Submitted to
manuscript (Please, provide the manuscript number!)

Communication, Commitment, and Persuasion in Service Operations: Theory and Experiment

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Information design is an important managerial lever for service firms to control demand for scarce resources. Information-sharing policies, in particular, can leverage uncertainty inherent in service systems and the firm's informational advantage (about relevant parts of the system) over customers. This effectively turns the design and implementation of information-sharing policies into a communication game between the firm and its customers, with issues of informativeness and credibility at its core. While a growing empirical literature has studied customer response to shared information in service systems (e.g., delay announcements), it remains an open empirical question whether effective information policies can arise in equilibrium. Because the effectiveness of information-sharing policies depends as much on customer behaviour as it does on the firm's ability to implement and communicate an information policy, this question is difficult to study in the field due to the lack of control and observability of relevant variables. To overcome these challenging data requirements, we turn to controlled laboratory conditions to test the key predictions of a queueing-game theoretic model that endogenizes the implementation of information-sharing policies in service systems.

Key words: communication; persuasion; queueing

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1. Introduction

Among several other options (such as capacity adjustments, admission controls, or queue discipline), information design is an important managerial lever for service firms to control demand for scarce resources. In particular, information-sharing policies can positively affect service outcomes via two mechanisms related to the uncertainty inherent in service systems and the information asymmetry (about relevant parts of the system) between the firm and its customers. Besides improving the experiences of customers by resolving uncertainty, properly designed information-sharing policies can impact customers' decisions. For instance, sharing queue-length information represents a tool of *voluntary demand modulation* that encourages customers to join low-congestion states, and deters them from joining high-congestion states (Ibrahim 2018).

Most service firms have an informational advantage over customers (about the service system), which effectively turns the design of information-sharing policies into a communication game between the firm and its customers, with issues of informativeness and credibility at its core. In particular, the service provider's ability to *commit* to an information-sharing policy (i.e., the ability to bind to a specific way in which information is disclosed) renders shared information credible (Lingenbrink and Iyer 2019, Anunrojwong et al. 2022). In this case, because of commitment power, customers know that the service provider will not disclose information in a different way, even if it is in the service provider's best interest to do so. This provides credibility and allows to influence customers' decisions. The question is how to strategically disclose information (i.e., the design of the information-sharing policy) to shape customer decision-making in the desired direction. In contrast, without commitment power, the service provider can make statements or promises to customers about how information is disclosed, but these statements are non-binding (i.e, cheap talk) and thus *generally* lack credibility. In this case, customers are aware that the statements may not be trustworthy, and as a result the provided information is viewed with skepticism, which generally limits its impact on customers' decision-making if the conflict of interest between customers and the service provider is sufficiently high (Allon et al. 2011).

We develop a game that provides sharp theoretical predictions which we subsequently test empirically under controlled laboratory conditions. We study firm and customer decision making in a setting that shares several of the features that characterize operational systems in practice and render effective communication both difficult and important. Arriving in random order at a system, customers need to decide whether to join a waitlist for service, without the ability to actually observe the waitlist. Customers are heterogenous in their need for service, which creates a known dilemma that characterizes many systems with negative externalities (Naor 1969): rational and self-interested *low-need* customers join at rates that hurt *high-need* customers. The firm can communicate information to influence customer choices. Specifically, the firm selects a threshold such that arriving customers receive a *short wait* signal if the waitlist is shorter than the threshold, and a *long wait* signal otherwise. Our analyses show that the effectiveness of such communication depends crucially on the the credibility of signals. With commitment, the firm implements the threshold it communicates, which renders signals credible by design. As a result, we observe welfare increases that arise from the firm's ability to persuade low-need customers to balk when it is in their best individual interest to join. In the absence of a commitment device, however, the firm has the incentive to implement a lower threshold than communicated, to send more *long wait* signals that sway low-need customers to *not* join the waitlist. Customers ignore signals, such that communication effectively breaks down, with no positive welfare effects over the case where the firm does not communicate at all.

We test these predictions under controlled laboratory conditions. Our experimental design varies the (human) service provider's ability to communicate to their (human) customers information about the system state. We observe that, although a system without any communication whatsoever fares substantially better than theoretically predicted, communication improves social welfare by mitigating the overjoining behavior of low-need customers. Our main results, and key managerial insights, concern the role of commitment and its combined effect on the credibility of communication and customer behavior. Even though service providers attempt to reduce (over)joining of low-need customers by implementing lower thresholds than communicated, and despite the fact that customers can easily detect such untruthful communication in our experimental setting, there is a degree of trust and trustworthiness, such that communication still influences customer decisions positively. As the surprising overall result, the effectiveness of communication does not depend on the service provider's ability to publicly commit to an information policy. This result stands in sharp contrast to theoretical predictions that such communication is not credible and thus has no effect on customer behavior. The important practical implication is that firms can leverage communication as a (potentially) low-cost mechanism to influence customer behavior towards socially beneficial outcomes even when lacking the ability to commit. This is an important insight in light of the fact that credible commitment mechanisms are hard or impossible to design in most practical settings.

The remainder of the paper is structured as follows. In §2, we review the relevant literature. In §3, we describe the queueing-game-theoretic model and key predictions. In §4, we describe our experiments and results. In §5 we provide explanations for the observed behaviour. Finally, in §6, we draw conclusions.

2. Related Literature

Most of the work on the impact of information sharing on customer strategic behaviour is theoretical. The seminal papers by Naor (1969) and Edelson and Hilderbrand (1975) were the first ones to study joining decisions in an M/M/1 queue for the observable and unobservable queue respectively. In those papers, both the problems of maximizing social welfare and revenue were investigated. We refer the reader to Ibrahim (2018), Economou (2021) for a comprehensive review of the relevant literature regarding the impact of sharing delay information in service systems. More recently, the literature has highlighted the issues of *credibility* that are inherent in the communication between the service provider and customers. Allon et al. (2011) consider a cheap talk setting where the firm wants to maximize profit but lacks commitment power. The authors show that for shared information to be credible and thus to influence customers' decisions, the service provider's and the customers' incentives should be *sufficiently aligned*. When incentives are sufficiently aligned, the authors show that the optimal profit can be achieved by a binary signaling mechanism with a threshold structure. Moreover, the authors find that a babbling equilibrium, where customers disregard any information given to them, always exists. Contrary to this, Lingenbrink and Iyer (2019) consider a bayesian persuasion setting where the firm wants to maximize profit and has the ability to commit to a signaling mechanism. They show that it suffices to consider binary signaling mechanisms and that the optimal signaling mechanism has a threshold structure. In contrast to a cheap talk setting where the provider cannot commit to a signaling mechanism, they find that the service provider can always influence customers' decisions. Similar to this, Anunrojwong et al. (2022) consider a bayesian persuasion setting where the firm cares about social welfare and has the ability to commit to a signaling mechanism. They show that it suffices to consider binary signaling mechanisms and that the optimal signaling mechanism has a threshold structure. We contribute to this literature by experimentally testing how real human decision-makers behave in comparison to the theoretical predictions in both a commitment and no-commitment setting. Importantly, we show that even if the incentives of the service provider and customers are sufficiently misaligned, shared information has a positive influence on customer decisions with and without commitment. We believe that this is an important contribution since it is not clear how a service firm can commit to an information-sharing policy in practice.

There are a few recent papers that empirically explore the impact of information sharing, mainly on abandonment behaviour. Yu et al. (2017) analyze the reneging behaviour from a medium-sized call center. They find that delay announcements not only impact customers' beliefs about the system but also that customers' per-unit waiting cost decreases with the announced waiting times. They also show that providing announcements with very fine granularity may not be necessary. Akşin et al. (2017) study the impact of delay announcements on customers' abandonment behaviour. They find that customers react to longer delay announcements by abandoning earlier, that less patient customers react more to delay announcements, and that congestion at the time of the call affects caller reactions to delay announcements. Webb et al. (2019) examine the reference-dependent impact of delay announcements in a call center on both customer abandonment behaviour and time spent in service. They find that delay announcements induce a reference point such that customers behave differently before and after this reference point. Dong et al. (2019) using a combination of empirical observations and numerical experiments investigate the impact of delay announcements on patients' choice, and the effect of patients' choice on hospital synchronization and expected wait times. They provide empirical evidence that suggests that patients take delay information into account when choosing emergency service providers and that such information can help increase coordination in the network. Overall, this stream of empirical literature shows that shared information influence customers' experiences and decisions. By conducting controlled experiments, we contribute to this literature by understanding the mechanisms that drive customers' decisions, and answering whether the impact of shared information is good/bad for individual customers and for the system (this requires some benchmark, which is hard to establish in the field). Moreover, our experimental setting allows us to study the role of commitment (or the lack thereof), primarily, because of the challenge to find a setting that varies commitment/no commitment in a way that it is amenable for empirical inquiry. In relation to this, another main contribution of our work is that our experimental design allows us to study not only customer decisions but also the service providers' ability to implement an information-sharing policy.

Similar to our work, there is a stream of literature that investigates the impact of shared information experimentally, but mainly on service evaluation and abandonment behaviour, and not in strategic settings. Hui and Tse (1996) study the impact of waiting-time information and queueing information on customers' service evaluations. They find that both types of information present a differentiated effect depending on the length of the actual wait. Munichor and Rafaeli (2007) study the effect of time perception and sense of progress in telephone queues on caller satisfaction to different telephone waiting time fillers: music, apologies, and information about location in the queue. They find that apologies heard while waiting were found to yield the most negative caller reactions, whereas information about location in the queue produced the most positive reactions. Yu et al. (2022) study in a field experiment how the wait time information, both its initial magnitude and its subsequent progress over time, impacts customers' abandonment behaviour in virtual queues. They find that both factors have a significant impact on customer abandonment. Ansari et al. (2022) study in a field experiment at an urban emergency department, how the precision of the delay announcements affects satisfaction (i.e., precision understood as whether the announcement over or underestimates the realized waiting time of customers). We contribute to this literature by experimentally studying a strategic setting in which we study simultaneously how service providers implement information-sharing policies, and how provided information impacts customers joining decisions. Studying a strategic setting allows us to answer questions relevant to the communication between service providers and customers (e.g., are service providers able to persuade customers? what is the informativeness of the selected delay announcement policies? do service providers engage in deceptive behaviour? do customers trust service providers' delay announcements?).

3. Model

We develop a queueing game in which the service provider has the incentive to communicate queue-length information to deter some customers from joining. For example, in highly-congested social services, such as public housing, the service provider generally seeks to maximize the social welfare in the system and commonly faces the challenge of reducing joining rates. In those systems, congestion partly stems from the fact that the service is available to all arriving customers, even to those who have reasonable outside options. To maximize social welfare, the service provider can share queue-length information to persuade some customers to forgo the service, and thus better serve those customers who do not have any outside options (Anunrojwong et al. 2022).

Our theoretical framework helps us develop testable predictions concerning the role of informativeness and credibility of queue-length information communication, and their effects on customer join/balk behaviour. Our model makes several simplifying assumptions for the sake of being testable experimentally, e.g., finite number of customers, the way the queue is formed and service is provided. However, it retains the main elements of real service systems relevant to the strategic interaction between customers and the service provider. For example, in our model: (a) Customers decide whether to join or not join a system; (b) customer utilities depend on their decisions (and on the decisions of others), and on the system state which determines wait-time related costs; (c) customers exert negative externalities (from joining) on later arriving customers; (d) unless informed by the service provider, customers do not know the state of the system when making their joining decisions; (e) there is a tension between what is best from an individual and social perspectives; (f) service providers have an informational advantage over customers (they know the state of the system), and they can leverage that information to improve social outcomes; and (g) system dynamics and properties (e.g., expected waiting times) are endogenously determined in equilibrium based on the decisions of customers and the service provider.

3.1. Basic Setup: A Waitlist Model

There are $\Lambda \in \mathbb{N}$ customers that arrive sequentially, according to a randomly assigned index $k \in \{1, \cdots, \Lambda\}$. Customers do not know their indices in the sequence upon arrival, nor can they observe the indices of other customers. Customers are of type High-need (H) with probability p_h and of type Low-need (L) with probability $1 - p_h$. Customer types differ as high-need customers do not have an outside option (i.e., they always join the system). While the service provider cannot observe the types of individual customers, she knows the probability distribution of customer types. Upon arrival, customers observe their type and some delay-related information, and make a join/balk decision. We do not allow for subsequent customer abandonment after the initial join decision. For experimental amenability and without loss of generality we assume that once all customers have made their decisions, the service provider commences to service customers (with deterministic service time normalized to 1) in order of their position in the waitlist.

We let U_k denote the utility accrued by customer k, and assume that customers make decisions to maximize their expected utility $\mathbb{E}[U_k]$. In particular, the utility that an low-need customer accrues from joining a waiting list at the $(q+1)^{st}$ position, i.e., with q customers ahead, is equal to $u_k = r - c(q+1)$. That is, customers earn a reward r upon completion of their service, and incur a delay cost $c(q+1)$, where c represents customer delay sensitivity. The utility that low-need customers experience if they balk is normalized to 0, while high-need customers do not have an available outside option so that their utility from balking is equal to $-\infty$. We assume that $r - c > 0$ since otherwise low-need customers would never join even if the system is empty. We also assume that $r - c\Lambda < 0$ since otherwise low-need customers would never balk even if the system is full.

The service provider aims at maximizing the *expected social welfare* Ω:

$$\Omega = \mathbb{E}\left[\sum_{k=1}^{\Lambda} U_k\right] = r\mathbb{E}[J] - c\mathbb{E}\left[\sum_{k=1}^{J} k\right] = r\mathbb{E}[J] - \frac{c}{2}\left(\mathbb{E}[J^2] + \mathbb{E}[J]\right), \tag{1}$$

where J is a random variable that represents the total number of customers that *join* the system. Let $p_s \in [0,1]$ denote an arbitrary joining probability for low-need customers, we can easily show that:

Proposition 1. *There is a unique joining probability $p_s^* \in [0,1)$ which maximizes expected social welfare Ω. If $\frac{r}{c} \leq 1 + p_h(\Lambda - 1)$ then $p_s^* = 0$, otherwise we have that $p_s^* = \frac{r - c(1 + p_h(\Lambda - 1))}{c(\Lambda - 1)(1 - p_h)} < 1$.*

We will see that without communication, in equilibrium, low-need customers over-join the system with a probability larger than p_s^*.

3.2. No communication and welfare loss

We start studying the case in which customers do not receive any information about the waiting list. To maximize their expected utility $\mathbb{E}[U_k]$, low-need customers decide to join whenever $r - c(\mathbb{E}[Q] + 1) > 0$, where Q represents the random number of other customers in the waitlist a customer encounters upon arrival. To solve this problem, customers compute the expected number of customers in the system, $\mathbb{E}[Q]$, based on system parameters and on their belief of how other customers behave. Let γ_e be the equilibrium joining probability of low-need customers. Proposition 2 describes the resulting equilibrium in this case.

Proposition 2. *A unique equilibrium exists where low-need customers join with probability:*

$$\gamma_e = \begin{cases} 0 & \text{if } \frac{r}{c} \leq \frac{(\Lambda-1)p_h}{2} + 1, \\ \frac{2r - c(2 + p_h(\Lambda - 1))}{c(\Lambda - 1)(1 - p_h)} & \text{if } \frac{(\Lambda-1)p_h}{2} + 1 < \frac{r}{c} < \frac{(\Lambda-1)}{2} + 1, \\ 1 & \text{if } \frac{r}{c} \geq \frac{\Lambda-1}{2} + 1. \end{cases}$$

Corollary 1. *From Propositions 1 and 2, if $\frac{r}{c} \leq \frac{(\Lambda-1)p_h}{2} + 1$, then it is always the case that $\gamma_e = p_s^* = 0$. Moreover, if $\frac{r}{c} > \frac{(\Lambda-1)p_h}{2} + 1$, then it is always the case that $\gamma_e > p_s^*$.*

From Corollary 1, when low-need customers do not join ($\gamma_e = 0$), we know that such behaviour is *socially optimal* such that the service provider does not have an incentive to communicate information to customers to modify their behaviour. However, whenever low-need type customers do join with positive probability ($\gamma_e > 0$), Corollary 1 shows that low-need customers over-join the system, because they disregard the negative externalities their joining decisions impose on later arrivals.

In the following, we restrict attention to the case in which $p_s^* = 0$ and $\gamma_e = 1$, i.e., where the over-joining of low-need customers is maximal. For this, we assume that $\frac{r}{c} \geq \frac{\Lambda-1}{2} + 1$ and $\frac{r}{c} \leq \Lambda p_h$, where the latter restriction ensures that $p_s^* = 0$ and that the interests of the service provider and customers are sufficiently misaligned. This allows us to derive sharp theoretical predictions to experimentally test the effect of communication on customers' decision-making and social welfare.

3.3. Communication and Commitment

In this section, we assume that the service provider sends a binary signal $\varsigma = \{s, l\}$ (e.g., short wait, and long wait) to each arriving customer. In particular, the service provider implements a signaling mechanism with threshold θ such that a customer receives a *s*hort wait signal when arriving at a system with $q < \theta$ customers, and *l*ong wait signal otherwise.[1] Importantly, the service provider publicly communicates the threshold θ' that will be used for generating the signals. Whether communication can be effective towards the reduction of low-need customers' overjoining behavior then crucially depends on the credibility of signals sent by the service providers. We consider two cases.

With commitment, the service provider makes binding claims θ' about the implemented information-sharing policy θ, i.e., customers are guaranteed that $\theta' = \theta$ - signals are credible. In contrast, without commitment, the service provider makes non-binding claims θ', i.e., customers know that θ' is not necessarily equal to θ. For signals to be credible in the absence of commitment, it is necessary that the service provider does not have the incentive to communicate a threshold θ' that differs from the implemented threshold θ that actually generates the signals - credibility of signals (if any), in this case, would arise endogenously at equilibrium.[2]

When low-need customers arrive, while they do not observe the system state q, they can compute the expected wait list length based on the provider's signals and their belief of equilibrium strategies

[1] The choice of a simple threshold signaling mechanism has both theoretical and empirical appeal. On the theoretical front, the threshold structure captures the main decision trade-offs of interest. Moreover, recent theoretical work on $M/M/1$ steady-state queue setting (Allon et al. 2011, Anunrojwong et al. 2022) identifies optimal signaling mechanism that have a threshold structure similar to our specification. From the perspective of experimental amenability, the threshold structure is easy to understand, which is essential for service providers and customers participants to understand the underlying trade-offs in our information-design problem.

[2] Formally, for a given communicated threshold θ', and customer response probabilities $({\alpha^{s}}'_e, {\alpha^{l}}'_e)$, for signals to be credible, it is required that $\Omega(\theta', \alpha_e^{s'}, \alpha_e^{l'}) \geq \Omega(\theta, \alpha_e^{s'}, \alpha_e^{l'})$ for all possible thresholds θ.

of other customers. We let $\alpha^s \doteq \mathbb{P}(\text{Join}|\varsigma = s)$ and $\alpha^l \doteq \mathbb{P}(\text{Join}|\varsigma = l)$ be the joining probabilities of low-need customers conditional on receiving signal ς under a communicated threshold θ'. In the following Lemma 1, we derive the equilibrium joining probability under both the commitment and no commitment cases.

LEMMA 1. ***(Customer Equilibrium)*** *For a given communicated threshold θ', a unique customer equilibrium (α_e^s, α_e^l) exists, given by*

(a) With commitment: $\alpha_e^s = 1$ and

$$\alpha_e^l = \begin{cases} 1 & \text{if } \theta \leq \bar{\bar{\theta}}; \\ \frac{2r - c(2(\theta+1) + p_h(\Lambda-\theta-1))}{c(1-p_h)(\Lambda-\theta-1)} & \text{if } \bar{\bar{\theta}} < \theta < \bar{\theta}; \\ 0 & \text{if } \theta \geq \bar{\theta}. \end{cases}$$

where $\bar{\theta} = \lceil \frac{2r - 2c - cp_h(\Lambda-1)}{c(2-p_h)} \rceil$, and $\bar{\bar{\theta}} = \lfloor \frac{2r - c(\Lambda+1)}{c} \rfloor \geq 0$.

(b) With no commitment: $\alpha_e^s = 1$ and $\alpha_e^l = 1$. Moreover, we have that $\{0, \cdots, \bar{\bar{\theta}}, \Lambda\}$ is the set of thresholds that generate credible signals.

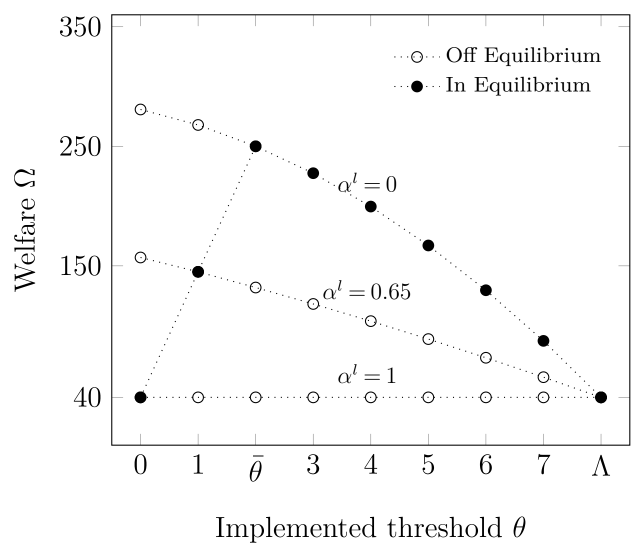
With commitment, Lemma 1(a) shows that the service provider can communicate some thresholds to reduce equilibrium joining rates. To build intuition, using the parameters from our experiments, Figure 1 illustrates customer equilibrium behavior and its interaction with the fundamental trade-off that the service provider faces. Key to reducing overjoining behavior is to send *l*ong wait signals that dissuade low-need customers from joining the wait list. Setting $\theta' = 0$ is not conducive to the idea, because the resulting signals (always *l*ong wait) carry no information whatsoever such that customers would simply ignore them and resort to the overjoining behavior from the setting without signals ($\gamma_e = 1$).[3] The service provider can render signals informative by increasing θ', but faces a trade-off. On the one hand, increasing θ' will lower the probability that low-need customers join when receiving *l*ong wait signals ($\alpha_e^l = 0.65$ for $\theta = 1$, and $\alpha_e^l = 0$ for $\theta \geq \bar{\theta} = 2$). On the other hand, increasing θ' will generate more *s*hort wait signals under which low-need customers always join ($\alpha_e^s = 1$). Thus,

[3] The same argument is true for $\theta' = \Lambda$ ($= 8$, in the example).

because low-need customers already balk at $\bar{\theta}$, increasing θ' further only increases overall joining and hence reduces welfare.

Without commitment, given the ability to implement a threshold θ that differs from the communicated threshold θ', would the service provider be able to reduce joining of low-need customers? Lemma 1(b) shows the answer is no. Although the service provider can communicate a threshold $\theta \geq \bar{\theta} = 2$, such that customers do not join when receiving *l*ong wait signals ($\alpha_e^l = 0$), they have an incentive to implement a lower-than-communicated threshold θ. This is to reduce, or eliminate (at $\theta = 0$), the occurrence of *short wait* signals under which low-need customers join ($\alpha_e^l = 1$). Because signals under the communicated threshold are thus not credible ($\theta \in \{1, .., 7\}$), or they are credible but uninformative ($\theta \in \{0, 8\}$),[4] customers will disregard signals and default to their behavior in the absence of any communication - they join the wait list regardless of the signals received.

Figure 1 Social Welfare, communication, and customer behavior ($\Lambda = 8$, $r = 185$, $c = 40$, $p_h = 0.65$**)**



The following Proposition 3 succinctly summarizes the equilibrium that arises between the service provider and its customers.

[4] Signals under $\theta' \in \{0, 8\}$ are credible because $\Omega(\theta' \in \{0, \Lambda\}, {\alpha^s}'_e = 1, {\alpha^l}'_e = 1) = \Omega(\theta, {\alpha^s}'_e = 1, {\alpha^l}'_e = 1)$ for all θ. However, in this case, because the provider sends the same signal in all queue states, signals carry effectively no information to customers and hence do not influence behaviour.

PROPOSITION 3. ***(Game Equilibrium)***

- *With commitment: A unique equilibrium between the service provider and customers exists such that* $\theta^* = \lceil \frac{2r-2c-cp_h(\Lambda-1)}{c(2-p_h)} \rceil < \lfloor \frac{r}{c} \rfloor$, $\alpha_e^s = 1$, *and* $\alpha_e^l = 0$.
- *With no commitment: Equilibria between the service provider and customers exist such that* θ^* *is any threshold,* $\alpha_e^s = 1$, *and* $\alpha_e^l = 1$.

