes: $I(stand = \overline{\theta}) \times (\overline{\theta}\overline{\mathrm{e}} - \overline{\mathrm{e}}^2) + I(stand = \underline{\theta}) \times (\underline{\theta}\underline{\mathrm{e}} - \underline{\mathrm{e}}^2)$. Using the first order condition with respect to $\overline{\mathrm{e}}$ and $\underline{\mathrm{e}}$, we get $\mathrm{e}_H = \frac{\overline{\theta}}{2}$ for the agent who runs a high-productivity stand, and $\mathrm{e}_L = \frac{\underline{\theta}}{2}$ for the agent who runs a low-productivity stand. Since $Y(\mathrm{e}) = \theta \times \mathrm{e}$, $Y_H = \frac{\overline{\theta^2}}{2}$ and $Y_L = \frac{\underline{\theta}^2}{2}$. Note we use $\mathrm{e}_H(\mathrm{e}_L)$ instead of $\overline{\mathrm{e}^*}(\underline{\mathrm{e}^*})$ to represent equilibrium efforts for a cleaner presentation.

Meanwhile, an agent's incentive compatibility constraint must be satisfied for getting the first best outcomes. By maximizing $\underline{U_A}$ and $\overline{U_A}$ with respect to $\underline{\mathrm{e}}$ and $\overline{\mathrm{e}}$, we get $\overline{\beta}^* = \underline{\beta}^* = 1$. In addition, $\overline{\alpha^*} = (\mathrm{e}_H)^2 - \overline{\theta}\mathrm{e}_H = -\frac{\overline{\theta^2}}{4}$ and $\underline{\alpha^*} = (\mathrm{e}_L)^2 - \underline{\theta}\mathrm{e}_L = -\frac{\underline{\theta}^2}{4}$ from the binding IR constraints.

The negative fixed payments can be interpreted as maximum rental fees that agents are able to pay for renting and operating the stands.[1] For convenience, let $A = -\alpha$ represent

[1] ↑See the discussion in Charness, Kuhn, and Villeval [5]

the money that the principal receives from the agent, and this is the only source of profit the principal can obtain in the equilibrium. Hence, the maximum rental fee that the agent who runs a high-productivity stand can afford is $\overline{A^*} = \frac{\overline{\theta}}{4}$, and the maximum rental fee that the agent who runs a low-productivity stand can afford is $\underline{A^*} = \frac{\underline{\theta}}{4}$. Note that this maximum rental fee is also the maximum surplus from the contract between the principal and the agent. The principal earns full surplus from the contract, and the agent obtains zero surplus.

Note the first best outcome is based on the condition that the agent has revealed the type of his stand to the principal at the beginning of the first stage. However, if the principal can only learn the type of the stand at the end of the first stage through the first-stage output, the agent might have incentives to shirk in the first stage.

In the first stage, since the firm does not know the productivity of a stand and wants to hire the agent to run the stand, we assume the firm charges a fixed rental fee $R > 0$ for the agent and $\overline{\beta} = \underline{\beta} = 1$ for simplicity. If an agent's objective is to maximize his first-stage expected payoff, he provides $\mathrm{e}_H = \frac{\overline{\theta}}{2}$ and consequently produces $Y_H = \frac{\overline{\theta}^2}{2}$ if he runs a high-productivity stand. If this agent runs a low-productivity stand, he provides $\mathrm{e}_L = \frac{\underline{\theta}}{2}$ and produces $Y_L = \frac{\underline{\theta}^2}{2}$. As a result, the principal learns the type of the stand clearly through the output produced by that agent. In order to maximize her profit in the second stage, a rational principal charges $\overline{A^*}$ for the agent who produced Y_H and $\underline{A^*}$ for the agent who produced Y_L. Accordingly, the agent earns zero in the second stage. On the contrary, if the agent who runs a high-productivity stand strategically shirks and exerts $\mathrm{e}_S = \frac{\underline{\theta}^2}{2\overline{\theta}}$, then he produces Y_L in the first stage. The principal may think he is running a low-productivity stand and then chooses a low rental fee ($\underline{A^*}$). Because of this, this agent earns positive payoffs instead of zero in the second stage.

Restricting output in the first stage causes a loss in the first stage. In the first stage, the agent earns $Y_L - \mathrm{e}_S^2 - R = \frac{2\underline{\theta}^2\overline{\theta}^2 - \underline{\theta}^4}{4\overline{\theta}^2} - R$ by exerting e_S and producing Y_L. But this agent could have earned $Y_H - \mathrm{e}_H - R$ if he exerted e_H. The loss in the first stage is $\frac{(\overline{\theta}^2 - \underline{\theta}^2)^2}{4\overline{\theta}^2}$.

Nevertheless, if the gain in the second stage is larger than the loss in the first stage, the agent will have an incentive to shirk in the first stage if he runs a high-productive stand. If an agent who runs a high-productivity stand strategically shirks by exerting e_S and producing Y_L in the first stage, the principal might charge $\underline{A^*}$ for him in the second stage. Therefore, he earns $\underline{\alpha} + \overline{\theta}\mathrm{e}_H - \mathrm{e}_H^2 = \frac{\underline{\theta}^2(\overline{\theta}^2 - \underline{\theta}^2)}{4\overline{\theta}^2}$ instead of zero in the second stage. Given $\overline{\theta} = 14$, $\underline{\theta} = 10$ and $R = 15$ in our experiment, the gain in the second stage is larger than the loss in the first stage if an agent who runs a high-productivity stand shirks in the first stage.

In the experiment, the second stage is twice as long as the first stage regarding the payoff space. Therefore, the maximum rental fee that the principal is able to get from two types of stands are $2\overline{A^*} = 98$ and $2\underline{A^*} = 50$. In the practice, we allow principals to choose either $R_H = 60$ or $R_L = 30$ as the rental fee instead. This ensures that the agent earns a positive payoff even if he reveals the type of his stand and the principal earns the larger share of the contract's surplus.

A.2 Additional Tables

Table A.1. Determinants of a firm choosing a high rental fee

	No Rotation	*Pooling data*
Variables	rentalFee	rentalFee
roundFirms	0.0144	-0.005
	(0.0134)	(0.016)
roundWorkers	-0.02274	-0.0110
	(0.0172)	(0.007)
output	2.328***	2.29***
	(0.24)	(0.195)
exog		0.015
		(0.163)
endo		0.1
		(0.2)
exog× output		-0.37*
		(0.197)
endo× output		-0.34
		(0.284)
constant	-1.028***	-1.041***
	(0.113)	(0.081)
observations	1080	3240
Number of id	36	108

Note: Standard errors (clustered at session level) are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.3 Switch Behavior

To determine the effect of being switched on a worker's future behavior, we conduct a random-effect probit regression which only includes the observations that workers chose to shirk in the previous round. The dependent variable "effort "is one if the worker picks the high output in the first period and zero otherwise. "L.switch" is a dummy independent variable, which is one if the worker was switched in the previous round when he is in a high-productivity stand, and zero otherwise. Table 6 shows the results of the estimation. Tables 6 shows no evidence to support the effect of being switched on a worker's behavior in the following round.

Table A.2. Determinants of choosing high effort in the first stage

	No Rotation	*Pooling data*
Variables	Effort	Effort
roundFirms	-0.152**	-0.207***
	(0.061)	(0.031)
roundWorkers	-0.0631	0.0246
	(0.045)	(0.026)
exog		3.002***
		(0.609)
endo		1.464***
		(.333)
constant	3.132***	1.970***
	(0.740)	(0.518)
observations	351	1047
Number of id	36	108

Note: Standard errors (clustered at session level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

A.4 Instructions

We thank you for participating in this economic experiment on decision-making. During this experiment, you can earn money. The amount of your earnings depends on your decisions and on the decisions of the other participants in this experiment. It is therefore important you understand these instructions well. At the end of the instructions there will be a ten-question comprehension quiz which tests your understanding of these instructions. You will earn $0.50 for each correct answer provided the quiz.

Your total earnings (including a $5.00 show-up fee and your quiz earnings) will be paid to you in cash in private at the end of the experiment. During the experiment, your earnings will be calculated in Experimental Points, with:

$$100 \text{ Points} = 4 \text{ U.S. Dollars}$$

Throughout the entire session, direct communication between participants and using cell-phones are strictly forbidden. If you have any questions regarding these instructions, please raise your hand, but do not speak.

Today's experiment consists of **45** decision-making rounds. These 45 rounds are broken down into nine **5 rounds**. There are 3 roles of players: Firm, Worker W1 and Worker W2.

Table A.3. Determinants of Switching (Random Effect Probit)

	(1)	(2)	(3)
Variables	switch	switch	switch
roungFirms	0.0015	0.0015	0.0014
	(0.004)	(0.004)	(0.004)
roundWorkers	-0.00399*	-0.004*	-0.003*
	(0.002)	(0.002)	(0.002)
TwoLow	0.174***	0.052	-
	(0.064)	(0.058)	
OneLowOneHigh	0.122***	-	-
	(0.007)		
TwoHigh	-	-0.122***	-
		(0.007)	
AtLeastOneLow	-	-	0.153***
			(0.039)
Constant	0.059***	0.182***	0.0584
	(0.072)	(0.0403)	(0.0726)
observations	540	540	540
Number of id	36	36	36

Note: Standard errors (clustered at session level) are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4. The effect of switching

Variables	Effort
round	0.00155
	(0.00252)
L.switch	0.105
	(0.0770)
Constant	0.157
	(0.129)
observations	81
Number of id	15

Note: Standard errors are in parentheses. The dependent variable is 1 if the worker picks high output in the first period and 0 otherwise. "L.switch" is 1 if the worker was switched in the last round when she is in a high productivity stand, and 0 otherwise. *** p¡0.01, ** p¡0.05, * p¡0.1.

You will be informed of your role at the beginning of each 5 rounds, and you will keep the same role throughout these 5 rounds. You will experience each role three times, and the order is randomly determined.

During each **round**, one Firm is matched with two randomly selected Workers (W1 and W2) in this room. Firms and Workers are re-matched randomly at the beginning of **each round**.

Each **round** consists of two periods. Period 1 represents the first week of operation. Period 2 represents the following two weeks of operation.

Period 1

The Firm is the owner of 2 new food concession stands (S1 and S2) on a University campus, but does not know the exact productivity of these two stands.

There is a 1 in 3 chance **(33%)** that stand S1 is of high productivity and 2 in 3 chance **(67%)** that stand S1 is of low productivity. Similarly, there is a 1 in 3 chance **(33%)** that stand S2 is of high productivity and 2 in 3 chance **(67%)** that stand S2 is of low productivity. It is possible that both stands are of high productivity; it is possible that both stands are of low productivity; and it is possible that one stand is of low productivity and another one is of high productivity.

In Period 1, the Firm is willing to rent one stand to one Worker (i.e., Worker W1 can run stand S1 for one week and Worker W2 can run stand S2 for one week). The Firm charges a rental fee of 15 points to use each stand, and the two rental fees are the only source of earnings for the Firm in Period 1.

The Worker will know the productivity of the stand once he or she receives the offer, but the Firm will not.

