Consumer Learning from Own Experience and Social Information: An Experimental Study

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We investigate how different types of social information affect the demand characteristics of firms competing through service quality. We first generate behavioral hypotheses around both consumers’ learning behavior and firms’ corresponding demand characteristics: market share, demand uncertainty, and rate of convergence. We then conduct a controlled human-subject experiment where a consumer chooses to visit one of two firms, each with unknown service quality, in a repeated interaction and is exposed to different information treatments from a social network: (1) no social information, (2) share-based social information which details the percentage of people that visited each firm, (3) quality-based social information which illustrates the percentage of people that received a satisfactory experience from each firm, or (4) full social information which contains both share-based and quality-based social information. A key insight from our study is that different types of social information have different effects on firms’ demand. First, promoting quality-based social information leads to a significantly higher market share, lower demand variability, and faster rate of convergence, for a firm with significantly better service quality. Second, when the higher quality firm has only a marginal advantage over the other firm, promoting only share-based information leads to significantly higher market share and lower demand variability. A third important result is that providing only one type of social information can actually be more helpful to the higher quality firm than providing full social information.

Key words: Social information, behavioral operations management, service competition, online retail.

1. Introduction

In the services industry, consumers are typically not well-informed about the level of quality of different service providers. They rely on social information and their own prior experience to learn about the quality of service, form expectations, and choose which firm to visit. With the rapid growth of online communities and social networks, recommendations from friends and consumer opinions posted online have become a critical source of information about quality and a key driver of demand. According to the Nielsen Global Surveys of Trust in Advertising conducted in 2013 and
2015, they rank among the three topmost trusted channels of advertising by consumers worldwide (Nielsen Holdings N.V. 2015).

Investments in social media marketing by firms have followed suit, doubling between 2014 and 2017, from roughly $16 billion to over $32 billion, and are expected to reach $48 billion in 2021 according to a worldwide survey of marketers (Statista 2018). However, social information captures a wide range of attributes and formats, e.g., ratings, rankings, volume and content of online reviews, engagement in a firm’s website or online community, etc. Do consumers respond equally to different types of social information? Which ones should a manager promote? There is little guidance available to firms to answer these questions. Thus, the effectiveness of social media marketing remains poor: only 13% of marketers in the Statista survey rated the effectiveness of their social media marketing as very successful and only 38% stated that they were able to measure the return on investment for their social media activities. Our paper addresses these challenges through the following research questions: (1) how do consumers learn from own experiences and different types of social information to decide which firm to visit? (2) what are the effects of social information on the demand and long-run market shares of firms competing in a marketplace? (3) are different types of social information equally valuable to competing firms?

To answer these questions, we follow the experimental approach of Gans et al. (2007). Gans et al. (2007) study a repeated two-armed Bernoulli bandit experiment with human decision-makers learning from their own choices. We generalize this approach to include social information, wherein a consumer learns not only the service outcomes of her own previous choices, but also information from her network. Similar to Gans et al. (2007), in our experiment, each participant acts as a consumer choosing between two firms of dissimilar quality over several periods. However, we then manipulate, depending on the treatment, the gap in average service quality between the two firms, large or small, and the type of social information provided.

In practice, social information can be biased, noisy, and comprised of many attributes. Moreover, trust in social information can vary with its source; for instance, word-of-mouth from friends evokes a higher level of trust than anonymous online reviews. We abstract away from these complexities in our controlled experiment and focus on two stylized types of social information, quality and market-share. Quality-based social information (or quality-SI) is defined as the fraction of people in a network who received a satisfactory experience from each firm in the previous round. It enables participants to learn about each other’s experiences. In practice, such information is provided by consumer ratings, online reviews, and peer-to-peer sharing of experiences. Market share-based social information (or share-SI) is defined as the fraction of people in a network who visited each
firm in the previous round. In contrast to quality-SI, this enables participants to learn about each other’s choices or actions. In practice, such information is obtained through sales ranks and bestseller lists or through location-based social media features. For example, when a customer checks into a restaurant, a retail store, a bank, or an airline lounge, she may share her location with her Facebook network. With these two types of SI, we manipulate four treatments: no-SI, quality-SI, share-SI, and full-SI. No-SI refers to the control treatment when participants do not receive any social information. Full-SI is the treatment when participants receive both share-SI and quality-SI. In each treatment, information is collected within the experiment from the participants’ choices, experiences, and network, and is shared directly with them real-time. This then potentially contributes to the evolution of their beliefs and choices. This stylized setup enables us to evaluate in a controlled environment the effects of different kinds of information that a consumer may obtain through her social network.