Proposition 3 shows that when the provider has the ability to commit, it is optimal to select a threshold such that low-need customers join when they receive a *s*hort wait signal, and balk when they receive *l*ong wait signal. This type of behaviour is commonly known as an *obedient equilibrium* (Anunrojwong et al. 2022, Lingenbrink and Iyer 2019). In the case of no commitment, Proposition 3 characterizes a *babbling equilibrium* where no credible information is transmitted (Allon et al. 2011), with the result that the service provider can use any threshold and customers will always disregard such signals and behave as if they were in a setting with no communication whatsoever.

3.4. Informativeness and Persuasion

The fact that the service provider has an informational advantage over customers raises the question of how much information is transmitted to customers, and how such information shapes the game equilibrium characterized in Proposition 3. Similar to communication games in the economics literature (Fréchette et al. 2022), as a proxy for informativeness, we focus on how well customers match their actions with true system states. For this, we note that joining customers experience non-negative utility $r - c(q+1) \geq 0 \iff q+1 \leq \frac{r}{c}$, whenever their position in the wait list does not exceed $q^* = \lfloor \frac{r}{c} \rfloor$ (Naor 1969). It follows that low-need customers' decision-making is subsumed to a *binary guess*: to maximize their individual expected utility, customers only need to guess correctly if the system state q is below q^* and match their joining decisions accordingly (i.e., join given that $q < q^*$ and balk given that $q \geq q^*$).[5] Based on this, we use the bookmaker informedness BM metric[6]

[5] The individual optimality of their decision does not depend on how precise their estimate of q is, it only depends on identifying whether or not the number of people that they encounter in the system upon their arrival is less than q^*.

[6] We note that in communication games, the correlation between actions and true states is a standard measure used to quantify in a single numerical value the amount of information transmitted from a sender to a receiver (Fréchette

which captures in a single numerical value the amount of transmitted information in our setting (Chicco et al. 2021):

$$BM = \mathbb{P}(\text{Join}|q < q^*) + \mathbb{P}(\text{Balk}|q \geq q^*) - 1. \tag{2}$$

From the customer perspective, $BM = 0$ represents a customer that makes decisions without any information (e.g., random guess), and $BM = 1$ one that decides with all necessary information to match their actions perfectly with the system state. The following Proposition 4 characterizes informativeness of signals in our game.

Proposition 4. *In equilibrium:*

(a) With commitment, we have that $P(Join|q < q^*) \in (0,1)$, $\mathbb{P}(Balk|q \geq q^*) = 1$, *and* $BM \in (0,1)$.

(b) Without commitment, we have that $P(Join|q < q^*) = 1$, $\mathbb{P}(Balk|q \geq q^*) = 0$, *and* $BM = 0$.

With commitment, the service provider can achieve $BM = 1$, by implementing a threshold $\theta = q^*$ under which signals perfectly reveal to customers if the wait list is below q^* or not (see Figure 2a). While the service provider thus has the ability to share all the necessary information for customers to make individually optimal choices, Proposition 4 shows that the service provider finds it optimal to share information only *partially*, i.e., $BM \in (0,1)$ (see Figure 2a). Proposition 4 shows a precise pattern in which partial information is transmitted, which resonates with Kamenica and Gentzkow (2011)'s optimal persuasion mechanism: whenever a low-need customer takes the service provider's preferred action (i.e., balk), the customer has no full certainty about her decision, and so makes balking mistakes sometimes, i.e., $\mathbb{P}(Balk|q < q^*) = 1 - \mathbb{P}(Join|q < q^*) \in (0,1)$ (see Figure 2b). Contrary to this whenever the customer takes the provider's least-preferred action (i.e., join), the customer knows with certainty that it is in her best interest, and thus never makes joining mistakes, i.e., $\mathbb{P}(Join|q \geq q^*) = 1 - \mathbb{P}(Balk|q \geq q^*) = 0$ (see Figure 2c).

et al. 2022). However, in our setting it is possible for all customers to join with probability 1 (i.e., the action is constant) in equilibrium, rendering the correlation *undefined* because the variance is 0. To circumvent this technical problem, we use the BM metric, which is similar to correlation (i.e., $BM \propto$ correlation) (Chicco et al. 2021)

Persuasion happens when the provider communicates in a way (here a *l*ong signal with $\theta^* < q^*$) that makes customers take actions (here to balk) that they would not take if they observed the system state (here $\theta^* \leq q < q^*$). The main insight of selecting an appropriate threshold, $\theta^* < q^*$, that neither fully reveals nor fully conceals information, is that in equilibrium, the service provider is able to coalesce favorable (i.e., $q < q^*$) and unfavorable states (i.e., $q \geq q^*$) for customers (Lingenbrink and Iyer 2019), such that they find the action of always balking when receiving a *l*ong signal to maximize their individual utility in expectation. Importantly, while persuasion influences customer decisions, not all types of influence are persuasion. For instance, the provider can select a threshold $\theta \geq q^*$ such that customers who receive an l signal balk more than customers in environments without signals. While such an l signal indeed influences customers' decisions, it does not represent persuasion since in this case, customers would still balk if they knew the actual state in the system q. Indeed, for persuasion to be possible, it is required that $\theta < q^*$. Based on this, we measure the *persuasiveness* of signals as:

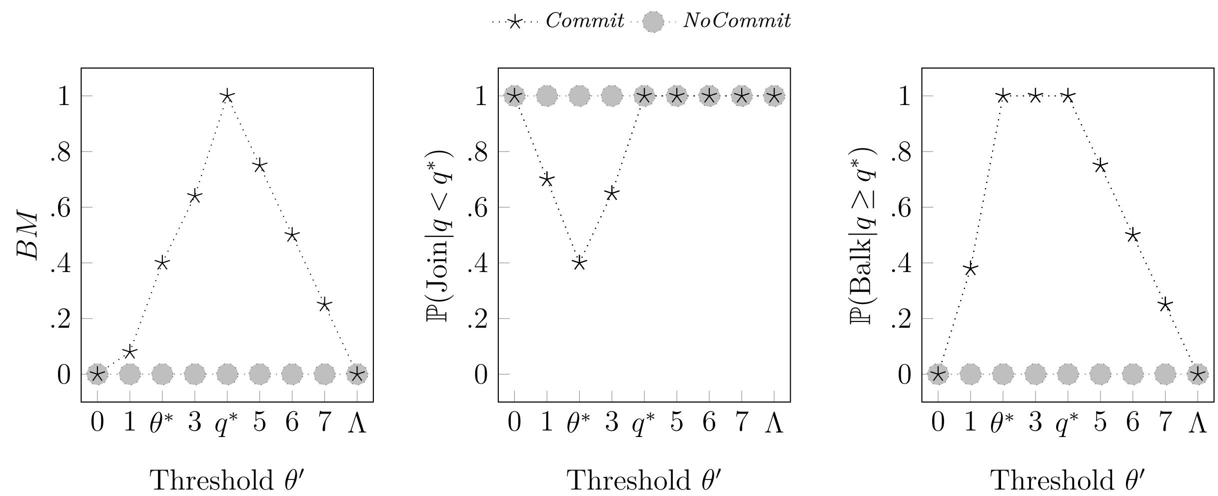
$$\mathcal{P} = \mathbb{P}(\text{Balk}|\varsigma = l, \theta < q^*). \tag{3}$$

From Proposition 3, it is easy to see that $\mathcal{P} = 1$ for the case of commitment in equilibrium, because $\theta^* < q^*$ and customers always balk when receiving an l signal (i.e., $\alpha_e^l = 0$).

Finally, for the case without commitment, and by analogy for the case of no communication, Proposition 4 shows that $BM = 0$, because customers disregard all information shred by the service provider and join with a fixed probability irrespective of queue states such that $\mathbb{P}(\text{Join}|q < q^*) = \mathbb{P}(\text{Join}) = 1$, and $\mathbb{P}(\text{Balk}|q \geq q^*) = \mathbb{P}(\text{Balk}) = 1 - \mathbb{P}(\text{Join}) = 0$ (see Figure 2).[7] Obviously, $\mathcal{P} = 0$ in the case of no commitment where the provider is not able to influence customer behaviour at all.

[7] Similarly, in the communication with commitment case, whenever the service provider selects $\theta \in \{0, \Lambda\}$, we have that $BM = 0$ (see Figure 2a). This is intuitive since under such thresholds, customers receive the same signal irrespective of the true queue state, such that customers join with a fixed probability in all queue states.

Figure 2 **Thresholds and signal informativeness (**$\Lambda = 8$**,** $r = 185$**,** $c = 40$**,** $p_h = 0.65$**).**



(a) BM (b) $\mathbb{P}(\text{Join}|q < q^*)$ (c) $\mathbb{P}(\text{Balk}|q \geq q^*)$

4. Experiment

Our theoretical results show that a service provider can improve social welfare with a properly designed information-sharing policy *if and only if* the service provider can credibly commit to it. We designed an experimental study to test these predictions under controlled laboratory conditions that gives theory its best shot.

4.1. Task

Participants in our experiment faced the task described in §3.1, in the role of either a service provider or a customer. In each of a total of $T = 40$ experimental rounds, the service provider serves a market of $\Lambda = 8$ potential customers. At the beginning of each round, all customers are randomly and independently assigned a type: high-need with probability $p_h = 0.65$, and low-need $1 - p_h = 0.35$.

Decisions and system dynamics. Customers arrive to the market sequentially, according to randomly assigned and unknown indices $k \in \{1, \cdots, \Lambda\}$. High-need customers automatically join the wait list as they do not have an outside option, and low need customers need to decide whether to join the wait list or not. When a customer joins, the wait list increases by one. After the arrivals and decisions of all Λ customers, the provider delivers service to the customers in the sequence in which they joined the wait list.

Financials. Customers that join the wait list at position $q+1$ earn $r-c(q+1)$, and we set the service value of $r=\$185$ and the delay cost of $c=\$40$. Customers who do not join receive value of \$0 from their outside option. The service provider's objective is to maximize social welfare, which is the average utility of all Λ customers.

4.2. Design and Hypotheses

We implement three experimental treatments that vary the service provider's ability to communicate to customers and to commit to a communication strategy. In our baseline *NoSignal* treatment, the service provider cannot send to the arriving customers any signals about the length of the wait list. We then implement two treatments in which the service provider can signal information, but differ in the provider's ability to commit to the signals. In the *Commit* treatment, at the beginning of each round, the service provider defines a threshold θ used to generate a binary signal $\varsigma=\{s,l\}$ that customers receive upon their arrival. This threshold is publicly communicated to all customers. Specifically, customers receive the signal s when they arrive at a wait list with less than θ customers, and receive l otherwise. In contrast, service providers in the *NoCommit* treatment first define a threshold θ that is used to generate signals, then publicly communicate a threshold θ'. While customers do not observe θ itself, it is public knowledge that the service provider has the discretion to implement a threshold θ that is different from θ'.

Table 1 summarizes our experimental design and theoretical predictions (for providers' signalling strategies, customers' joining strategies, and resulting welfare) that allow us to test our main hypothesis:

Hypothesis 1A. Signals with commitment improve welfare, i.e., $\Omega^{Commit} > \Omega^{NoSignal}$.

Hypothesis 1B. Signals without commitment do not improve welfare, i.e., $\Omega^{NoCommit} = \Omega^{NoSignal}$.

Table 1 also summarizes the mechanisms underlying the main hypothesis. Our analyses predict that the ability to commit to a signalling threshold allows the service provider to influence customer behaviour through *informative* signals. Without commitment power, there is no transmission of

Table 1 Treatments, Sample Sizes, and Theory Predictions.

Treatment	Sessions	N	θ^*	Equil.	Ω	$\mathbb{P}$(Join)	$\mathbb{P}(\text{Join}\mid q<q^*)$	$\mathbb{P}(\text{Balk}\mid q\geq q^*)$	BM	$\mathcal{P}$
Commit	5	90	2	$(\alpha_e^s=1,\alpha_e^l=0)$	\$250	0.25	0.4	1	0.4	1
NoCommit	7	126	Any	$(\alpha_e^s=1,\alpha_e^l=1)$	\$40	1	1	0	0	0
NoSignal	3	54	-	All join	\$40	1	1	0	0	-

information, i.e., $BM=0$, and thus the service provider is not able to influence customer behaviour. Indeed, the *NoCommit* and *NoSignal* treatments present the same predictions in terms of BM and customer behaviour. In contrast, with commitment power, signals are *partially informative*, i.e., $BM\in(0,1)$, such that the service provider influences customers to never make joining mistakes i.e., $1-\mathbb{P}(\text{Balk}|q\geq q^*)=\mathbb{P}(\text{Join}|q\geq q^*)=0$, and to only make some balking mistakes, i.e., $1-\mathbb{P}(\text{Join}|q<q^*)=\mathbb{P}(\text{Balk}|q<q^*)\in(0,1)$. That is, the service provider is able to successfully persuade low-need customers to balk: $\mathcal{P}=1$.

4.3. Discussion of Design Choices

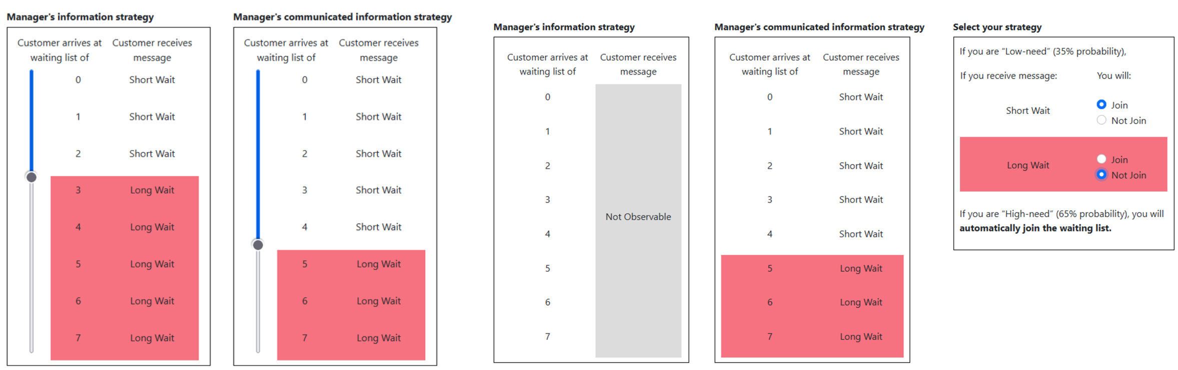
We now briefly discuss our main experimental design choices.

Human service providers. Because we want to study if effective communication can arise in equilibrium, our experiments feature both human customers and human service providers. Because the presence of a human service provider might affect customer decisions for behavioural reasons not considered in our theoretical analyses, and to allow for a clean comparison with the communication treatments (*Commit, NoCommit*), we include a human service provider even in the *NoSignal* treatment where service providers do not make decisions that affect the game outcomes.

Strategy method. We use the strategy method to elicit from participants the choices (i.e., join or balk) that they would make as low-need customers before they learn about their actual type for the round (Figure 3b). That is, given potential communicated thresholds θ, in treatments *Commit* and *NoCommit*, we elicit from participants their choices in response to signals that they could receive. The strategy method, extensively used in the experimental economics literature (see e.g. Brandts 2011, Beer et al. 2022), addresses two challenges related to data availability and consistency between model setting and experimental implementation. On the issue of data, the strategy method allows us to observe participants' choices as low-need customers even in rounds that assigns them a high-need type, and to fully understand customer behaviour even in scenarios that are unlikely to happen in our data.[8] Besides increasing considerably the number and types of decisions that we can observe in our data, the strategy method is crucial to establish consistency between our experimental implementation and the unobservable rank assumption that is at the core of our theoretical developments. We need to ensure that participants cannot (even imperfectly) infer their rank k, e.g., from how long they have waited after all participants moved to the next round. The strategy method rules out such inferences.

Figure 3 Screenshots (treatment *NoCommit*)

(a) Service provider: Elicit θ and θ' (b) Customer: Elicit $a(\varsigma = s|\theta')$ and $a(\varsigma = l|\theta')$



Notes: This figure presents screenshots once service providers and customers have made their selections. To avoid anchoring, players do not see any default selection.

Feedback and learning. At the end of each round, using the strategies elicited from participants (service provider communication decisions, and customer joining decisions) and the realizations of random events (customer type and index), the computer simulates the system; see Figure 4.

All participants, regardless of their role, receive full feedback which includes the communicated threshold, customer order of arrival, customer types, signals received, customer decisions, customer

[8] On the first point, remember we automate high-need customer decisions because our setting renders these uninformative. e.g., if a service provider communicates a threshold of $\theta = 7$, we observe customers decisions for an H signal even if it is unlikely that customer decisions will actually take the system to that level.

positions in the wait list, and the utilities generated. This ensures that the joining decisions of customers are based solely on their payoff function, and not on other factors such as their desire to gain information for future rounds, e.g., customers could join to know how others behave. Although service systems in practice rarely provide such extensive information, it is desirable in our experimental implementation because it gives theory its best shot, by reinforcing participant understanding about the dynamics in the queue, the signalling threshold, and the computation of their payoffs.

Finally, we note that the full access to results also means that customers in the *NoCommit* treatment would observe whether the provider's implemented threshold matched the communicated threshold. Since there is no guarantee that all participants would arrive at the right conclusion (or if they engage at all in such computation), and to better control for the influence of the availability of this information, we show the service provider's communicated and implemented policy side-by-side. In §4.7 we discuss the *NoCommit* treatment findings in light of this latter experimental design choice.

Figure 4 End-of-round feedback (treatment *Commit*)

Customer	Order of Arrival	Type	Arriving at waiting list of	Received Message	Decision	Position in Waiting List (P)	Service Value (S)	Waiting Cost (W) = $40*(P)	Customer Payoff = (S)-(W)
CC	1	High-need	0	Short Wait	Join	1	$185	$40	$145
CF	2	High-need	1	Short Wait	Join	2	$185	$80	$105
CA	**3**	**Low-need**	**2**	**Short Wait**	**Join**	**3**	**$185**	**$120**	**$65**
CH	4	High-need	3	Long Wait	Join	4	$185	$160	$25
CB	5	Low-need	4	Long Wait	Join	5	$185	$200	-$15
CE	6	Low-need	5	Long Wait	Not Join	None	$0	$0	$0
CG	7	Low-need	5	Long Wait	Not Join	None	$0	$0	$0
CD	8	High-need	5	Long Wait	Join	6	$185	$240	-$55
								Manager's Payoff = Average Customer Payoff	$33.75

Notes: This figure illustrates the results table that customer CA observes.

Parameters. For our chosen parameter values (r, c, p_h, Λ), all low-need customers should theoretically join the system when no information is communicated (see Proposition 2), thus creating a loss in social welfare that can be mitigated by a properly designed communication strategy (see §3.3).

Our choice of $\Lambda = 8$ deserves further comment. Although service environments typically involve a large number of customers that interact with the system, the practical realities of our laboratory environment required a careful selection of Λ. We selected a Λ that is small enough to be able to increase the number of sessions (i.e., independent observations) as much as possible given a fixed pool of subjects, while large enough to retain the complexity of the decision-making task that arises from the interaction of multiple players.

4.4. Software, Recruitment, and Payment

We implemented the experiment in the software otree (Chen et al. 2016). In total, 270 participants were included in our study and each subject participated in one treatment only. We recruited participants from a subject pool associated with the experimental laboratory at a large public university in Europe. In each session, after arriving at the laboratory, participants were randomly assigned to isolated cubicles and read instructions presented on-screen in an easy to navigate format. Participants in all treatments then played five practice rounds of the *NoSignal* treatment to familiarize themselves with the task and computer interface with the option to ask clarification questions. The computer then randomly assigned to each participant a role (provider or customer) that they would keep for the duration of the experiment. Exactly 18 participants were in a session, for 2 cohorts of 9 (1 provider and 8 customers) and participants did not know the session size. At the beginning of each round, each service provider was randomly matched with 8 customers to eliminate reputational concerns.

Each session lasted around 90 minutes, and subjects were paid €7 for their participation, in cash at the end of the session, plus a bonus based on their average payoff from all 40 rounds, at a conversion rate of €0.5 for each $1 experimental dollar. Total earnings ranged from €7.44 to €33.38 with an average of €19. Prior to collecting data for our studies, we pre-registered the main research hypotheses, key dependent and independent variables, analysis plans, target sample sizes, and exclusion criteria. The full pre-registration documents are available at `https://aspredicted.org/H92_D94` and `https://aspredicted.org/MXN_MJZ`.

4.5. Data and Analysis

At the most granular level, in each round $t \in \{1, \ldots, T\}$ and for each cohort $c \in \{1, \ldots, C\}$, we observe the provider j's implemented threshold decision θ_{jtc} in *Commit* and *NoCommit*, as well as the communicated threshold decision θ'_{jtc} in *NoCommit*. For each customer $i \in \{1, \cdots, \Lambda\}$, we observe their strategy $A_{itc} \equiv \{a_{itc}\}$ in *NoSignal*, $A_{itc} \equiv \{a_{itc}(\varsigma = s|\theta_{jtc}), a_{itc}(\varsigma = l|\theta_{jtc})\}$ in *Commit*, and $A_{itc} \equiv \{a_{itc}(\varsigma = s|\theta'_{jtc}), a_{itc}(\varsigma = l|\theta'_{jtc})\}$ in *NoCommit*, where $a_{itc} \in \{0, 1\}$, such that 1 represents the *Join* action and 0 the *Balk* action. We also observe the realized welfare w_{ct}, but we use for our analyses the *expected* welfare Ω_{ct} conditional on the observed joining strategies A_{itc} and implemented thresholds θ_{jtc}. This eliminates from our data the impact of variability from random realizations of customer arrival indices and types, which provides a clean comparison with theoretical predictions. In Appendix B, we describe how we compute Ω_{ct} and, similarly, other key metrics that we analyze.

To compare metrics across treatments, or against theoretical predictions, we use session-level averages as the unit of analysis for our statistical tests. In addition, we also report several regression-based analyses with standard errors clustered at the appropriate level to accommodate the dependency of observations in our data. In Appendix C, we present the details of all reported statistical results and robustness tests.

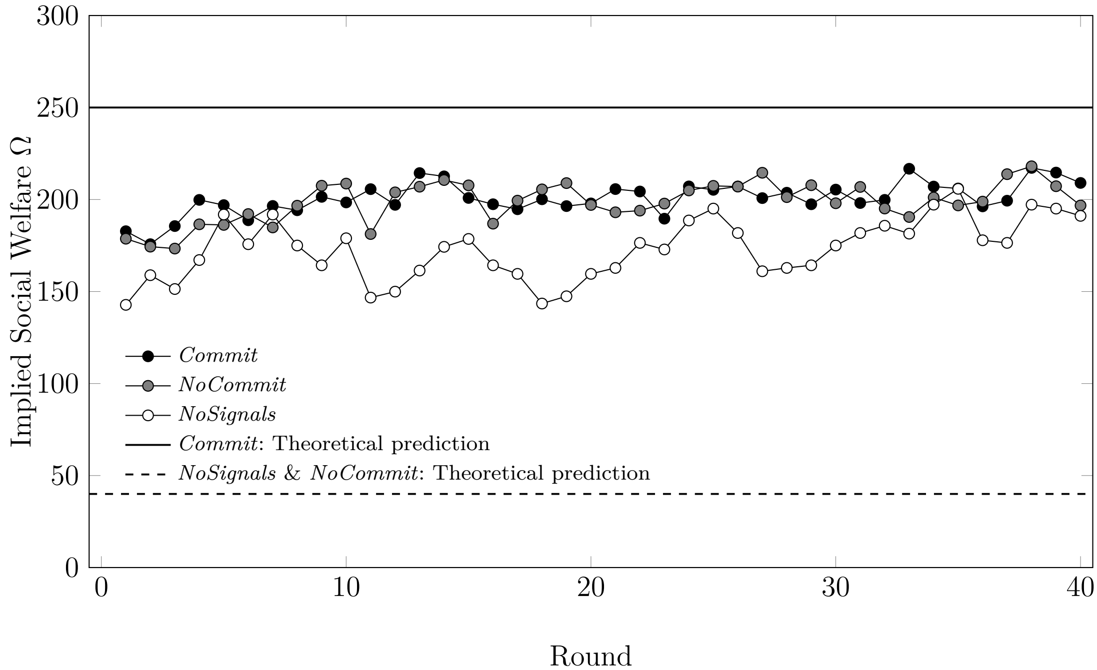
4.6. Results

Table 2 displays the main results for total welfare, service provider behavior, and customer behavior. We next discuss these in more detail.