All Workers accept the offer by default in Period 1. If a Worker is in a **high productivity stand**, he or she can choose to deliver either a **Low output** (i.e., serving a small number of customers) or a **High output** (i.e., serving a large number of customers) in Period 1. If the worker chooses to deliver a **High output**, he or she earns **34 points** in Period 1. If this Worker chooses to deliver a Low output, he or she earns **22 points** in Period 1. If a Worker is in a **low productivity stand**, he or she can only deliver a **Low output**, which earn **10 points** in Period 1.

The net payoffs in Period 1 associated with each possible decision of the participants are summarized in the **green table**.

Period 1 ends after all participants have made their decisions. A summary of your decisions and your net payoffs will be displayed. At that time the Firm will see the outputs delivered by each stand.

<u>Period 2</u>

In Period 2, the Firm is willing to rent these stands to the Workers again. **In particular, the two workers will be switched between two stands** (i.e., Worker W1 will be switched to run stand S2, and Worker W2 will be switched to run stand S1 for next two weeks). **The productivity of the two stands will stay the same as in Period 1.**

The Firm can offer a **rental fee** of either **30** or **60** **points** for each worker in Period 2. The rental fees are the only source of earnings for the Firm in Period 2. However, unlike Period 1, Workers have an option to reject an offer in Period 2. If the Worker **rejects** the offer in Period 2, the Worker and the Firm earn **0 points** in Period 2.

If the Worker **accepts** the offer in Period 2, he or she can choose different actions based on the productivity of the stand that he or she is in. As long as the new offer is accepted, the Firm earns the rental fee from this stand regardless of the output chosen by the Worker.

The net payoffs associated with each possible decision of the participants in Period 2 for the case that **the Firm charges 30 as the rental fee** are summarized in the **red table**.

The net payoffs associated with each possible decision of the participants in Period 2 for the case that **the Firm charges 60 as the rental fee** are summarized in the **blue table**.

You will see a summary of your decisions and your net payoffs at the end of each round. A new round starts after the summary. Prior to a new round you will be re-matched with two randomly selected participants in this room.

At the end of the experiment, the computer will randomly select 3 rounds (one from being each role). Your earnings for the experiment will be the sum of your points earned in these **3 rounds**.

A.5 Payoff Tables

Period 1:

The net payoffs and outputs in **period 1** associated with each possible decision of the participants are summarized in the following table:

	Stand Productivity	**Worker's Choice**	**Firm's Payoff**	**Worker's Payoff**
Green	**Low Productivity**	Low output	15	10
	High Productivity	High output	15	34
		Low output	15	22

Period 2:

The net payoffs associated with each possible decision of the participants in Period 2 for the case that **the Firm charges 30 as the rental fee** are summarized in the following table:

	Stand Productivity	**Worker's Choice**	**Firm's Payoff**	**Worker's Payoff**
Red	**Low Productivity**	Reject	0	0
		Low output	30	20
	High Productivity	Reject	0	0
		High output	30	68
		Low output	30	44

The net payoffs associated with each possible decision of the participants in Period 2 for the case that **the Firm charges 60 as the rental fee** are summarized in the following table:

	Stand Productivity	Worker's Choice	Firm's Payoff	Worker's Payoff
Blue	Low Productivity	Reject	0	0
		Low output	60	-10
	High Productivity	Reject	0	0
		High output	60	38
		Low output	60	14

A.6 Quizzes

Figure A.1. Screen Shot of Quiz Page

1. I am paired with the same two participants in the two Periods of each Round.

   ○ True ○ False

2. I am always paired with the same two participants during the entire experiment.

   ○ True ○ False

3. The chance that stand S1 is of high productivity is 1 in 2 (50%).

   ○ True ○ False

4. The chance that stand S2 is of high productivity is 1 in 3 (33%).

   ○ True ○ False

5. Worker W1 run stand S1 in Period 1, but run stand S2 in Period 2.

   ○ True ○ False

6. At the end of Period 1, the Firm will see the outputs delivered by each stand.

   ○ True ○ False

7. In Period 2, the productivity of the two stands stay the same as in Period 1.

   ○ True ○ False

8. In Period 1, if a worker who is in a high productivity stand chooses the High Output, he or she earns 22 points.

   ○ True ○ False

9. In Period 2, if a worker who is in a high productivity stand was charged the rental fee of 30 and chooses the High Output, he or she earns 68 points.

   ○ True ○ False

10. In Period 2, if a worker who is in a high productivity stand was charged the rental fee of 60 and chooses the High Output, he or she earns 68 points.

    ○ True ○ False

B. APPENDIX FOR: COOPERATION IN QUEUEING SYSTEMS

B.1 Microfoundations

B.1.1 Cost Function

As described in the second paragraph of Section 2.4, the cost of processing $m_{\mathrm{i}}(.)$ orders with low effort is $c(l, \mathrm{e_j}, \theta) = am_{\mathrm{i}}(l, \mathrm{e_j}, \theta)^2 + bm_{\mathrm{i}}(l, \mathrm{e_j}, \theta) + c$ with $a = 22$, $b = -37$, and $c = 40$; and the cost of processing $m_{\mathrm{i}}(.)$ orders with high effort is $c(h, \mathrm{e_j}, \theta) = xm_{\mathrm{i}}(h, \mathrm{e_j}, \theta)^2 + ym_{\mathrm{i}}(h, \mathrm{e_j}, \theta) + z$ with $x = 22$, $y = -37$, and $z = 49$. Figure B.1 presents the two cost functions in the same graph given $m_{\mathrm{i}}(.)$ ranges between 1 and 2. Figure B.1 also labels all possible costs that could realize in the setup used for the experiment. In particular, point A in the Figure corresponds to the cost of providing low effort. Note that for the setup used in study 1, the cost of providing low effort is independent of the effort provided by the the other server. Points B, C, and D correspond to the cost of providing high effort. The cost varies depending on the state and the actions of the other server. For example, if the state is 2, then the server will only process one order, whereas if the state is 4 then the server will process two orders.

B.1.2 Compensation Function

As described in the third paragraph of Section 2.4, an individual server is compensated based on the group performance. Specifically, if the group processes $M(.)$ orders, the compensation function is $r(\mathrm{e_i}, \mathrm{e_j}, \theta) = kM(\mathrm{e_i}, \mathrm{e_j}, \theta) + \mathbf{1}_{M(\mathrm{e_i}, \mathrm{e_j}, \theta)=4} bonus$ with $k = 25$ and $bonus = 11$.

B.1.3 Examples

Here we provide two examples of how the cost and compensation function maps the payoff matrices.

- **Example 1**: Suppose there are 2 tasks in the queue in a given period. If a server chooses high effort and her teammate also chooses high effort, then both 2 tasks are

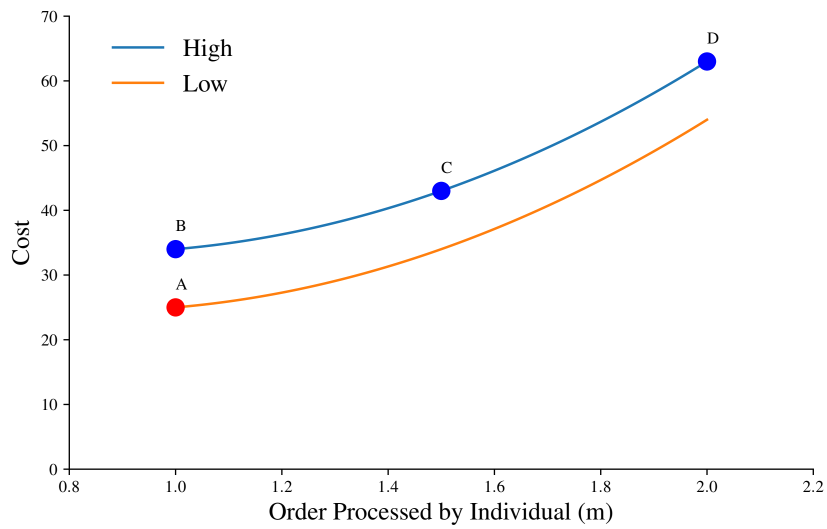


Figure B.1. Cost Function

Notes: **A:** (l,l,2), (l,h,2), (l,l,3), (l,h,3), (l,l,4), and (l,h,4); **B:** (h,h,2) and (h,l,2); **C:** (h,h,3); **D:** (h,l,3), (h,h,4), and (h,l,4). The first item in the tuple (e_i,e_j,θ) represents server's own effort; the second item represents the other server's effort; the last item represents the state of the queue (i.e., the number of orders in the queue).

processed (each server processes 1 task). This leads to the server's cost 34(=22×1^2-37×1+49), and the revenue 50(=25×2). Therefore, this server's payoff is 16(=50-34).

- **Example 2**: Suppose there are 4 tasks in the queue in a given period. If a server chooses low effort and her teammate chooses high effort, then the team is able to process 3 tasks. This leads to the server's cost 25(=22×1^2-37×1+40). The revenue is 75(=25×3). Therefore, this server's payoff is 50(=75-25).

B.1.4 Comparative Statics

Combined, the compensation function and the cost function have 8 parameters. Figure B.2 presents comparative statics of the critical thresholds of four *GT* strategies for each of the eight parameters. In particular, for each subfigure, we vary only one parameter and hold all other parameters constant at the experimental value. For example, in the top right figure, we study the relationship between the the critical thresholds of the *GT* (solid red),

GT^4 (dashed green), GT^{34} (dashed orange), and GT^{234} (dashed blue) and the value of k while keeping $bonus = 11, a = 22, b = -37, c = 40, x = 22, y = -37, z = 49$.

