Cooperation in Queueing Systems

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Abstract

We study a social dilemma in 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 and provide low effort). 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 effort is increasing in the expected duration of the interaction. We also find that visibility has a strong impact on the strategies that human subjects use; however, the overall impact on effort provision is modest. We discuss implications for managers and firms that are trying to improve service systems.

Keywords: Behavioral Operations, Single-Queue Systems, Stochastic Dynamic Games, Indefinitely Repeated Prisoner's Dilemma, Finite Mixture Models

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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, 1909; Kolmogorov, 1931; Kendall, 1951), operations research (Cobham, 1954; Little, 1961), management (Kao and Tung, 1981; Graves, 1982), and economics (Sah, 1987; Polterovich, 1993). 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, 2001; Hopp, Iravani, and Yuen, 2007), being utility maximizing (Gopalakrishnan, Doroudi, Ward, and Wierman, 2016), or being susceptible to behavioral biases (Bendoly, Croson, Goncalves, and Schultz, 2010).

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., servers). Although such strategies have been studied in the theoretical and experimental literature on repeated games (Dal Bó and Fréchette, 2018), 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, few 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 servers work together to repeatedly process orders from a single queue. In particular, we focus on a scenario in which 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 equilibrium of the game if the expected length of the indefinite 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-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, 2009).

We use a controlled laboratory experiment to test our theoretical predictions for a simplified two-server three-state queueing system. 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 is increasing in 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 provide high effort when the queue is long, but provide low effort when the queue is short. When servers cannot see the state of the queue, 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 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-contingent versions of tit-for-tat and 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, we review related literature in operations management and economics. In section 3, we develop the notation and set up theoretical characterization of a subgame perfect Nash equilibrium. In section 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 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 6.

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 dimension. The first dimension includes the theoretical analysis of the effort provision when servers are utility-maximizing (e.g., Zhan and Ward, 2018, 2019). Among the most relevant theoretical papers along this dimension is Gopalakrishnan, Doroudi, Ward, and Wierman (2016), 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 subgame-perfect Nash equilibrium 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

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[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 (2018). 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.

dimension include Schultz, Juran, Boudreau, McClain, and Thomas (1998), Schultz, Juran, and Boudreau (1999) and Powell and Schultz (2004), who consider behavioral factors that influence effort provision in variety of queueing systems. More recent work along this dimension also includes Buell, Kim, and Tsay (2017), who find that operational transparency increases customers' perceptions of service quality and reduces throughput times, Shunko, Niederhoff, and Rosokha (2018), who find that the visibility of the queue may speed up servers' service rate, and Hathaway, Kagan, and Dada (2020), 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 server's behavior and highlight that visibility of the queue may have different consequences on server's effort provision depending on the expected duration of an interaction among servers.[2] In addition, we Finally, although a large body of literature has considered empirical regularities associated with human-server behavior (e.g., a review by Delasay, Ingolfsson, Kolfal, and Schultz, 2019), 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. Papers in this stream of literature include Nosenzo, Offerman, Sefton, and van der Veen (2016), who investigate the threat of punishment and power of rewards in the repeated inspection game; Davis and Hyndman (2018), who investigate the efficacy of relational incentives for managing the quality of a product in a two-tier supply chain; Beer, Ahn, and Leider (2018), who show that the benefits of buyer-specific investments for both suppliers and buyers are strengthened when firms interact repeatedly; and Hyndman and Honhon (2019), 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 Prisoner's Dilemma (henceforth PD) game (see Dal Bó and Fréchette, 2018, 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, 2011; Blonski, Ockenfels, and Spagnolo, 2011). Regarding the strategies that human subjects use in PD experiments, recent papers including Dal Bó and Fréchette (2011, 2019) and Romero and Rosokha (2018, 2019b) show that simple strategies such as Grim Trigger, Always Defect, and Tit-for-Tat are prevalent. The extent to which these strategies will be played in a stochastic

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[2] In this paper, we consider customers as non-strategic agents. Previous work has shown that the visibility of the queue may impact customers' decisions of joining/reneging 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, 2016). As a direction for future research, it would be interesting to build a model that considers both – strategic servers that interact repeatedly, and strategic customers that have a choice of when to join/renege the queue.

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 (2000), Peysakhovich and Rand (2016), and Cason, Lau, and Mui (2019), and path dependence in equilibrium selection studied by Romero (2015).

The fourth stream of literature that we contribute to explores dynamic and stochastic repeated games.[3] Early papers in this literature include work by Green and Porter (1984) and Rotemberg and Saloner (1986), who theoretically show that collusion among firms can be supported in the presence of stochastic demand shocks. Recent experimental work by Rojas (2012) confirmed that collusion in such environments can arise in the lab. In an experimental study of the dynamic oligopoly game, Salz and Vespa (2017) 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 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, 2015, 2019) and stochastic (Kloosterman, 2019) variations of the repeated PD game. Vespa and Wilson (2015) 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 (2019) test the extent to which subjects internalize the incentives of changing the transition rule from endogenous to stochastic. Kloosterman (2019) 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 stochastic components. 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 relies on history-contingent repeated-game strategies to sustain high-effort cooperation.

3 Theoretical Background

In this section we provide a theoretical background for the case of 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 $\Theta = \left\{ \theta \in \mathbb{N} \mid \lambda_{min} \leq \theta \leq B \right\}$ 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

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[3] Our work is also related to the study of dynamic common-pool resource games (Walker, Gardner, and Ostrom, 1990; Gardner, Ostrom, and Walker, 1990). Recent papers that experimentally study common-pool resource games by Vespa (2017) 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.

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.[4] Regarding the free-riding incentives, we assume that individual payoff, $r(.)$, is a function of the total number of customers processed by the group.[5] Next, we focus on the case of a two-server queuing system in which each server has a discretion over two effort levels.