Table 2 Experimental Results (Standard deviations in parentheses)

	Welfare	$\mathbb{P}$(Join)	$\mathbb{P}(\text{Join}\|q < q^*)$	$\mathbb{P}(\text{Balk}\|q \geq q^*)$	BM	$\mathcal{P}$
NoSignals	172.84	0.57	0.57	0.43	0	-
	(22.59)	(0.09)	(0.09)	(0.09)	(0.00)	-
Commit	200.70	0.48	0.66	0.74	0.41	0.74
	(10.86)	(0.05)	(0.06)	(0.09)	(0.12)	(0.09)
NoCommit	198.70	0.48	0.61	0.68	0.29	0.66
	(10.20)	(0.05)	(0.11)	(0.09)	(0.18)	(0.09)

Figure 5 Social Welfare



4.6.1. Social Welfare. Figure 5 shows, for each treatment, the average implied social welfare over the course of the experiment.

We make several observations. Notably, the welfare in the *NoSignal* treatment is substantially better than theoretically predicted (172.84 vs. 40, $p = 0.005$). Although our data thus leaves less room (than theoretically predicted) for effective communication to increase social welfare, we observe that *Commit* improves welfare over *NoSignal* (200.7 vs. 172.84, $p = 0.026$), despite falling short of theory predictions (200.7 vs. 250, $p < 0.001$). Overall, the data supports Hypothesis 1A ($\Omega^{Commit} > \Omega^{NoSignal}$). We observe that welfare also improves under *NoCommit* (198.7 vs. 172.84, $p = 0.016$), rejecting Hypothesis 1B ($\Omega^{NoCommit} = \Omega^{NoSignal}$) that signals without commitment do not improve social welfare. In fact, surprisingly, social welfare does not differ between the two signal treatments (200.7 vs. 198.7, $p = 0.376$).

Result 1. *Signals with and without commitment improve social welfare to the same extent.*

The aggregate nature of our analysis thus far leaves open the question of why communication is effective even without commitment. We next study the reasons for this result in more detail.

4.6.2. Informativeness and Persuasiveness. A possible reason for the higher than predicted effectiveness of the *NoCommit* treatment is that signals are informative and persuasive even though they theoretically should not be. Recall that, as a proxy for informativeness, the metric BM captures how well customers match their actions with the real queueing state. Not surprisingly, we observe that the average BM is higher in *Commit* than in *NoSignal* (0.41 vs. 0, $p = 0.001$). In fact, signal informativeness in *Commit* is about as high as theoretically predicted (0.41 vs. 0.4, $p = 0.908$). Contrary to theoretical predictions, our data further shows that signals in *NoCommit* are also informative even though theory predicts they are not (0.29 vs. 0, $p = 0.003$), and statistically no less so than in *Commit* (0.29 vs. 0.41, $p = 0.127$). This shows that in both *Commit* and *NoCommit* treatments, service providers are able to transmit queue-length information to customers, and customers are able to use such information.

RESULT 2. *Signals with and without commitment transmit the same amount of information.*

We observe a particular pattern in which customers match their actions better with the system state (than without any signals) in both signals treatments. Recall that service providers have the incentive to convince as many low-need customers to balk as possible, and that they can do so via two related mechanisms formally encapsulated in our informativeness metric $BM = \mathbb{P}(\text{Join}|q < q^*) + \mathbb{P}(\text{Balk}|q \geq q^*) - 1$. First, service providers aim to reduce customers' propensity to join (i.e., $\mathbb{P}(\text{Join}|q < q^*)$) when it is in the customers' best interest to join. Table 2 shows that, relative to *NoSignal* (where $\mathbb{P}(\text{Join}|q < q^*) = 0.57$), service providers are not significantly able to send signals that reduce customers' ability to join, in *Commit* (0.66 vs. 0.57, $p = 0.063$) and in *NoCommit* (0.61 vs. 0.57, $p = 0.306$). Second, service providers have the incentive to increase customers' ability to balk (i.e., $\mathbb{P}(\text{Balk}|q \geq q^*)$) when it is customers' best interest to balk. Indeed, relative to *NoSignal* (where $\mathbb{P}(\text{Balk}|q \geq q^*) = 0.43$), service providers are able to improve customers' ability to balk, in *Commit* (0.74 vs. 0.43, $p = 0.001$) and in *NoCommit* (0.68 vs. 0.43, $p = 0.002$).

Signals are influential, but are they persuasive? Recall that we measure persuasiveness as $\mathcal{P} = \mathbb{P}(\text{Balk}|\varsigma = l)$ for $\theta < q^*$, which captures the propensity of customers to balk when receiving an l

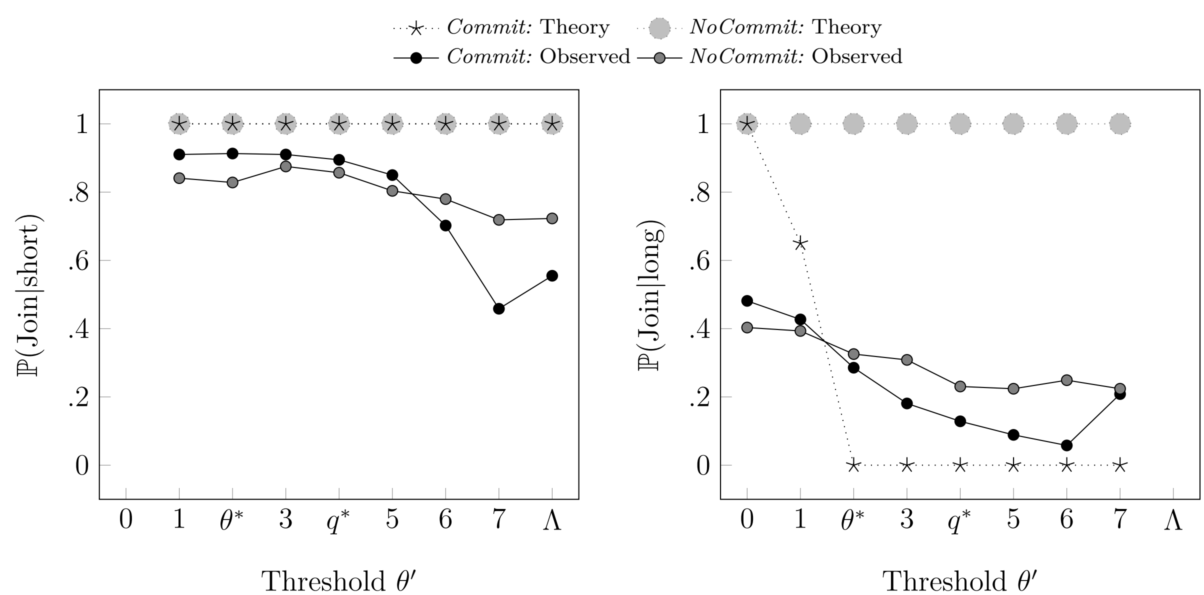
signal when the service provider uses a persuasive threshold (i.e., $\theta < q^*$). Table 2 shows that, relative to the overall baseline balking probability in the *NoSignal* treatment (which is on average 0.43), $\mathcal{P}$ is higher in *Commit* (0.74 vs. 0.43, $p = 0.001$) and in *NoCommit* (0.66 vs. 0.43, $p = 0.002$). Indeed, the level of persuasion is the same in both treatments (0.74 vs. 0.66, $p = 0.071$).

Result 3. *Signals with and without commitment are equally persuasive.*

Although there is indeed persuasion in the data, the fact that service providers failed to reduce customers' ability to join (i.e., $\mathbb{P}(\text{Join}|q < q^*)$) suggests that the frequency in which persuasive thresholds were used and the extent to which customers were persuaded was not sufficient, leaving potential social welfare improvements on the table.

4.6.3. Choices: Customers. A possible reason for the observed aggregate-level equivalence in social welfare between *Commit* and *NoCommit* is that customers react in the same way to signals regardless of whether or not the signals are credible (via commitment). We now study if commitment (or the lack thereof) has an effect on customers' joining decisions. Figure 6 presents the average customer joining probabilities, for a given communicated threshold and signal, calculated based on customers' strategies A_{itc}.

Figure 6 Customer Joining Decisions.



(a) $\mathbb{P}(\text{Join}|\varsigma = short)$ (b) $\mathbb{P}(\text{Join}|\varsigma = long)$

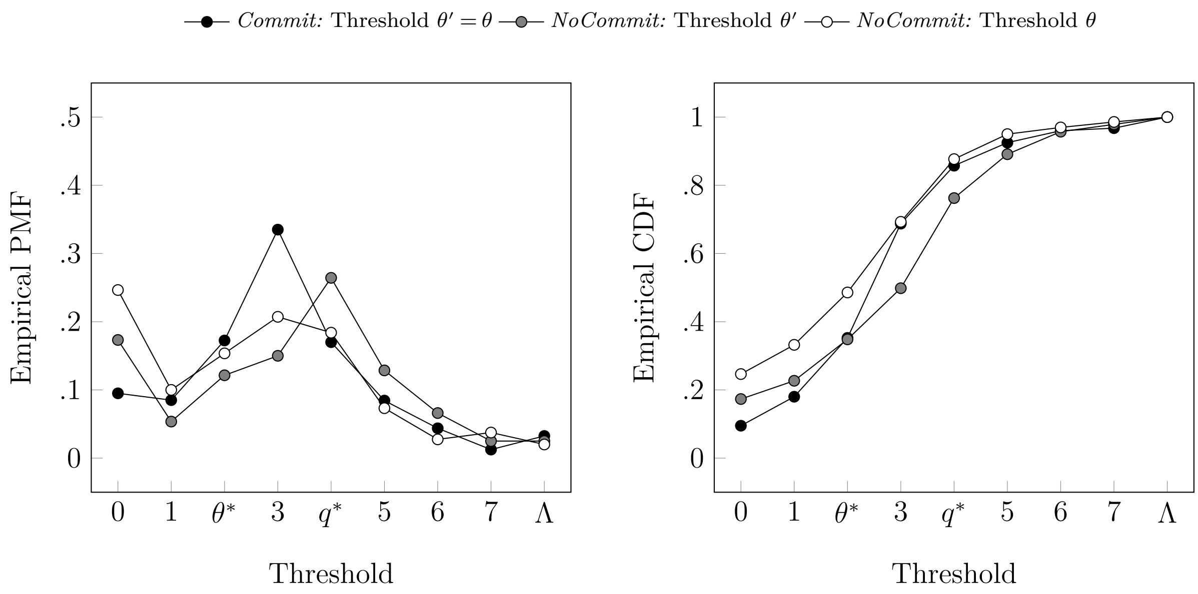
We observe that the joining probability in *Commit* decreases in the communicated threshold θ', more than predicted for *s*hort signals (where theory predicts that choices are not sensitive to θ' at all; Figure 6a), but less than predicted for *l*ong signals (Figure 6b). In contrast, the joining probability in *NoCommit* is relatively more constant across communicated thresholds, and it is generally lower than theory predictions (Figures 6a and 6b). To test these observations more formally, we run several logistic regressions with customer joining decisions as dependent variable(Appendix C.4, Table 4). The results show that customers in the *Commit* and *NoCommit* treatments react differently to the communicated thresholds. In particular, the regressions show that for a *s*hort wait signal, the probability to join in the *Commit* treatment decreases significantly in the communicated threshold, but does not vary significantly in the *NoCommit* treatment. For the *l*ong wait signal, the regressions show that the probability to join decreases significantly in the communicated threshold in both *Commit* and *NoCommit* treatments, but decreases more markedly in the *Commit* treatment.

Result 4. *Customers are more sensitive to thresholds with commitment.*

The post-experimental self-reports (Appendix C.6) provide further evidence for this result, showing that customers in the *Commit* treatment felt that the service provider's information strategy had more impact on their decisions in comparison to those in *NoCommit* (5.65 vs. 4.41, $p = 0.005$).

4.6.4. Choices: Service providers. Result 4 has profound implications for the decisions made by service providers, and hence for the game equilibrium and resulting system performance. Figure 7 shows service providers' threshold selections. Because customers in *NoCommit* respond to thresholds even when theory predicts they should not, we see that service providers strategically implement and communicate thresholds to influence customer behavior even in the absence of commitment. However, because customers are less sensitive to thresholds in *NoCommit*, we see that efficient (towards the goal of increasing social welfare) communication requires service providers to implement and communicate thresholds differently when they cannot credibly commit. Indeed, we conduct two-sample Kolmogorov-Smirnov tests and find that the distribution of thresholds in *Commit* is significantly different from both the distribution of implemented thresholds ($D = 0.19$, p-value < 0.001), and communicated thresholds ($D = 0.19$, p-value < 0.001) in *NoCommit*.

Figure 7 Service Providers' Communicated (θ') and Implemented (θ) Thresholds



(a) Empirical PMF (b) Empirical CDF

Result 5. *Commitment influences how service providers implement and communicate thresholds*

Importantly, we observe that service providers in *NoCommit* do not communicate truthfully. Specifically, on average, service providers implement a threshold different from the one communicated 52% of the time. To quantify the direction and magnitude of this miscommunication, we define the metric $Lie = \theta' - \theta$. Conditional on service providers deciding to lie (i.e., $Lie \neq 0$), implemented thresholds are on average about three thresholds apart from what service providers communicate ($|Lie| = 2.97 > 0, p < 0.001$), and the deviations appear to be strategic: the average *Lie* of 1.42 ($> 0, p = 0.035$) shows that service providers implement thresholds that are systematically lower than the communicated ones. Given that customers do not entirely discard the information they receive (Result 4), service providers indeed have the incentive to implement $\theta < \theta'$ given that their payoff (i.e., social welfare) increases in low-need customers' balking probability(see Figure 1).

Result 6. *Without commitment, service providers implement lower thresholds than communicated.*

Does non-truthful communication pay off service providers, i.e., does it increase social welfare in the *NoCommit* treatment? To formally answer the question, we estimate simple OLS regressions on the data from the *NoCommit* treatment. For example, we have $w_{cst} = \beta_0 + \beta_1 Lie.Type(\theta' > \theta) + \beta_2 Lie.Type(\theta' > \theta) + \beta_3 Round + \beta_4 Gender.M + \epsilon_c$, where $Lie.Type$ represent indicator variables. See details in Appendix C.5. The results show that service providers that inflated communicated thresholds such that $\theta' > \theta$ achieved a higher social welfare in comparison to those that were honest (i.e., $\theta' = \theta$). Moreover, we see that service providers that selected thresholds such that $\theta' < \theta$ achieved a lower social welfare in comparison to those that were honest.

RESULT 7. *Service providers that communicate inflated thresholds achieve higher social welfare.*

Our observation that service providers lie (Result 6), yet successfully (Result 7) manage to influence customers with non-credible signals (Results 2 and 3), deserves further discussion in light of our design that allows customers to observe both implemented threshold θ and communicated threshold θ' at the end of each round (Section 4.3, Figure 3). At the surface, this simple lie detection device effectively increases the lying cost and hence may act like an informal behavioral commitment device - fearing detection and the resulting game collapse to the babbling equilibrium and the low welfare it implies, service providers may refrain from implementing lower thresholds than communicated. While consistent with the observed welfare equivalence (Result 1), such a mechanism is not consistent with extent of lying we observe. Communication without formal commitment works, but it is not because the high lie detection probability turns service providers into trustworthy communicators.[9]

4.7. Discussion

We observe that both *Commit* and *NoCommit* increase welfare over the *NoSignal* treatment (Result 1). In other words, communication can effectively improve social welfare even when the service provider lacks the ability to commit, in contrast to the prediction of standard theory (Section 3.3).

[9] While speculative, it is not obvious that a design that prevents customers from directly observing each lie would result in the babbling equilibrium predicted by theory. In fact, it might further benefit the *NoCommit* if an increased tendency to implement lower thresholds than communicated coincides with sustained customer trust in the informativeness of signals (not an unlikely scenario given that customers in our data exhibit significant trust in the informativeness of signals despite the fact that they can easily detect the extant lying on the part of the service providers).

Notably, we observe the welfare equivalence between *Commit* and *NoCommit* despite the fact that commitment *does* change both customers' and service providers' behavior (Results 4 and 6), which points to a subtle interplay not predicted by theory. Because customers observe or expect considerable lying, service providers in *NoCommit* have less influence over customers' balking decisions than in *Commit* (Result 4). Nonetheless, customers are not entirely insensitive to information and service providers in *NoCommit* implement lower thresholds than communicated (Result 6), slightly increasing the balking probability for customers receiving the *Long Wait* signal (by increasing the communicated threshold) and also increasing the occurrence of *Long Wait* signals in more queue states (by decreasing the implemented thresholds). By the same token, since service providers set lower thresholds in *NoCommit* than in *Commit*, customers receive *Long Wait* signals more frequently in *NoCommit*. Overall, while the lack of commitment limits service providers' influence on customers' decisions, it allows them to lie and implement lower thresholds. This behaviour is intriguing, as it reveals a delicate balance between service providers and customers, resulting in information transmission and improved social welfare even in the absence of a commitment device.

5. Explaining main departures from theory

In this section, we present behavioural accounts to provide some explanations for the observed deviations from theoretical predictions in all experimental treatments. For this, we study customers' and service providers' behaviour under the Quantal Response Equilibrium (QRE) framework(Goeree et al. 2016), which has recently been popularized in the behavioral operations literature (e.g., Chen et al. 2012, Huang et al. 2013, Kremer and Debo 2016, Goldschmidt et al. 2021). The QRE is appealing because it preserves the basic decision-making features of our game while allowing for decision mistakes (where better decisions are made more often), and the incorporation other behavioural factors (e.g., lying aversion).

5.1. NoSignals treatment

In this treatment, given the experiment parameters, Proposition 2 predicts that L type customers join with probability 1 in equilibrium. In fact, this equilibrium strategy is a dominant strategy: customers can realize that no matter what others are doing, always joining provides a positive expected utility (even when everyone else is joining all the time). We clearly observe that customer behaviour deviates from such prediction. To allow for decision mistakes, we study the logit QRE that arises in our game, such that customers choose to join the queue with probability:

$$\varphi(\beta) = \frac{e^{(r-c(\mathbb{E}[Q]+1))/\beta}}{1+e^{(r-c(\mathbb{E}[Q]+1))/\beta}}. \tag{4}$$

In this model, β captures the level of bounded rationality. As $\beta \to 0$, the joining behaviour of L type customers converges to full rationality (i.e., the theoretical prediction). At the other extreme, as $\beta \to \infty$ customers join or balk with equal fractions, i.e., random guess. Note that the expected number of customers in the queue $\mathbb{E}[Q]$ is itself a function of customers joining probability $\varphi(\beta)$, i.e., the equilibrium joining probability $\varphi^*(\beta)$ is the solution of a fixed-point problem in equation 4. In Appendix D.1 we describe how we obtain such equilibrium probability. We observe that under the QRE customers join with probability $\varphi^*(\beta) \in [0.5, 1]$ for all values of $\beta \geq 0$. Our experimental data is consistent with this prediction (see the overall joining probability of 0.57 in Table 2). A joining probability below 0.5 would have otherwise falsified the QRE explanation. Moreover, we observe that the expected social welfare is at its minimum when $\beta = 0$, and then it increases in customers' bounded rationality β.

The intuition is that fully rational customers are able to maximize their individual utility, which generates negative externalities to others. However, when customers are bounded rational, they are not able to act in their own best interest as they make mistakes. These mistakes favor social welfare. This provides an explanation for why the observed social welfare in the *NoSignals* treatment was very high in comparison to the theoretical prediction. Finally, we conduct a structural estimation analysis to identify the bounded rationality parameter $\hat{\beta}$ that best fits our experimental data. We present our structural estimation procedure in Appendix D.1, and Table 7 presents the results of the estimation.

5.2. Commit treatment

In this treatment, given the experiment parameters, Proposition 3 predicts that the service provider selects a threshold $\theta^* = 2$, and that L type customers join with probability 1 when receiving a *Short Wait* message (i.e., a *s*hort signal), and balk with probability 1 when receiving a *Long Wait* message (i.e., a *l*ong signal). We clearly observe that service providers' and customers' behaviour deviates from such prediction. To allow for decision mistakes, we study the logit QRE that arises in our game, such that customers, conditional on a threshold θ and a signal, choose to join the queue with probability:

$$\varphi_s(\beta) = \frac{e^{(r-c(\mathbb{E}[Q|\varsigma=s]+1))/\beta}}{1+e^{(r-c(\mathbb{E}[Q|\varsigma=s]+1))/\beta}}, \tag{5}$$

$$\varphi_l(\beta) = \frac{e^{(r-c(\mathbb{E}[Q|\varsigma=l]+1))/\beta}}{1+e^{(r-c(\mathbb{E}[Q|\varsigma=l]+1))/\beta}}. \tag{6}$$

As before, β captures the level of customers bounded rationality. Also, equations 7 and 8 represent a fixed-point problem, and the $\varphi_s^*(\beta)$ and $\varphi_l^*(\beta)$ that arise in equilibrium come from the solution of such fixed-point problems. In Appendix D.2 we describe how we obtain such equilibrium probabilities. Moreover, the service provider selects a probability distribution $\varphi_\theta(\beta_m)$ over the choice of thresholds θ:

$$\varphi_\theta(\beta_m) = \frac{e^{\Omega(\beta)/\beta_m}}{\sum_\beta e^{\Omega(\beta)/\beta_m}} \quad \text{for} \quad \theta = 0, 1, 2, \cdots, \Lambda,$$

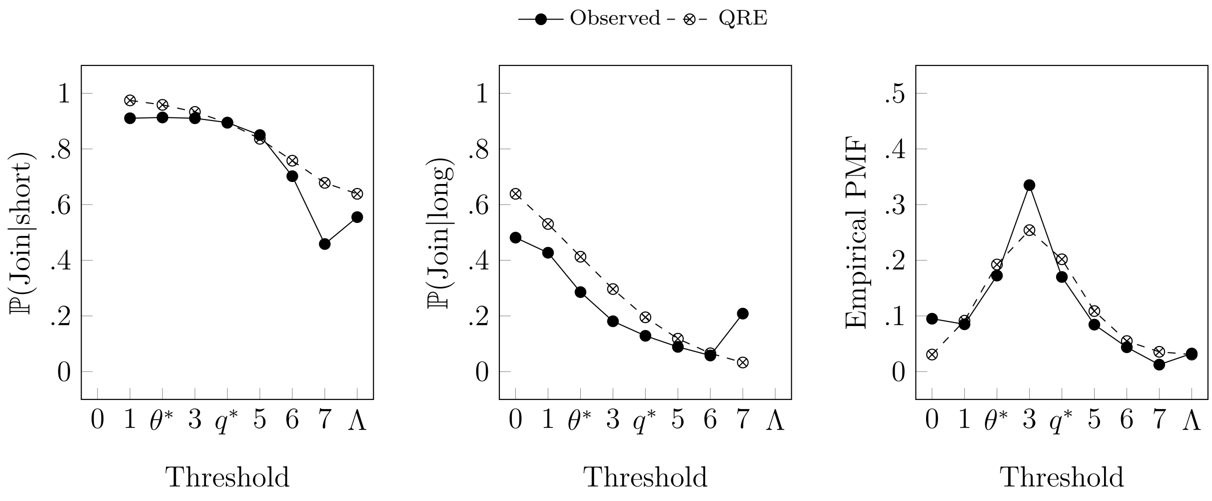
where we recall that Ω represents the expected social welfare. In here, β_m captures the level of service providers' bounded rationality. We note that $\Omega(\beta)$ does not depend on the probability $\varphi_\theta(\beta_m)$, such that $\varphi_\theta(\beta_m)$ represents the equilibrium distribution $\varphi_\theta^*(\beta_m)$. In Appendix D.2 we describe how we obtain such equilibrium. We also conduct a structural estimation analysis to identify the bounded rationality parameters $\hat{\beta}$ and $\hat{\beta}_m$ that best fit our experimental data. We present our structural estimation procedure in Appendix D.2, and Table 7 presents the results of the estimation.

Figure 8 presents the predictions of customers' and service providers' decisions under such estimation, in comparison to the observed ones in the data. We can observe from Figure 8, that the QRE prediction captures well the patterns in customers joining probabilities and service providers threshold selections. Under the QRE, the players' decisions with higher expected utilities are chosen more frequently than those with lower expected utility. That is, players make the correct decision more often than the incorrect ones. On the customer side, recalling the theoretical predictions from Lemma 1, we see from Figure 8a and 8b, that this is indeed the case for how customers behaved in most thresholds. On the side of the service provider, we note that conditional on how customers behaved in the experiment (not according to theoretical predictions), the expected social welfare is maximized at a threshold equal to 3. This is the reason why the QRE prediction in Figure 8c peaks at such a threshold. We can clearly see that the QRE prediction captures well the service providers' threshold selections.