It is well-known in the behavioral operations literature that consumers may not behave in practice as rational Bayesian decision-makers, and may instead follow simple decision rules. It is thus an empirical question to determine how a consumer includes different kinds of information in a simple decision rule. Thus, instead of treating consumers as Bayesian, we utilize a general hidden Markov chain framework to analyze the experimental data and test hypotheses. In this framework, consumer beliefs about the relative quality of the competing firms are represented via latent states of a Markov chain, their choice probabilities are state-dependent, and the updating of beliefs occurs through transitions between states. This model provides us with several useful properties: it provides a way to combine various kinds of information in consumer learning, it captures correlations in choices across consumers induced by the social sharing of information, and its steady-state behavior can be analyzed to compute the firms’ long-run aggregate demand characteristics and rate of convergence. We benchmark the results of this model against those from rational Bayesian learning models with and without social information and a myopic win-stay-lose-shift model.

Our results show that different types of social information have significantly different effects on consumer choice and outcomes for competing firms, and moreover, their effects vary with the quality gap between the firms. Most importantly, we observe significant differences in the long-run market shares of the firms across quality-SI, share-SI, and full-SI and the differences in service quality between the firms. Compared to the case without any social information, when there is a large difference in service quality between the firms, the firm with the higher service quality achieves a 22% increase in market share, from 70.7% to 86.2%, by promoting quality-SI, but obtains a smaller increase in market share from share-SI. In fact, its market share under quality-SI is similar to that
under a Bayesian benchmark. This finding suggests that social information can act as a substitute for more complex optimal decision-making rules in practice. Alternatively, when there is a small difference in service quality, then the firm with (marginally) higher quality actually experiences no benefit from promoting quality-SI relative to when there is no social information, but benefits from a 6.4% increase in market share from share-SI from 56.4% to 60.0%. When participants are provided with both types of SI, our evidence shows that the benefit of one type of SI is crowded out by the presence of the other type of SI. Thus, full-SI yields market shares that are in between those from quality-SI and share-SI under both large and small gap treatments.

Our experimental data indicate that the contrasting effects of quality-SI and share-SI extend to other demand characteristics, such as demand uncertainty and rate of convergence to steady state. For example, when there is a large difference in service quality between the firms, quality-SI not only increases the higher quality firm’s market share, but also leads to the lowest demand uncertainty and fastest convergence to steady state. This result does not carry over when there is marginal difference in service quality between the firms. On the other hand, share-SI reduces demand uncertainty due to herding in later periods regardless of the service quality levels. There is a growing literature on tools that firms can use to manage their social information. The results of our paper can help practitioners decide which social information to promote in order to increase market share and reduce demand uncertainty. In particular, a significantly higher quality firm can increase its market share by promoting quality-SI. In contrast, a marginally higher quality firm can increase its market share by promoting share-SI.

To our knowledge, this is the first behavioral operations paper to study social information using a human-subject experiment. It contributes to the operations literature on social information in a few ways. First, our controlled experiment permits us to tease out the effects of two common, but different, types of social information as well as own learning on consumers’ choices. Second, we propose an estimation model of individual-level learning that can be used to explain the mechanisms for the effect of social information on both one-period-ahead and long-run demand. Although we limit this paper to two types of social information, our model can easily be expanded to incorporate a larger dimensionality of information.