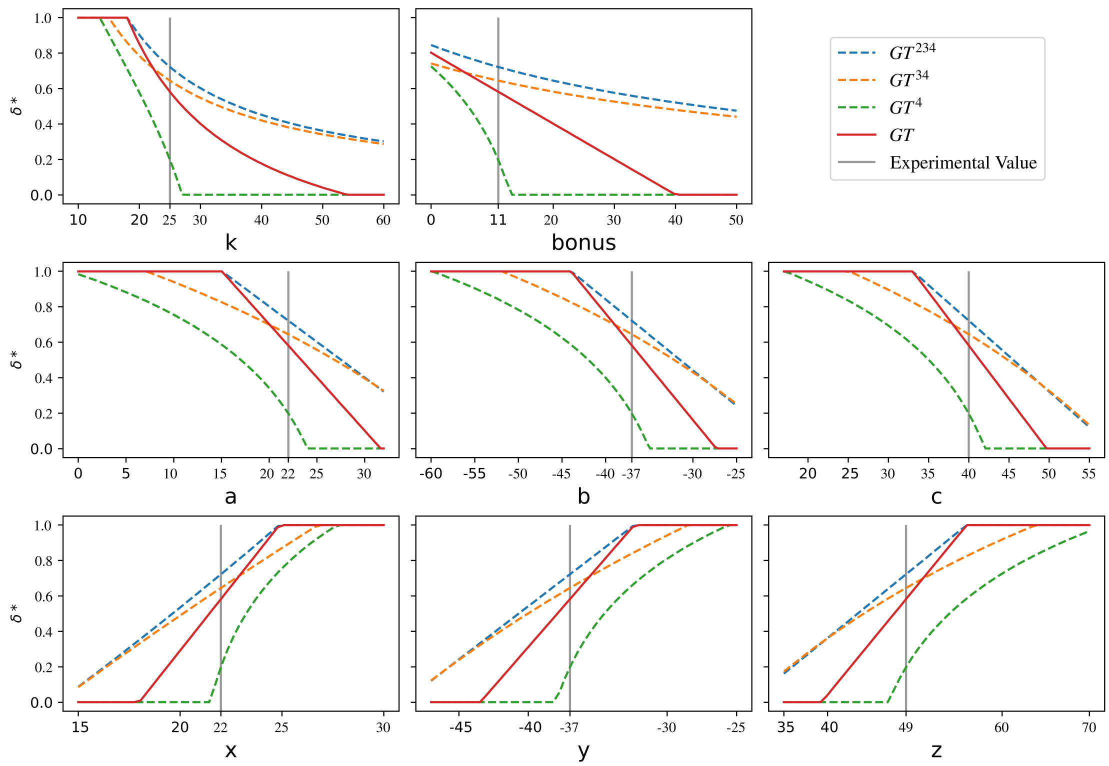


Figure B.2. Comparative Statics and Parameters

Notes: For each graph, we hold the other parameters constant as the experimental value when varying a given parameter. The experimental values are $k = 25, bonus = 11, a = 22, b = -37, c = 40, H = 1, d = 9$.

The eight graphs in Figure B.2 share two common patterns. The first pattern is that $\delta_v^*(GT^4) \leq \delta_v^*(GT^{34}) \leq \delta_v^*(GT^{234})$ when $\delta_v^*(GT^4) > 0$.[1] The interpretation of this result is that when the queue is visible it is easier to sustain cooperation when the queue is long than when it is short. The second pattern is that $\delta_v^*(GT^4) \leq \delta_{nv}^*(GT) \leq \delta_v^*(GT^{234})$. This means that while it is easier to sustain high effort across all states when the queue is not visible, it is easier to sustain high effort across a subset of the states (e.g., $\theta = 4$) when the queue is

[1]↑$\delta_v^*(GT^4)$=0 indicates the incentives to provide the high effort is large. If the incentives to provide the high effort is large enough (or the cost to provide the high effort is small enough), servers may play a prisoner dilemma game when state is 2. Therefore, it is possible that $\delta_v^*(GT^{34}) > \delta_v^*(GT^{234})$.

visible. These two common patterns are consistent with our hypotheses discussed in section 2.4.2.

B.1.5 Theoretical Predictions with Experimental Results

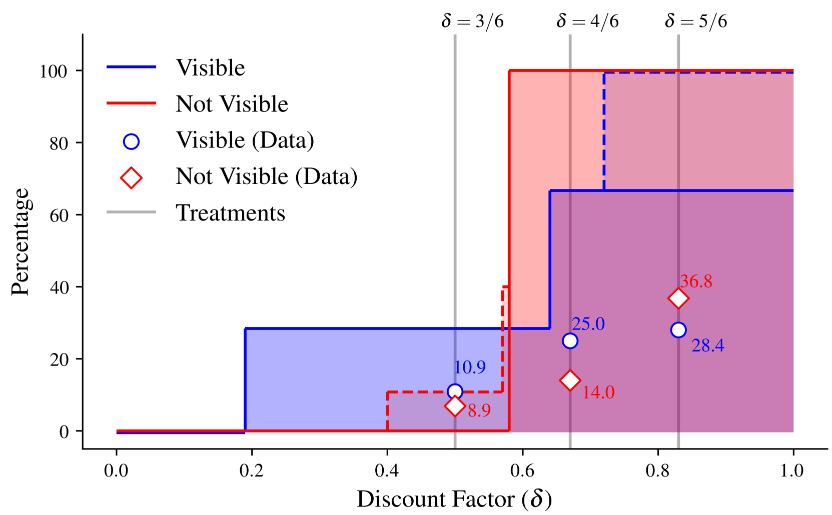


Figure B.3. High Effort, Discount Factor, and Data

Notes: Data is the percentage of high effort chosen by subjects across all periods in the second half of matches. Servers are assumed to use GT-type strategies in this figure ($\delta^*_{nv}(GT) = 0.58$; $\delta^*_v(GT^4) = 0.19$; $\delta^*_v(GT^{34}) = 0.64$ and $\delta^*_v(GT) = 0.72$). Even GT is an equilibrium strategy when the queue is visible and $\delta > 0.72$, we assume servers provide low effort when the state is 2 since it is the efficient choice. Strategies like $D.AlT^4$ are also SPE when the queue is not visible and δ is large enough, they does not change the main hypotheses ($\delta^*_{nv}(D.AlT^4)$=0.40).

B.2 Experimental Design

B.2.1 Supergame Length Realizations

Table B.1. Supergame Lengths

(a) $\delta = \frac{3}{6}$

Supergame Number:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Realization #1:	4	2	1	5	1	1	1	1	2	1	1	1	3	1	1	9	5	3	1	2	2	2	2	7	1
Realization #2:	2	2	1	4	3	1	1	1	2	1	1	1	2	1	1	1	1	2	1	1	4	1	2	2	1
Realization #3:	1	1	2	2	2	2	2	1	4	2	2	1	3	2	2	1	1	3	3	6	1	1	2	2	1
Realization #4:	2	2	4	1	1	2	3	2	2	4	1	1	2	3	1	2	2	1	1	3	1	3	3	2	1
Supergame Number:	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**
Realization #1:	4	1	1	1	3	1	1	2	1	1	2	4	1	2	2	6	3	1	6	12	2	2	2	2	1
Realization #2:	2	1	2	1	1	2	2	2	1	7	1	1	1	1	2	3	1	1	1	1	5	3	3	5	5
Realization #3:	3	2	2	2	1	1	1	1	1	1	1	1	2	1	1	1	1	2	2	2	3	2	1	4	1
Realization #4:	2	2	1	5	1	2	4	3	1	1	1	1	1	2	2	2	1	2	1	1	1	2	1	2	2
Supergame Number:	**51**	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**	**61**	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**
Realization #1:	1	1	2	3	7	1	1	3	1	1	1	1	5	2	2	2	1	1	4	2	1	2	1	2	6
Realization #2:	1	1	4	2	13	2	1	1	1	2	1	2	3	2	1	3	1	1	2	1	2	2	2	4	1
Realization #3:	1	4	1	1	4	2	1	1	1	2	1	3	7	7	1	1	1	2	1	1	5	3	3	4	1
Realization #4:	2	4	1	6	3	2	2	1	1	1	4	4	2	1	2	2	2	2	2	2	2	4	1	1	3
Supergame Number:	**76**	**77**	**78**	**79**	**80**																				
Realization #1:	1	1	1	1	2																				
Realization #2:	1	1	1	3	1																				
Realization #3:	1	4	3	1	3																				
Realization #4:	2	1	4	1	1																				

(b) $\delta = \frac{4}{6}$

Supergame Number:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Realization #1:	4	3	7	1	1	5	3	1	1	9	8	1	2	4	10	4	1	1	1	4	1	4	2	4	1
Realization #2:	1	2	1	2	6	2	1	1	2	2	2	5	3	1	1	4	1	1	2	2	2	3	1	4	6
Realization #3:	3	2	1	3	1	1	2	1	4	2	4	1	1	1	4	3	2	4	2	2	7	3	3	2	3
Realization #4:	2	4	7	7	1	1	1	3	1	5	3	3	5	1	7	1	3	2	2	5	6	8	1	1	5
Supergame Number:	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**
Realization #1:	2	8	3	7	12	4	2	2	1	2	2	3	7	1	1	3	2	1	1	9	2	1	1	4	2
Realization #2:	2	1	2	2	2	2	2	9	1	1	3	3	1	1	7	3	3	5	5	1	1	4	15	4	6
Realization #3:	1	3	3	6	1	6	3	2	2	2	1	1	4	1	3	2	1	1	6	3	3	6	4	2	9
Realization #4:	1	2	3	1	3	4	5	1	2	2	1	5	3	7	1	2	4	4	1	2	1	4	3	4	4

(c) $\delta = \frac{5}{6}$

Supergame Number:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Realization #1:	4	12	30	4	15	1	10	2	5	2	11	19	6	2	1	2	5	7	2	3	2	2	9	8	6
Realization #2:	8	3	15	1	11	10	6	2	3	2	4	16	4	1	13	11	20	4	6	9	2	3	4	8	1
Realization #3:	7	6	4	7	8	3	1	3	9	1	6	3	2	2	2	38	22	7	2	1	4	5	3	3	6
Realization #4:	11	15	8	1	7	6	3	4	5	6	16	2	4	4	3	1	7	8	12	2	1	10	11	6	4

B.2.2 Screenshots

Queue Visible Treatment Decision Screen

Queue Visible Treatment Waiting Screen

Queue Not Visible Treatment Decision Screen

Table 2

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	16	16	25	25
Other's Payoff	16	25	16	25

Table 3

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	32	12	50	25
Other's Payoff	32	50	12	25

Table 4

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	48	12	50	25
Other's Payoff	48	50	12	25

Round	1	2
Number of New Tasks	4	
Table #	4	
My Choice	2	?
Other's Choice	1	
My Payoff	12	
Other's Payoff	50	
Dice Roll	1	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Please select your choice for Round **2** of Match #1

2 1

Queue Not Visible Treatment Waiting Screen

Table 2

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	16	16	25	25
Other's Payoff	16	25	16	25

Table 3

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	32	12	50	25
Other's Payoff	32	50	12	25

Table 4

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	48	12	50	25
Other's Payoff	48	50	12	25

Round	1	2
Number of New Tasks	4	
Table #	4	
My Choice	2	1
Other's Choice	1	
My Payoff	12	
Other's Payoff	50	
Dice Roll	1	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Please wait while the other participant makes a choice.

B.2.3 Instructions

Experiment Overview

Today's experiment will last about 60 minutes.

You will be paid a show-up fee of $5 together with any money you accumulate during this experiment. The amount of money you accumulate will depend partly on your actions and partly on the actions of other participants. This money will be paid at the end of the experiment in private and in cash.

It is important that during the experiment you remain **silent**. If you have a question or need assistance of any kind, please **raise your hand, but do not speak** - and an experiment administrator will come to you, and you may then whisper your question.

In addition, please **turn off your cell phones and put them away now**.

Anybody that breaks these rules will be asked to leave.

Agenda

1. Instructions
2. Quiz
3. Experiment

How Matches Work

The experiment is made up of **80 matches**.

At the start of each match you will be randomly paired with another participant in this room.

You will then play a number of rounds with that participant (this is what we call a "match").

Each match will last for a random number of **rounds**:

- At the end of each round the computer will roll a twelve-sided fair dice.
- If the computer rolls a number less than 7, then the **match continues** for at least one more round (**50% probability**).
- If the computer rolls a 7 or greater, then the **match ends** (**50% probability**).

To test this procedure, click 'Test' button below. You will need to test this procedure 10 times.