3.1 One-shot Game

Suppose that in each period, server $i \in N$ decides on whether to provide high effort or low effort, $e_i \in E_i := \{h, l\}$. For simplicity, assume that with the low effort, each server can process up to one order per period, while with the high effort, each server can process up to two orders per period. Let $m_i(e_i, e_{-i}, \theta)$ denote the number of orders actually processed within a period by server i and $c(e_i, e_{-i}, \theta)$ denote the corresponding personal cost. Next, suppose the service process is such that the manager cannot observe the effort levels contributed by each server, but can only observe the total output each period. That is the compensation to server i, $r(e_i, e_{-i}, \theta)$, is a function of the total number of customer orders processed by the group, $M(e_i, e_{-i}, \theta) = \sum_{i \in \{1,2\}} m_i(e_i, e_{-i}, \theta)$. Then, the net payoff within a period to server i is $u(e_i, e_{-i}, \theta) = r(e_i, e_{-i}, \theta) - c(e_i, e_{-i}, \theta)$.

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 $E = \prod E_i$, and the set of payoffs is given by $U(\theta) = \{u(e, \theta) : e \in E\}$. 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:

$$u_i(l, e_j, \theta) > u_i(h, e_j, \theta) \; \forall \; e_j \in E_j, \theta \in \Theta, \tag{1}$$

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

Inequality (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, (1) implies that effort profile $e^d = (l, l)$ is the unique *Nash equilibrium* of the stage game $g(\theta) \; \forall \theta \in \Theta$. Inequality (2)

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[4] The convex cost assumption is a standard component across the theoretical, empirical, and experimental streams of literature (e.g., Mas and Moretti, 2009; Ortega, 2009; Clark, Masclet, and Villeval, 2010; Gill and Prowse, 2012).

[5] Group-based payment schemes are frequently observed in the real world. For example, Ortega (2009) find 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 (2019) who document that restaurant workers face, at least in-part, team-based incentives, and Hamilton, Nickerson, and Owan (2003) 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).

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. Notice that (1) and (2) imply that the game played in state θ' is a 2-player *Prisoner's Dilemma*. In practice, the two conditions are satisfied if the extra cost of providing high effort, $c_i(h, e_j, \theta) - c_i(l, e_j, \theta)$, is greater than the individual benefit of increasing the capacity by an extra order, $r(h, e_j, \theta) - r(l, e_j, \theta)$, but less than the total benefit to both players, $2r(h, e_j, \theta) - 2r(l, e_j, \theta)$.

Our goal is to investigate the server's behavior when interactions are repeated. In particular, it is well known from the repeated-PD literature 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. Next, we formally set up the stochastic game and consider some of the strategies the players may use to sustain high effort in equilibrium.

3.2 Stochastic Game

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 $\mathcal{P}_{\theta\theta'}^{e_i e_j} := \mathcal{P}(\theta'|\theta, e)$ denote the probability that the next state is θ' given the current state θ and the effort profile $e \in E$. Notice that the transition probability is fully determined by the current state, the action profile by the servers, and the arrival process.

We distinguish between 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 defect 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 a *subgame perfect Nash equilibrium* (henceforth, 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: (1) after histories in which all players provided high effort and (2) 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 $V^c(\theta)$, and the total value of deviating, which we denote as $V^{dev}(\theta)$. Formally,

$$V^c(\theta) = u(e^c, \theta) + \delta \sum_{\theta'} \mathcal{P}^{hh}_{\theta\theta'} V^c(\theta') \tag{3}$$

$$V^{dev}(\theta) = u(e^{dev}, \theta) + \delta \sum_{\theta'} \mathcal{P}^{lh}_{\theta\theta'} V^d(\theta') \tag{4}$$

$$V^d(\theta) = u(e^d, \theta) + \delta \sum_{\theta'} \mathcal{P}^{ll}_{\theta\theta'} V^d(\theta'). \tag{5}$$

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 a subgame perfect Nash equilibrium of Γ if

$$V^c(\theta) - V^{dev}(\theta) \geq 0 \; \forall \; \theta. \tag{6}$$

3.3 Uncertainty about the State

As discussed in the introduction and the literature review, several existing papers have proposed modifying queue visibility as a useful tool to improve server effort provision. In this paper, we consider queue visibility from the perspective of strategies that servers use during their repeated interactions. In particular, if the queue is visible, players have common knowledge about the state θ; however, if queue is not visible, the state of the game is not known. Common knowledge about the state is important in the repeated-interaction context because it affects the type of strategies that servers can implement to enforce high effort in equilibrium. For example, suppose servers do not know the state of the game (i.e., the queue is not visible) but have access to the history of actions by the other servers, then a repeated-game strategy can condition on the history of action profiles but cannot condition on the current state θ. In particular, a strategy profile s^{GT} is a subgame perfect Nash equilibrium if

$$\mathbf{E}_\theta \left[V^c(\theta) - V^{dev}(\theta) \right] \geq 0. \tag{7}$$

Notice the difference between (6) and (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. We show in section 4.1 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.

4 Experimental Design and Theoretical Predictions

For the experiment, we set $B = 4$, G uniform, $\lambda_{min} = 2$, $\lambda_{max} = 4$, and $\Theta = \{2, 3, 4\}$. We chose the environmental 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 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, 2011).[6,7] The resulting payoffs for each combination of effort choices are presented in Figure 1.