Also, under QRE, those correct decisions that are easier to identify (in the sense that they present a bigger difference between their expected utility and the expected utility from the alternative decision) are chosen more frequently. In our game, this is reflected by the decreasing joining probability in Figures 8a and 8b as thresholds get higher. For example, consider thresholds equal to 1 and 6. In this case, with a threshold equal to 1, it is easier (in comparison to threshold 6) to understand that joining is better than balking upon receiving a *Short Wait* message. In contrast, with a threshold equal to 6, it is easier (in comparison to threshold 1) to understand that balking is better than joining upon receiving a *Long Wait* message. We see from Figures 8a and 8b, that customers (generally) presented such decreasing joining probability property as thresholds increased.

Overall, we believe that the QRE model describes quite well the data in this treatment and provides insightful and intuitive explanations for the observed patterns in both customers' and service providers' decisions. Moreover, since the QRE preserves the trade-offs and the main decision features in the problem, these results show that human behaviour is in the direction of theoretical predictions, where a simple relaxation in the form of bounded rationality provides a good descriptor of real human behaviour.

Figure 8 QRE Predictions Commitment (bounded rationality parameters: $\hat{\beta} = 39.85, \hat{\beta_m} = 13.42$)



(a) $\mathbb{P}(\text{Join}|\varsigma = \mathit{short})$ (b) $\mathbb{P}(\text{Join}|\varsigma = \mathit{long})$ (c) Empirical PMF

5.3. NoCommit treatment

Our model predicted that customers should disregard any information provided by the service provider, as they should be able to identify that the service provider has the incentive to deviate from the communicated threshold θ'. Given the observed deviation from such theoretical prediction, here we make the simplifying assumption that customers take the communicated threshold θ' at *face value* and identify the equilibrium that arises in these circumstances. This allows us to understand if bounded rationality alone can explain the observed customer behaviour. Based on this, similar to the *Commit* case, we study the logit QRE that arises in our game, such that customers, conditional on a communicated threshold θ' and a signal, choose to join the queue with probability:

$$\varphi_s(\beta) = \frac{e^{(r - c(\mathbb{E}[Q|\varsigma = s]+1))/\beta}}{1 + e^{(r - c(\mathbb{E}[Q|\varsigma = s]+1))/\beta}}, \tag{7}$$

$$\varphi_l(\beta) = \frac{e^{(r - c(\mathbb{E}[Q|\varsigma = l]+1))/\beta}}{1 + e^{(r - c(\mathbb{E}[Q|\varsigma = l]+1))/\beta}}. \tag{8}$$

As before, β captures the level of customers bounded rationality. Moreover, in this treatment, the service provider selects a joint probability distribution $\varphi_{\theta,\theta'}(\beta_m)$ over the choice of the pair of thresholds θ and θ':

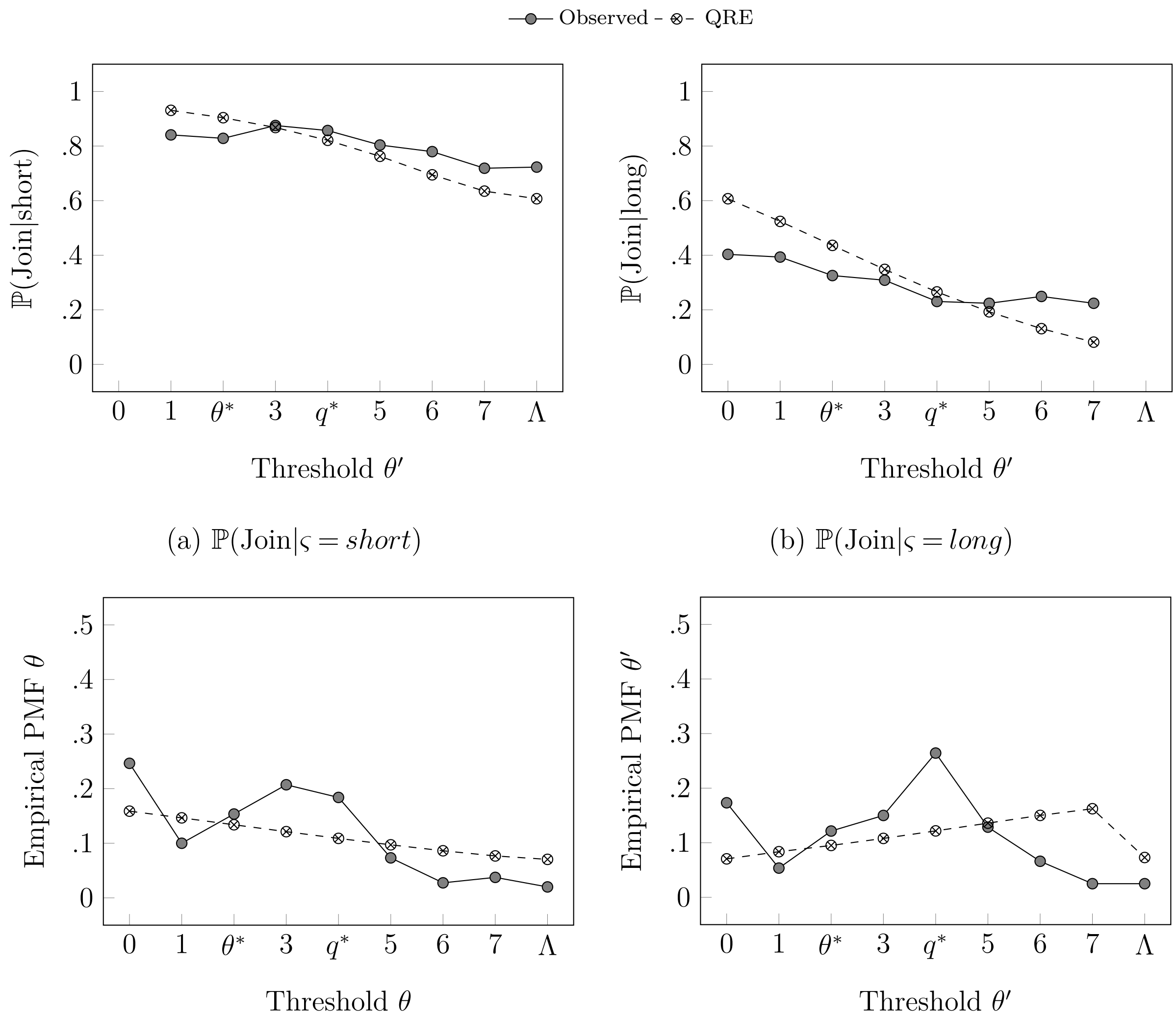
$$\varphi_{\theta,\theta'}(\beta_m) = \frac{e^{\Omega(\theta,\theta')/\beta_m}}{\sum_{\beta} \sum_{\beta'} e^{\Omega(\theta,\theta')/\beta_m}} \quad \text{for} \quad \theta = 0, 1, 2, \cdots, \Lambda; \quad \theta' = 0, 1, 2, \cdots, \Lambda,$$

where we recall that Ω represents the expected social welfare. Here, β_m captures the level of service providers' bounded rationality. Also, $\Omega(\theta, \theta')$ represents the achieved expected social welfare when the service provider communicates threshold θ', customers react with equilibrium $\varphi_s^*(\beta)$ and $\varphi_l^*(\beta)$ taking θ' at face value, and based on such reactions the service provider implements a threshold θ. We note that $\Omega(\theta, \theta')$ does not depend on the probability $\varphi_{\theta,\theta'}(\beta_m)$, such that $\varphi_{\theta,\theta'}(\beta_m)$ represents the equilibrium joint distribution $\varphi^*_{\theta,\theta'}(\beta_m)$. In Appendix D.3 we describe how we obtain such equilibrium. We also conduct a structural estimation analysis to identify the bounded rationality parameters $\hat{\beta}$ and $\hat{\beta}_m$ that best fit our experimental data. We present our structural estimation procedure in Appendix D.3, and Table 7 presents the results of the estimation. Figure 9 presents the predictions of customers' and service providers' decisions under such estimation, in comparison to the observed ones in the data.

On the customer side, in Figures 9a and 9b we observe that the QRE predictions are not able to capture the fact that changes in the communicated threshold affect customers' joining decisions only slightly. Since in our QRE estimation, we assume that customers take at face value the communicated thresholds, this indicates that bounded rationality alone cannot explain completely the observed behaviour. One potential explanation could be that customers generate a belief about the implemented threshold based on the communicated one. For example, for any communicated threshold customers may believe that the implemented one is given by $\theta = \lfloor \theta'^{\tau} \rfloor$, where $\tau \in [0,1]$ represents a trust parameter. In the post-experimental customer's self-reports presented in Appendix C.6, we find that customers in the *NoCommit* treatment claim to trust the service provider's information strategy, but not as much as those in the *Commit* treatment (3.28 vs. 3.98, $p = 0.042$).

On the service provider side, Figures 9c and 9d we present the equilibrium marginal distributions $\varphi^*_\theta(\beta_m) = \sum_{\theta'} \varphi^*_{\theta,\theta'}(\beta_m)$ and $\varphi^*_{\theta'}(\beta_m) = \sum_{\theta} \varphi^*_{\theta,\theta'}(\beta_m)$ from the equilibrium joint distribution $\varphi^*_{\theta,\theta'}(\beta_m)$. We see in Figures 9c and 9d that while the QRE predictions are able to capture the incentive of the service provider to communicate a high threshold and implement a low one, they are not able to capture the fact that service providers restrain from communicating a very high threshold. This

Figure 9 QRE Predictions No Commitment: Communicated (θ') and Implemented (θ) Thresholds (bounded rationality parameters: $\hat{\beta} = 55.48, \hat{\beta_m} = 132.75$)



(a) $\mathbb{P}(\text{Join}|\varsigma = short)$

(b) $\mathbb{P}(\text{Join}|\varsigma = long)$

(c) Empirical PMF

(d) Empirical PMF

indicates that bounded rationality alone cannot explain completely the observed behaviour. One potential explanation could be that service providers experience lying costs such that they select thresholds θ, θ' in order to maximize the social welfare $\Omega(\theta, \varphi_s^*(\theta'), \varphi_l^*(\theta'))$ but incur a lying cost, e.g., $\kappa|\theta' - \theta|$.

6. Conclusions

The contribution of this paper lies in the experimental testing of predictions regarding the strategic interactions of both customers and the service provider. This has allowed us to gain insight into the mechanisms behind their decision-making and communication dynamics related to persuasion, deception, and trust, which are essential to understand the credibility and effectiveness of information-sharing policies. The experimental results of this paper have important practical implications for firms that employ information-sharing policies to influence customer decision-making. In particular, they highlight the operational value of information-sharing policies, since they show that even under no-commitment conditions where shared information is predicted to have limited impact, they are able to influence customer behaviour and improve social welfare as in a setting where service providers enjoy commitment power. Finally, our experimental findings show the ways in which customers react differently between the commitment and no-commitment settings. This opens up interesting avenues for future research to explore mechanisms that firms could implement to further enhance social welfare, such as commitment devices, lying detection mechanisms, trust-enhancing mechanisms, or automation of managerial roles.

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Appendix

A. Technical Proofs

A.1. Proposition 1

Proof. Let $p_s \in [0,1]$ be the equilibrium joining probability of L type customers. Since all H type customers always join in equilibrium, based on Equation (1) it follows that $J \sim \mathcal{B}(\Lambda, p_h + (1-p_h)p_s)$ is a binomial random variable, such that $\mathbb{E}[J] = \Lambda(p_h + (1-p_h)p_s)$, and $\mathbb{E}[J^2] = \Lambda(p_h + (1-p_h)p_s) + \Lambda(\Lambda-1)(p_h + (1-p_h)p_s)^2$. Based on this, after some algebra, we have that:

$$\frac{\partial \Omega}{\partial p_s} = FOC = \Lambda(1-p_h)(r - c(1 + p_h(\Lambda-1)(1-p_s) + p_s(\Lambda-1))),$$
$$FOC(p_s = 0) = \Lambda(1-p_h)(r - c(1 + p_h(\Lambda-1))),$$
$$FOC(p_s = 1) = \Lambda(1-p_h)(r - c\Lambda) < 0,$$
$$\frac{\partial^2 \Omega}{\partial p_e^2} = SOC = -c(\Lambda-1)\Lambda(1-p_h)^2 < 0.$$

Since the FOC decreases strictly in p_s, and since $FOC(p_s = 1) < 0$, we note that whenever $FOC(p_s = 0) \leq 0 \iff \frac{r}{c} \leq 1 + p_h(\Lambda-1)$, the expected welfare in the system decreases for all values of p_s. This means that for $\frac{r}{c} \leq 1 + p_h(\Lambda-1)$, $p_s^* = 0$ maximizes social welfare. Now, for the case $\frac{r}{c} > 1 + p_h(\Lambda-1)$, we have that $FOC(p_s = 0) > 0$. Since the FOC decreases strictly in p_s, and since $FOC(p_s = 1) < 0$, it follows that there is a unique $p_s^* \in (0,1)$ that maximizes social welfare. In particular, such p_s^* satisfies $FOC(p_s^*) = 0$. It is easy to see that in this case we have that $p_s^* = \frac{r - c(1 + p_h(\Lambda-1))}{c(\Lambda-1)(1-p_h)}$. ■

A.2. Proposition 2

Proof. Let $\gamma_e \in [0,1]$ be the equilibrium joining probability of L type customers. Since all H type customers always join in equilibrium, a typical customer will join the system with probability $p_h + (1-p_h)\gamma_e$. When customers arrive, they do not know the number of people in the system, however, they can compute the expected number in equilibrium:

$$\mathbb{E}[Q] = \sum_{t=0}^{\Lambda-1} \mathbb{E}[Q|t]\mathbb{P}(t) = \frac{1}{\Lambda}\sum_{t=0}^{\Lambda-1} \mathbb{E}[Q|t],$$

where t is the remaining customers to arrive behind. Since customers are randomly ordered, they have t remaining customers behind them with probability $\frac{1}{\Lambda}$ for all $t \in \{0, 1, \cdots, \Lambda-1\}$. Conditional on t, customers can arrive to a system with up to $\Lambda - 1 - t$ customers. For example, the first customer (i.e., $t = \Lambda - 1$) arrives to a system with 0 customers, and the last customer (i.e., $t=0$) arrives to a system with 0 or 1 or 2, and so on up to $\Lambda-1$ customers. Moreover, notice that conditional on t the probability to find q customers, depends on how many customers joined in the previous times $\Lambda-1, \Lambda-2, \cdots, t+1$; that is, in the previous $\Lambda-1-t$ times. Based on the above we have that $q|t \sim \mathcal{B}(\Lambda-1-t, p_h+(1-p_h)\gamma_e)$ is a binomial random variable with expected value $\mathbb{E}[q|t]=(\Lambda-1-t)(p_h+(1-p_h)\gamma_e)$. With this, we can compute the expected number of people that customers find upon arrival:

$$\begin{aligned}
\mathbb{E}[Q] &= \frac{1}{\Lambda}\sum_{t=0}^{\Lambda-1}\mathbb{E}[Q|t] = \frac{1}{\Lambda}\sum_{t=0}^{\Lambda-1}(\Lambda-1-t)(p_h+(1-p_h)\gamma_e) \\
&= \frac{p_h+(1-p_h)\gamma_e}{\Lambda}\sum_{k=1}^{\Lambda-1}k = \frac{(p_h+(1-p_h)\gamma_e)(\Lambda-1)\Lambda}{2\Lambda} \\
&= \frac{(p_h+(1-p_h)\gamma_e)(\Lambda-1)}{2}.
\end{aligned}$$

Consider now a tagged customer that joins with probability γ', when the other customers join with probability γ. Then, his expected utility is $\mathbb{E}[U](\gamma',\gamma)=(1-\gamma')0+\gamma'(r-c(\mathbb{E}[Q]+1))$. To find his best response against γ, the tagged customer has to find the γ' that maximizes $\mathbb{E}[U]$. Note that the function $\mathbb{E}[U]$ is linear with respect to γ', so the tagged customer bases his decision on the sign of the quantity $r-c(\mathbb{E}[Q|\varsigma=l]+1)$. Let the root of $r-c(\mathbb{E}[Q]+1)=0$ be

$$\bar{\gamma} = \frac{2r-c(2+p_h(\Lambda-1))}{c(\Lambda-1)(1-p_h)}$$

Then the set of best responses against γ, $BR(\gamma)$, is given by

$$BR(\gamma) = \begin{cases} 0 & \text{if } \gamma > \bar{\gamma} \\ [0,1] & \text{if } \gamma = \bar{\gamma} \\ 1 & \text{if } \gamma < \bar{\gamma} \end{cases}$$

We can now proceed to the computation of the equilibrium strategies:

- The strategy of ‘always balk’ ($\gamma_e=0$) is an equilibrium strategy, if and only if $0 \in BR(0)$, i.e., $0 \geq \bar{\gamma}$, which reduces to $\frac{(\Lambda-1)p_h}{2}+1 \geq \frac{r}{c}$.
- The strategy of ‘always join’ ($\gamma_e=1$) is an equilibrium strategy, if and only if $1 \in BR(1)$, i.e., $1 \leq \bar{\gamma}$, which reduces to $\frac{\Lambda-1}{2}+1 \leq \frac{r}{c}$.
- Finally, a strategy $\gamma_e \in (0,1)$ is an equilibrium strategy, if and only if $\gamma_e \in BR(\gamma_e)$, i.e., $\gamma_e=\bar{\gamma}$. This is valid as far as $\bar{\gamma} \in (0,1)$ which occurs if and only if $\frac{(\Lambda-1)p_h}{2}+1 < \frac{r}{c} < \frac{(\Lambda-1)}{2}+1$.

■

A.3. Corollary 1

Proof. From Propositions 1 and 2 we first note that since $\frac{(\Lambda-1)p_h}{2}+1<1+p_h(\Lambda-1)$, if $\gamma_e=0$ then $p_s^*=0$.

From Proposition 1 we consider the joining probability $p_s^*=\frac{r-c(1+p_h(\Lambda-1))}{c(\Lambda-1)(1-p_h)}<1$, and from Proposition 2 we consider the mixing probability $\gamma_e=\frac{2r-c(2+p_h(\Lambda-1))}{c(\Lambda-1)(1-p_h)}$. After some simple algebra, it is easy to see that $\gamma_e>p_s^* \iff r>c$, which is our assumption by construction. This also means that for $\gamma_e=1$ we have that $\gamma_e>p_s^*$. ■

A.4. Lemma 1.

Proof. We let $\alpha_e^s=\mathbb{P}(\text{Join}|\varsigma=s)$ and $\alpha_e^l=\mathbb{P}(\text{Join}|\varsigma=l)$ be the equilibrium mixing probabilities. We analyze the case with and without commitment separately.

With commitment. We recall from Proposition 2 that for this case all L type customers join with probability 1 since $r-c(\mathbb{E}[Q]+1)\geq 0$ in equilibrium. Based on this, it is easy to see that for any threshold θ and irrespective of how other customers are mixing, it is in the best interest of a focal customer to join the system with probability 1 upon receiving a *s*hort signal. Indeed in this case $r-c(\mathbb{E}[Q|\varsigma=s]+1)\geq 0$ since $\mathbb{E}[Q|\varsigma=s]\leq\mathbb{E}[Q]$ for any threshold. It follows that $\alpha_e^s=1$.

Now, when customers receive a *l*ong signal, they know that they are in a system with $q\in\{\theta,\theta+1,\cdots,\Lambda-1\}$ customers, this since L type customers that receive a *s*hort signal join the system with probability $\alpha_e^s=1$ in equilibrium. Upon receiving a *l*ong signal, H type customers always join the system and L type customers join the system with a certain probability α^l. Based on this, customers can condition on the indexes and compute the expected number of customers that arrived after the threshold θ. For example, conditional on having an index that coincides with the threshold θ, customers know that they are in a system with $q=\theta$ customers with probability 1. Conditional on having an index that coincides with $\theta+1$, customers know that they are in a system with $q=\{\theta,\theta+1\}$ customers. The probability of being in either of this states depends on the number customers N that arrived after the threshold and before this focal customer. For this case, we have that $\mathbb{P}(q=\theta)=\mathbb{P}(N=0)$, and $\mathbb{P}(q=\theta+1)=\mathbb{P}(N=1)$, where $N\sim\mathcal{B}(1,p_h+(1-p_h)\alpha^l)$ is a binomial random variable. Thus, conditional on having an index that coincides with $\theta+1$ a customer expects to find $\theta+\mathbb{E}[N]=\theta+p_h+(1-p_h)\alpha^l$ customers.

More generally, conditional on having an index that coincides with $\theta+j$ ($j\in\{0,1,\cdots,\Lambda-\theta-1\}$), customers know that they are in a system with $q=\{\theta,\theta+1,\cdots,\theta+j\}$ customers, with respective probabilities $\mathbb{P}(N=$

$0), \mathbb{P}(N=1), \cdots, \mathbb{P}(N=j)$, with $N \sim \mathcal{B}(j, p_h + (1-p_h)\alpha^l)$. And, thus conditional on having an index that coincides with $\theta + j$ a customer expects to find $\theta + \mathbb{E}[N] = \theta + j(p_h + (1-p_h)\alpha^l)$ customers. Based on this we compute:

$$\begin{aligned}\mathbb{E}[Q|\varsigma = l] &= \frac{1}{\Lambda - \theta}(\theta + (\theta + (p_h + (1-p_h)\alpha^l)) + (\theta + 2(p_h + (1-p_h)\alpha^l)) \\ &+ \cdots + (\theta + (\Lambda - \theta - 1)(p_h + (1-p_h)\alpha^l))) \\ &= \frac{1}{\Lambda - \theta}(\theta(\Lambda - \theta) + \frac{(p_h + (1-p_h)\alpha^l)(\Lambda - \theta - 1)(\Lambda - \theta)}{2}) \\ &= \frac{2\theta + (p_h + (1-p_h)\alpha^l)(\Lambda - \theta - 1)}{2}.\end{aligned}$$

Consider now a tagged customer that joins with probability $\alpha^{l\prime}$ upon receiving a *l*ong signal, when the other customers join with probability α^l. Then, his expected utility is $\mathbb{E}[U](\alpha^{l\prime}, \alpha^l) = (1-\alpha^{l\prime})0 + \alpha^{l\prime}(r - c(\mathbb{E}[Q|\varsigma = l] + 1))$. To find his best response against α^l, the tagged customer has to find the $\alpha^{l\prime}$ that maximizes $\mathbb{E}[U]$. Note that the function $\mathbb{E}[U]$ is linear with respect to $\alpha^{l\prime}$, so the tagged customer bases his decision on the sign of the quantity $r - c(\mathbb{E}[Q|\varsigma = l] + 1)$. Let the root of $r - c(\mathbb{E}[Q|\varsigma = l] + 1) = 0$ be

$$\bar{\alpha^l} = \frac{2r - c(2(qr+1) + p_h(\Lambda - \theta - 1))}{c(1-p_h)(\Lambda - \theta - 1)}$$

Then the set of best responses against α^l, $BR(\alpha^l)$, is given by

$$BR(\alpha^l) = \begin{cases} 0 & \text{if } \alpha^l > \bar{\alpha^l} \\ [0,1] & \text{if } \alpha^l = \bar{\alpha^l} \\ 1 & \text{if } \alpha^l < \bar{\alpha^l} \end{cases}$$

We can now proceed to the computation of the equilibrium strategies:

- The strategy of 'always balk' ($\alpha_e^l = 0$) upon receiving a *l*ong signal is an equilibrium strategy, if and only if $0 \in BR(0)$, i.e., $0 \geq \bar{\alpha^l}$, which reduces to $\theta \geq \frac{2r-2c-cp_h(\Lambda-1)}{c(2-p_h)}$. Recall that $\bar{\theta} = \lceil \frac{2r-2c-cp_h(\Lambda-1)}{c(2-p_h)} \rceil$. That is, we have $\alpha_e^l = 0$ whenever $\theta \in \{\bar{\theta}, \cdots, \Lambda - 1\}$.

- The strategy of 'always join' ($\alpha_e^l = 1$) upon receiving a *l*ong signal is an equilibrium strategy, if and only if $1 \in BR(1)$, i.e., $1 \leq \bar{\alpha^l}$, which reduces to $\theta \leq \frac{2r-c(\Lambda+1)}{C}$. If let $\bar{\bar{\theta}} = \lfloor \frac{2r-c(\Lambda+1)}{c} \rfloor$, we have that $\alpha_e^l = 1$ whenever $\theta \in \{0, \cdots, \bar{\bar{\theta}}\}$.

- Finally, a strategy $\alpha_e^l \in (0,1)$ is an equilibrium strategy, if and only if $\alpha_e^l \in BR(\alpha_e^l)$, i.e., $\alpha_e^l = \bar{\alpha^l}$. This is valid as far as $\bar{\alpha^l} \in (0,1)$ which occurs if and only if $\frac{2r-c(\Lambda+1)}{c} < \theta < \frac{2r-2c-cp_h(\Lambda-1)}{c(2-p_h)}$, that is, $\bar{\bar{\theta}} < \theta < \bar{\theta}$.