Choices and Payoffs

Table 2

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	16	16	25	25
Other's Payoff	16	25	16	25

Table 3

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	32	12	50	25
Other's Payoff	32	50	12	25

Table 4

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	48	12	50	25
Other's Payoff	48	50	12	25

In each round of a match, you will choose whether to complete **1** or **2** tasks. The participant you are paired with will also choose whether to complete **1** or **2** tasks.

In each round of a match, your payoff will be according to **one** of the three tables (labeled **Table 2**, **Table 3**, and **Table 4**). Each table presents payoffs from the four pairs of choices that are possible. These payoffs are in **points**.

The **Table #** is determined based on the number of total tasks available in that round. Thus, when there are 2 tasks available, the payoff is based on **Table 2**; when there are 3 tasks available, the payoff is based on **Table 3**; and when there are 4 tasks available, the payoff is based on **Table 4**.

For example, if you choose $\boxed{\mathbf{2}}$ and the participant you are paired with chooses $\boxed{\mathbf{2}}$ and if the payoff

- is according to **Table 2**, then your payoff for the round will be 16 points, and the other's payoff will be 16 points.
- is according to **Table 3**, then your payoff for the round will be 32 points, and the other's payoff will be 32 points.
- is according to **Table 4**, then your payoff for the round will be 48 points, and the other's payoff will be 48 points.

At the end of the experiment, your total points will be converted into cash at the exchange rate of 250 points = $1.

Which Table Will be Used

In each round, a random number of new tasks will become available. This number will be drawn at random from a set of numbers $\{2, 3, 4\}$, with each number equally likely. We will refer to this random number as the **Number of New Tasks**.

To determine the **Table #** in a round, we will use the **Number of New Tasks** together with any leftover tasks from the previous round as follows:

- In Round 1, there are no previous rounds and, therefore, **Table #** will be equal to the **Number of New Tasks**.
- In Round > 1, **Table #** will be determined in two steps
  - First, we will determine the **Number of Leftover Tasks** from the previous round. Notice that if (**Table #** in the previous round) is less than the sum of (My Choice in the previous round) and (Other's Choice in the previous round) then there will be no leftover tasks and, therefore, **Number of Leftover Tasks** will be equal to 0.

  - Second, we will determine the **Table #** in the current round by adding the **Number of Leftover Tasks** from the previous round to the **Number of New Tasks** in the current round. Importantly, the number of tasks available in each round could be at most 4, so any tasks beyond 4 will be discarded.

For example:

- Suppose that in Round 1 the **Number of New Tasks** is randomly drawn to be **4**, then the payoff in Round 1 will be determined by **Table 4**.
- If you choose to complete **1** task while the participant you are paired with chooses to complete **2** tasks, then your payoff for Round 1 will be 50 points, and the other's payoff will be 12 points.
- Suppose that in Round 2 the **Number of New Tasks** is **2**, then your payoff in Round 2 will be determined by **Table 3**.
  - Specifically, we first determine that the **Number of Leftover Tasks** from the first round is **1**(=4-[1+2]). Second, we add the **Number of Leftover Tasks** to the **Number of New Tasks** and determine that **Table #** for the second round is **3** (=**1**+**2**).

How History Will be Recorded

Round	1	2	3
Number of New Tasks	4	2	2
Table #	4	3	2
My Choice	1	2	2
Other's Choice	2	2	1
My Payoff	50	32	16
Other's Payoff	12	32	25
Dice Roll	3	1	11

The history of all variables will be recorded in a history table like the one presented above. In this table you can see an example history of a match in which the computer picked actions at random. The recorded variables include:

- Round −− round number.
- Number of New Tasks −− a random draw in that round (one number is drawn from $\{2, 3, 4\}$ with each number is equally likely).
- Table −− table that is used to determined the payoffs for that round (either **Table 2**, **Table 3**, or **Table 4** depending on the number of tasks available in that round).
- My choice −− your choice (either **1** or **2**).
- Other's Choice −− the choice by the participant that you are paired with (either **1** or **2**).
- My Payoff −− your payoff in that round.
- Other's Payoff −− payoff of the participant that you are paired with.

Reminder, your earnings will be the sum of your points across all matches converted into cash at the exchange rate of 250 points = $1. In addition, you will be paid your show-up fee of $5.

Quiz

Next, there will be a quiz with 10 questions.

You have to answer each question correctly in order to proceed to the next question.

If you answer a question incorrectly, you will see a hint. At that point you will have an opportunity to answer again.

Throughout the quiz, you may refer to the printed instructions.

Matches 1–80

During today's experiment, the **Number of New Tasks** will be randomly drawn **after** you and the participant with whom you are matched make decisions.

This means that in each round, you and the participant with whom you are matched make decisions **without knowing the Number of New Tasks** for that round.

The above instructions were used for the no visibility and $\delta = .5$ treatment. The number of matches, probability of continuation, and the information about the timing of the decisions relative to the revelation of the Number of New Tasks were adjusted for each treatment.

B.2.4 Quiz

The top third of each screen contains the three payoff tables

Table 2

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	16	16	25	25
Other's Payoff	16	25	16	25

Table 3

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	32	12	50	25
Other's Payoff	32	50	12	25

Table 4

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	48	12	50	25
Other's Payoff	48	50	12	25

Round	1
Number of New Tasks	3
Table #	?
My Choice	
Other's Choice	
My Payoff	
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 1: If the **Number of New Tasks** is 3, what **Table #** will be used to determine payoffs in Round 1?

Table 2 | Table 3 | Table 4

Round	1
Number of New Tasks	3
Table #	3
My Choice	2
Other's Choice	1
My Payoff	?
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 2: If you choose 2 and the participant you are paired with chooses 1, what will be your payoff in Round 1?

12 | 16 | 25 | 32 | 48

Round	1	2
Number of New Tasks	3	2
Table #	3	?
My Choice	2	
Other's Choice	1	
My Payoff	12	
Other's Payoff	50	
Dice Roll	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 3: If the **Number of New Tasks** is 2, what **Table #** will be used to determine payoffs in Round 2?

Table 2 | Table 3 | Table 4

Round	1	1
Number of New Tasks	3	2
Table #	3	2
My Choice	2	2
Other's Choice	1	2
My Payoff	12	
Other's Payoff	50	?
Dice Roll	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 4: If you choose 2 and the participant you are paired with chooses 2, what will be the other participant's payoff in Round 2?

12 | 16 | 25 | 32 | 48

Round	1	1
Number of New Tasks	3	2
Table #	3	2
My Choice	2	2
Other's Choice	1	2
My Payoff	12	16
Other's Payoff	50	16
Dice Roll	2	?

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 5: What is the probability that the match will end in the current round? (rounded to the nearest integer)

0 % | 25 % | 33 % | 50 % | 67 % | 75 % | 100 %

Round	1
Number of New Tasks	2
Table #	?
My Choice	
Other's Choice	
My Payoff	
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 6: If the **Number of New Tasks** is 2, what **Table #** will be used to determine payoffs in Round 1?

Table 2 | Table 3 | Table 4

Round	1
Number of New Tasks	2
Table #	2
My Choice	1
Other's Choice	2
My Payoff	?
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 7: If you choose 1 and the participant you are paired with chooses 2, what will be your payoff in Round 1?

12 | 16 | 25 | 32 | 48

Round	1	2	3	4	5	6
Number of New Tasks	2	2	4	2	4	3
Table #	2	2	4	3	4	?
My Choice	1	2	2	2	1	
Other's Choice	2	1	1	2	1	
My Payoff	25	16	12	32	25	
Other's Payoff	16	25	50	32	25	
Dice Roll	1	1	1	3	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 8: If the **Number of New Tasks** is 3, what **Table #** will be used to determine payoffs in Round 6?

Table 2 | Table 3 | Table 4

Round	1	2	3	4	5	6
Number of New Tasks	2	2	4	2	4	3
Table #	2	2	4	3	4	4
My Choice	1	2	2	2	1	2
Other's Choice	2	1	1	2	1	1
My Payoff	25	12	12	32	25	
Other's Payoff	12	25	50	32	25	?
Dice Roll	1	1	1	3	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 9: If you choose 2 and the participant you are paired with chooses 1, what will be the other participant's payoff in Round 6?

12 | 16 | 25 | 32 | 48 | 50

Round	1	2	3	4	5	6
Number of New Tasks	2	2	4	2	4	3
Table #	2	2	4	3	4	4
My Choice	1	2	2	2	1	2
Other's Choice	2	1	1	2	1	1
My Payoff	25	12	12	32	25	12
Other's Payoff	12	25	50	32	25	50
Dice Roll	1	1	1	3	2	?

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

Question 10: What is the probability that the match will continue to the next round? (rounded to the nearest integer)

0 % | 25 % | 33 % | 50 % | 67 % | 75 % | 100 %

B.3 Additional Tables and Figures

Table B.2. Self-reported Strategies and Decisions

	Visibility	$\delta = \frac{3}{6}$	$\delta = \frac{4}{6}$	$\delta = \frac{5}{6}$	Average
Decisions depends on previous periods	Yes	52.3	50.0	58.3	53.5
	No	50.0	58.3	56.3	54.9
Strategy in later matches differs from earlier matches	Yes	42.9	54.3	75.0	57.4
	No	50.0	60.4	50.0	53.5
AD strategies	Yes	35.7	21.7	20.8	26.1
	No	56.3	56.3	35.4	49.3
GT like strategies	Yes	16.7	30.4	25.0	24.0
	No	2.1	6.2	25.0	11.1
TFT like strategies	Yes	11.9	2.2	8.3	7.5
	No	12.5	8.3	2.1	7.6
DALT like strategies	Yes	0	0	0	0
	No	0	8.0	2.0	3.3

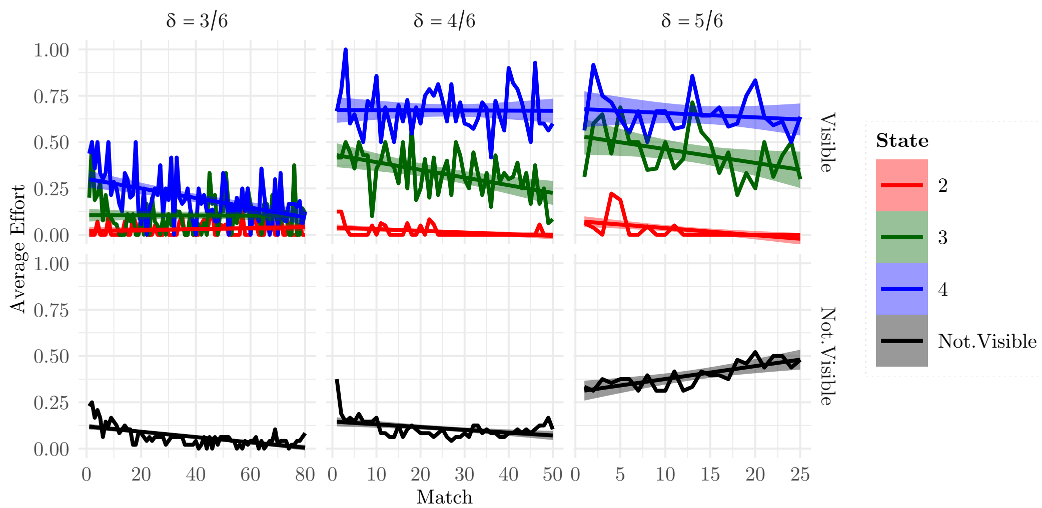
Notes: The first row reports the percentage of subjects who answered "yes" for the question "Did your decision in a round depend on what happened in the previous rounds?". The second row reports the percentage of subjects who answered "yes" for the question "Was your strategy different between the initial matches and the later matches of the experiment?". The next four rows reports the answers for the question "What was your strategy during the experiment? (Please be specific)". The third row shows the percentage of subjects whose description of their strategy is like a AD strategy.