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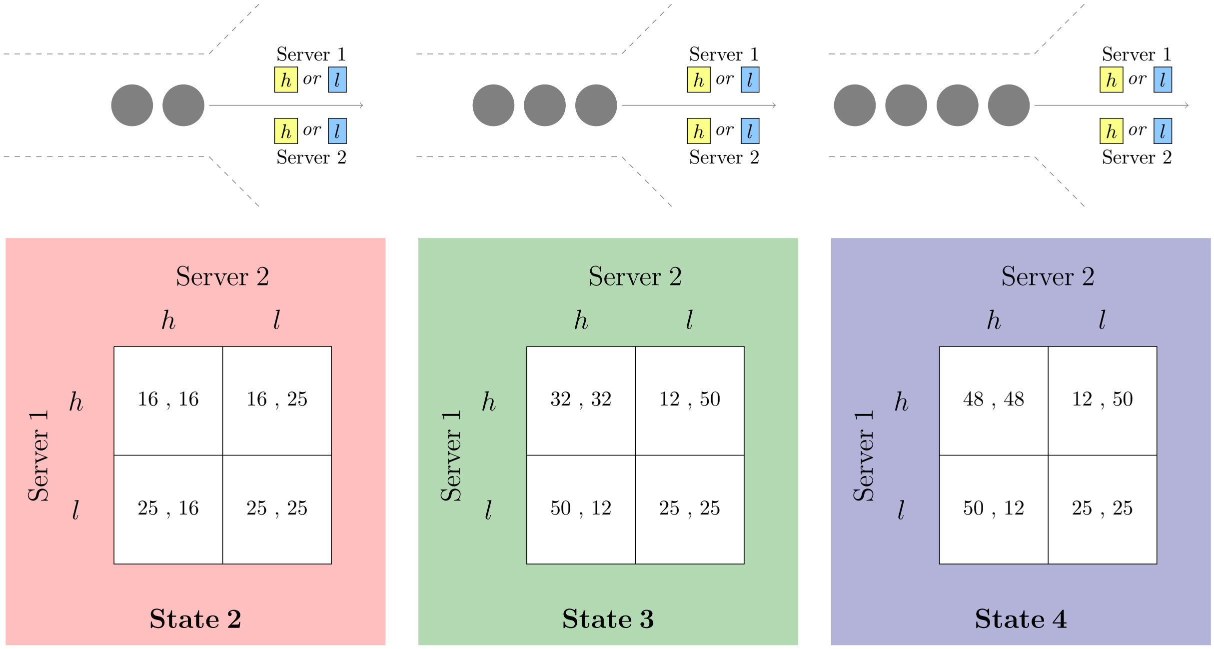
[6] The cost of processing $m_i(.)$ orders with high effort is $c(h, e_j, \theta) = b_0^h + b_1^h m_i(h, e_j, \theta) + b_2^h m_i(h, e_j, \theta)^2$ with $b_0^h = 49$, $b_1^h = -37$, $b_2^h = 22$. The cost of processing $m_i(.)$ order with low effort is $c(l, e_j, \theta) = b_0^l + b_1^l m_i(l, e_j, \theta) + b_2^l m_i(l, e_j, \theta)^2$ with $b_0^l = 40$, $b_1^l = -37$, $b_2^l = 22$. Notice that the only difference is that $b_0^h > b_0^l$, and thus, *ceteris paribus*, providing high effort is more costly.

[7] The individual compensation when the group processes $M(.)$ orders is $r(e_i, e_j, \theta) = b_0^r M(e_i, e_j, \theta) + b_1^r \mathbf{1}_{M(e_i, e_j, \theta)=4}$ with $b_0^r = 25$ and $b_1^r = 11$. 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. The second is a bonus that is paid when the favorable output is observed. Notice that 4 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., Hashimoto, 1979; Blakemore, Low, and Ormiston, 1987; Bell and Reenen, 2014; Hathaway, Kagan, and Dada, 2020).

Figure 1: Stage-Game Payoffs in Each State



State 2

Server 1 \ Server 2	h	l
h	16 , 16	16 , 25
l	25 , 16	25 , 25

State 3

Server 1 \ Server 2	h	l
h	32 , 32	12 , 50
l	50 , 12	25 , 25

State 4

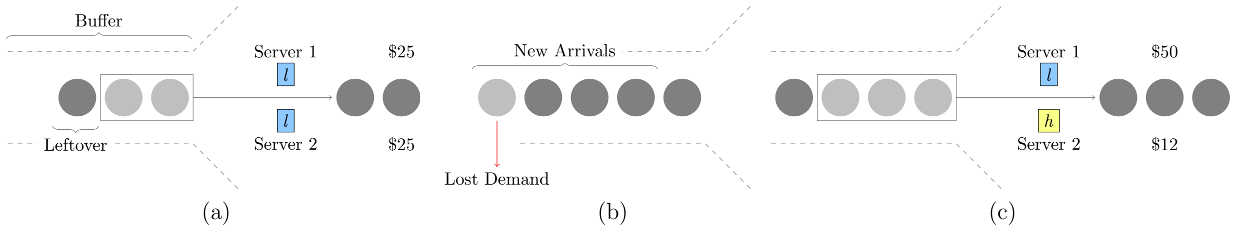
Server 1 \ Server 2	h	l
h	48 , 48	12 , 50
l	50 , 12	25 , 25

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. Notice that stage games played in states 3 and 4 are PD, and the stage game played in state 2 is non-PD.

The consequence of the payoffs presented in Figure 1 is that when two customer orders are available, the dominant action is to provide low effort (i.e., process one order), which is also the socially optimal outcome in that state. However, when three or four customer orders are available, then the socially optimal outcome is for both servers to provide high effort even though, individually, each would prefer to provide low effort. In other words, 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 presents example dynamics in our experimental environment. In particular, panel (a) presents an example in which there are three customer orders in line, and both servers select low effort. In such a case, one order will be leftover for the next period. Panel (b) presents an example in which four new customer order arrive. In which 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 a the outcome if one server provides high effort and the other server provides low effort.[8]

Figure 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 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 1 corresponding to state 4.

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.

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 $\mathcal{P}^{ll}$:

$$\mathcal{P}^{hh} = \begin{array}{c|ccc} \theta & 2 & 3 & 4 \\ \hline 2 & 1/3 & 1/3 & 1/3 \\ 3 & 1/3 & 1/3 & 1/3 \\ 4 & 1/3 & 1/3 & 1/3 \end{array} \quad \mathcal{P}^{lh} = \begin{array}{c|ccc} \theta & 2 & 3 & 4 \\ \hline 2 & 1/3 & 1/3 & 1/3 \\ 3 & 1/3 & 1/3 & 1/3 \\ 4 & 0 & 1/3 & 2/3 \end{array} \quad \mathcal{P}^{ll} = \begin{array}{c|ccc} \theta & 2 & 3 & 4 \\ \hline 2 & 1/3 & 1/3 & 1/3 \\ 3 & 0 & 1/3 & 2/3 \\ 4 & 0 & 0 & 1 \end{array} \tag{8}$$

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[8] A non-stochastic version of the study would be identical to the classic Prisoner's Dilemma game with the exception of the action labels.