2. Related Literature and Hypothesis Development

Our paper is related to the rich literature on consumer learning through one’s own choices, observational learning, belief formation through social information, herding, and implications of social information on managerial decisions. We motivate our hypotheses from this literature.
First consider how individuals learn based on their own decisions. While the literature in this research field is relatively vast (see Erev and Haruvy (2017) for a summary), the papers by Gans et al. (2007), Gaur and Park (2007), and DeCroix et al. (2019) are especially relevant to our study. Specifically, Gans et al. (2007) compare alternative learning heuristics in a bandit experiment with human decision-makers. They show that consumers learn from their own past choices, and that relatively simple heuristics such as exponential smoothing perform well in explaining consumers’ choices. Importantly, many of the favorable models incorporate features which coincide with a consumer’s limited memory or recency bias. Gaur and Park (2007) study this problem theoretically when consumers learn from their past experiences using exponential smoothing. DeCroix et al. (2019) study a theoretical model of own learning with exponential smoothing focused on quality variability and dynamic pricing for a monopoly firm. Given that we investigate a similar setting, we posit that consumers will learn based on their own service outcomes but will also exhibit a recency bias. This motivates our first hypothesis:

**Hypothesis 1 (Own Learning).** Consumers will demonstrate learning and recency bias with respect to own experiences irrespective of the presence of social information.

Consumer learning from social information has also been studied from various perspectives. One form of social information is *observational learning*, in which consumers observe the choices of those who came before them either individually or in the aggregate. The seminal works of Bikhchandani et al. (1992) and Banerjee (1992) present important results on herding and information cascades in observational learning, wherein consumers, arriving sequentially, are perfect Bayesian decision makers, yet they (i) disregard their own private signal and simply follow the herd, and (ii) there is a non-zero probability of herding on the wrong action. Both these results have been extensively tested in the subsequent literature. Smith and Sorensen (2000) relax the assumption of bounded private beliefs, and show that there is asymptotic convergence to the correct action when beliefs are unbounded. Ellison and Fudenberg (1995) study a different twist by considering a repeated word-of-mouth interaction among players who use naive decision rules, and show that a superior outcome is obtained. Banerjee and Fudenberg (2004) allow a continuum of agents with proportional sampling, and show that asymptotic learning (i.e., convergence to the highest pay-off action, as against herding) is achieved. Acemoglu et al. (2011) examine the effects of unbounded beliefs and network structure on asymptotic learning. Acemoglu et al. (2014) further endogenize the network structure and allow agents to procure costly information, characterizing the roles of hubs, connectors, and information mavens.
In operations management, many papers have investigated the effect of social information on consumer learning, markets, and operational decisions. Ifrach et al. (2019) examine asymptotic learning and optimal dynamic pricing by a monopoly seller in a market where consumers post online reviews of their experiences and observe the *experiences* of previous consumers rather than just their *actions*. Starting with a similar model, Besbes and Scarsini (2018) allow quality to be arbitrary rather than binary and consider two types of information usage—a fully Bayesian customer and a boundedly rational customer who only observes the first moment of previous reviews. Using behavioral experiments, Kremer and Debo (2015) investigate whether the number of consumers in a queue can act as a signal of quality for a firm, Jin et al. (2017) study observational learning from majority wisdom and minority wisdom when consumers are uncertain about quality, and Çelen and Hyndman (2012) test a theory of social learning through endogenous information acquisition in experiments where subjects can observe others’ decisions by forming links at a cost.

Thus, the implications of social information have been studied in the literature from both normative and behavioral perspectives. Our paper adds to this literature by asking how consumers integrate different kinds of social information with their own experience in a behavioral repeated-interaction setting. Researchers have recently begun to examine the belief ‘evolution’ of consumers through *both* own and social learning, in particular, Allon and Zhang (2017) and DeCroix et al. (2019). The former study a model where the consumer takes a weighted average of her friends’ service quality outcomes and forms a new belief as a linear combination of her past belief and influence from her social network. The latter focus on own learning in a similar model structure, but also investigate the implications of social information as well. Whereas Allon and Zhang (2017) focus on deriving the optimal service differentiation strategy under this behavior, we focus on empirically characterizing decision rules used by consumers and their implications for firms. This literature on observational and social learning leads to our second hypothesis on social learning. Together, Hypotheses 1 & 2 enable us to characterize individual-level consumer learning and choice. (We note that the literature on herding suggests that Hypothesis 1 may not be supported under social learning. Moreover, convergence of beliefs suggests that both Hypotheses 1 & 2 would lose support as the number of time periods increases. We examine these aspects in our analysis.)