Without commitment. In this case, due to the lack of commitment, customers do not have the guarantee that the service provider's communicated threshold θ' is the implemented threshold θ that generates the signals. First, we note that in Proposition 2, without communication, all L type customers join with probability 1 since $r - c(\mathbb{E}[Q]+1) \geq 0$ in equilibrium. Based on this, it is easy to see that for any implemented threshold θ (irrespective of the lack of commitment) and irrespective of how other customers are mixing, it is in the best interest of a focal customer to join the system with probability 1 upon receiving a $s$hort signal. Indeed in this case $r - c(\mathbb{E}[Q|\varsigma = s]+1) \geq 0$ since $\mathbb{E}[Q|\varsigma = s] \leq \mathbb{E}[Q]$ for any implemented threshold. It follows that $\alpha_e^s = 1$.

Now, for the case of $l$ong signals, customers will take them into consideration only if the service provider does not have the incentive to deviate from the communicated threshold θ' given customers' response to it. That is, for a given communicated threshold θ', and $({\alpha^s}'_e = 1, {\alpha^l}'_e)$ as the associated customers' reaction to such θ', for signals to be credible, it is required that the expected social welfare complies with $\Omega(\theta', {\alpha^s}'_e = 1, {\alpha^l}'_e) \geq \Omega(\theta, {\alpha^s}'_e = 1, {\alpha^l}'_e)$ for all possible thresholds θ.

We will now show that for sufficiently high p_h, the service provider always has the incentive to deviate from all the communicated thresholds that would influence customer behaviour. For this, let $J(\theta) = \theta + N$ be a random variable that represents the total number of customers that *join* the system in equilibrium (recall all customers join when receiving a $s$hort signal since $\alpha_e^s = 1$), where $N \sim \mathcal{B}(\Lambda - \theta, p_h + (1-p_h)\alpha_e^l)$ is a binomial random variable that represents the total number of customers that join after a given threshold θ. Based on this, the *expected social welfare* is:

$$\begin{aligned}\Omega(\theta, \alpha_e^l) &= r\mathbb{E}[J(\theta)] - \frac{c}{2}(\mathbb{E}[J(\theta)^2] + \mathbb{E}[J(\theta)]) \\ &= r(\theta + \mathbb{E}[N]) - \frac{c}{2}(\theta^2 + 2\theta\mathbb{E}[N] + \mathbb{E}[N^2] + \theta + \mathbb{E}[N]),\end{aligned}$$

where $\mathbb{E}[N] = (\Lambda - \theta)(p_h + (1-p_h)\alpha_e^l)$, and $\mathbb{E}[N^2] = (\Lambda - \theta)(p_h + (1-p_h)\alpha_e^l) + (\Lambda - \theta)(\Lambda - \theta - 1)(p_h + (1 - p_h)\alpha_e^l)^2$. Now, consider the following expression:

$$\Omega(\theta, \alpha_e^l) - \Omega(\theta - 1, \alpha_e^l) = (1 - p_h - (1-p_h)\alpha_e^l)(r - c\Lambda(p_h + (1-p_h)\alpha_e^l) - c(1 - p_h - (1-p_h)\alpha_e^l)\theta).$$

First, note that if $\alpha_e^l = 1$ we have that $\Omega(\theta, \alpha_e^l = 1) = \Omega(\theta - 1, \alpha_e^l = 1)$ for any threshold θ. Also, from above we know that a customer equilibrium with $\alpha_e^l = 1$ is induced with a threshold $\theta \in \{0, \cdots, \bar{\bar{\theta}}\}$. This implies that a communicated threshold $\theta' \in \{0, \cdots, \bar{\bar{\theta}}\}$ is a credible one as the service provider does not have the incentive to deviate from it. Indeed, we have seen that $\Omega(\theta, \alpha_e^l = 1) = \Omega(\theta - 1, \alpha_e^l = 1)$ for any threshold θ. This also holds for a threshold equal to Λ, where all L type customers join since they always receive a *s*hort signal.

Since we have by construction that for $p_h \geq \frac{r}{c\Lambda}$, it follows that $\Omega(\theta, \alpha_e^l) - \Omega(\theta - 1, \alpha_e^l) \leq 0$ for all thresholds θ and all values $\alpha_e^l \in [0, 1)$. This means that if $p_h \geq \frac{r}{c\Lambda}$, for any $\alpha_e^l \in [0, 1)$, the social welfare is at its maximum at a threshold $\theta = 0$. This implies that for any communicated threshold $\theta' > 0$, the service provider has always the incentive to implement a threshold $\theta = 0$, making the communicated threshold not credible. In this case, customers disregard any information and behave according to their priors, and thus always join the system. In sum, we have seen that only communicated thresholds $\theta' \in \{0, \cdots, \bar{\bar{\theta}}, \Lambda\}$ are credible for which customers join with probabilities $\alpha_e^s = 1$ and $\alpha_e^l = 1$. Any other communicated threshold is not credible, for which customers disregard the information and always join.

■

A.5. Proposition 3.

Proof. We analyze the case with and without commitment separately.

With commitment. Based on Lemma 1, we consider three different cases separately: (1) $\theta \leq \bar{\bar{\theta}}$, (2) $\theta \geq \bar{\theta}$, and (3) $\bar{\bar{\theta}} < \theta < \bar{\theta}$.

Case: $\theta \leq \bar{\bar{\theta}}$

From Lemma 1, a threshold $\theta \leq \bar{\bar{\theta}}$ induces a customer equilibrium where every L type customer decides to join irrespective of the signal, i.e., $\alpha_e^s = 1, \alpha_e^l = 1$. We will see that a threshold in $\theta \geq \bar{\theta}$ allows to improve social welfare, and thus $\theta \leq \bar{\bar{\theta}}$ does not arise in equilibrium.

Case: $\theta \geq \bar{\theta}$

From Lemma 1, a threshold $\theta \geq \bar{\theta}$ induces a customer equilibrium where L type customers that receive a *s*hort signal join with probability $\alpha_e^s = 1$, and those that receive a *l*ong signal join with probability $\alpha_e^l = 0$. To compute the social welfare in the system, let $J(\theta) = \theta + N$ be a random variable that represents the total number of customers that *join* the system in equilibrium (recall all customers join when receiving a *s*hort signal since $\alpha_e^s = 1$), where $N \sim \mathcal{B}(\Lambda - \theta, p_h + (1-p_h)\alpha_e^l)$ is a binomial random variable that represents the total number of customers that join after a given threshold θ. Based on this, the *expected social welfare* is:

$$\begin{aligned}\Omega(\theta) &= r\mathbb{E}[J(\theta)] - \frac{c}{2}(\mathbb{E}[J(\theta)^2] + \mathbb{E}[J(\theta)]) \\ &= r(\theta + \mathbb{E}[N]) - \frac{c}{2}(\theta^2 + 2\theta\mathbb{E}[N] + \mathbb{E}[N^2] + \theta + \mathbb{E}[N]),\end{aligned}$$

where $\mathbb{E}[N] = (\Lambda - \theta)p_h$, and $\mathbb{E}[N^2] = (\Lambda-\theta)p_h + (\Lambda-\theta)(\Lambda-\theta-1)p_h^2$. Now, consider the following expression:

$$\Omega(\theta) - \Omega(\theta - 1) = (1-p_h)(r - c\Lambda p_h - c(1-p_h)\theta).$$

Since we have by construction that for $p_h \geq \frac{r}{c\Lambda}$, it follows that $\Omega(\theta) - \Omega(\theta-1) < 0$ for all thresholds θ. It follows that the expected social welfare decreases strictly for all $\theta \geq \bar{\theta}$. This implies that from the thresholds such that $\theta \geq \bar{\theta}$, the threshold $\bar{\theta}$ yields the highest social welfare. Moreover, we note that with a threshold $\theta = \Lambda$, all customers join the system (as in the previous described case for $\theta \leq \bar{\bar{\theta}}$). Since the expected social welfare decreases strictly for all $\theta \geq \bar{\theta}$, it follows that the social welfare achieved at $\bar{\theta}$ is higher than that achieved with any threshold in $\theta \leq \bar{\bar{\theta}}$.

Case: $\bar{\bar{\theta}} < \theta < \bar{\theta}$

From Lemma 1, a threshold $\bar{\bar{\theta}} < \theta < \bar{\theta}$ induces a customer equilibrium where L type customers that receive a *s*hort signal join $\alpha_e^s = 1$, and those that receive a *l*ong signal balk with probability $\alpha_e^l = \frac{2r - c(2(qr+1) + p_h(\Lambda-\theta-1))}{c(1-p_h)(\Lambda-\theta-1)}$. To compute the social welfare in the system, let $J(\theta) = \theta + N$ be a random variable that represents the total number of customers that *join* the system in equilibrium (recall all customers join when receiving a *s*hort signal since $\alpha_e^s = 1$), where $N \sim \mathcal{B}(\Lambda - \theta, p_h + (1-p_h)\alpha_e^l)$ is a binomial random variable that represents the total number of customers that join after a given threshold θ. Based on this, the *expected social welfare* in the system can be written as:

$$\begin{aligned}\Omega(\theta) &= r\mathbb{E}[J(\theta)] - \frac{c}{2}(\mathbb{E}[J(\theta)^2] + \mathbb{E}[J(\theta)]) \\ &= r(\theta + \mathbb{E}[N]) - \frac{c}{2}(\theta^2 + 2\theta\mathbb{E}[N] + \mathbb{E}[N^2] + \theta + \mathbb{E}[N]),\end{aligned}$$

where $\mathbb{E}[N] = (\Lambda - \theta)(p_h + (1-p_h)\alpha_e^l)$, and $\mathbb{E}[N^2] = (\Lambda-\theta)(p_h + (1-p_h)\alpha_e^l) + (\Lambda-\theta)(\Lambda-\theta-1)(p_h + (1-p_h)\alpha_e^l)^2$. Now, consider the following expression:

$$\Omega(\theta) - \Omega(\theta - 1) = r - c\theta.$$

Since we know that $\bar{q} \le q^* = \lfloor \frac{r}{c} \rfloor$, it follows that $\Omega(\theta) - \Omega(\theta-1) > 0$. This means that the expected social welfare increases in θ whenever $\bar{\bar{\theta}} < \theta < \bar{\theta}$, and thus from all the threshold such that $\bar{\bar{\theta}} < \theta < \bar{\theta}$, the threshold $\theta = \bar{q} - 1$ achieves the maximum social welfare.

Based on the above, it remains to see which threshold from $\bar{\theta} - 1$ and $\bar{\theta}$ achieves a higher social welfare. For this, consider the following inequality:

$$\begin{aligned} &\Omega(\bar{\theta}) - \Omega(\bar{\theta} - 1) \ge 0 \\ &\iff 2(r - c\bar{\theta}) + (\Lambda - \bar{\theta})p_h(2r - c(2(1+\bar{\theta}) + p_h(\Lambda - \bar{\theta} - 1))) \ge 0. \end{aligned}$$

We let $g(\bar{\theta}) \doteq 2(r - c\bar{\theta}) + (\Lambda - \bar{\theta})p_h(2r - c(2(1+\bar{\theta}) + p_h(\Lambda - \bar{\theta} - 1)))$. We note that the quantity $r - c\bar{\theta} \ge 0 \iff \bar{\theta} \le \frac{r}{c}$ since $\bar{\theta} \le q^*$, and that the quantity $2r - c(2(1+\bar{\theta}) + p_h(\Lambda - \bar{\theta} - 1)) \le 0 \iff \bar{\theta} \ge \frac{2r-2c-cp_h(\Lambda-1)}{c(2-p_h)}$, since $\bar{\theta} = \lceil \frac{2r-2c-cp_h(\Lambda-1)}{c(2-p_h)} \rceil$. Depending on the parameters in the system it is possible for $g(\bar{\theta}) < 0$, $g(\bar{\theta}) = 0$, or $g(\bar{\theta}) > 0$. Thus, to avoid customer randomization we restrict to the case in which $g(\bar{\theta}) \ge 0$.

Without commitment. From Lemma 1 we have seen that irrespective of the implemented threshold, L type customers decide to always join the system. Since the expected social welfare is the same for any threshold decision, the service provider is indifferent and can select any threshold in equilibrium.

■

A.6. Proposition 4

Proof. We define the following random variables:

$$Q_b = \begin{cases} 1 & \text{if } q < q^*, \\ 0 & \text{if } q \ge q^*. \end{cases}$$

$$A_b = \begin{cases} 1 & \text{if } Join, \\ 0 & \text{if } Balk. \end{cases}$$

Based on this we have:

$$\mathbb{P}(Join|q < q^*) = \mathbb{P}(A_b = 1|Q_b = 1) = \frac{\mathbb{P}(Q_b = 1, A_b = 1)}{\mathbb{P}(Q_b = 1)},$$

$$\mathbb{P}(Balk|q \ge q^*) = \mathbb{P}(A_b = 0|Q_b = 0) = \frac{\mathbb{P}(Q_b = 0, A_b = 0)}{\mathbb{P}(Q_b = 0)},$$

$$BM = \mathbb{P}(Join|q < q^*) + \mathbb{P}(Balk|q \ge q^*) - 1.$$

No communication and communication without commitment. In this case from Propositions 2 and 3 we know that L type customers join with probability 1 in equilibrium, irrespective of the true state Q_b. Based on this, we have that $\mathbb{P}(A_b = 1|Q_b = 1) = 1$, and $\mathbb{P}(A_b = 0|Q_b = 0) = 0$. It follows that:

$$\begin{aligned}\mathbb{P}(Join|q < q^*) &= \mathbb{P}(A_b = 1|Q_b = 1) = 1,\\ \mathbb{P}(Balk|q \geq q^*) &= \mathbb{P}(A_b = 0|Q_b = 0) = 0,\\ BM &= 0.\end{aligned}$$

Communication with commitment. We define the random variable:

$$\theta = \begin{cases} 1 & \text{if } q < \theta, \\ 0 & \text{if } q \geq \theta. \end{cases}$$

We also define the joint distribution of the random variables Q_b and θ as follows:

- If $\theta \leq q^*$:

	θ	
Q_b	1	0
1	$\mathbb{P}(\theta = 1)$	$1 - \mathbb{P}(\theta = 1) - \mathbb{P}(Q_b = 0)$
0	0	$\mathbb{P}(Q_b = 0)$

- If $\theta > q^*$:

	θ	
Q_b	1	0
1	$\mathbb{P}(Q_b = 1)$	0
0	$1 - \mathbb{P}(Q_b = 1) - \mathbb{P}(\theta = 0)$	$\mathbb{P}(\theta = 0)$

Notice that $\alpha_e^s = \mathbb{P}(Join|\varsigma = s) = \mathbb{P}(A_b = 1|\theta = 1)$ and $\alpha_e^l = \mathbb{P}(Join|\varsigma = l) = \mathbb{P}(A_b = 1|\theta = 0)$. From Lemma 1, we can see that since it is always the case that $\alpha_e^s = 1$, such that $\mathbb{P}(A_b = 1|\theta = 1) = 1$, and $\mathbb{P}(A_b = 0|\theta = 1) = 0$. Also, since the metrics of interest are expressed in terms of A_b and Q_b, we now study how such variables are related through θ (i.e., how the signaling affects the interaction between the real state and customers' actions):

$$\mathbb{P}(A_b|Q_b) = \sum_{\theta} \mathbb{P}(A_b|Q_b,\theta)\mathbb{P}(\theta|Q_b) = \sum_{\theta} \mathbb{P}(A_b|\theta)\mathbb{P}(\theta|Q_b).$$

$$\begin{aligned}\mathbb{P}(A_b=1|Q_b=1) &= \mathbb{P}(A_b=1|\theta=1)\mathbb{P}(\theta=1|Q_b=1) + \mathbb{P}(A_b=1|\theta=0)\mathbb{P}(\theta=0|Q_b=1)\\ &= \mathbb{P}(\theta=1|Q_b=1) + \mathbb{P}(A_b=1|\theta=0)\mathbb{P}(\theta=0|Q_b=1).\end{aligned}$$

$$\begin{aligned}\mathbb{P}(A_b=0|Q_b=1) &= \mathbb{P}(A_b=0|\theta=1)\mathbb{P}(\theta=1|Q_b=1) + \mathbb{P}(A_b=0|\theta=0)\mathbb{P}(\theta=0|Q_b=1)\\ &= \mathbb{P}(A_b=0|\theta=0)\mathbb{P}(\theta=0|Q_b=1).\end{aligned}$$

$$\begin{aligned}\mathbb{P}(A_b=1|Q_b=0) &= \mathbb{P}(A_b=1|\theta=1)\mathbb{P}(\theta=1|Q_b=0) + \mathbb{P}(A_b=1|\theta=0)\mathbb{P}(\theta=0|Q_b=0)\\ &= \mathbb{P}(\theta=1|Q_b=0) + \mathbb{P}(A_b=1|\theta=0)\mathbb{P}(\theta=0|Q_b=0).\end{aligned}$$

$$\begin{aligned}\mathbb{P}(A_b=0|Q_b=0) &= \mathbb{P}(A_b=0|\theta=1)\mathbb{P}(\theta=1|Q_b=0) + \mathbb{P}(A_b=0|\theta=0)\mathbb{P}(\theta=0|Q_b=0)\\ &= \mathbb{P}(A_b=0|\theta=0)\mathbb{P}(\theta=0|Q_b=0).\end{aligned}$$

Based on the above and Lemma 1, we compute the metrics of interest separately in 4 different cases: (1) $\theta \le \bar{\bar{\theta}}$, (2) $\bar{\bar{\theta}} < \theta < \bar{\theta}$, (3) $\bar{\theta} \le \theta \le q^*$, and (4) $\theta > q^*$.

Case 1: $\theta \le \bar{\bar{\theta}}$

In this case we know that $\alpha_e^l = 1$ and thus we have that $\mathbb{P}(A_b=1|\theta=0)=1$, $\mathbb{P}(A_b=0|\theta=0)=0$. It follows that:

$$\mathbb{P}(A_b=1|Q_b=1) = \mathbb{P}(\theta=1|Q_b=1) + \mathbb{P}(\theta=0|Q_b=1).$$

$$\mathbb{P}(A_b=0|Q_b=1) = 0.$$

$$\mathbb{P}(A_b=1|Q_b=0) = \mathbb{P}(\theta=1|Q_b=0) + \mathbb{P}(\theta=0|Q_b=0).$$

$$\mathbb{P}(A_b=0|Q_b=0) = 0.$$

We can further express previous equations as follows:

$$\mathbb{P}(A_b=1,Q_b=1) = \mathbb{P}(\theta=1,Q_b=1) + \mathbb{P}(\theta=0,Q_b=1).$$

$$\mathbb{P}(A_b=0,Q_b=1) = 0.$$

$$\mathbb{P}(A_b=1,Q_b=0) = \mathbb{P}(\theta=1,Q_b=0) + \mathbb{P}(\theta=0,Q_b=0).$$

$$\mathbb{P}(A_b=0,Q_b=0) = 0.$$

Now, we know that $\bar{\bar{\theta}} \leq q^*$, therefore from previous tables it follows that:

$$\mathbb{P}(A_b = 1, Q_b = 1) = \mathbb{P}(\theta = 1) + (1 - \mathbb{P}(\theta = 1) - \mathbb{P}(Q_b = 0)) = \mathbb{P}(Q_b = 1).$$

$$\mathbb{P}(A_b = 0, Q_b = 1) = 0.$$

$$\mathbb{P}(A_b = 1, Q_b = 0) = \mathbb{P}(Q_b = 0).$$

$$\mathbb{P}(A_b = 0, Q_b = 0) = 0.$$

It follows that:

$$\mathbb{P}(Join|q < q^*) = \mathbb{P}(A_b = 1|Q_b = 1) = 1,$$

$$\mathbb{P}(Balk|q \geq q^*) = \mathbb{P}(A_b = 0|Q_b = 0) = 0,$$

$$BM = 0.$$

Case 2: $\bar{\bar{\theta}} < \theta < \bar{\theta}$

In this case we know that $\alpha_e^l \in (0,1)$ and thus we have that $\mathbb{P}(A_b = 1|\theta = 0) \in (0,1)$, $\mathbb{P}(A_b = 0|\theta = 0) \in (0,1)$. It follows that:

$$\mathbb{P}(A_b = 1|Q_b = 1) = \mathbb{P}(\theta = 1|Q_b = 1) + \mathbb{P}(A_b = 1|\theta = 0)\mathbb{P}(\theta = 0|Q_b = 1).$$

$$\mathbb{P}(A_b = 0|Q_b = 1) = \mathbb{P}(A_b = 0|\theta = 0)\mathbb{P}(\theta = 0|Q_b = 1).$$

$$\mathbb{P}(A_b = 1|Q_b = 0) = \mathbb{P}(\theta = 1|Q_b = 0) + \mathbb{P}(A_b = 1|\theta = 0)\mathbb{P}(\theta = 0|Q_b = 0).$$

$$\mathbb{P}(A_b = 0|Q_b = 0) = \mathbb{P}(A_b = 0|\theta = 0)\mathbb{P}(\theta = 0|Q_b = 0).$$

We can further express previous equations as follows:

$$\mathbb{P}(A_b = 1, Q_b = 1) = \mathbb{P}(\theta = 1, Q_b = 1) + \alpha_e^l \mathbb{P}(\theta = 0, Q_b = 1).$$

$$\mathbb{P}(A_b = 0, Q_b = 1) = (1 - \alpha_e^l)\mathbb{P}(\theta = 0, Q_b = 1).$$

$$\mathbb{P}(A_b = 1, Q_b = 0) = \mathbb{P}(\theta = 1, Q_b = 0) + \alpha_e^l \mathbb{P}(\theta = 0, Q_b = 0).$$

$$\mathbb{P}(A_b = 0, Q_b = 0) = (1 - \alpha_e^l)\mathbb{P}(\theta = 0, Q_b = 0).$$

Now, we know that $\bar{\theta} \leq q^*$, therefore from previous tables it follows that:

$$\mathbb{P}(A_b = 1, Q_b = 1) = \mathbb{P}(\theta = 1) + \alpha_e^l (1 - \mathbb{P}(\theta = 1) - \mathbb{P}(Q_b = 0)).$$

$$\mathbb{P}(A_b=0,Q_b=1)=(1-\alpha_e^l)(1-\mathbb{P}(\theta=1)-\mathbb{P}(Q_b=0)).$$

$$\mathbb{P}(A_b=1,Q_b=0)=\alpha_e^l\mathbb{P}(Q_b=0).$$

$$\mathbb{P}(A_b=0,Q_b=0)=(1-\alpha_e^l)\mathbb{P}(Q_b=0).$$

It follows that:

$$\mathbb{P}(Join|q<q^*)=\frac{\mathbb{P}(q<\theta)+\alpha_e^l(1-\mathbb{P}(q<\theta)-\mathbb{P}(q\geq q^*))}{\mathbb{P}(q<q^*)},$$
$$\mathbb{P}(Balk|q\geq q^*)=1-\alpha_e^l,$$
$$BM=\frac{\mathbb{P}(q<\theta)+\alpha_e^l(1-\mathbb{P}(q<\theta)-\mathbb{P}(q\geq q^*))}{\mathbb{P}(q<q^*)}-\alpha_e^l.$$

Case 3: $\bar{\theta}\leq\theta\leq q^*$

In this case we know that $\alpha_e^l=0$ and thus we have that $\mathbb{P}(A_b=1|\theta=0)=0$, $\mathbb{P}(A_b=0|\theta=0)=1$. It follows that:

$$\mathbb{P}(A_b=1|Q_b=1)=\mathbb{P}(\theta=1|Q_b=1).$$

$$\mathbb{P}(A_b=0|Q_b=1)=\mathbb{P}(\theta=0|Q_b=1).$$

$$\mathbb{P}(A_b=1|Q_b=0)=\mathbb{P}(\theta=1|Q_b=0).$$

$$\mathbb{P}(A_b=0|Q_b=0)=\mathbb{P}(\theta=0|Q_b=0).$$

This implies that $\mathbb{P}(Q_b,A_b)=\mathbb{P}(Q_b,\theta)$. It follows that:

$$\mathbb{P}(Join|q<q^*)=\frac{\mathbb{P}(q<\theta)}{\mathbb{P}(q<q^*)},$$
$$\mathbb{P}(Balk|q\geq q^*)=1,$$
$$BM=\frac{\mathbb{P}(q<\theta)}{\mathbb{P}(q<q^*)}.$$

Moreover, notice that whenever $\theta=q^*$ we have that $\mathbb{P}(\theta=1)=\mathbb{P}(Q_b=1)$, and thus $\mathbb{P}(Join|q<q^*)=1$, and $BM=1$. Also, recall that in equilibrium we have that $\theta^*=\bar{\theta}\leq q^*$. We can observe that whenever $\theta^*<q^*$, customers do not match their actions A_b perfectly with the state Q_b. In particular we have that $\mathbb{P}(Join|q<q^*)\in(0,1)$, $\mathbb{P}(Balk|q\geq q^*)=1$, and $BM=\in(0,1)$.