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 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:

$$u^c = \begin{pmatrix} 16 \\ 32 \\ 48 \end{pmatrix} \qquad u^{dev} = \begin{pmatrix} 25 \\ 50 \\ 50 \end{pmatrix} \qquad u^d = \begin{pmatrix} 25 \\ 25 \\ 25 \end{pmatrix}. \tag{9}$$

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

$$V^c = [I - \delta \mathcal{P}^{hh}]^{-1} u^c \qquad V^{dev} = u^{dev} + \delta \mathcal{P}^{lh} V^d \qquad V^d = [I - \delta \mathcal{P}^{ll}]^{-1} u^d. \tag{10}$$

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 this holds when δ is 0.72. We denote this critical threshold as $\delta^*_v(GT)$. When the queue is not visible, we solve (7) and find that $\delta^*_{nv}(GT)$ is 0.58, which means that full effort can be supported at a lower discount factor.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 under some conditions, reducing visibility may be beneficial.

Notice that GT does not distinguish among the states. Next, 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 $u^c = \left(\begin{smallmatrix} 25 \\ 32 \\ 48 \end{smallmatrix}\right)$, which leads to $\delta^*(GT^{34}) = 0.64$. 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

$$\mathcal{P}^c = \begin{array}{c} \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{ccc} \theta\;\; 2 & 3 & 4 \end{array} \\ \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 1/3 & 1/3 & 1/3 \end{pmatrix} \end{array} \qquad \mathcal{P}^{dev} = \begin{array}{c} \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{ccc} \theta\;\; 2 & 3 & 4 \end{array} \\ \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 0 & 1/3 & 2/3 \end{pmatrix} \end{array} \qquad \mathcal{P}^{ll} = \begin{array}{c} \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{ccc} \theta\;\; 2 & 3 & 4 \end{array} \\ \begin{pmatrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \\ 0 & 0 & 1 \end{pmatrix} \end{array} \tag{11}$$

$$u^c = \begin{pmatrix} 25 \\ 25 \\ 48 \end{pmatrix} \qquad u^{dev} = \begin{pmatrix} 25 \\ 25 \\ 50 \end{pmatrix} \qquad u^d = \begin{pmatrix} 25 \\ 25 \\ 25 \end{pmatrix}. \tag{12}$$

Notice 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 $\delta^*(GT^4)$, we get 0.19. Thus, in terms of the server discount factors, GT^4 is the easiest to sustain, followed by GT^{34}, and GT being the most difficult to sustain when the queue is visible. An interpretation of this result is that cooperating is easier when the queue is long than when it is short.

Lastly, we would like to note that it is possible to sustain some amount of high effort in equilibrium 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 very high. If, in addition, players can observe (or infer) partial history of states, they can reach this conclusion with more certainty. For example, for our parameter combination, if players have observed that $\theta_{t-1} = 4$ and $e_{t-1} = (l, l)$, 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 round 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.

4.2 Treatments and Hypotheses

In the experiment, 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 (1978). 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 subjects 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 D1 in the Appendix D.

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. Other than the timing of the new orders, the instructions for different visibility treatments were the same.

Note that the three values of δ were picked so that in combination with the variation in visibility, we obtained distinct predictions regarding the SPE strategies that can sustain high effort across the three states of the visible treatment. Table 1 presents the summary of the six treatments of our experiment. For each treatment, we list the SPE strategy as well as the expected amount of high effort, the waiting time, and the throughput losses of the queuing system if subjects are using those strategies.

Table 1: Summary of Theoretical Predictions

Treatment		Subgame Perfect Equilibrium			
Visibility	δ	Strategy	High Effort (%)	Waiting Time	Throughput Losses
Yes	$\frac{3}{6}$	GT^{4+}	28.4	0.999	3.4
Yes	$\frac{4}{6}$	GT^{3+}	66.7	0.806	0.0
Yes	$\frac{5}{6}$	GT^{3+}	66.7*	0.806	0.0
No	$\frac{3}{6}$	$D.AlT^{4}$	10.8	1.154	10.2
No	$\frac{4}{6}$	GT	100.0	0.639	0.0
No	$\frac{5}{6}$	GT	100.0	0.639	0.0

Notes: Strategies supported as a subgame perfect equilibrium and the resulting cooperation percentages (i.e., high effort percentages) during interactions. 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. $GT^{\theta+}$ denotes a trigger strategy that plays GT across states $\{\theta, \theta+1, ...\}$ and plays AD across states $\{\theta-1, \theta-2, ...\}$. $D.AlT^{\theta}$ denotes a trigger strategy that provides high effort immediately after observing mutual defection in state θ. *When $\delta = \frac{5}{6}$, GT^{2+} is also an equilibrium strategy, however, we expect that because players can see the state, they will learn to provide low effort when $\theta = 2$, and high effort when $\theta \in \{3, 4\}$ thereby achieving an efficient outcome in all states.

Next, we provide three general hypotheses based on the theoretical predictions summarized in Table 1. 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 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 in Dal Bó and Fréchette, 2018).

Our second hypothesis deals with the effect of queue visibility on cooperation:

Hypothesis 2 *For low δ, effort will be higher when the queue is visible; for high δ, effort will be 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 higher 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 Grim-trigger-like strategies can be supported in SPE. When delta is $\frac{4}{6}$, the prediction flips and we expect higher effort if the queue is not visible than when it is visible. Lastly, when delta is $\frac{5}{6}$, 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 provide high effort when the queue is long.

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

Hypothesis 3 *When the queue is (not) visible, subjects will (not) use state-contingent strategies.*

A nice feature of our design is that, with an exception of one treatment, the strategies that lead to maximum effort in each treatment are distinct. In particular, we expect to observe state-contingent strategies when the queue is visible but no state-contingent strategies when the queue is not visible. In addition, when the queue is visible, we expect subjects to play strategies that provide high effort across more states as δ increases.

Lastly, we would like to note that the Always Defect strategy (providing low effort regardless of what the other player does) is an SPE strategy in all treatments. In addition, 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. Thus, without conducting lab experiments, it is not clear whether and to what extent subjects will learn to play strategies that cooperate across more state and whether there will be any differences among the treatments.

4.3 Experiment Details and Administration

We recruited 280 students on the campus of a large public US university between January and February of 2020 using ORSEE software (Greiner, 2015). We ran 24 sessions with the experimental interface programmed in oTree (Chen, Schonger, and Wickens, 2016) (see Appendix A for screenshots of the interface). 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, as well as a printed copy that subjects could use for reference during the experiment (see Appendix B). At the end of the instructions, subjects completed a 10-question quiz (see Appendix C).

Table 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.