**Hypothesis 2 (Social Learning).** *In addition to learning from own experiences, consumers respond to social information and demonstrate social learning.*

Third, we consider the distribution of demand under social learning. The value of social information for markets has been empirically studied in economics, marketing, operations, and finance.
Different studies in these domains have investigated the effect of social information on book sales, television shows, movie selections, Facebook fan pages, and sales at Amazon.com (Godes and Mayzlin 2004, Chevalier and Mayzlin 2006, Liu 2006, Goh et al. 2013, Chen and Xie 2008). Other research papers have analyzed the characteristics and implications of online reviews, ratings, and ranking systems (see, for example, Ghose et al. (2012) and Dellarocas (2003)). Among them, Goh et al. (2013) show that engagement in social media communities leads to an increase in purchase expenditures, with user-generated social information exhibiting a stronger impact than marketer-generated content. Chen et al. (2011) use a natural experiment at Amazon.com to study the comparative effects of two kinds of social information—word-of-mouth (online reviews) and observational learning (purchase decisions)—on product sales. They show that consumers’ purchase decisions can be influenced differently by others’ opinions and others’ actions. Lee et al. (2015) differentiate the effect of social information between friends and other crowds, and show that a friends’ rating always induces herding unlike others.

In the theoretical literature, many applications of social information for firm-level decisions have emerged, including stocking policies (Hu et al. 2016), design of quality attributes (Zhang et al. 2015), demand forecasting (Cui et al. 2018), healthcare offerings (Xu et al. 2017), pricing (Papanastasiou and Savva 2016), the design of new experience products (Feldman et al. 2019), and targeted marketing of exclusive luxury products (Momot et al. 2016). These applications are predicated on consumer response to social information.

This literature on the value of social information leads us to our third hypothesis that social information benefits the higher-quality firm relative to the lower quality firm in terms of demand characteristics and convergence.

**Hypothesis 3 (Demand).** Comparing the marketplace under social information with the marketplace without social information, the firm with the higher average service quality rate

(i) realizes a higher market share,
(ii) realizes a lower variance of demand, and
(iii) has a faster rate of convergence of its market share to the steady state value.

The rationale for the third hypothesis is as follows. Hypothesis 1 (Own Learning) posits that consumers will learn from their own experience and outcomes. Further, Hypothesis 2 (Social Learning) conjectures that when exposed to social information, consumers will utilize the increased availability of information. If we expect both types of social information, share-SI and quality-SI, to be positively correlated with the true quality of the firms, consumers exposed to social information
will learn at a faster rate as to which firm has a higher average service quality. This will likely lead to a higher market share for the better firm, lower variance of demand, and faster convergence to steady state. However, it is worth noting that not all of the existing literature is consistent with this. For instance, the literature on herding suggests that convergence to the inferior outcome may occur, that sharing of information among a limited number of agents is better than full information, and that observational learning may result in higher demand uncertainty (Jin et al. 2017).

In our fourth hypothesis, we distinguish between alternative types of social information: quality-SI and share-SI. The former represents the fraction of people in a network who received a satisfactory experience (in the last visit decision), whereas the latter represents the fraction of people in a network who visited each firm (in the last visit decision). Beginning with quality-SI, this type of SI is generated from other consumers’ actual service outcomes. In other words, it is likely to play an informative role to consumers when updating their beliefs, as in Allon and Zhang (2017). In contrast, share-SI measures the choices but not the experiences of others in one’s social network. Thus, from a Bayesian perspective, we expect quality-SI to benefit the higher-quality firm more than share-SI.