Case 4: $\theta > q^*$

In this case we know that $\alpha_e^l = 0$ and thus we have that $\mathbb{P}(A_b = 1|\theta = 0) = 0$, $\mathbb{P}(A_b = 0|\theta = 0) = 1$. It follows that:

$$\mathbb{P}(A_b = 1|Q_b = 1) = \mathbb{P}(\theta = 1|Q_b = 1).$$

$$\mathbb{P}(A_b = 0|Q_b = 1) = \mathbb{P}(\theta = 0|Q_b = 1).$$

$$\mathbb{P}(A_b = 1|Q_b = 0) = \mathbb{P}(\theta = 1|Q_b = 0).$$

$$\mathbb{P}(A_b = 0|Q_b = 0) = \mathbb{P}(\theta = 0|Q_b = 0).$$

This implies that $\mathbb{P}(Q_b, A_b) = \mathbb{P}(Q_b, \theta)$. It follows that:

$$\begin{aligned}
&\mathbb{P}(Join|q < q^*) = 1,\\
&\mathbb{P}(Balk|q \geq q^*) = \frac{\mathbb{P}(q \geq \theta)}{\mathbb{P}(q \geq q^*)},\\
&BM = \frac{\mathbb{P}(q \geq \theta)}{\mathbb{P}(q \geq q^*)}.
\end{aligned}$$

Notice that if the threshold $\theta = \Lambda$, then we have that $\mathbb{P}(\theta = 0) = 0$, and thus $\mathbb{P}(Balk|q \geq q^*) = 0$, and $BM = 0$.

Queueing Dynamics

Finally, to compute some of the metrics we need to understand the dynamics in the queue captured by the state probabilities $\mathbb{P}(q,t)$. First, notice that states (q,t) can be reached only from states $(q-1,t+1)$ and $(q,t+1)$. Under customer behaviour $(\alpha_e^s = 1, \alpha_e^l)$, if the system is in state $(q-1,t+1)$, then the system transitions into state (q,t) with probability $p_h + (1-p_h)(\sigma(q-1,t+1) + (1-\sigma(q-1,t+1))\alpha_e^l)$. On the other hand, if the system is in state $(q,t+1)$, then the system transitions into state (q,t) with probability $(1-p_h)(1-\sigma(q,t+1))(1-\alpha_e^l)$.Based on this, we can capture the queueing dynamics with the following recursive expression:

$$\begin{aligned}
\mathbb{P}(q,t) =& \mathbb{P}(q-1,t+1)(p_h + (1-p_h)(\sigma(q-1,t+1) + (1-\sigma(q-1,t+1))\alpha_e^l))\\
&+ \mathbb{P}(q,t+1)(1-p_h)(1-\sigma(q,t+1))(1-\alpha_e^l),
\end{aligned}$$

with boundary conditions $\mathbb{P}(0,\Lambda-1) = 1/\Lambda$, $\mathbb{P}(0,t) = \mathbb{P}(0,t+1)(1-p_h)(1-\sigma(0,t+1))(1-\alpha_e^l)$ for all $t < \Lambda-1$, and $\mathbb{P}(q,t) = \mathbb{P}(q-1,t+1)(p_h + (1-p_h)(\sigma(q-1,t+1) + (1-\sigma(q-1,t+1))\alpha_e^l))$ for all $q > 0, t < \Lambda - 1$

such that $q + t = \Lambda - 1$. In particular, since we are focusing on the fixed threshold mechanism, we have that $\sigma(q,t) = 1$ if $q < \theta$ and $\sigma(q,t) = 0$ if $q \geq \theta$. Based on the above we can determine the state distribution $\mathbb{P}(q) = \sum_t \mathbb{P}(q,t)$ in order to compute the relevant informativeness metrics.

■

B. How to compute expected/implied metrics

We focus on the performance optimality of participant choices. To reduce the role of luck (i.e., variability due to the random matching of customer choices and realizations of customer types and order of arrivals) we compute the expected value of diverse metrics given the participant strategies in our data. Given the design of our experiment, it is natural to compute these implied metrics at the round-cohort level: we will see that in the *Commit* and *NoCommit* treatments, the computation of most of these metrics requires the input of the implemented threshold θ_{jtc}. This input is by definition an integer number, and thus averaging across rounds or cohorts may generate average thresholds that are not integer-valued. We now describe how to compute the expected value of these metrics for all the treatments.

B.1. NoSignal treatment

In this treatment, in each period $t \in \{1, \dots, T\}$, for each cohort $c \in \{1, \dots, C\}$, and for each customer $i \in \{1, \cdots, \Lambda\}$, we observe their strategy $A_{itc} \equiv \big\{a_{itc} \in \{1, 0\}\big\}$, where 1 represents the *Join* action and 0 the *Balk* action. Based on this, we compute $\varphi_{tc} = \frac{1}{\Lambda}\sum_i a_{itc}$, that is, the implied joining proportion in a particular round and cohort. Note that φ_{tc} is not necessarily the same as the *realized* joining proportion in our data (due to the random matching of customer choices and realizations of customer types).

Social Welfare. Let $J_{tc} \sim \mathcal{B}(\Lambda, p_h + (1-p_h)\varphi_{tc})$ be a binomial random variable that represents the number of customers that join in a given round and cohort. It follows that the expected social welfare is given by:

$$\Omega_{tc} = \mathbb{E}[rJ_{tc} - c\sum_{k=1}^{J_{tc}} k] = r\mathbb{E}[J_{tc}] - \frac{c}{2}\mathbb{E}[J_{tc}(J_{tc}+1)] = r\mathbb{E}[J_{tc}] - \frac{c}{2}(\mathbb{E}[J_{tc}^2] + \mathbb{E}[J_{tc}]),$$

with $\mathbb{E}[J_{tc}] = \Lambda(p_h + (1-p_h)\varphi_{tc})$, and $\mathbb{E}[J_{tc}^2] = \Lambda(p_h + (1-p_h)\varphi_{tc}) + \Lambda(\Lambda-1)(p_h + (1-p_h)\varphi_{tc})^2$.

Overall Joining Probability of L Types. In this case, it simply follows that $\mathbb{P}_{tc}(Join) = \varphi_{tc}$.

Joining Probability of L Types given that $q < q^*$. Recall that q^* represents the Naor threshold. In this treatment it simply follows that $\mathbb{P}_{tc}(Join|q < q^*) = \varphi_{tc}$. Indeed, since customers do not have any information about the queue state when they make their decisions, their joining is independent of queue states.

Balking Probability of L Types given that $q \geq q^*$. In this treatment it simply follows that $\mathbb{P}_{tc}(Balk|q \geq q^*) = 1 - \varphi_{tc}$. Similarly, since customers do not have any information about the queue state when they make their decisions, their balking is independent of queue states.

Queue-length Informativeness We recall that $BM_{tc} = \mathbb{P}_{tc}(Join|q < q^*) + \mathbb{P}_{tc}(Balk|q \geq q^*) - 1$. In this treatment, it is easy to see that $BM_{tc} = 0$.

B.2. Commit and NoCommit treatment

In these treatments, in each period $t \in \{1, \ldots, T\}$, for each cohort $c \in \{1, \ldots, C\}$, we observe the provider j's implemented threshold decision θ_{jtc} (*Commit*,*NoCommit*), and the communicated threshold decision θ'_{jtc} (*NoCommit*). For each customer $i \in \{1, \cdots, \Lambda\}$, we observe their strategy $A_{itc} \equiv \{a_{itc}(\varsigma = s|\theta_{jtc}), a_{itc}(\varsigma = l|\theta_{jtc})\}$ (*Commit*), and $A_{itc} \equiv \{a_{itc}(\varsigma = s|\theta'_{jtc}), a_{itc}(\varsigma = l|\theta'_{jtc})\}$ (*NoCommit*), where $a_{itc} \in \{0, 1\}$, such that 1 represents the *Join* action and 0 the *Balk* action. Based on this, in the *Commit* treatment, we compute $\varphi^s_{tc} = \frac{1}{\Lambda}\sum_i a_{itc}(\varsigma = s|\theta_{jtc})$ and $\varphi^l_{tc} = \frac{1}{\Lambda}\sum_i a_{itc}(\varsigma = l|\theta_{jtc})$, that is, the implied joining proportion for a given message in a particular round and cohort. Similarly, in the *NoCommit* treatment, we compute $\varphi^s_{tc} = \frac{1}{\Lambda}\sum_i a_{itc}(\varsigma = s|\theta'_{jtc})$ and $\varphi^l_{tc} = \frac{1}{\Lambda}\sum_i a_{itc}(\varsigma = l|\theta'_{jtc})$. We note that φ^s_{tc} and φ^l_{tc} are not necessarily the same as the *realized* joining proportions in our data (due to the random matching of customer choices and realizations of customer types and order of arrivals).

System Dynamics. In both *Commit* and *NoCommit* treatment, for a given set of φ^s_{tc}, φ^l_{tc}, and θ_{jtc} we can capture the expected dynamics in the queue with the state probabilities $\mathbb{P}_{tc}(q, w)$. We have that $q \in \{0, 1, \cdots, \Lambda - 1\}$ represents the number of customers in queue that an arriving tagged customer encounters, and $w \in \{\Lambda - 1, \cdots, 1, 0\}$ represents the remaining number of customers to arrive after an arriving tagged customer. We let $\sigma_{tc}(q, w)$ be the probability $\mathbb{P}_{tc}(\varsigma = s|q, w)$, that is, the probability that a L signal is sent in state (q, w). Also, we have that $1 - \sigma_{tc}(q, w)$ is the probability $\mathbb{P}_{tc}(\varsigma = l|q, w)$, that is, the probability that a H signal is sent in state (q, w).

Notice that state (q, w) can be reached only from states $(q-1, w+1)$ and $(q, w+1)$. If the system is in state $(q-1, w+1)$, then the system transitions into state (q, w) with probability $p_h + (1-p_h)(\sigma(q-1, w+1)\varphi^s_{tc} + (1 - \sigma_{tc}(q-1, w+1))\varphi^l_{tc})$. On the other hand, if the system is in state $(q, w+1)$, then the system transitions into state (q, w) with probability $(1-p_h)(\sigma_{tc}(q-1, w+1)(1-\varphi^s_{tc}) + (1 - \sigma_{tc}(q-1, w+1))(1-\varphi^l_{tc}))$. Based on the above, we can capture the queueing dynamics with the following recursive expression:

$$\begin{aligned}\mathbb{P}_{tc}(q, w) = &\mathbb{P}_{tc}(q-1, w+1)(p_h + (1-p_h)(\sigma_{tc}(q-1, w+1)\varphi^s_{tc} \\ &+ (1 - \sigma_{tc}(q-1, w+1))\varphi^l_{tc}))\end{aligned}$$

$$+\mathbb{P}_{tc}(q,w+1)(1-p_h)(\sigma_{tc}(q-1,w+1)(1-\varphi^s_{tc})$$
$$+(1-\sigma_{tc}(q-1,w+1))(1-\varphi^l_{tc})),$$

with boundary conditions $\mathbb{P}_{tc}(0,\Lambda-1)=1/\Lambda$, $\mathbb{P}_{tc}(0,w)=\mathbb{P}_{tc}(0,w+1)(1-p_h)(\sigma_{tc}(0,w+1)(1-\varphi^s_{tc})+(1-\sigma_{tc}(0,w+1))(1-\varphi^l_{tc}))$ for all $w<\Lambda-1$, and $\mathbb{P}_{tc}(q,w)=\mathbb{P}_{tc}(q-1,w+1)(p_h+(1-p_h)(\sigma_{tc}(q-1,w+1)\varphi^s_{tc}+(1-\sigma_{tc}(q-1,w+1))\varphi^l_{tc}))$ for all $q>0, w<\Lambda-1$ such that $q+w=\Lambda-1$.

Note that given the fixed threshold structure of the signaling mechanism we have that $\sigma_{tc}(q,w)=\sigma_{tc}(q)$ for all w, and that $\sigma_{tc}(q)=1$ if $q<\theta_{jtc}$ and $\sigma_{tc}(q)=0$ otherwise. Finally, we note that given the set of φ^s_{tc}, φ^l_{tc}, and θ_{jtc}, in the *NoCommit* treatment, the system dynamics do not depend on the announced θ'_{jtc}.

Social Welfare. We consider the value function $V_{tc}(q,w)$. For a given state (q,w), the expected future utility $V_{tc}(q,w)$ is equal to the immediate expected utility, $p_h(r-c(q+1))+(1-p_h)(r-c(q+1))(\sigma_{tc}(q,w)\varphi^s_{tc}+(1-\sigma_{tc}(q,w))\varphi^l_{tc})$, plus the expected utility from time $w-1$ onward, $(p_h+(1-p_h)(\sigma_{tc}(q,w)\varphi^s_{tc}+(1-\sigma_{tc}(q,w))\varphi^l_{tc}))V_{tc}(q+1,w-1)+(1-p_h)((\sigma_{tc}(q,w)(1-\varphi^s_{tc})+(1-\sigma_{tc}(q,w))(1-\varphi^l_{tc})))V(q,w-1)$. After some simple algebra we can simplify the expression of the expected future utility:

$$\begin{aligned}V_{tc}(q,w)=&(r-c(q+1)+V_{tc}(q+1,w-1))(p_h+(1-p_h)(\sigma_{tc}(q,w)\varphi^s_{tc}\\&+(1-\sigma_{tc}(q,w))\varphi^l_{tc}))+(1-p_h)((\sigma_{tc}(q,w)(1-\varphi^s_{tc})\\&+(1-\sigma_{tc}(q,w))(1-\varphi^l_{tc})))V_{tc}(q,w-1),\end{aligned}$$

with boundary conditions $V_{tc}(q,0)=(r-c(q+1))(p_h+(1-p_h)(\sigma_{tc}(q,w)\varphi^s_{tc}+(1-\sigma_{tc}(q,w))\varphi^l_{tc}))$ for all q. Notice that based on the recursive nature of the value function $V_{tc}(q,w)$, the expected social welfare in the system, Ω_{tc}, is given by $V_{tc}(0,\Lambda-1)$. Note that given the fixed threshold structure of the signaling mechanism we have that $\sigma_{tc}(q,w)=\sigma_{tc}(q)$ for all w, and that $\sigma_{tc}(q)=1$ if $q<\theta_{jtc}$ and $\sigma_{tc}(q)=0$ otherwise.

Joining Probability of L Types for a given message. In this case, we simply have that $\mathbb{P}_{tc}(Join|\varsigma=l)=\varphi^l_{tc}$ and that $\mathbb{P}_{tc}(Join|\varsigma=s)=\varphi^s_{tc}$.

Overall Joining Probability of L Types. In this case, we can condition on the received message as follows:

$$\begin{aligned}\mathbb{P}_{tc}(Join)&=\mathbb{P}_{tc}(Join|\varsigma=s)\mathbb{P}_{tc}(\varsigma=s)+\mathbb{P}_{tc}(Join|\varsigma=l)\mathbb{P}_{tc}(\varsigma=l)\\&=\varphi^s_{tc}\mathbb{P}_{tc}(\varsigma=s)+\varphi^l_{tc}(1-\mathbb{P}_{tc}(\varsigma=s)).\end{aligned}$$

Finally, we can compute the probabilities for a message based on the state probabilities as $\mathbb{P}_{tc}(\varsigma = s) = \sum_w \sum_q \sigma_{tc}(q,w)\mathbb{P}_{tc}(q,w)$, and $\mathbb{P}_{tc}(\varsigma = l) = 1 - \mathbb{P}_{tc}(\varsigma = s)$.

Joining Probability of L Types given that $q < q^*$. In this case, we can condition on the received message as follows:

$$
\begin{aligned}
\mathbb{P}_{tc}(Join|q<q^*) &= \mathbb{P}_{tc}(Join|q<q^*,\varsigma=s)\mathbb{P}_{tc}(\varsigma=s|q<q^*) + \mathbb{P}_{tc}(Join|q<q^*,\varsigma=l)\mathbb{P}_{tc}(\varsigma=l|q<q^*) \\
&= \mathbb{P}_{tc}(Join|\varsigma=s)\mathbb{P}_{tc}(\varsigma=s|q<q^*) + \mathbb{P}_{tc}(Join|\varsigma=l)\mathbb{P}_{tc}(\varsigma=l|q<q^*) \\
&= \varphi^s_{tc}\mathbb{P}_{tc}(\varsigma=s|q<q^*) + \varphi^l_{tc}\mathbb{P}_{tc}(\varsigma=l|q<q^*) \\
&= \varphi^s_{tc}\sum_q \mathbb{P}_{tc}(\varsigma=s|q<q^*,q)\mathbb{P}_{tc}(q|q<q^*) + \varphi^l_{tc}\sum_q \mathbb{P}_{tc}(\varsigma=l|q<q^*,q)\mathbb{P}_{tc}(q|q<q^*) \\
&= \varphi^s_{tc}\sum_q \mathbb{P}_{tc}(\varsigma=s|q)\mathbb{P}_{tc}(q|q<q^*) + \varphi^l_{tc}\sum_q \mathbb{P}_{tc}(\varsigma=l|q)\mathbb{P}_{tc}(q|q<q^*) \\
&= \varphi^s_{tc}\sum_{q=0}^{q^*-1}\sigma_{tc}(q)\frac{\mathbb{P}_{tc}(q)}{\sum_{q=0}^{q^*-1}\mathbb{P}_{tc}(q)} + \varphi^l_{tc}\sum_{q=0}^{q^*-1}(1-\sigma_{tc}(q))\frac{\mathbb{P}_{tc}(q)}{\sum_{q=0}^{q^*-1}\mathbb{P}_{tc}(q)} \\
&= \frac{\sum_{q=0}^{q^*-1}(\varphi^s_{tc}\sigma_{tc}(q) + \varphi^l_{tc}(1-\sigma_{tc}(q)))\mathbb{P}_{tc}(q)}{\sum_{q=0}^{q^*-1}\mathbb{P}_{tc}(q)} \\
&= \frac{\sum_{q=0}^{q^*-1}(\varphi^s_{tc}\sigma_{tc}(q) + \varphi^l_{tc}(1-\sigma_{tc}(q)))\sum_w \mathbb{P}_{tc}(q,w)}{\sum_{q=0}^{q^*-1}\sum_w \mathbb{P}_{tc}(q,w)}.
\end{aligned}
$$

We recall that $\sigma_{tc}(q) = 1$ if $q < \theta_{jtc}$ and $\sigma_{tc}(q) = 0$ otherwise.

Balking Probability of L Types given that $q \geq q^*$. In this case, we can condition on the received message as follows:

$$
\begin{aligned}
\mathbb{P}_{tc}(Balk|q\geq q^*) &= \mathbb{P}_{tc}(Balk|q\geq q^*,\varsigma=s)\mathbb{P}_{tc}(\varsigma=s|q\geq q^*) + \mathbb{P}_{tc}(Balk|q\geq q^*,\varsigma=l)\mathbb{P}_{tc}(\varsigma=l|q\geq q^*) \\
&= \mathbb{P}_{tc}(Balk|\varsigma=s)\mathbb{P}_{tc}(\varsigma=s|q\geq q^*) + \mathbb{P}_{tc}(Balk|\varsigma=l)\mathbb{P}_{tc}(\varsigma=l|q\geq q^*) \\
&= (1-\varphi^s_{tc})\mathbb{P}_{tc}(\varsigma=s|q\geq q^*) + (1-\varphi^l_{tc})\mathbb{P}_{tc}(\varsigma=l|q\geq q^*) \\
&= (1-\varphi^s_{tc})\sum_q \mathbb{P}_{tc}(\varsigma=s|q\geq q^*,q)\mathbb{P}_{tc}(q|q\geq q^*) + (1-\varphi^l_{tc})\sum_q \mathbb{P}_{tc}(\varsigma=l|q\geq q^*,q)\mathbb{P}_{tc}(q|q\geq q^*) \\
&= (1-\varphi^s_{tc})\sum_q \mathbb{P}_{tc}(\varsigma=s|q)\mathbb{P}_{tc}(q|q\geq q^*) + (1-\varphi^l_{tc})\sum_q \mathbb{P}_{tc}(\varsigma=l|q)\mathbb{P}_{tc}(q|q\geq q^*) \\
&= (1-\varphi^s_{tc})\sum_{q=q^*}^{\Lambda-1}\sigma_{tc}(q)\frac{\mathbb{P}_{tc}(q)}{\sum_{q=q^*}^{\Lambda-1}\mathbb{P}_{tc}(q)} + (1-\varphi^l_{tc})\sum_{q=q^*}^{\Lambda-1}(1-\sigma_{tc}(q))\frac{\mathbb{P}_{tc}(q)}{\sum_{q=q^*}^{\Lambda-1}\mathbb{P}_{tc}(q)} \\
&= \frac{\sum_{q=q^*}^{\Lambda-1}((1-\varphi^s_{tc})\sigma_{tc}(q) + (1-\varphi^l_{tc})(1-\sigma_{tc}(q)))\mathbb{P}_{tc}(q)}{\sum_{q=q^*}^{\Lambda-1}\mathbb{P}_{tc}(q)}
\end{aligned}
$$

$$= \frac{\sum_{q=q^*}^{\Lambda-1}((1-\varphi_{tc}^s)\sigma_{tc}(q) + (1-\varphi_{tc}^l)(1-\sigma_{tc}(q)))\sum_w \mathbb{P}_{tc}(q,w)}{\sum_{q=q^*}^{\Lambda-1}\sum_w \mathbb{P}_{tc}(q,w)}.$$

We recall that $\sigma_{tc}(q) = 1$ if $q < \theta_{jtc}$ and $\sigma_{tc}(q) = 0$ otherwise.

Queue-length Informativeness This is imply computed as $BM_{tc} = \mathbb{P}_{tc}(Join|q < q^*) + \mathbb{P}_{tc}(Balk|q \geq q^*) - 1$.

Persuasiveness of Signals. We recall that $\mathcal{P}_{ct} = \mathbb{P}_{tc}(Balk|\varsigma = l)$ if $\theta_{jtc} < q^*$. It simply follows that:

$$\mathcal{P}_{ct} = \begin{cases} 1-\varphi_{tc}^l & \text{if } \theta_{jtc} < q^*, \\ \text{not defined} & otherwise. \end{cases}$$

Note that a natural metric to compare against in the *NoSignals* treatment (as a baseline) is $\mathbb{P}_{tc}(Balk|q < q^*) = 1 - \mathbb{P}_{tc}(Join|q < q^*) = 1 - \varphi_{tc}$.

C. Experiment

C.1. Analysis of Social Welfare

Table 3 presents OLS regressions with cluster standard errors to accommodate the dependency of observations.

Table 3 Social Welfare OLS Regressions

	Realized Social Welfare				Implied Social Welfare			
	(1a)	(2a)	(3a)†	(4a)	(1b)	(2b)	(3b)†	(4b)
(Intercept)	146.46***	146.46***	179.23***	146.46***	157.80***	157.80***	188.40***	157.80***
	(9.56)	(9.43)	(10.65)	(9.26)	(14.57)	(14.36)	(6.97)	(14.10)
Commit	35.60*	-	2.83	35.60**	33.81·	-	3.20	33.81*
	(11.59)	-	(12.42)	(11.22)	(14.96)	-	(7.72)	(14.48)
NoCommit	-	32.77*	-	32.77*	-	30.61·	-	30.61·
	-	(14.30)	-	(14.05)	-	(15.99)	-	(15.71)
Round	1.26**	1.26**	0.75*	1.26**	0.73**	0.73**	0.50*	0.73***
	(0.35)	(0.35)	(0.31)	(0.34)	(0.16)	(0.15)	(0.20)	(0.15)
Commit∗Round	-0.42	-	0.09	-0.42	-0.29	-	-0.06	-0.29
	(0.54)	-	(0.50)	(0.52)	(0.31)	-	(0.33)	(0.30)
NoCommit∗Round	-	-0.51	-	-0.51	-	-0.23	-	-0.23
	-	(0.46)	-	(0.46)	-	(0.26)	-	(0.25)
N	640	800	960	1200	640	800	960	1200
R^2	0.04	0.02	0.01	0.02	0.16	0.11	0.03	0.11

$^{\cdot}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

Each data point consists of the total social welfare achieved by a cohort in a given round and session. Thus N = Number of sessions∗2(cohorts)∗40(rounds).

Standard errors clustered at the session level.

† : Models (3a) and (3b) do not consider the *NoSignal* treatment, and take as baseline the *NoCommit* treatment to compare it with the *Commit* treatment.