We used a between-subjects design whereby each participant took part in only one experimental treatment. Table 2 presents 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 equal $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).

5 Experimental Results

Table 3 presents the percentage of high effort observed in the second half of our experiment.[9] 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. Combined with effort across all periods, the first-period effort also provides indirect evidence on the dynamics within the interaction. For example, the fact that in the visible treatment, effort in state 4 across all periods is half the effort in state 4 in the first period suggests that subjects may

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[9] Figure D1 in the Appendix presents evolution of effort across all matches of our experiment.

be using strategies that punish deviation from full effort.

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

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

There are several noteworthy observations from Table 3. 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. This finding is reassuring in that subjects cannot 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% 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.

The second observation is 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 depend on what happened initially. To formally test whether this difference is significant, we run a probit regression of the choice of high effort in the first period on the dummy for whether the discount factor is high ($\delta = \frac{5}{6}$), with standard errors clustered at the session level. We find a significant difference (p-value <0.01) both when the queue is visible, and when the queue is not visible. We summarize these observations as Result 1.

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

The third observation from Table 3 is that servers provide higher effort when the queue is visible than when it is not visible if the discount factor is $\delta = \frac{3}{6}$ and $\delta = \frac{4}{6}$. To formally test whether the difference is significant, we run a probit regression of high effort in the first period on the dummy for whether the state is visible, with standard errors clustered at the session level. Taken separately, when the discounting factor is low ($\delta = \frac{3}{6}$), the difference is significant at the 0.10 level (p-value 0.052). When the discount factor is medium ($\delta = \frac{4}{6}$), the difference is again significant at the 0.10 level (p-value 0.062). Taken together, the difference is significant at the 0.05 level (p-value of 0.025).[10] However, when the discount factor is high ($\delta = \frac{5}{6}$), we do not find such a difference. In fact, when $\delta = \frac{5}{6}$, 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 0.33). We summarize these findings as Result 2.

Result 2 *When the expected duration of future interaction is short, servers provide higher effort when queue is visible. When the expected duration of future interaction is long, there is no difference in aggregate effort.*

The fact that effort provision depends on the state realization when the queue is visible leads us to believe that subjects use state-contingent strategies. The fact that effort in the first period is greater than the effort across all periods leads us to believe that subjects are using history-contingent strategies. Next, we use a finite-mixture estimation approach to formally estimate the strategies underlying choices in our experiment. The finite-mixture models have been widely used in economics (e.g., Haruvy, Stahl, and Wilson, 2001; Dal Bó and Fréchette, 2011) to estimate the proportion of subjects that 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 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:

$$P = \beta^X \circ (1 - \beta)^Y, \tag{13}$$

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

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[10] A probit regression of high effort in the first period on two dummy variables – visibility and discount factor – yields p-values of 0.008 and 0.004 when clustering standard errors at the session level.

k generated the observed choices by subject n. Then, using the matrix dot product, we define the log-likelihood function $\mathcal{L}$:

$$\mathcal{L}(\beta, \phi) = ln\big(\phi' \cdot P\big) \cdot \mathbf{1}, \tag{14}$$

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 (2018). We also include modified versions of these strategies that condition on either state 4 or both states 3 and 4. Notably, we include GT^{3+} and GT^{4} that 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 $D.AlT^{3+}$ and $D.AlT$ strategies).

Table 4: Estimated Percentage of Strategies

Visibility	δ	AD	AC	TFT	GT	$D.TFT$	$D.AlT$	AC^{3+}	TFT^{3+}	GT^{3+}	$D.TFT^{3+}$	$D.AlT^{3+}$	AC^{4+}	TFT^{4+}	GT^{4+}	$D.TFT^{4+}$	$D.AlT^{4}$	β (%)	$\mathcal{L}$
Yes	$\frac{3}{6}$	59.4				6.5		2.4			22.5		2.4	2.4		4.3		93.7	-895.9
		(9.5)				(4.4)		(2.3)			(8.4)		(2.4)	(3.0)		(4.8)		(1.5)	
Yes	$\frac{4}{6}$	37.9							11.2	14.2	2.5			15.6	18.6			92.0	-1053.6
		(7.8)							(5.1)	(5.6)	(2.5)			(13.5)	(13.1)			(0.9)	
Yes	$\frac{5}{6}$	32.7							32.1	13.7	4.5		5.5	5.4	6.2			93.7	-904.9
		(6.6)							(7.9)	(6.0)	(3.1)		(3.6)	(4.4)	(5.1)			(0.8)	
No	$\frac{3}{6}$	65.8	2.1			17.0	4.1					2.1				6.8	2.1	93.1	-1096.1
		(7.6)	(2.0)			(6.5)	(2.5)					(2.0)				(4.4)	(2.1)	(1.2)	
No	$\frac{4}{6}$	56.7		6.3	2.1	21.4						4.1				3.2	6.3	92.2	-1082.3
		(7.4)		(3.7)	(2.0)	(6.6)						(2.6)				(3.8)	(3.0)	(1.2)	
No	$\frac{5}{6}$	36.6	2.1	37.2	6.2	15.8											2.1	89.5	-1244.4
		(7.6)	(2.1)	(7.9)	(3.3)	(4.9)											(1.9)	(1.4)	

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 Always Defect (AD). Bootstrap standard errors are in parentheses. The unit of observation is one subject.

Table 4 presents the estimation results.[11] We find that the most common strategy across all

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[11] 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 (2018) and Romero and Rosokha (2019a). However, when the queue is not visible, the values are somewhat lower, suggesting that the set of strategies may be missing relevant strategies. Table D2 of the Appendix presents the estimates when using

four treatments is the AD strategy. This finding is not surprising given the prevalence of the AD strategy in the literature on the indefinitely repeated PD with parameters similar to ours (e.g., Dal Bó and Fréchette, 2011). Even so, we find a clear pattern in the type of other strategies used across the treatments. In particular, when the queue is not visible, over 88% of subjects in each treatment play strategies that do not condition on the state realization, whereas when the queue is visible, the proportion of subjects that play strategies that do not condition on the state realization is 64.4%, 37.9%, and 32.7%. The difference is significant at the 0.01 level using non-parametric randomization test. We summarize this finding as Result 3.