Table B.3. SFEM Estimates – First Half of Matches

Visibility	δ	AD	AC	TFT	GT	$D.TFT$	$D.AlT$	AC^{34}	TFT^{34}	GT^{34}	$D.TFT^{34}$	$D.AlT^{34}$	AC^{4}	TFT^{4}	GT^{4}	$D.TFT^{4}$	$D.AlT^{4}$	β (%)	$\mathcal{L}$
Yes	$\frac{3}{6}$	63.2							0.2	2.1	20.6			9.5		4.2		91.3	-1026.9
		(8.1)							(1.0)	(2.0)	(7.0)			(5.1)		(5.1)		(1.2)	
Yes	$\frac{4}{6}$	29.0			1.9				13.5	15.0			16.4	15.8	4.8	3.6		87.7	-1325.0
		(6.6)			(2.0)				(6.0)	(6.5)			(6.2)	(8.5)	(6.5)	(3.5)		(1.2)	
Yes	$\frac{5}{6}$	30.0			4.1				33.1	3.4	2.0		2.1	18.6	5.0	1.6		86.3	-1768.8
		(6.7)			(3.2)				(7.4)	(2.7)	(1.9)		(2.5)	(6.2)	(4.3)	(2.0)		(1.1)	
No	$\frac{3}{6}$	59.1			2.1	18.5	4.1				7.8	4.2					4.1	90.9	-1199.5
		(8.5)			(1.9)	(8.8)	(2.8)				(6.4)	(2.4)					(2.6)	(1.4)	
No	$\frac{4}{6}$	68.1		5.5		20.2					1.0						5.2	88.3	-1292.3
		(7.4)		(3.6)		(7.3)					(3.0)						(3.5)	(1.6)	
No	$\frac{5}{6}$	49.8	2.1	13.2	10.6	17.4				2.4		2.1					2.5	86.2	-1788.7
		(7.5)	(1.9)	(4.2)	(5.0)	(5.1)				(2.3)		(2.0)					(2.9)	(1.3)	

Table B.4. SFEM Estimates – Set of strategies from Fudenberg et al. (2012)

Visibility	δ	AC	AD	TFT	$DTFT$	$TF2T$	$TF3T$	$2TFT$	$2TF2T$	$T2$	$GRIM$	$GRIM2$	$GRIM3$	$WSLS$	$2WSLS$	$CtoD$	$DTF2T$	$DTF3T$	$DGRIM2$	$DGRIM3$	$DCAlt$	β (%)	$\mathcal{L}$
No	$\frac{3}{6}$	2.1	70.6		17.2												8.1			2.0		92.9	-1107.3
		(1.9)	(7.6)		(5.8)												(4.4)			(1.7)		(1.4)	
No	$\frac{4}{6}$		60.1	6.2	26.0											2.1		5.6				91.7	-1112.5
			(7.5)	(3.5)	(7.2)											(1.8)		(3.5)				(1.3)	
No	$\frac{5}{6}$	2.1	39.0	19.4	10.6	5.3			5.6		2.5	5.3	3.6				2.5		4.1			90.6	-1176.8
		(2.4)	(7.3)	(5.6)	(4.6)	(3.4)			(4.6)		(2.5)	(3.5)	(3.0)				(2.1)		(2.5)			(1.1)	



(a) First Period

Figure B.4. Evolution of Effort

Notes: High effort is coded as 1, and low effort is coded as 0. We find evidence that subjects' choices have a time trend effect. For example, when $\delta = 4/6$ and the queue is visible, we run a probit regression of subjects' first period choice at state 3 on the match number, and find the effect of match number is significant at 5 percent level if standard errors are clustered at individual level (p-value=0.035). When $\delta = 5/6$ and the queue is not visible, we run a probit regression of subjects' first period choice on the match number, and find the effect of match number is also significant at 5 percent level if standard errors are clustered at individual level (p-value=0.019). For these two cases, the time trend effect is not statistically significant when the standard errors are clustered at session level (p-value=0.359 for the first case, and p-value=0.142 for the second case).

C. APPENDIX FOR: COOPERATION IN QUEUEING SYSTEMS: A REVISIT

C.1 Microfoundations

C.1.1 Cost Function

As described in the third paragraph of section 3.2, the cost of working T fraction of a period with 1 unit of effort (i.e., capacity) is $c(1,T) = aT^2 + bT + c$ with $a = 2$, $b = 18$, and $c = 20$. The cost of choosing 2 units of capacity is $c(2,T) = xT^2 + yT + z$ with $x = 6$, $y = 54$, and $z = 20$. Figure C.1 draws the two cost functions in the same graph given T ranges between 0 and 1. Figure C.1 also labels all possible costs that relate to the three payoff matrices in the second study. In particular, point A and B in the Figure C.1 correspond to the cost of providing 1 unit of capacity. Points C, D, E, and F correspond to the cost of providing 2 units of capacity. Note that in study 2, since $T = min(1, \frac{\theta}{total\ capacity})$ is the fraction of time that person ends up working in a period, individual's cost varies depending on the state and the actions of both servers. .

C.1.2 Compensation Function

As described in the third paragraph of section 3.2, an individual server is compensated based on the group performance. Specifically, if the group processes $M(.)$ orders, the compensation function is $r(\mathrm{e_i}, \mathrm{e_j}, \theta) = kM(\mathrm{e_i}, \mathrm{e_j}, \theta) + \mathbf{1}_{M(\mathrm{e_i},\mathrm{e_j},\theta)=4} bonus$ with $k = 36$ and $bonus = 0$.

C.1.3 Examples

Here we provide two examples of how the cost and compensation function maps the payoff matrices.

- **Example 1**: Suppose there are 2 tasks in the queue in a given period. If a server chooses 2 units of capacity and her teammate chooses 2 units of capacity, then the total capacity is 4(=2+2) and 2 tasks are processed. The fraction of the time that the

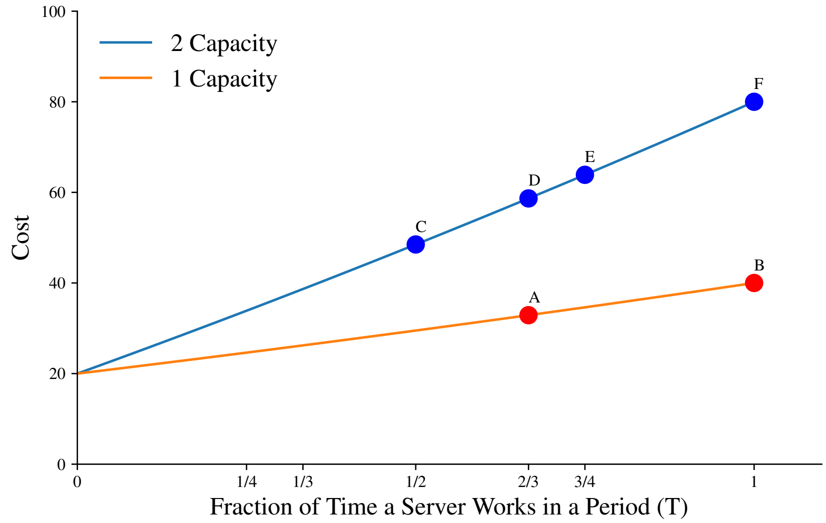


Figure C.1. Cost Function

Notes: A: (1,2,2); B: (1,1,2), (1,2,3), (1,1,3), (1,2,4) and (1,1,4); C: (2,2,2); D: (2,1,2); E: (2,2,3); F: (2,1,3), (2,2,4), (2,1,4). The first item in the tuple(e_i,e_j,θ) represents a server's own capacity choice; the second item represents the other server's capacity choice; the last item represents the state of the queue (i.e., the number of orders in the queue).

team ends up working T is 2/4, which leads to the server's cost 48(=6×T^2+54×T+20). The revenue is 72(=36×2). Therefore, this server's payoff is 24(=72-48).

- **Example 2**: Suppose there are 4 tasks in the queue in a given period. If a server chooses 1 units of capacity and her teammate chooses 2 units of capacity, then the total capacity is 3(=1+2) and 3 tasks are processed. The fraction of the time that the team ends up working T is 1($=min(1, \frac{4}{3})$), which leads to the server's cost 40(=2×T^2+18×T+20). The revenue is 108(=36×3). Therefore, this server's payoff is 68(=108-40).

C.1.4 Comparative Statics

As in study 1, the compensation function and the cost function have 8 parameters in study 2. Figure C.2 presents comparative statics of the critical thresholds of four *GT* strategies for each of the eight parameters. In particular, for each subfigure, we vary one parameter, while holding the all other parameters constant at the experimental value. For example, in the top right figure, we study the relationship between the the critical thresholds of the GT (solid red), GT^4 (dashed green), GT^{34} (dashed orange), and GT^{234} (dashed blue) and the value of k while keeping $bonus = 0, a = 2b = 18, c = 20, x = 6, y = 54, z = 20$.

The patterns observed in Figure B.2 can also be observed in Figure C.2. Specifically, when $\delta_v^*(GT^4) > 0$, we find $\delta_v^*(GT^4) \leq \delta_v^*(GT^{34}) \leq \delta_v^*(GT^{234})$. This result suggests that when the queue is visible, it is easier to sustain cooperation when the queue is long than when it is short. Then, $\delta_v^*(GT^4) \leq \delta_{nv}^*(GT) \leq \delta_v^*(GT^{234})$. This means that while it is easier to sustain high effort across all states when the queue is not visible, it is easier to sustain high effort across a subset of the states (e.g., $\theta = 4$) when the queue is visible. These two common patterns are consistent with the hypotheses discussed in section 3.2.