This reasoning is supported by the literature. Specifically, when share-SI is available, it allows people to observe the visit decisions of others. As such, herding may occur. In order for this to be rational, observers must make correct attributional inferences about the behaviors they observe (called rational herding (Simonsohn and Ariely 2008)), and if the observed decisions reveal valuable information, it may be optimal for observers to imitate others (Banerjee 1992, Bikhchandani et al. 1992). However, when observing the earlier choices of others, consumers often misinterpret the causality of others’ choices (irrational herding). For example, Simonsohn and Ariely (2008) and Zhang (2010) show that drawing quality inference from the preceding choices of others may lead to a systematic bias since irrational herding generates correlation in visits. Zhang and Liu (2012) also distinguish between rational and irrational herding and show that the results of the herding momentum can vary in loan markets. If only share-SI is provided in our setting, a subject may not be able to infer whether the other consumers’ visit decisions are due to an exploration of a new firm or due to an exploitation of their private signals, especially in early periods. Therefore, we hypothesize that the informativeness of quality-SI is superior to share-SI, and posit the following hypothesis:

1 In reality, social information can be biased due to the self-selection process of consumers, e.g., extremely negative/positive opinions more often are expressed or shared than moderate opinions. In our controlled lab experiment, we rule out this potential of bias by collecting and reporting the information to participants directly.
Hypothesis 4 (SI Type). The firm with higher average service quality will have more favorable demand characteristics, i.e., higher market share, lower variance of demand, and faster rate of convergence to steady state, under quality-based social information than under market share-based social information.

Finally, in addition to exploring how different types of SI affect consumers and firms’ demand characteristics, we investigate how consumers and firms are impacted when both types of SI are presented simultaneously. In this situation, a rational consumer can use the perfect information on visits and experiences of others and update her beliefs on the firms’ true average service quality levels. Therefore, we hypothesize that compared to the cases where consumers have access to only one type of SI, participants can update their estimate of service quality faster and more accurately when they receive both quality- and share-SI. This gives our fifth hypothesis:

Hypothesis 5 (Full-SI). The firm with higher average service quality will have more favorable demand characteristics when both types of SI are present than when only one type of SI is present.

Some additional comments are in order for Hypothesis 5. Although it is clear that rational consumers will benefit from having both types of SI available, there are reasons that this may not be true with human decision makers. For instance, many research papers in the literature suggest that consumers are susceptible to information overload. Specifically, a consumer benefits from additional information up to a certain point, but as the available information increases beyond this point it may negatively affect their decisions. Schroder et al. (1967) were the first to refer to the relationship between information and decision accuracy as an inverted U-curve (see Eppler and Mengis (2004) and Edmunds and Morris (2000) for a review of the literature on information overload). Further, when people face multiple source of information, they may not be able to utilize all information due to limited attention (Kahneman 1973). Even though our experiment contains only two types of SI, this may still be relevant to our setting because when the two types of SI are conflicting with one another, consumers receive mixed signals and the benefits of one type of SI may effectively be cancelled or crowded out by the other type. Thus, our test of Hypothesis 5 will show if more social information is indeed beneficial, or if one of these behavioral biases generates a different outcome.

3. Experimental Design

We use a controlled laboratory experiment to test our hypotheses. This approach is attractive as it gives us a clean set up where we can control the types of information revealed to each participant.
It also enables us to collect a complete panel of the visit choices made by individuals and the outcomes of those visits for all time periods and firms. Each participant in the experiment plays the role of a consumer choosing from two firms (or stores) competing through their service quality. In each round, after a participant chooses to visit a store, the computer returns either Satisfaction or Dissatisfaction from the chosen store, generated by a Bernoulli distribution, where the mean service quality levels of each firm, \( q_1 \) and \( q_2 \), are unknown to the consumer.