Result 3 *When the queue is (not) visible, servers (do not) use state-contingent strategies.*

In terms of the particular strategies played, we find that when the queue is visible, subjects play sophisticated TFT- and GT-like strategies that provide high effort when the queue is long, but low effort when the queue is 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. In particular, we observed 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 $\delta = \frac{5}{6}$).[12] The decrease was due to the switch to strategies that cooperated across more state (e.g., TFT^{3+} and GT^{3+}). For example, when $\delta = \frac{5}{6}$, 45.8% of subjects used cooperative strategies that provided high effort in states 3 and 4 as compared to 25.4% when $\delta = \frac{3}{6}$, and 0.0% when $\delta = \frac{3}{6}$. When the queue is 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 comprise 43.4% when $\delta = \frac{5}{6}$).

6 Discussion

In this paper, we theoretically and experimentally investigate 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 there are short-term incentives to deviate for each server in each of the possible states of the queue (i.e., number of customers in line). Furthermore, if servers are patient enough, high effort can be sustained regardless of whether the queue is visible. However, as players become less patient, visibility becomes an important determinant of the types of strategies that can support high effort

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an expanded set of strategies. In particular, we use 20 commonly studied strategies in the indefinitely repeated PD literature (Fudenberg, Rand, and Dreber, 2012; Cason and Mui, 2019).

[12] 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.

in equilibrium. In particular, we theoretically show that providing less visibility of the queue may sometimes be better because players will average incentives across multiple states, and may 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 are 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, 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. Second, based on our experimental results, ensuring that the queue is visible would be useful when the expected duration of interaction is short. When the interactions are long, not providing information about the state of the queue, may be beneficial if the manager would like to instill homogeneous processing speeds across all of the states of the queue. In particular, it is theoretically possible to sustain high effort across all states when the queue is not visible; however, full effort is difficult to achieve in practice. Third, because a large proportion of subjects in our experiment play state-contingent strategies, the managers should take into account particular dynamics such as servers providing low effort when the queue is short and higher effort when the queue is long.

Our paper 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 focused 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 analyzed 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, 2012), considering a similar setting with continuous variables along each of those dimensions would be interesting. Third, we considered 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. Lastly, the extent to which communication among servers and different matching mechanisms (such as studied by Honhon and Hyndman, 2015) can improve effort provision in the queueing setting would be of great interest.

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Appendices

A Screenshots

Queue 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	2	3
Table #	2	3
My Choice	2	?
Other's Choice	1	
My Payoff	16	
Other's Payoff	25	
Dice Roll	6	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 7 or greater.

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

Queue 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	2	3
Table #	2	3
My Choice	2	1
Other's Choice	1	
My Payoff	16	
Other's Payoff	25	
Dice Roll	6	

Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 7 or greater.

Please wait while the other participant makes a choice.

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

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 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

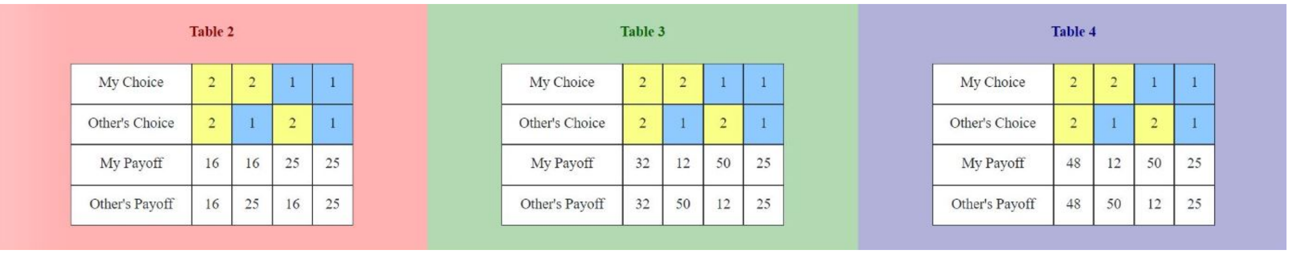


Table 2

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 **2** and the participant you are paired with chooses **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:

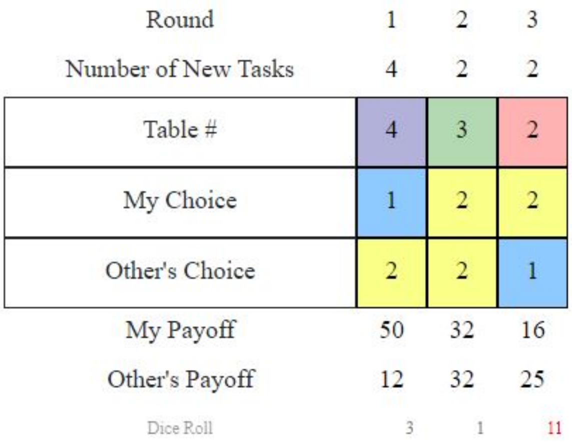
- In Round 1, there are no previous rounds and, therefore, **Table #** will be equal to the **Number of New Tasks**.
- In Round > 1, **Table #** will be determined in two steps

  - 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.