C.1.5 Theoretical Predictions with Experimental Results

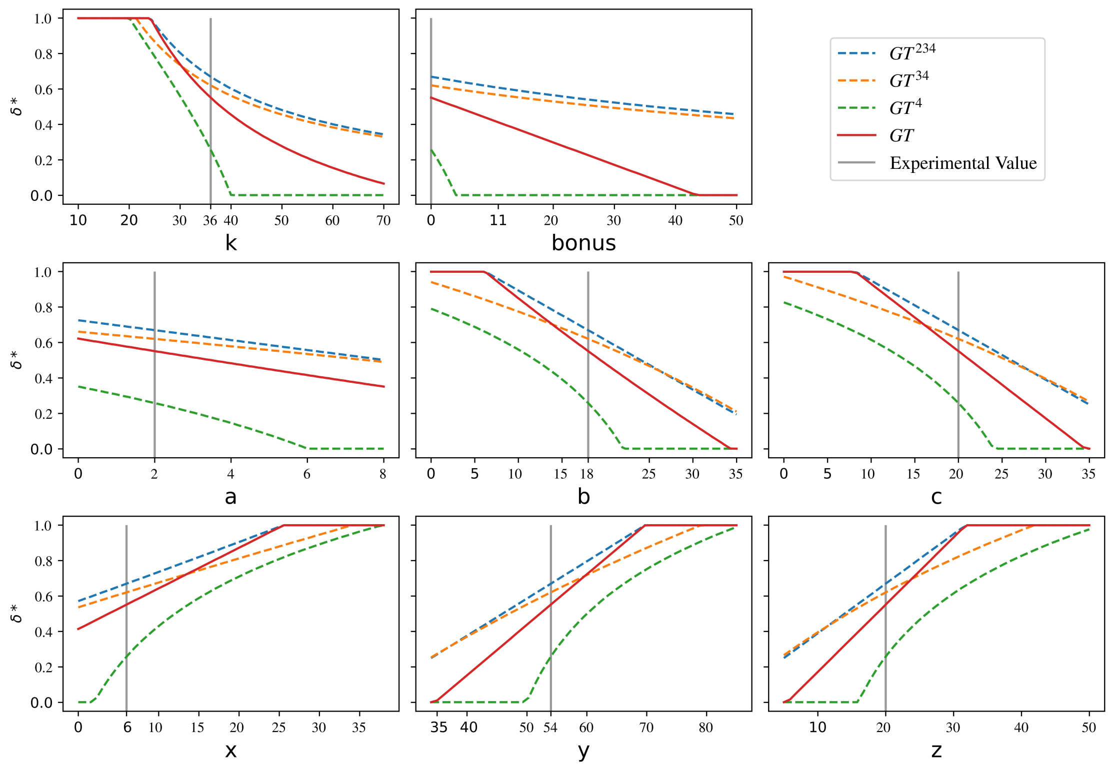


Figure C.2. Comparative Statics and Parameters

Notes: For each graph, we hold the other parameters constant as the experimental value when varying a given parameter. The experimental values are $k = 36, bonus = 0, a = 2, b = 18, c = 20, x = 6, y = 54, z = 20$.

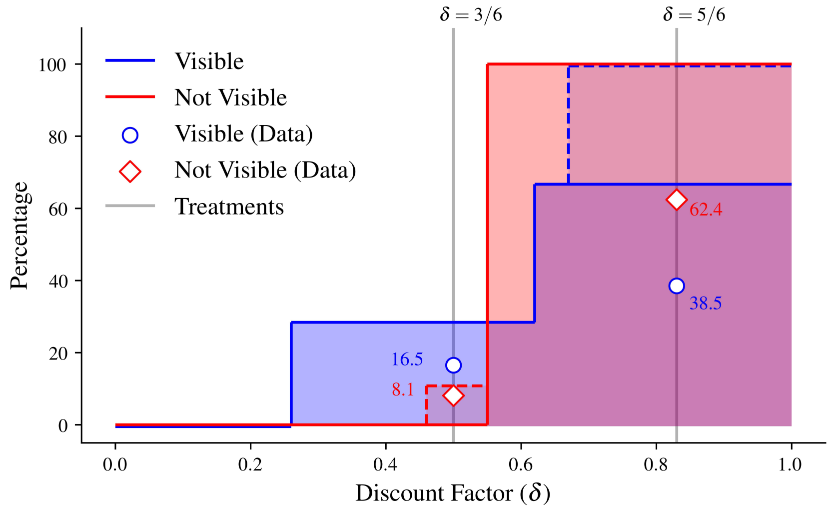


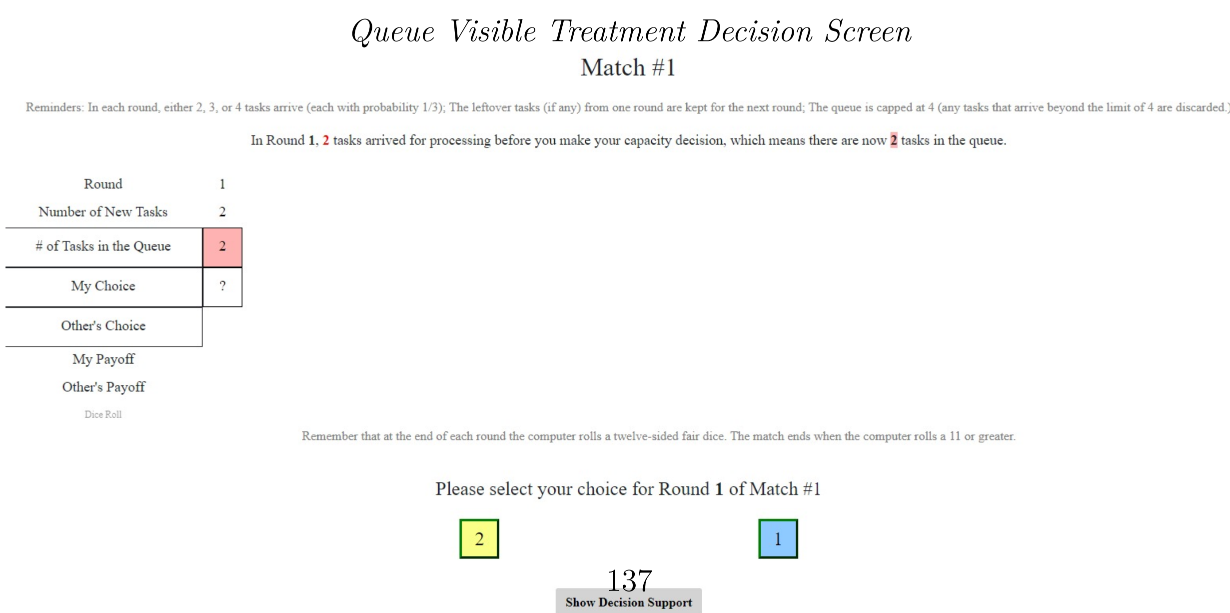
Figure C.3. High Effort, Discount Factor, and Data

Notes: Data is the percentage of high capacity chosen by subjects across all periods in the second half of matches. Servers are assumed to use GT-type strategies in this figure ($\delta^*_{nv}(GT) = 0.55$; $\delta^*_v(GT^4) = 0.26$; $\delta^*_v(GT^{34}) = 0.62$ and $\delta^*_v(GT) = 0.67$). Even GT is an equilibrium strategy when the queue is visible and $\delta > 0.67$, we assume servers provide low capacity when the state is 2 since it is the efficient choice. Strategies like $D.AlT^4$ are also SPE when the queue is not visible and δ is large enough, they does not change the main hypotheses ($\delta^*_{nv}(D.AlT^4)$=0.46).