No signals present higher social welfare than predicted. We compute the average social welfare at the session level, which is the coarsest partition of the data that can be assumed to be independent. With these independent observations (i.e., 3 observations) we run t-tests for both realized and implied social welfare. For the realized social welfare, we identify a significantly higher social welfare in the *NoSignals* treatment in comparison to the theoretical prediction of 40; $t(2) = 20.21$, p-value $= 0.001$. We also run a bootstrap t-test (p-value $= 0.038$). For the implied social welfare, we identify a significantly higher social welfare in the *NoSignals* treatment in comparison to the theoretical prediction of 40; $t(2) = 10.18$, p-value $= 0.005$. We also run a bootstrap t-test (p-value $= 0.071$), which is significant at the 10% level. Overall, we conclude that there is sufficient statistical evidence to conclude that the *NoSignals* treatment achieves a higher social welfare in comparison to the theoretical prediction.

Signals with commitment present lower social welfare than predicted. We compute the average social welfare at the session level, which is the coarsest partition of the data that can be assumed to be independent. With these independent observations (i.e., 5 observations) we run t-tests for both realized and implied social welfare. For the realized social welfare, we identify a significantly lower social welfare in the *Commit* treatment in comparison to the theoretical prediction of 250; $t(4) = -14.09, \text{p-value} < 0.001$. We also run a bootstrap t-test (p-value $= 0.013$). For the implied social welfare, we identify a significantly lower social welfare in the *Commit* treatment in comparison to the theoretical prediction of 250; $t(4) = -10.15, \text{p-value} < 0.001$. We also run a bootstrap t-test (p-value $= 0.001$). Overall, we conclude that there is sufficient statistical evidence to conclude that the *Commit* treatment achieves a lower social welfare in comparison to the theoretical prediction.

Signals with no commitment present higher social welfare than predicted. We compute the average social welfare at the session level, which is the coarsest partition of the data that can be assumed to be independent. With these independent observations (i.e., 7 observations) we run t-tests for both realized and implied social welfare. For the realized social welfare, we identify a significantly higher social welfare in the *NoCommit* treatment in comparison to the theoretical prediction of 40; $t(6) = 28.10, \text{p-value} < 0.001$. We also run a bootstrap t-test (p-value < 0.001). For the implied social welfare, we identify a significantly higher social welfare in the *Commit* treatment in comparison to the theoretical prediction of 40; $t(6) = 41.13, \text{p-value} < 0.001$. We also run a bootstrap t-test (p-value < 0.001). Overall, we conclude that there is sufficient statistical evidence to conclude that the *NoCommit* treatment achieves a higher social welfare in comparison to the theoretical prediction.

Signals with commitment improve social welfare. From Table 3 we see that the coefficients for *Commit* are positive. In model (1b) the coefficient is significant at a 10% level and in model (4b) at the 5% level. We note that these significance levels are based on two-tailed p-values. Thus, for a one-tailed test, the coefficient in both models is significant at the 5% level. As a conservative approach, we also compute the average social welfare at the session level, which is the coarsest partition of the data that can be assumed to be independent. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *Commit*) we run t-tests for both realized and implied social welfare. For the realized social welfare, we identify a significantly higher social welfare in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 3.99, \text{p-value} = 0.004$. We also run a bootstrap t-test (p-value $= 0.004$). For the implied social welfare, we identify a significantly higher social welfare in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 2.42, \text{p-value} = 0.026$. We also run a bootstrap t-test (p-value $= 0.023$). Overall, we conclude that there is sufficient statistical evidence to support Hypothesis 1A that signals with commitment improve social welfare.

Signals without commitment improve social welfare. From Table 3 we see that the coefficients for *NoCommit* are positive. In model (2b) and model (4b) the coefficient is significant at a 10% level. We note that this significance level is based on two-tailed p-values. Thus, for a one-tailed test, the coefficient in both models is significant at the 5% level. We also compute the average social welfare at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied social welfare. For the realized social welfare, we identify a significantly higher social welfare in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 2.34, \text{p-value} = 0.024$. We also run a bootstrap t-test (p-value $= 0.015$). For the implied social welfare, we identify a significantly higher social welfare in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 2.61, \text{p-value} = 0.016$. We also run a bootstrap t-test (p-value $= 0.017$). Overall, we conclude that there is sufficient statistical evidence to reject Hypothesis 1B that signals without commitment do not improve social welfare.

Signals with and without commitment present the same social welfare. From Table 3 we see that the coefficient for *Commit* in model (3b) is positive but close to cero and not significant. We also compute the average social welfare at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied social welfare. For the realized social welfare, we do not identify a significantly higher social welfare in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 0.657, \text{p-value} = 0.263$. We also run a bootstrap t-test (p-value $= 0.255$). For the implied social welfare, we do not identify a significantly higher social welfare in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 0.32, \text{p-value} = 0.376$. We also run a bootstrap t-test (p-value $= 0.373$). Overall, we conclude that signals with and without commitment allow to improve social welfare to the same extent.

C.2. Analysis of Joining Rates

We look at the aggregate patterns of L type customers' overall joining behaviour.

Signals with commitment reduce overall joining rates. We compute the average joining probability at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *Commit*) we run t-tests for both realized and implied joining probability. For the realized joining probability, we identify a significantly lower joining probability in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = -3.52, \text{p-value} = 0.006$. We also run a bootstrap t-test ($\text{p-value} = 0.007$). For the implied joining probability, we identify a significantly lower joining probability in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = -2.01, \text{p-value} = 0.045$. We also run a bootstrap t-test ($\text{p-value} = 0.046$).

Signals with no commitment reduce overall joining rates. We compute the average joining probability at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied joining probability. For the realized joining probability, we identify a significantly lower joining probability (at the 10% level) in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 1.71, \text{p-value} = 0.063$. We also run a bootstrap t-test ($\text{p-value} = 0.051$). For the implied joining probability, we identify a significantly lower joining probability in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = -2.27, \text{p-value} = 0.027$. We also run a bootstrap t-test ($\text{p-value} = 0.027$).

Signals with and without commitment present the same overall joining rates. We compute the average joining probability at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied joining probability. For the realized joining probability, we do not identify a significantly lower joining probability in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = -0.66, \text{p-value} = 0.260$. We also run a bootstrap t-test ($\text{p-value} = 0.255$). For the implied joining probability, we do not identify a significantly lower joining probability in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 0.03, \text{p-value} = 0.514$. We also run a bootstrap t-test ($\text{p-value} = 0.508$).

We now look at the aggregate patterns of L type customers' overall joining probability $\mathbb{P}(\text{Join}|q < q^*)$.

Signals with commitment do (not) increase $\mathbb{P}(\text{Join}|q < q^*)$. We compute the average joining probability $\mathbb{P}(\text{Join}|q < q^*)$ at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *Commit*) we run t-tests for both realized and implied joining probability $\mathbb{P}(\text{Join}|q < q^*)$. For the realized joining probability, we identify a significantly higher joining probability in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 2.09, \text{p-value} = 0.040$. We also run a bootstrap t-test (p-value $= 0.037$). For the implied joining probability, we do not identify a significantly higher joining probability in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 1.77, \text{p-value} = 0.063$. We also run a bootstrap t-test (p-value $= 0.067$).

Signals without commitment do not increase $\mathbb{P}(\text{Join}|q < q^*)$. We compute the average joining probability $\mathbb{P}(\text{Join}|q < q^*)$ at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied joining probability $\mathbb{P}(\text{Join}|q < q^*)$. For the realized joining probability, we do not identify a significantly higher joining probability in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 0.49, \text{p-value} = 0.319$. We also run a bootstrap t-test (p-value $= 0.322$). For the implied joining probability, we do not identify a significantly higher joining probability in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 0.53, \text{p-value} = 0.306$. We also run a bootstrap t-test (p-value $= 0.318$).

Signals with and without present the same $\mathbb{P}(\text{Join}|q < q^*)$. We compute the average joining probability probability $\mathbb{P}(\text{Join}|q < q^*)$ at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied joining probability $\mathbb{P}(\text{Join}|q < q^*)$. For the realized joining probability, we do not identify a significantly higher joining probability in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 0.87, \text{p-value} = 0.202$. We also run a bootstrap t-test (p-value $= 0.205$). For the implied joining probability, we do not identify a significantly higher joining probability in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 0.94, \text{p-value} = 0.184$. We also run a bootstrap t-test (p-value $= 0.183$).

Signals with commitment increase $\mathbb{P}(\text{Balk}|q \geq q^*)$. We compute the average balking probability $\mathbb{P}(\text{Balk}|q \geq q^*)$ at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *Commit*) we run t-tests for both realized and implied joining probability $\mathbb{P}(\text{Balk}|q \geq q^*)$. For the realized balking probability, we identify a significantly higher balking probability in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 8.34, \text{p-value} = 0.000$. We also run a bootstrap t-test (p-value $= 0.004$). For the implied balking probability, we identify a significantly higher balking probability in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 4.85, \text{p-value} = 0.001$. We also run a bootstrap t-test (p-value $= 0.005$).

Signals without commitment increase $\mathbb{P}(\textbf{Balk}|q \geq q^*)$. We compute the average balking probability $\mathbb{P}(\text{Balk}|q \geq q^*)$ at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *NoCommit*) we run t-tests for both realized and implied joining probability $\mathbb{P}(\text{Balk}|q \geq q^*)$. For the realized balking probability, we identify a significantly higher balking probability in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 4.50, \text{p-value} = 0.001$. We also run a bootstrap t-test (p-value $= 0.002$). For the implied balking probability, we identify a significantly higher balking probability in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 3.94, \text{p-value} = 0.002$. We also run a bootstrap t-test (p-value $= 0.003$).

Signals with and without commitment (do not) present the same $\mathbb{P}(\textbf{Balk}|q \geq q^*)$. We compute the average balking probability $\mathbb{P}(\text{Balk}|q \geq q^*)$ at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied joining probability $\mathbb{P}(\text{Balk}|q \geq q^*)$. For the realized balking probability, we identify a significantly higher balking probability in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 1.97, \text{p-value} = 0.038$. We also run a bootstrap t-test (p-value $= 0.030$). For the implied balking probability, we do not identify a significantly higher balking probability in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 1.14, \text{p-value} = 0.140$. We also run a bootstrap t-test (p-value $= 0.148$).

C.3. Analysis of Informativeness and Persuasion

Signals with commitment present the same BM as predicted. We compute the average BM at the session level. With these independent observations (i.e., 5 observations) we run t-tests for both realized and implied BM. For the realized BM, the value in the *Commit* treatment does not differ significantly from the theoretical prediction of 0.4; $t(4) = 0.26, \text{p-value} = 0.805$. We also run a bootstrap t-test (p-value $= 0.818$). For the implied BM, the value in the *Commit* treatment does not differ significantly from the theoretical prediction of 0.4; $t(4) = 0.12, \text{p-value} = 0.908$. We also run a bootstrap t-test (p-value $= 0.940$).

Signals without commitment present a higher BM than predicted. We compute the average BM at the session level. With these independent observations (i.e., 7 observations) we run t-tests for both realized and implied BM. For the realized BM, we identify a significantly higher BM in the *NoCommit* treatment in comparison to the predicted value of 0; $t(6) = 3.47, \text{p-value} = 0.007$. We also run a bootstrap t-test (p-value $= 0.002$). For the implied BM, we identify a significantly higher BM in the *NoCommit* treatment in comparison to the predicted value of 0; $t(6) = 4.19$, p-value $= 0.003$. We also run a bootstrap t-test (p-value < 0.001).

Signals with commitment increase BM. We compute the average BM at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *Commit*) we run t-tests for both realized and implied BM. For the realized BM, we identify a significantly higher BM in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 7.28$, p-value $= 0.000$. We also run a bootstrap t-test (p-value $= 0.003$). For the implied BM, we identify a significantly higher BM in the *Commit* treatment in comparison to the *NoSignals* treatment; $t(6) = 5.73$, p-value $= 0.001$. We also run a bootstrap t-test (p-value $= 0.001$).

Signals without commitment increase BM. We compute the average BM at the session level. With these independent observations (i.e., 3 observations for the *NoSignals* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied BM. For the realized BM, we identify a significantly higher BM in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 2.59$, p-value $= 0.016$. We also run a bootstrap t-test (p-value $= 0.015$). For the implied BM, we identify a significantly higher BM in the *NoCommit* treatment in comparison to the *NoSignals* treatment; $t(8) = 2.65$, p-value $= 0.014$. We also run a bootstrap t-test (p-value $= 0.008$).

Signals with and without commitment present the same BM. We compute the average BM at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied BM. For the realized BM, we do not identify a significantly higher BM in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 1.57$, p-value $= 0.074$. We also run a bootstrap t-test (p-value $= 0.074$). For the implied BM, we do not identify a significantly higher BM in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 1.20$, p-value $= 0.127$. We also run a bootstrap t-test (p-value $= 0.121$).

Signals with commitment increase $\mathcal{P}$. We compute the average $\mathcal{P}$ at the session level for *Commit* and the average balking probability at the session level for *NoSignals*. With these independent observations (i.e., 3 observations for the *NoSignals* and 5 observations for the *Commit*) we run t-tests for both realized and implied metrics. For the realized $\mathcal{P}$, we identify a significantly higher $\mathcal{P}$ in the *Commit* treatment in comparison to the balking probability in the *NoSignals* treatment; $t(6) = 6.28$, p-value < 0.001. We also run a bootstrap t-test (p-value $= 0.003$). For the implied $\mathcal{P}$, we identify a significantly higher $\mathcal{P}$ in the *Commit* treatment in comparison to the balking probability in the *NoSignals* treatment; $t(6) = 4.95$, p-value $= 0.001$. We also run a bootstrap t-test (p-value $= 0.005$).

Signals without commitment increase $\mathcal{P}$. We compute the average $\mathcal{P}$ at the session level for *NoCommit* and the average balking probability at the session level for *NoSignals*. With these independent observations (i.e., 3 observations for the *NoSignals* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied metrics. For the realized $\mathcal{P}$, we identify a significantly higher $\mathcal{P}$ in the *NoCommit* treatment in comparison to the balking probability in the *NoSignals* treatment; $t(8) = 3.84$, p-value $= 0.002$. We also run a bootstrap t-test (p-value $= 0.003$). For the implied $\mathcal{P}$, we identify a significantly higher $\mathcal{P}$ in the *NoCommit* treatment in comparison to the balking probability in the *NoSignals* treatment; $t(8) = 3.89$, p-value $= 0.002$. We also run a bootstrap t-test (p-value $= 0.004$).

Signals with and without commitment (do not) present the same $\mathcal{P}$. We compute the average $\mathcal{P}$ at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests for both realized and implied $\mathcal{P}$. For the realized $\mathcal{P}$, we identify a significantly higher $\mathcal{P}$ in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 2.45$, p-value $= 0.017$. We also run a bootstrap t-test (p-value $= 0.017$). For the implied $\mathcal{P}$, we do not identify a significantly higher $\mathcal{P}$ in the *Commit* treatment in comparison to the *NoCommit* treatment; $t(10) = 1.59$, p-value $= 0.071$. We also run a bootstrap t-test (p-value $= 0.072$).

C.4. Analysis of Customers' Choices

Table 4 presents Logistic regressions with cluster standard errors to accommodate the dependency of observations.

C.5. Analysis of service providers' Choices

Threshold distributions are different in the *Commit* and *NoCommit* We collect all the threshold selections for all service providers in all rounds in the *Commit* treatment, and all the communicated and implemented thresholds in the *NoCommit* treatments. We conduct two-sample Kolmogorov-Smirnov tests and find that the distribution of thresholds in the *Commit* is significantly different from both the distribution of communicated thresholds ($D = 0.19$, p-value < 0.001) and from the distribution of implemented thresholds ($D = 0.19464$, p-value < 0.001).

Service providers Lie metric in the *NoCommit* treatment We compute the metric *Lie* = *Communicated threshold* - *Implemented Threshold* for all service providers in all rounds. We then compute the

Table 4 Customer Strategies Logistic Regressions

	$\mathbb{P}$(Join|Short Wait)			$\mathbb{P}$(Join|Long Wait)		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
(Intercept)	3.61***	1.55**	2.80***	0.11	-0.09	0.05
	(0.72)	(0.58)	(0.54)	(0.33)	(0.39)	(0.40)
NoCommit	-	-	-0.82*	-	-	-0.11
	-	-	(0.35)	-	-	(0.28)
Communicated Threshold	-0.14*	0.03	-0.14*	-0.38***	-0.18***	-0.37***
	(0.07)	(0.05)	(0.06)	(0.06)	(0.04)	(0.06)
*NoCommit * Communicated Threshold*	-	-	0.18*	-	-	0.20**
	-	-	(0.08)	-	-	(0.07)
Round	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Gender.M	-0.82**	-0.13	-0.38	-0.14	-0.16	-0.15
	(0.28)	(0.35)	(0.26)	(0.16)	(0.30)	(0.20)
N	3200	4480	7680	3200	4480	7680

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Each data point represents the answer (Join/Not Join) by a Customer in a given round.

Models (1a) and (1b) are restricted to the *Commit* treatment, and models (2a) and (2b) are restricted to the *NoCommit* treatment.

Standard errors clustered at the session level.

average *Lie* and the average absolute *Lie* at the session level. With these independent observations (i.e., 7 observations) we run t-tests. For the average *Lie*, we identify that it is significantly different than 0; $t(6) = 2.7$, p-value $= 0.035$. We also run a bootstrap t-test (p-value $= 0.023$). For the average absolute *Lie*, we identify that it is significantly higher than 0; $t(6) = 7.40$, p-value < 0.001. We also run a bootstrap t-test (p-value < 0.001). We also restrict to those cases in which the *Lie* is different from 0. For those cases, we compute both the average *Lie* and the average absolute *Lie* at the session level. With these independent observations (i.e., 7 observations) we run t-tests. For the average *Lie*, we identify that it is significantly different than 0; $t(6) = 2.88$, p-value $= 0.028$. We also run a bootstrap t-test (p-value $= 0.037$). For the average absolute *Lie*, we identify that it is significantly higher than 0; $t(6) = 9.41$, p-value < 0.001. We also run a bootstrap t-test (p-value < 0.001). We also restrict to those cases in which the *Lie* is positive. For those cases, we compute the average *Lie* at the session level. With these independent observations (i.e., 7 observations) we run t-tests. For the average *Lie*, we identify that it is significantly higher than 0; $t(6) = 7.36$, p-value < 0.001. We also run a bootstrap t-test (p-value < 0.001). Finally, we also restrict to those cases in which the *Lie* is negative. For those cases, we compute the average *Lie* at the session level. With these independent observations (i.e., 7 observations) we run t-tests. For the average *Lie*, we identify that it is significantly lower than 0; $t(6) = -9.7, \text{p-value} < 0.001$. We also run a bootstrap t-test (p-value < 0.001).

Service providers that communicate higher thresholds than those implemented achieve higher social welfare

From Table 5, we can observe from models (1a) and (1b) that service providers that used a higher *Lie* = *Communicated Threshold* - *Implemented Threshold* achieved a significantly higher social welfare. Notice from models (2a) and (2b) that service providers that used a higher absolute *Lie* did not achieve higher social welfare. Indeed, as discussed before, in our game service providers have the incentive to communicate thresholds that are higher than those implemented (i.e., $\theta' > \theta$), that is, to have a positive *Lie* metric. This is further evidenced in models (3a) and (3b) where we observe that service providers that used lies such that $\theta' > \theta$ achieved a higher social welfare in comparison to those that were honest (i.e., $\theta' = \theta$), while service providers that used lies such that $\theta' < \theta$ achieved a lower social welfare in comparison to those that were honest.

Table 5 OLS Regressions service providers' Lying Behaviour

	Realized Social Welfare			Implied Social Welfare		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
(Intercept)	168.75***	188.75***	174.42***	186.54***	199.31***	189.47***
	(13.68)	(17.17)	(15.91)	(8.46)	(11.10)	(9.18)
Lie	10.75***	-	-	8.40***	-	-
	(1.12)	-	-	(0.79)	-	-
Absolute Lie	-	0.74	-	-	$2.40^{\cdot}$	-
	-	(2.12)	-	-	(1.13)	-
Lie.Type ($\theta' > \theta$)	-	-	24.42*	-	-	23.97**
	-	-	(7.94)	-	-	(5.12)
Lie.Type ($\theta' < \theta$)	-	-	-53.57***	-	-	-27.45**
	-	-	(7.74)	-	-	(4.62)
Round	0.43	$0.74^{\cdot}$	0.41	0.25	$0.48^{\cdot}$	0.27
	(0.33)	(0.33)	(0.29)	(0.25)	(0.24)	(0.22)
Gender.M	5.99	-6.85	7.42	0.65	-8.92	-0.36
	(5.01)	(6.10)	(6.56)	(2.91)	(4.63)	(3.54)
N	560	560	560	560	560	560
R^2	0.07	0.01	0.07	0.32	0.06	0.26

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Each data point consists of the total social welfare achieved by a service provider in a given round in the NoComit treatment.

Standard errors clustered at the session level.

In models (3a) and (3b) the baseline for Lie.Type is $\theta' = \theta$, such that the coefficients for Lie.Type ($\theta' > \theta$) and Lie.Type ($\theta' < \theta$) correspond to differences when service providers lie in comparison to when they are honest.

C.6. Survey data

At the end of the experiment, all participants responded to a survey relevant to their experiences in the experiment. Participants answered with a number between 1 to 7 (where 1 represents *strongly disagree*, 3 *neutral*, and 7 *strongly agree*) to the following statements:

For customers:

- Q1: I was in good mood
- Q2: I felt in control of my outcomes
- Q3: The service provider and the customers shared the same objective
- Q4: I understood the service provider's information strategy (*Commit*, *NoCommit*)
- Q5: The service provider's information strategy had an impact on my decisions (*Commit*, *NoCommit*)
- Q6: I trusted the information strategy (*Commit*, *NoCommit*)

For service providers:

- Q1: I was in good mood
- Q2: I felt in control of my outcomes
- Q3: The service provider and the customers shared the same objective
- Q4: I understood the service provider's information strategy (*Commit*, *NoCommit*)
- Q5: My information strategy had an impact on customers' decisions (*Commit*, *NoCommit*)
- Q6: The information strategy was trusted by customers (*Commit*, *NoCommit*)

Following Table 6 presents the average results at the treatment level for each of the described statements above.

Customers in the *Commit* treatment felt that the information strategy had more impact on their decisions than those in the *NoCommit* treatment We compute the average customer response for Q5 at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests. We identify a significantly higher average in the *Commit* treatment in comparison to the *No Commit*; $t(10) = 3.25$, p-value $= 0.005$. We also run a bootstrap t-test (p-value $= 0.003$).

Table 6 Average Survey Responses at Treatment Level

Statement	Customers			Service Providers		
	NoSignals	*Commit*	*NoCommit*	*NoSignals*	*Commit*	*NoCommit*
Q1	4.69	4.45	4.54	4.83	4.2	4.07
Q2	3.10	3.38	3.22	2.33	3.6	3.21
Q3	3.21	3.55	3.43	3.33	3.1	3.86
Q4	-	4.39	3.94	-	4.1	5
Q5	-	5.65	4.41	-	4.6	4.64
Q6	-	3.98	3.28	-	2.6	4.14

Notes: Results are rounded to 2 decimals places.

Customers in the *Commit* treatment trusted the information strategy more than those in the *NoCommit* treatment We compute the average customer response for Q6 at the session level. With these independent observations (i.e., 5 observations for the *Commit* and 7 observations for the *NoCommit*) we run t-tests. We identify a significantly higher average in the *Commit* treatment in comparison to the *No Commit*; $t(10) = 1.91$, p-value $= 0.042$. We also run a bootstrap t-test (p-value $= 0.042$).

D. Quantal Response Equilibrium (QRE)

D.1. No Signals Treatment

Consider the case in which the service provider does not reveal any information. In this case, customers make their join/balk decisions based on their priors and based on what other customers do in equilibrium (this is equivalent to an unobservable queue). Importantly, customers form correct beliefs about the expected queue length considering that all the other customers are also boundedly rational. Based on this, L type customers join with probability

$$\varphi(\beta) = \frac{e^{(r-c(\mathbb{E}[Q]+1))/\beta}}{1+e^{(r-c(\mathbb{E}[Q]+1))/\beta}}.$$

Recall that H type customers always join. In this setting, the equilibrium requires that the number of people that customers expect to encounter in the system $\mathbb{E}[Q]$ is consistent with customer behaviour in equilibrium. We now elaborate on this. Let $\varphi(\beta)$ be the probability that a L type customer joins the system in equilibrium. Based on this probability, a typical customer will join the system with probability $p_h + (1-p_h)\varphi(\beta)$ (recall that all H type customers always join). Now, when customers arrive, they do not know the number of people in the system, however, they can compute the expected number since they know the equilibrium joining probability.