C Quiz

The top third of each screen contains the three payoff tables

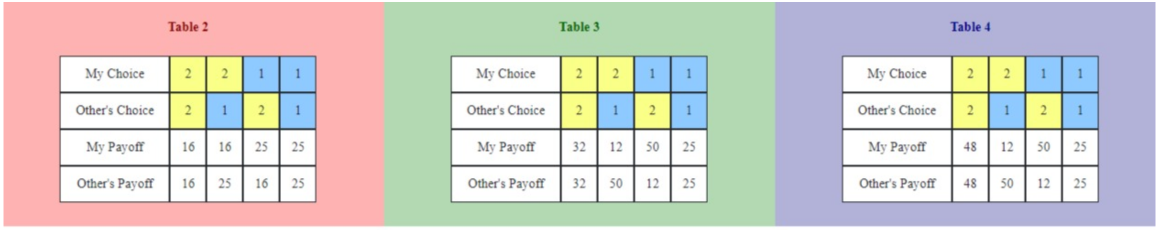


Table 2

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

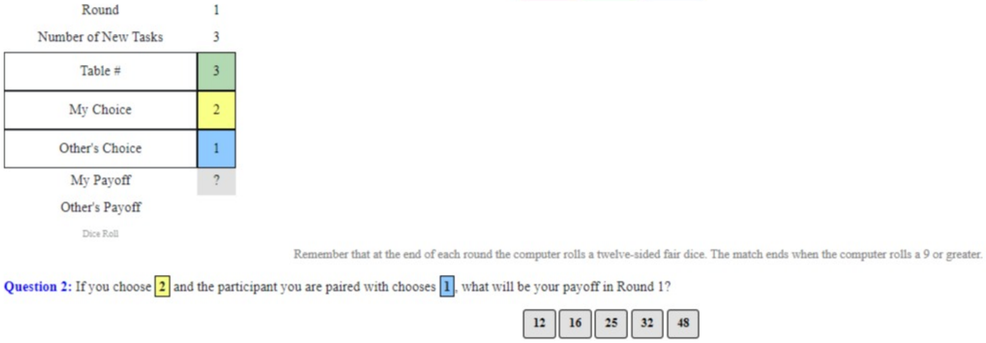
Table 4

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?



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

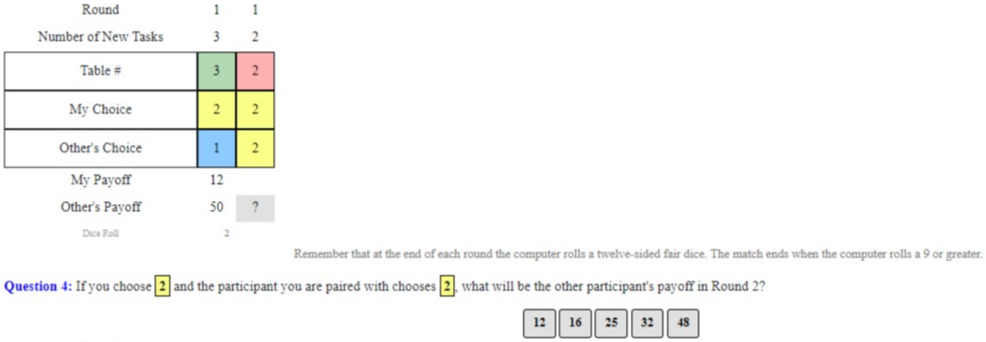
Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

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

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.

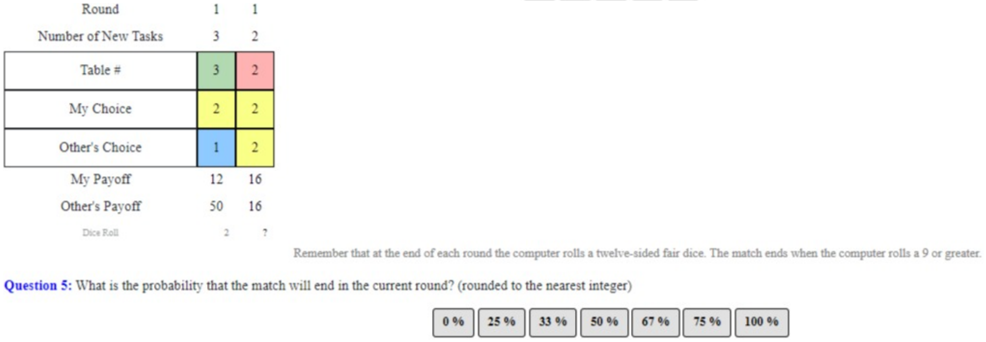
Question 3: If the **Number of New Tasks** is 2, what **Table #** will be used to determine payoffs in Round 2?



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?



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	?

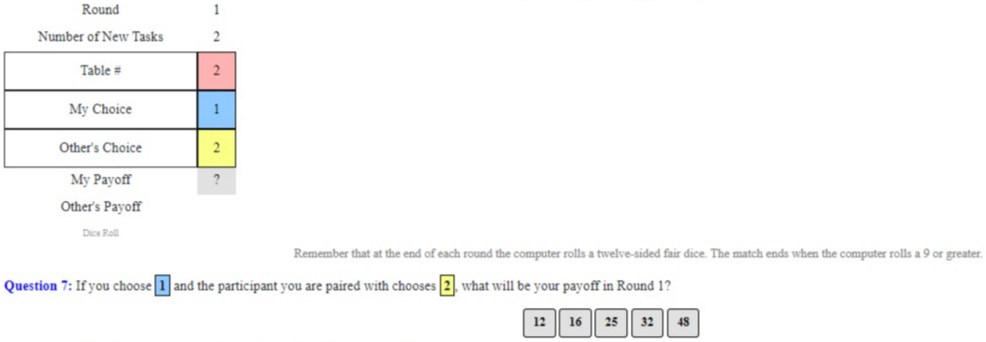
Remember that at the end of each round the computer rolls a twelve-sided fair dice. The match ends when the computer rolls a 9 or greater.

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

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.

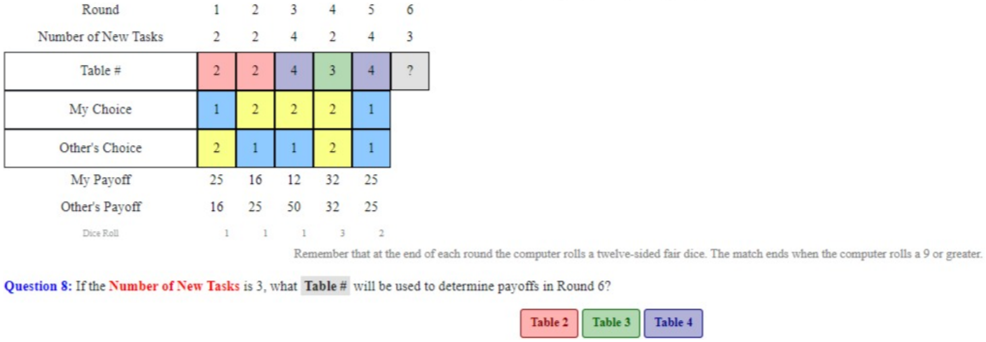
Question 6: If the **Number of New Tasks** is 2, what **Table #** will be used to determine payoffs in Round 1?



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.