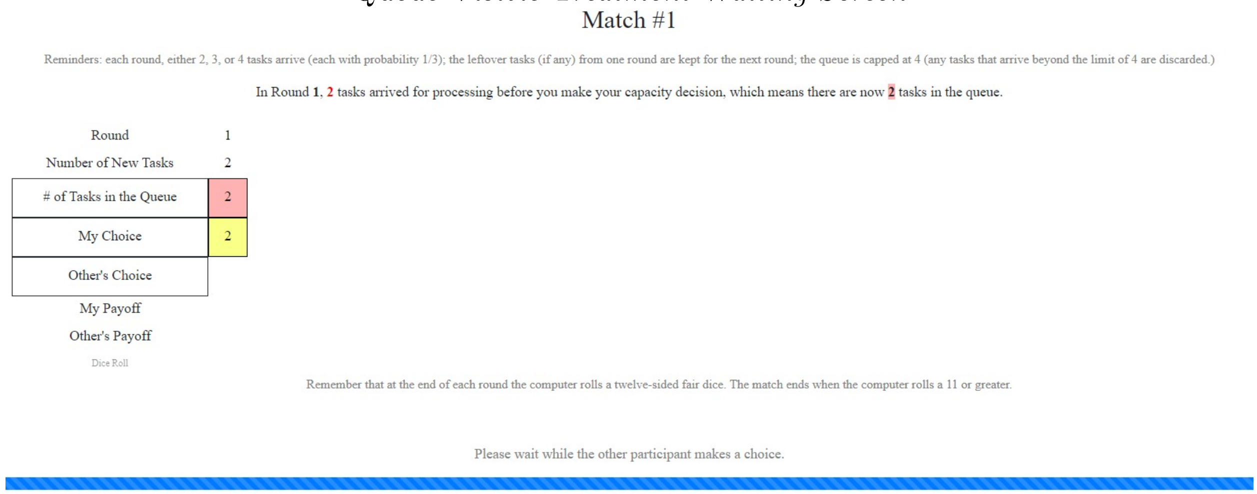
C.2 Experimental Design

C.2.1 Supergame Length Realizations

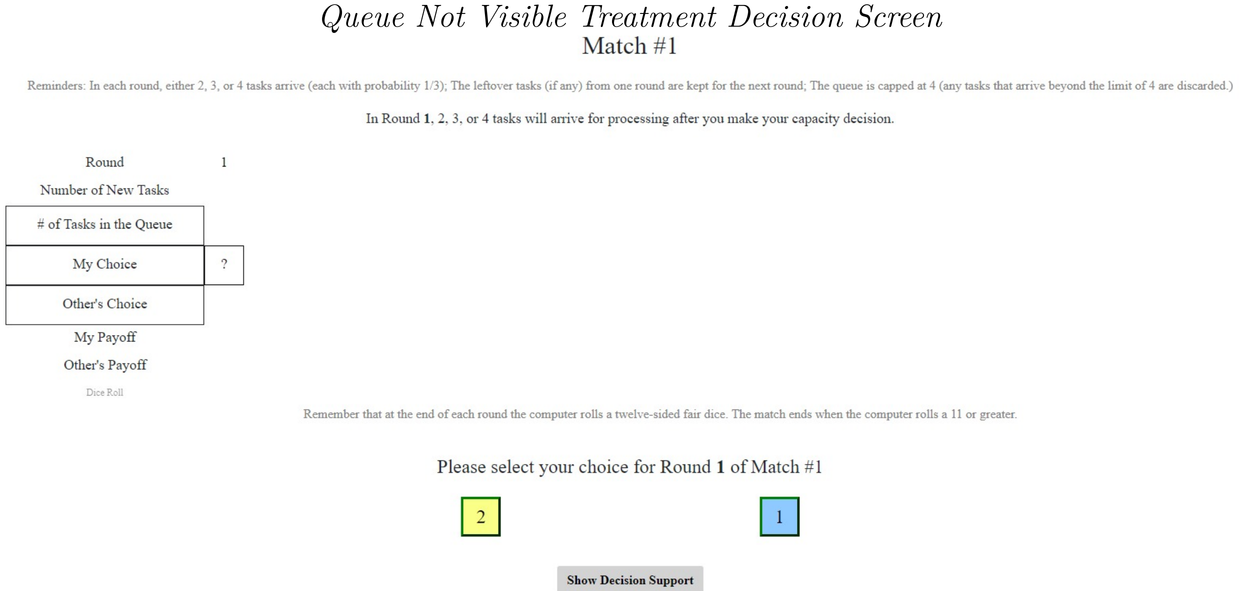
C.2.2 Screenshots



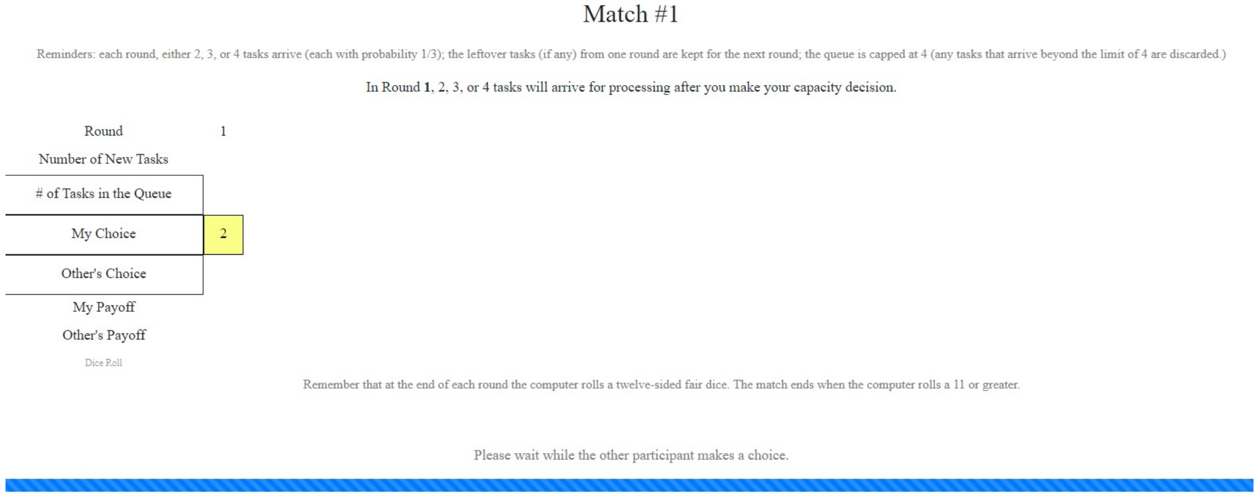
Queue Visible Treatment Waiting Screen



Queue Not Visible Treatment Decision Screen



Queue Not Visible Treatment Waiting Screen



C.2.3 Instructions

Experiment Overview

Today's experiment will last about 60 minutes.

You will be paid a show-up fee of $5 together with any money you accumulate during this experiment. The amount of money you accumulate will depend partly on your actions and partly on the actions of other participants. This money will be paid at the end of the experiment in private and in cash.

It is important that during the experiment you remain **silent**. If you have a question or need assistance of any kind, please **raise your hand, but do not speak** - and an experiment administrator will come to you, and you may then whisper your question.

In addition, please **turn off your cell phones and put them away now**.

Anybody that breaks these rules will be asked to leave.

Agenda

1. Instructions
2. Quiz
3. Experiment

How Matches Work

The experiment is made up of **100 matches**.

At the start of each match you will be randomly paired with another participant in this room.

You will then play a number of rounds with that participant (this is what we call a "match").

Each match will last for a random number of **rounds**:

- At the end of each round the computer will roll a twelve-sided fair dice.
- If the computer rolls a number less than 7, then the **match continues** for at least one more round (**50% probability**).
- If the computer rolls a 7 or greater, then the **match ends** (**50% probability**).

To test this procedure, click 'Test' button below. You will need to test this procedure 10 times.

Round Description

In each round of a match, "tasks" will arrive for processing and join the **Task Queue**.

You and the participant you are paired with will work together to process the task queue. Specifically, in each round, you will choose how much capacity to allocate (either **1** unit or **2** units). The participant you are paired with will also choose how much capacity to allocate (either **1** unit or **2** units).

We denote the **sum** of your choice and the choice of the participant you are paired with as **Total Capacity** in that round. For example, if you choose **2** and the participant you are paired with chooses **2** then the Total Capacity is 4.

The number of tasks that can be processed in a given round is the smaller of the **Total Capacity** and the **# of Task in the Queue**. For example, if the total capacity is 4 but there are 3 tasks in the queue, then 3 tasks will be processed in that round. Another example – if the total capacity is 2 but there are 3 tasks in the queue, then 2 tasks will be processed in that round and ***1 Leftover Task*** will remain in the queue for the next round. Thus, the two of you can process available tasks in a round up to the total capacity in that round.

Round Payoffs

2 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	24	14	40	32
Other's Payoff	24	40	14	32

3 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	44	28	68	32
Other's Payoff	44	68	28	32

4 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	64	28	68	32
Other's Payoff	64	68	28	32

Possible combinations of choices and the resulting payoffs are summarized in the three tables above (labeled **2 Tasks in the Queue**, **3 Tasks in the Queue**, and **4 Tasks in the Queue**). These payoffs are determined based on the revenue and costs associated with the capacity choices and the tasks in the queue. The details of how the payoffs are determined will be described next, for now, we will provide a few examples of how to read these summary tables. In particular, if you choose **2** and the participant you are paired with chooses **2** and there are

- **2 tasks in the queue**, then your payoff for the round will be 24 points, and the other's payoff will be 24 points.
- **3 tasks in the queue**, then your payoff for the round will be 44 points, and the other's payoff will be 44 points.
- **4 tasks in the queue**, then your payoff for the round will be 64 points, and the other's payoff will be 64 points.

At the end of the experiment, your total points (accumulated across all rounds and matches) will be converted into cash at the exchange rate of 250 points = $1. In addition, you will be paid your show-up fee of $5.

How Round Payoffs are Determined

Your **Payoff** in a given round is the difference between the **Revenue** that you get and the **Cost** that you incur from processing tasks.

The **Revenue** is a function of the tasks processed by you and the participant you are paired with. Specifically, you will receive **36 points per task** processed.

The **Cost** is a function of your capacity choice and the fraction of the time that you end up working in that round (which we denote **T**). We calculate T as the smaller between 1 and the ratio of (# of Tasks in the Queue) and (Total Capacity). That is, if the total capacity in a given round is less than or equal to the # of tasks in the queue, then you work the whole round (T=1). However, if the Total Capacity in a given round is larger than the # of tasks in the queue, then the fraction of the time that you work is T=(# of Tasks in the Queue) / (Total Capacity). For example, if in a given round the total capacity is 4, and there are 3 tasks in the queue, then 3 tasks will be processed and the fraction of time you work in that round will be 34.

The cost function is increasing in your capacity choice and the fraction of the time you work as follows:

- if you choose to allocate $\boxed{\mathbf{1}}$ unit, your cost is $(2 \times T^2 + 18 \times T + 20)$
- if you choose to allocate $\boxed{\mathbf{2}}$ units, your cost is $(6 \times T^2 + 54 \times T + 20)$

The payoffs for the participant that you are paired with are calculated in the same way.

Next, we will consider a specific example.

Payoff Calculations Example

2 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
Revenue	72	72	72	72
T	2/4	2/3	2/3	2/2
Cost	48	58	32	40
My Payoff	**24**	**14**	**40**	**32**

3 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
Revenue	108	108	108	72
T	3/4	3/3	3/3	1
Cost	64	80	40	40
My Payoff	**44**	**28**	**68**	**32**

4 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
Revenue	144	108	108	72
T	4/4	1	1	1
Cost	80	80	40	40
My Payoff	**64**	**28**	**68**	**32**

Possible combination of choices, tasks in the queue, and the resulting payoffs are presented in the tables above. In addition, we present revenue, cost, and the fraction of the time you will work associated with those combinations.

For example, if in a given round there are **2 Tasks in the Queue**, you choose $\boxed{\mathbf{2}}$ and the participant that you are paired with chooses $\boxed{\mathbf{2}}$, then

- the total capacity is $4(=\boxed{\mathbf{2}}+\boxed{\mathbf{2}})$.
- **2** tasks are processed (the smaller between **2 Tasks in the Queue** and the total capacity of 4).
- the **Revenue** is **72**$(=36 \times 2)$.
- the fraction of the time you end up working T is 2/4 (=(2 tasks in the queue)/(total capacity of 4)).

- the Cost is **48**(=6 × $(24)^2$ + 54 × (24) + 20, rounded to the nearest integer)
- your **Payoff** is **24**(=72-48)

The payoffs for the participant that you are paired with are calculated in the same way.

How # of Tasks in the Queue are Determined

In each round, a random number of new tasks will become available to join the queue. This number will be drawn at random from a set of numbers $\{2, 3, 4\}$, with each number equally likely. We will refer to this random number as the **Number of New Tasks**.

To determine the **# of Task in the Queue** in a given round, we will use the **Number of New Tasks** together with any ***leftover tasks*** from the previous round as follows:

- In Round 1, there are no previous rounds and, therefore, the **# of Task in the Queue** will be equal to the **Number of New Tasks**.
- In Round > 1, **# of Task in the Queue** will be determined in two steps:
  - First, we will determine the number of ***leftover tasks*** from the previous round.
    * If the **# of Task in the Queue** in the previous round is less than the **Total Capacity** in the previous round, then the number of ***leftover tasks*** is 0.
    * If the **# of Task in the Queue** in the previous round is greater than the **Total Capacity** in the previous round, then the number of ***leftover tasks*** is (**# of Task in the Queue** −**Total Capacity**)
  - Second, we will determine the **# of Task in the Queue** in the current round by adding the ***leftover tasks*** to the **Number of New Tasks** in the current round.
- Importantly, the Queue is capped at 4 tasks. That is, any tasks that arrive beyond the limit of 4 will be discarded. For example, if in a given round there are 2 leftover

tasks in the queue and 3 new tasks arrive that round, then the queue will contain 4 tasks and 1 will be discarded.

How History Will be Recorded

Round	1	2	3
Number of New Tasks	4	2	2
# of Tasks in the Queue	4	3	2
My Choice	1	2	2
Other's Choice	2	2	1
My Payoff	68	44	14
Other's Payoff	28	44	40
Dice Roll	3	1	11

The history of all variables will be recorded in a history table like the one presented above. In this table you can see an example history of a match in which the computer picked actions at random. The recorded variables include:

- Round −− round number.
- Number of New Tasks −− a random draw in that round (one number is drawn from $\{2, 3, 4\}$ with each number is equally likely).
- # of Tasks in the Queue −− number of tasks in the queue in that round (either **2**, **3**, or **4**).
- My choice −− your choice (either **1** or **2**).
- Other's Choice −− the choice by the participant that you are paired with (either **1** or **2**).
- My Payoff −− your payoff in that round.
- Other's Payoff −− payoff of the participant that you are paired with in that match.

Reminder, your earnings will be the sum of your points across all matches converted into cash at the exchange rate of 250 points = $1. In addition, you will be paid your show-up fee of $5.