Since customers are randomly ordered, they have t remaining customers behind them with probability $\frac{1}{\Lambda}$ for all $t \in \{0, 1, \cdots, \Lambda-1\}$. Conditional on t, customers can arrive to a system with up to $\Lambda - 1 - t$ customers. For example, the first customer (i.e., $t = \Lambda - 1$) arrives to a system with 0 customers, and the last customer (i.e., $t = 0$) arrives to a system with 0 or 1 or 2, and so on up to $\Lambda - 1$ customers. Moreover, notice that conditional on t the probability to find q customers, depends on how many customers joined in the previous times $\Lambda - 1, \Lambda - 2, \cdots, t + 1$; that is, in the previous $\Lambda - 1 - t$ times. Based on the above we have that $Q|t \sim \mathcal{B}(\Lambda - 1 - t, p_h + (1-p_h)\varphi(\beta))$ is a binomial random variable with expected value $\mathbb{E}[Q|t] = (\Lambda - 1 - t)(p_h + (1-p_h)\varphi(\beta))$. With this, we can compute the expected number of people that customers find upon arrival:

$$\begin{aligned}
\mathbb{E}[Q] &= \sum_{t=0}^{\Lambda-1} \mathbb{E}[Q|t]\mathbb{P}(t) = \frac{1}{\Lambda}\sum_{t=0}^{\Lambda-1} \mathbb{E}[Q|t] = \frac{1}{\Lambda}\sum_{t=0}^{\Lambda-1} (\Lambda - 1 - t)(p_h + (1-p_h)\varphi(\beta)) \\
&= \frac{p_h + (1-p_h)\varphi(\beta)}{\Lambda}\sum_{k=1}^{\Lambda-1} k = \frac{(p_h + (1-p_h)\varphi(\beta))(\Lambda-1)\Lambda}{2\Lambda} \\
&= \frac{(p_h + (1-p_h)\varphi(\beta))(\Lambda-1)}{2}.
\end{aligned}$$

Based on this, we say that $\varphi(\beta)$ is an equilibrium joining probability for L type customers if it satisfies the following:

$$\varphi(\beta) = \frac{e^{(r-c(\frac{(p_h+(1-p_h)\varphi(\beta))(\Lambda-1)}{2}+1))/\beta}}{1+e^{(r-c(\frac{(p_h+(1-p_h)\varphi(\beta))(\Lambda-1)}{2}+1))/\beta}}.$$

Notice that previous expression yields a fixed-point problem since the logit expression in the right-hand side includes the equilibrium joining probability (i.e., the left-hand side). We can easily obtain the equilibrium joining probability numerically. We now show that there is a unique equilibrium for $\beta > 0$. For this, we define the function $h(\varphi(\beta))$ as follows:

$$h(\varphi(\beta)) = \varphi(\beta) - \frac{e^{(r-c(\frac{(p_h+(1-p_h)\varphi(\beta))(\Lambda-1)}{2}+1))/\beta}}{1+e^{(r-c(\frac{(p_h+(1-p_h)\varphi(\beta))(\Lambda-1)}{2}+1))/\beta}}.$$

We can see that $h(0) < 0$ and $h(1) > 0$. Since $h(\varphi(\beta))$ is continuous in $\varphi(\beta)$ it follows that there is at least one $\varphi^*(\beta) \in (0,1)$ such that $h(\varphi(\beta)^*) = 0$. Finally, since $h(\varphi(\beta))$ is strictly increasing in $\varphi(\beta)$, it follows that the solution $\varphi^*(\beta)$ is unique.

Finally, to compute the *expected social welfare*, let $J \sim \mathcal{B}(\Lambda, p_h + (1-p_h)\varphi(\beta))$ be a binomial random variable that represents the number of customers that join in equilibrium. It follows that the expected social welfare in the system Ω is given by:

$$\begin{aligned}\Omega &= \mathbb{E}[rJ - c\sum_{k=1}^{J} k] = r\mathbb{E}[J] - \frac{c}{2}\mathbb{E}[J(J+1)] \\ &= r\mathbb{E}[J] - \frac{c}{2}(\mathbb{E}[J^2] + \mathbb{E}[J]),\end{aligned}$$

with $\mathbb{E}[J] = \Lambda(p_h + (1-p_h)\varphi^*(\beta))$, and $\mathbb{E}[J^2] = \Lambda(p_h + (1-p_h)\varphi^*(\beta)) + \Lambda(\Lambda-1)(p_h + (1-p_h)\varphi^*(\beta))^2$.

D.1.1. Alternative Formulation to solve numerically We can also numerically compute the expected number of people that customers find upon arrival, by considering the dynamics in the queue captured by the state probabilities $\mathbb{P}(q,t)$. First, notice that states (q,t) can be reached only from states $(q-1,t+1)$ and $(q,t+1)$. In equilibrium, if the system is in state $(q-1,t+1)$, then the system transitions into state (q,t) with probability $p_h + (1-p_h)\varphi(\beta)$. On the other hand, if the system is in state $(q,t+1)$, then the system transitions into state (q,t) with probability $(1-p_h)(1-\varphi(\beta))$. Based on this, we can capture the queueing dynamics with the following recursive expression:

$$\begin{aligned}\mathbb{P}(q,t) =& \mathbb{P}(q-1,t+1)(p_h + (1-p_h)\varphi(\beta)) \\ &+ \mathbb{P}(q,t+1)(1-p_h)(1-\varphi(\beta)),\end{aligned}$$

with boundary conditions $\mathbb{P}(0,\Lambda-1)=1/\Lambda$, $\mathbb{P}(0,t)=\mathbb{P}(0,t+1)(1-p_h)(1-\varphi(\beta))$ for all $t<\Lambda-1$, and $\mathbb{P}(q,t)=\mathbb{P}(q-1,t+1)(p_h+(1-p_h)\varphi(\beta))$ for all $q>0, t<\Lambda-1$ such that $q+t=\Lambda-1$. Based on these recursive expressions, we can compute the expected number of customers that an arriving customer encounters as follows:

$$\mathbb{E}[Q]=\sum_{q=0}^{\Lambda-1} q\mathbb{P}(q)=\sum_{q=0}^{\Lambda-1} q\sum_{t=0}^{\Lambda-1}\mathbb{P}(q,t).$$

As before, we would then identify the $\varphi^*(\beta)$ that solves the fixed-point problem. We can also compute the expected social welfare numerically, we can consider the value function $V(q,t)$. For a given state (q,t) in equilibrium, the expected future utility $V(q,t)$ is equal to the immediate expected utility, $p_h(r-c(q+1))+(1-p_h)(r-c(q+1))\varphi^*(\beta)$, plus the expected utility from time $t-1$ onward, $(p_h+(1-p_h)\varphi^*(\beta))V(q+1,t-1)+(1-p_h)(1-\varphi^*(\beta))V(q,t-1)$. After some simple algebra, we can simplify the expression of the expected future utility:

$$\begin{aligned} V(q,t)=&(r-c(q+1)+V(q+1,t-1))(p_h+(1-p_h)\varphi^*(\beta))\\ &+(1-p_h)(1-\varphi^*(\beta))V(q,t-1), \end{aligned}$$

with boundary conditions $V(q,0)=(r-c(q+1))(p_h+(1-p_h)\varphi^*(\beta))$ for all q. Notice that based on the recursive nature of the value function $V(q,t)$, the expected social welfare in the system Ω is given by $V(0,\Lambda-1)$.

D.1.2. Estimation of Bounded Rationality Parameter Let $s^*(\beta)$ be the QRE of the game. The components of $s^*(\beta)$ for customer i and strategy j are represented by $s^*_{i,j}(\beta)$. For a given data set, we let the observed empirical frequencies of strategy choices be denoted by f, where $f_{i,j}$ represents the number of observations of customer i choosing strategy $s_{i,j}$. Based on this, the log-likelihood function given the data f is:

$$\mathcal{L}(\beta;f)=\sum_i\sum_j f_{i,j}\log(s^*_{i,j}),$$

In this case we have that $s^*_{i,j}(\beta)=\varphi^*(\beta)$ for the join strategy and $s^*_{i,j}(\beta)=1-\varphi^*(\beta)$ for the balk strategy such that:

$$\mathcal{L}(\beta;f)=\sum_i f_{i,join}\log(\varphi^*(\beta))+f_{i,balk}\log(1-\varphi^*(\beta)),$$

where the maximum-likelihood estimate is $\hat{\beta}=\arg\max_\beta\ \mathcal{L}(\beta;f)$.

D.2. Commitment Treatment

In this case, given a threshold and a signal, L type customers join with probability:

$$\varphi_s(\beta) = \frac{e^{(r-c(\mathbb{E}[Q|\varsigma=s]+1))/\beta}}{1+e^{(r-c(\mathbb{E}[Q|\varsigma=s]+1))/\beta}},$$
$$\varphi_l(\beta) = \frac{e^{(r-c(\mathbb{E}[Q|\varsigma=l]+1))/\beta}}{1+e^{(r-c(\mathbb{E}[Q|\varsigma=l]+1))/\beta}}.$$

In this setting, the equilibrium requires that the number of people that customers expect to encounter in the system $\mathbb{E}[Q|\varsigma]$ is consistent with customer behaviour in equilibrium. We note that when a customer receives a *s*hort signal, all previous customers also received a *s*hort signal. It follows that $\mathbb{E}[Q|\varsigma = s]$ depends only on $\varphi_s(\beta)$. From the above expressions, we can get the equilibrium $\varphi_s^*(\beta)$ solving a fixed-point problem with the first equation of above. Intuitively, $\mathbb{E}[Q|\varsigma = s]$ increases strictly in $\varphi_s(\beta)$, thus following the same reasoning as in the *NoSignals* case, the solution to the fixed point problem for $\varphi_s^*(\beta)$ is unique. Once we have the equilibrium $\varphi_s^*(\beta)$, we can plug it in the second equation above and solve the fixed-point problem for $\varphi_l^*(\beta)$. Similarly, $\mathbb{E}[Q|\varsigma = l]$ increases strictly in $\varphi_l(\beta)$, such that the solution to the fixed point problem for $\varphi_l^*(\beta)$ is unique.

We numerically compute the number of people that customers expect to find upon arrival for a given signal, by considering the dynamics in the queue captured by the state probabilities $\mathbb{P}(q,t)$. First, notice that states (q,t) can be reached only from states $(q-1,t+1)$ and $(q,t+1)$. In equilibrium, if the system is in state $(q-1,t+1)$, then the system transitions into state (q,t) with probability $p_h + (1-p_h)(\sigma(q-1,t+1)\varphi_s(\beta) + (1-\sigma(q-1,t+1))\varphi_l(\beta))$. On the other hand, if the system is in state $(q,t+1)$, then the system transitions into state (q,t) with probability $(1-p_h)(\sigma(q-1,t+1)(1-\varphi_s(\beta)) + (1-\sigma(q-1,t+1))(1-\varphi_l(\beta)))$. Based on this, we can capture the queueing dynamics with the following recursive expression:

$$\begin{aligned}\mathbb{P}(q,t) =& \mathbb{P}(q-1,t+1)(p_h + (1-p_h)(\sigma(q-1,t+1)\varphi_s(\beta) + (1-\sigma(q-1,t+1))\varphi_l(\beta)))\\ &+ \mathbb{P}(q,t+1)(1-p_h)(\sigma(q-1,t+1)(1-\varphi_s(\beta)) + (1-\sigma(q-1,t+1))(1-\varphi_l(\beta))),\end{aligned}$$

with boundary conditions $\mathbb{P}(0,\Lambda-1) = 1/\Lambda$, $\mathbb{P}(0,t) = \mathbb{P}(0,t+1)(1-p_h)(\sigma(0,t+1)(1-\varphi_s(\beta)) + (1-\sigma(0,t+1))(1-\varphi_l(\beta)))$ for all $t < \Lambda - 1$, and $\mathbb{P}(q,t) = \mathbb{P}(q-1,t+1)(p_h + (1-p_h)(\sigma(q-1,t+1)\varphi_s(\beta) + (1-\sigma(q-1,t+1))\varphi_l(\beta)))$ for all $q > 0, t < \Lambda - 1$ such that $q + t = \Lambda - 1$. Note that given the fixed threshold structure of the signaling mechanism we have that $\sigma(q,t) = \sigma(q)$ for all t, and that $\sigma(q) = 1$ if $q < \theta$ and $\sigma(q) = 0$ otherwise.

Based on these recursive expressions, we can compute the number of people that customers expect to find upon arrival for a given signal as follows:

$$\begin{aligned}\mathbb{E}[Q|\varsigma] &= \sum_{q=0}^{\Lambda-1} q\mathbb{P}(q|\varsigma) = \sum_{q=0}^{\Lambda-1} q\frac{\mathbb{P}(\varsigma|q)\mathbb{P}(q)}{\mathbb{P}(s)}\\ &= \sum_{q=0}^{\Lambda-1} q\frac{(\sum_{t=0}^{\Lambda-1}\mathbb{P}(\varsigma|q,t)\mathbb{P}(t|q))\mathbb{P}(q)}{\mathbb{P}(s)}\\ &= \sum_{q=0}^{\Lambda-1} q\frac{\sum_{t=0}^{\Lambda-1}\mathbb{P}(\varsigma|q,t)\mathbb{P}(q,t)}{\sum_{t=0}^{\Lambda-1}\sum_{q=0}^{\Lambda-1}\mathbb{P}(\varsigma|q,t)\mathbb{P}(q,t)},\end{aligned}$$

such that,

$$\begin{aligned}\mathbb{E}[Q|\varsigma=s] &= \sum_{q=0}^{\Lambda-1} q\frac{\sum_{t=0}^{\Lambda-1}\sigma(q,t)\mathbb{P}(q,t)}{\sum_{t=0}^{\Lambda-1}\sum_{q=0}^{\Lambda-1}\sigma(q,t)\mathbb{P}(q,t)},\\ \mathbb{E}[Q|\varsigma=l] &= \sum_{q=0}^{\Lambda-1} q\frac{\sum_{t=0}^{\Lambda-1}(1-\sigma(q,t))\mathbb{P}(q,t)}{\sum_{t=0}^{\Lambda-1}\sum_{q=0}^{\Lambda-1}(1-\sigma(q,t))\mathbb{P}(q,t)}.\end{aligned}$$

Now, to compute the expected social welfare numerically, we can consider the value function $V(q,t)$. For a given state (q,t) in equilibrium, the expected future utility $V(q,t)$ is equal to the immediate expected utility, $p_h(r-c(q+1))+(1-p_h)(r-c(q+1))(\sigma(q,t)\varphi_s^*(\beta)+(1-\sigma(q,t))\varphi_l^*(\beta))$, plus the expected utility from time $t-1$ onward, $(p_h+(1-p_h)(\sigma(q,t)\varphi_s^*(\beta)+(1-\sigma(q,t))\varphi_l^*(\beta)))V(q+1,t-1)+(1-p_h)((\sigma(q,t)(1-\varphi_s^*(\beta))+(1-\sigma(q,t))(1-\varphi_l^*(\beta))))V(q,t-1)$. After some simple algebra we can simplify the expression of the expected future utility:

$$\begin{aligned}V(q,t) =& (r-c(q+1)+V(q+1,t-1))(p_h+(1-p_h)(\sigma(q,t)\varphi_s^*(\beta)+(1-\sigma(q,t))\varphi_l^*(\beta)))\\ &+(1-p_h)((\sigma(q,t)(1-\varphi_s^*(\beta))+(1-\sigma(q,t))(1-\varphi_l^*(\beta))))V(q,t-1),\end{aligned}$$

with boundary conditions $V(q,0)=(r-c(q+1))(p_h+(1-p_h)(\sigma(q,t)\varphi_s^*(\beta)+(1-\sigma(q,t))\varphi_l^*(\beta)))$ for all q. Notice that based on the recursive nature of the value function $V(q,t)$, the expected social welfare in the system $\Omega(\theta,\varphi_s^*(\beta),\varphi_l^*(\beta))$, is given by $V(0,\Lambda-1)$.

Above we have characterized the *customer equilibrium*, $\varphi_s^*(\beta)$ and $\varphi_l^*(\beta)$, for any given threshold θ. Based on this, the service provider selects a probability distribution $\varphi_\theta(\beta_m)$ over the choices for a threshold:

$$\varphi_\theta(\beta_m)=\frac{e^{\Omega(\theta,\varphi_s^*(\beta),\varphi_l^*(\beta))/\beta_m}}{\sum_\theta e^{\Omega(\theta,\varphi_s^*(\beta),\varphi_l^*(\beta))/\beta_m}} \quad \text{for} \quad \theta=0,1,2,\cdots,\Lambda.$$

We note that $\Omega(\cdot)$ does not depend on the probability $\varphi_\theta(\beta_m)$, such that $\varphi_\theta(\beta_m)$ represents the equilibrium distribution $\varphi_\theta^*(\beta_m)$. Finally, we can compute the expected social welfare in equilibrium simply as $\sum_\theta \varphi_\theta^*(\beta_m)\Omega(\theta,\varphi_s^*(\beta),\varphi_l^*(\beta))$.

D.2.1. Estimation of Bounded Rationality Parameters Let $s^*(\beta)$ be the QRE of the game for customers. The components of $s^*(\beta)$ for customer i and strategy j are represented by $s^*_{i,j}(\beta)$. For a given data set, we let the observed empirical frequencies of strategy choices be denoted by f, where $f_{i,j}$ represents the number of observations of customer i choosing strategy $s_{i,j}$. Based on this, the log-likelihood function given the data f is:

$$\mathcal{L}(\beta; f) = \sum_i \sum_j f_{i,j} \log(s^*_{i,j}),$$

In this case we have that $s^*_{i,j}(\beta) = \varphi^\theta_s(\beta)\varphi^\theta_l(\beta)$ for the strategy to join for *s*hort signal and join for *l*ong signal given threshold θ; $s^*_{i,j}(\beta) = \varphi^\theta_s(\beta)(1-\varphi^\theta_l(\beta))$ for the strategy to join for *s*hort signal and balk for *l*ong signal given threshold θ; $s^*_{i,j}(\beta) = (1-\varphi^\theta_s(\beta))\varphi^\theta_l(\beta)$ for the strategy to balk for *s*hort signal and join for *l*ong signal given threshold θ; $s^*_{i,j}(\beta) = (1-\varphi^\theta_s(\beta))(1-\varphi^\theta_l(\beta))$ for the strategy to balk for *s*hort signal and balk for *l*ong signal given threshold θ. We note that for the case of $\theta = 0$, customers only care about the *l*ong signal, and thus in this case we have that $s^*_{i,j}(\beta) = \varphi^{\theta=0}_l(\beta)$ for the strategy to join for *l*ong signal and $s^*_{i,j}(\beta) = 1 - \varphi^{\theta=0}_l(\beta)$ for the strategy to balk for *l*ong signal. Similarly, for the case of $\theta = \Lambda$ we have that $s^*_{i,j}(\beta) = \varphi^{\theta=\Lambda}_s(\beta)$ for the strategy to join for *s*hort signal and $s^*_{i,j}(\beta) = 1 - \varphi^{\theta=\Lambda}_s(\beta)$ for the strategy to balk for *s*hort signal. It follows that:

$$\begin{aligned}
\mathcal{L}(\beta; f) = \sum_i \sum_{\theta=1}^{\Lambda-1} & f^\theta_{i,join,join}\log(\varphi^\theta_s(\beta)\varphi^\theta_l(\beta)) + f^\theta_{i,join,balk}\log(\varphi^\theta_s(\beta)(1-\varphi^\theta_l(\beta))) \\
& + f^\theta_{i,balk,join}\log((1-\varphi^\theta_s(\beta))\varphi^\theta_l(\beta)) + f^\theta_{i,balk,balk}\log((1-\varphi^\theta_s(\beta))(1-\varphi^\theta_l(\beta))) \\
& + \sum_i f^{\theta=0}_{i,-,join}\log(\varphi^{\theta=0}_l(\beta)) + f^{\theta=0}_{i,-,balk}\log(1-\varphi^{\theta=0}_l(\beta)) \\
& + \sum_i f^{\theta=\Lambda}_{i,-,join}\log(\varphi^{\theta=\Lambda}_s(\beta)) + f^{\theta=\Lambda}_{i,-,balk}\log(1-\varphi^{\theta=0}_s(\beta)),
\end{aligned}$$

where the maximum-likelihood estimate is $\hat{\beta} = \arg\max_\beta \mathcal{L}(\beta; f)$. Now once we estimate $\hat{\beta}$, we let $m^*(\beta_m)$ be the QRE of the game for the service providers. The components of $m^*(\beta_m)$ for service provider i and strategy j are represented by $m^*_{i,j}(\beta_m)$. For a given data set, we let the observed empirical frequencies of strategy choices be denoted by f, where $f_{i,j}$ represents the number of observations of service provider i choosing strategy $m_{i,j}(\beta_m)$. Based on this, the log-likelihood function given the data f is:

$$\mathcal{L}(\beta_m; f) = \sum_i \sum_j f_{i,j}\log(m^*_{i,j}(\beta_m)),$$

In this case we have that $m^*_{i,j}(\beta_m) = \varphi^*_\theta(\beta_m)$ for the strategy to use the threshold θ. We note that:

$$\varphi^*_\theta(\beta_m) = \frac{e^{\Omega(\theta,\varphi^*_s(\hat{\beta}),\varphi^*_l(\hat{\beta}))/\beta_m}}{\sum_\theta e^{\Omega(\theta,\varphi^*_s(\hat{\beta}),\varphi^*_l(\hat{\beta}))/\beta_m}} \quad \text{for} \quad \theta = 0,1,2,\cdots,\Lambda.$$

It follows that:

$$\mathcal{L}(\beta_m; f) = \sum_i \sum_\theta f_i^\theta \log(\varphi^*_\theta(\beta_m)),$$

where the maximum-likelihood estimate is $\hat{\beta}_m = \arg\max_{\beta_m} \mathcal{L}(\beta_m; f)$.

D.3. No Commitment Treatment

We first characterize the customer equilibrium in the same way as in the *Commit* treatment above. The difference is that here, the customer equilibrium, $\varphi^*_s(\beta)$ and $\varphi^*_l(\beta)$, is given for a communicated threshold θ' (rather than the implemented one θ). This assumes that customers take the communicated threshold θ' at face value. Moreover, in this treatment, the service provider selects a joint probability distribution $\varphi_{\theta,\theta'}(\beta_m)$ over the choice of the pair of thresholds θ and θ':

$$\varphi_{\theta,\theta'}(\beta_m) = \frac{e^{\Omega(\theta,\theta')/\beta_m}}{\sum_\theta \sum_{\theta'} e^{\Omega(\theta,\theta')/\beta_m}} \quad \text{for} \quad \theta = 0,1,2,\cdots,\Lambda; \quad \theta' = 0,1,2,\cdots,\Lambda,$$

We note that $\Omega(\theta,\theta')$ does not depend on the probability $\varphi_{\theta,\theta'}(\beta_m)$, such that $\varphi_{\theta,\theta'}(\beta_m)$ represents the equilibrium joint distribution $\varphi^*_{\theta,\theta'}(\beta_m)$.

D.3.1. Estimation of Bounded Rationality Parameters We estimate the customers' bounded rationality parameter in the same way as described in the *Commit* treatment above. The difference is that the relevant threshold used in the estimation is the communicated one θ'. For the service provider, we have that:

$$\varphi^*_{\theta,\theta'}(\beta_m) = \frac{e^{\Omega(\theta,\theta'\varphi^*_s(\hat{\beta}),\varphi^*_l(\hat{\beta}))/\beta_m}}{\sum_\theta e^{\Omega(\theta,\theta'\varphi^*_s(\hat{\beta}),\varphi^*_l(\hat{\beta}))/\beta_m}} \quad \text{for} \quad \theta = 0,1,2,\cdots,\Lambda; \quad \theta' = 0,1,2,\cdots,\Lambda,$$

Based on this, the log-likelihood function given the data f is:

$$\mathcal{L}(\beta_m; f) = \sum_i \sum_\theta \sum_{\theta'} f_i^{\theta,\theta'} \log(\varphi^*_{\theta,\theta'}(\beta_m)),$$

where the maximum-likelihood estimate is $\hat{\beta}_m = \arg\max_{\beta_m} \mathcal{L}(\beta_m; f)$.

Table 7 QRE Estimation Results

Treatment	*NoSignals*	*Commit*	*NoCommit*
$\hat{\beta}$	91.12***	39.85***	55.48***
	(16.63)	(0.98)	(1.28)
$\hat{\beta}_m$	-	13.42***	132.75***
	-	(1.04)	(13.59)
LL	-1311.51	-2604.63	-4275.49
LL_m	-	-775.87	-2410.73
N	48	80	112
N_m	-	10	14

$^{\cdot}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Standard errors are presented in parenthesis.