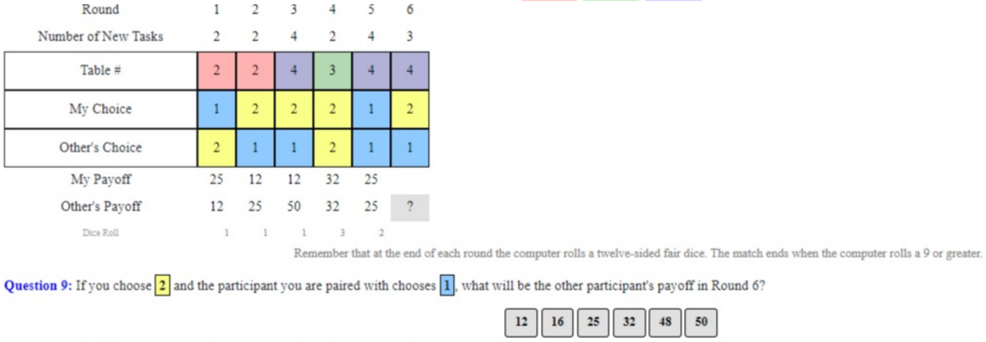
Question 7: If you choose 1 and the participant you are paired with chooses 2, what will be your payoff in Round 1?



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.

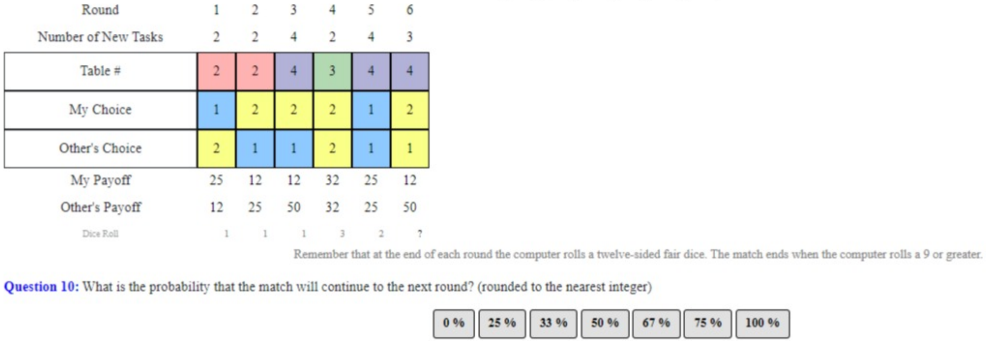
Question 8: If the **Number of New Tasks** is 3, what **Table #** will be used to determine payoffs in Round 6?



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?



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)

D Additional Tables and Figures

Table D1: 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																				

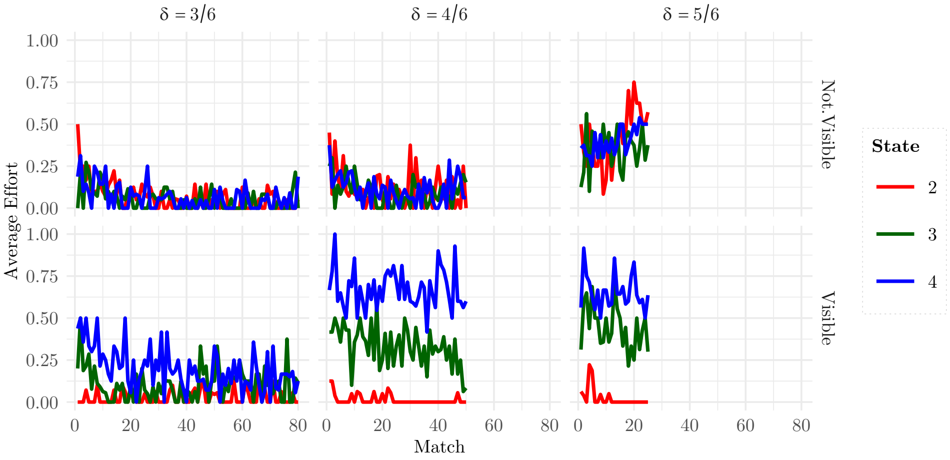
(b) $\delta = \frac{4}{6}$

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

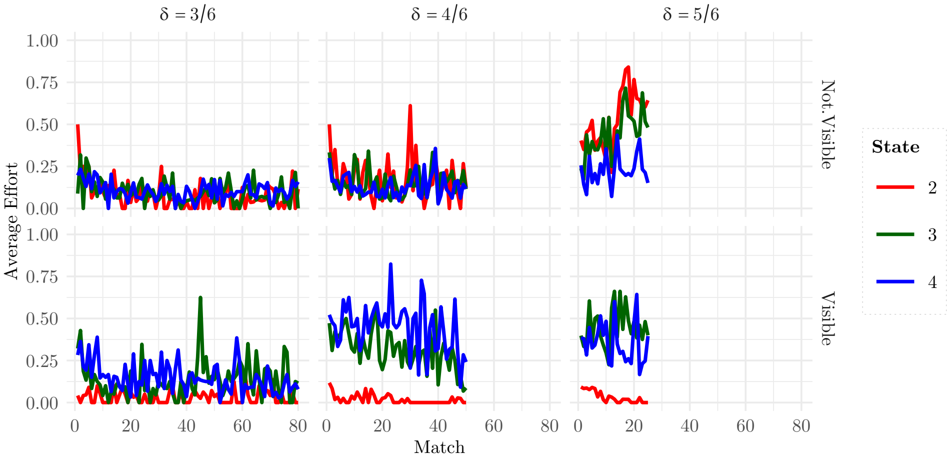
(c) $\delta = \frac{5}{6}$

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

Figure D1: Evolution of Effort



(a) First Period



(b) All Periods

Table D2: 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 (1.9)	70.6 (7.6)		17.2 (5.8)												8.1 (4.4)			2.0 (1.7)		92.9 (1.4)	-1107.3
No	$\frac{4}{6}$		60.1 (7.5)	6.2 (3.5)	26.0 (7.2)											2.1 (1.8)		5.6 (3.5)				91.7 (1.3)	-1112.5
No	$\frac{5}{6}$	2.1 (2.4)	39.0 (7.3)	19.4 (5.6)	10.6 (4.6)	5.3 (3.4)			5.6 (4.6)		2.5 (2.5)	5.3 (3.5)	3.6 (3.0)				2.5 (2.1)		4.1 (2.5)			90.6 (1.1)	-1176.8