Example

Round	1	2	3
Number of New Tasks	4	2	2
# of Tasks in the Queue	4	3	2
My Choice	1	2	2
Other's Choice	2	2	1
My Payoff	68	44	14
Other's Payoff	28	44	40
Dice Roll	3	1	11

The following example is visualized in the above history:

- Suppose that in Round 1, the **Number of New Tasks** is **4**, then there are **4 tasks in the queue** in Round 1.
- If you choose **1** while the participant you are paired with chooses **2**, then your payoff for Round 1 will be 68 points, and the other's payoff will be 28 points.
- Suppose that in Round 2 the **Number of New Tasks** is **2**, then there are **3 tasks in the queue** in Round 2.
  - First, we determine that the ***1*** (=4-[1+2]) ***leftover task*** remains in the queue at the end of Round 1.
  - Second, we add this ***leftover task*** to the **Number of New Tasks** and determine that for Round 2, # of tasks in the queue is **3** (=***1***+**2**).
- If you choose **2** and the participant you are paired with chooses **2**, then your payoff for Round 2 will be 44 points, and the other's payoff will be 44 points.

- Suppose that in Round 3 the **Number of New Tasks** is **2**, then there are **2 Tasks in the Queue** in Round 3.
  - First, we determine that there are ***no leftover task*** remains in the queue at the end of Round 2 (Total Capacity ≧3).
  - Therefore, the # of tasks in the queue is equal to the **Number of New Tasks** in Round 3, which means that # of tasks in the queue is **2** (=***0***+**2**)
- If you choose **2** and the participant you are paired with chooses **1**, then your payoff for Round 3 will be 14 points, and the other's payoff will be 40 points.

C.2.4 Quiz

The top third of each screen contains the three payoff tables

2 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	24	14	40	32
Other's Payoff	24	40	14	32

3 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	44	28	68	32
Other's Payoff	44	68	28	32

4 tasks in the queue

My Choice	2	2	1	1
Other's Choice	2	1	2	1
My Payoff	64	28	68	32
Other's Payoff	64	68	28	32

Round	1
Number of New Tasks	3
# of Tasks in the Queue	?
My Choice	
Other's Choice	
My Payoff	
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 1: If the **Number of New Tasks** is 3, how many tasks will be in the queue in Round 1?

2 3 4

Round	1
Number of New Tasks	3
# of Tasks in the Queue	3
My Choice	2
Other's Choice	1
My Payoff	?
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 2: If you choose 2 and the participant you are paired with chooses 1, what will be your payoff in Round 1?

14 24 28 32 44 68

Round	1	2
Number of New Tasks	3	2
# of Tasks in the Queue	3	?
My Choice	2	
Other's Choice	1	
My Payoff	28	
Other's Payoff	68	
Dice Roll	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 3: If in Round 2 the **Number of New Tasks** is 2, how many tasks will be in the queue in Round 2?

2 | 3 | 4

Round	1	1
Number of New Tasks	3	2
# of Tasks in the Queue	3	2
My Choice	2	2
Other's Choice	1	2
My Payoff	28	
Other's Payoff	68	?
Dice Roll	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 4: If you choose 2 and the participant you are paired with chooses 2, what will be the other participant's payoff in Round 2?

14 | 24 | 32 | 44 | 64

Round	1	1
Number of New Tasks	3	2
# of Tasks in the Queue	3	2
My Choice	2	2
Other's Choice	1	2
My Payoff	28	24
Other's Payoff	68	24
Dice Roll	2	?

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 5: What is the probability that the match will end in the current round? (rounded to the nearest integer)

0 % | 17 % | 25 % | 33 % | 50 % | 67 % | 75 % | 83 % | 100 %

Round	1
Number of New Tasks	2
# of Tasks in the Queue	?
My Choice	
Other's Choice	
My Payoff	
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 6: If in Round 1 the **Number of New Tasks** is 2, how many tasks will be in the queue in Round 1?

2 | 3 | 4

Round	1
Number of New Tasks	2
# of Tasks in the Queue	2
My Choice	1
Other's Choice	2
My Payoff	?
Other's Payoff	
Dice Roll	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 7: If you choose 1 and the participant you are paired with chooses 2, what will be your payoff in Round 1?

14 | 24 | 40 | 44 | 68

Round	1	2	3	4	5	6
Number of New Tasks	2	2	4	2	4	3
# of Tasks in the Queue	2	2	4	3	4	?
My Choice	1	2	2	2	1	
Other's Choice	2	1	1	2	1	
My Payoff	40	14	28	44	32	
Other's Payoff	14	40	68	44	32	
Dice Roll	1	1	1	3	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 8: If in Round 6 the **Number of New Tasks** is 3, how many tasks will be in the queue in Round 6?

2 | 3 | 4

Round	1	2	3	4	5	6
Number of New Tasks	2	2	4	2	4	3
# of Tasks in the Queue	2	2	4	3	4	4
My Choice	1	2	2	2	1	2
Other's Choice	2	1	1	2	1	1
My Payoff	40	14	28	44	32	
Other's Payoff	14	40	68	44	32	?
Dice Roll	1	1	1	3	2	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 9: If in Round 6 you choose 2 and the participant you are paired with chooses 1, what will be the other participant's payoff in Round 6?

14 | 28 | 32 | 44 | 64 | 68

Round	1	2	3	4	5	6
Number of New Tasks	2	2	4	2	4	3
# of Tasks in the Queue	2	2	4	3	4	4
My Choice	1	2	2	2	1	2
Other's Choice	2	1	1	2	1	1
My Payoff	25	12	12	32	25	28
Other's Payoff	12	25	50	32	25	68
Dice Roll	1	1	1	3	2	?

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 11 or greater.

Question 10: What is the probability that the match will continue to the next round? (rounded to the nearest integer)

0 % | 17 % | 25 % | 33 % | 50 % | 67 % | 75 % | 83 % | 100 %

C.3 Additional Tables and Figures

Table C.1. Supergame Lengths

(a) $\delta = \frac{3}{6}$

Supergame Number:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Realization #1:	2	2	4	1	1	2	3	2	2	4	1	1	2	3	1	2	2	1	1	3	1	3	3	2	1
Realization #2:	2	2	1	4	3	1	1	1	2	1	1	1	2	1	1	1	1	2	1	1	4	1	2	2	1
Realization #3:	4	2	1	5	1	1	1	1	2	1	1	1	3	1	1	9	5	3	1	2	2	2	2	7	1

Supergame Number:	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**
Realization #1:	2	2	1	5	1	2	4	3	1	1	1	1	1	2	2	2	1	2	1	1	1	2	1	2	2
Realization #2:	2	1	2	1	1	2	2	2	1	7	1	1	1	1	2	3	1	1	1	1	5	3	3	5	5
Realization #3:	4	1	1	1	3	1	1	2	1	1	2	4	1	2	2	6	3	1	6	12	2	2	2	2	1

Supergame Number:	**51**	**52**	**53**	**54**	**55**	**56**	**57**	**58**	**59**	**60**	**61**	**62**	**63**	**64**	**65**	**66**	**67**	**68**	**69**	**70**	**71**	**72**	**73**	**74**	**75**
Realization #1:	2	4	1	6	3	2	2	1	1	1	4	4	2	1	2	2	2	2	2	2	2	4	1	1	3
Realization #2:	1	1	4	2	13	2	1	1	1	2	1	2	3	2	1	3	1	1	2	1	2	2	2	4	1
Realization #3:	1	1	2	3	7	1	1	3	1	1	1	1	5	2	2	2	1	1	4	2	1	2	1	2	6

Supergame Number:	**76**	**77**	**78**	**79**	**80**	**81**	**82**	**83**	**84**	**85**	**86**	**87**	**88**	**89**	**90**	**91**	**92**	**93**	**94**	**95**	**96**	**97**	**98**	**99**	**100**
Realization #1:	2	1	4	1	1	1	1	1	3	1	2	4	1	2	1	1	1	4	1	5	2	1	2	2	1
Realization #2:	1	1	1	3	1	1	2	1	1	1	2	3	3	2	1	4	4	2	1	1	1	1	1	1	2
Realization #3:	1	1	1	1	2	2	1	1	1	5	1	1	6	1	3	1	1	2	2	1	1	1	1	1	4

(b) $\delta = \frac{5}{6}$

Supergame Number:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Realization #1:	11	15	8	1	7	6	3	4	5	6	16	2	4	4	3	1	7	8	12	2	1	10	11	6	4
Realization #2:	4	12	30	4	15	1	10	2	5	2	11	19	6	2	1	2	5	7	2	3	2	2	9	8	6
Realization #3:	8	3	15	1	11	10	6	2	3	2	4	16	4	1	13	11	20	4	6	9	2	3	4	8	1

Supergame Number:	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**
Realization #1:	6	1	4	18	2	9	1	6	10	20	1	1	1	3	5
Realization #2:	2	3	13	1	21	13	1	12	9	8	6	15	2	3	1
Realization #3:	10	6	12	14	11	14	3	2	11	6	5	12	12	2	3

Table C.2. SFEM Estimates – First Half of Matches

Visibility	δ	AD	AC	TFT	GT	$D.TFT$	$D.AlT$	AC^{34}	TFT^{34}	GT^{34}	$D.TFT^{34}$	$D.AlT^{34}$	AC^{4}	TFT^{4}	GT^{4}	$D.TFT^{4}$	$D.AlT^{4}$	β (%)	$\mathcal{L}$
Yes	$\frac{3}{6}$	53.0	2.8			1.2		2.8	6.4	2.3			8.2		11.3	9.6	2.4	86.1	-1566.3
		(9.1)	(2.3)			(2.3)		(2.7)	(4.5)	(3.0)			(4.8)		(6.4)	(5.1)	(2.7)	(1.8)	
Yes	$\frac{5}{6}$	13.9		5.6		8.3		2.8	49.5	8.3	2.8				8.8			86.4	-2043.2
		(5.5)		(3.4)		(4.3)		(2.6)	(8.8)	(5.2)	(3.1)				(4.2)			(1.4)	
No	$\frac{3}{6}$	66.2		2.8			1.6					9.4				3.2	16.8	89.0	-1334.5
		(7.3)		(2.8)			(2.2)					(4.2)				(3.5)	(5.9)	(1.5)	
No	$\frac{5}{6}$	6.0	3.0	47.2	16.1	19.8					2.1						5.9	82.5	-2235.2
		(4.2)	(3.1)	(9.7)	(6.1)	(7.4)					(2.4)						(4.7)	(1.5)	

VITA

EDUCATION

Ph.D. in Economics, Purdue University — August 2021

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RESEARCH PAPERS

- Can Job Rotation Eliminate the Ratchet Effect: Experimental Evidence
  Journal of Economic Behavior and Organization *(2020), 180, pp. 66-84*

- Cooperation in Queueing Systems *(with Yaroslav Rosokha)*
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HONORS, AWARDS, AND CERTIFICATES

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Econ 690 Agent-Based Computational Economics (*PhD*) *Fall 2019, Fall 2020*

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Econ 380 Money and Banking (*Undergrad*) *Fall 2016*

Econ 251 Microeconomics (*Undergrad*) *Spring 2018*

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