The experiment follows a 2×4 between-subjects design, given by two different quality competition settings and four information settings. For the quality competition settings, we use two different sets of mean service levels \((q_1, q_2) = (0.8, 0.5)\) which we refer to as a large-gap competition condition and \((q_1, q_2) = (0.55, 0.5)\), referred to as a small-gap competition condition. To validate the experiment design, we conducted a simulation study and verified that a Bayesian learner will be able to statistically identify the higher quality firm in both large-gap and small-gap treatments in 40 periods. Further, we wanted the small quality-gap to be sufficient to be distinguished by Bayesian learners but small enough to provide a contrast to large-gap. Gans et al. (2007) use similar quality gaps but with lower average service levels of \((0.15, 0.40)\), \((0.40, 0.40)\), \((0.40, 0.65)\). We instead set the service quality of each firm as 0.5 or higher to be more representative of practical scenarios.

To investigate the effect of different types of SI, we use four settings: (1) a control treatment with no SI (2) a share-based SI treatment, (3) a quality-based SI treatment, and (4) a full SI treatment. In the share-SI treatment, in each period, we provide participants with the percentage of visitors to each firm as additional feedback, e.g., “For this period, 25% of your acquaintances visited store A, and 75% of your acquaintances visited store B.” In the quality-SI treatment, in each period, we display the satisfaction rate of consumers for each firm, e.g., “For this period, 67% of your acquaintances who visited store A experienced satisfaction, and 20% of your acquaintances who visited store B experienced satisfaction.” In the full-SI treatment, we provide both share-SI and quality-SI. Table 1 illustrates our experimental design and number of participants. Each session of the experiment consists of 18 participants. We conducted three sessions each for the first six treatments and two sessions each for the full-SI treatments.

We create social networks for the SI treatments by randomly placing the participants in each session of the experiment into two disjoint groups of nine in each period. In this way, the social

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2 We note two nuances in the experiment design: (i) If no participant visited a store, then quality-based SI would reveal both quality and market-share information in that period, e.g., “For this period, none of your acquaintances visited store A, and 20% of your acquaintances who visited store B experienced satisfaction.” (ii) It is sometimes possible to infer the number of acquaintances who visited each store from the values of the satisfaction percentages. Our results presented in Section 5 are not affected by these nuances.
network is randomized in each period. Then, after each round, all of the decisions are collected from the eight other people in a participant’s group and used to generate the SI presented to that participant. Thus, each participant is presented with not only her own service encounter but also certain SI regarding eight other participants. In doing so, we use the real-time information of the actual participants’ choices/experiences instead of using pre-generated outcomes to better capture the true dynamic process of SI generation and market evolution in practice. We inform participants that all feedback provided, including the information on others’ visits and experiences, is generated from their actual choices and real-time experiences in the laboratory.

In each treatment, a participant’s task is to choose either store A or B on the computer screen in each time period. This decision task is conducted for 40 periods. The arrangement of displaying high- and low-quality store as store A or B on screen is randomized across participants (which is unknown to them). For the duration of the experiment, participants can observe their history of choices, outcomes, and SI, when applicable.

Participants in our experiment were recruited from a university located in the northeast U.S. The average total compensation was approximately $20 per participant. Each time a participant received satisfaction from her visit choice, one point was given, corresponding to $0.50. These earnings were totaled across the 40 rounds and added to a $5 participation fee. Each session lasted about 40 minutes, and the software was programmed using the z-Tree system (Fischbacher 2007). Instructions and screenshots are available upon request.

The key features of this experiment are consistent with the literature. Although quality outcomes in practice are continuous and multi-faceted, it is an open question as to how consumers assimilate and learn about quality in repeated games. Thus, a variety of models are used in the literature. Quality outcomes are modeled as binary in many papers on own learning and social learning (Acemoglu et al. 2011, Banerjee 1992, Gans et al. 2007, Gaur and Park 2007, Ifrach et al. 2019); others model quality as continuous (Besbes and Scarsini 2018, DeCroix et al. 2019). Firms are modeled as monopoly (Allon and Zhang 2017, Ifrach et al. 2019, DeCroix et al. 2019) or duopoly (Gans et al. 2007, Gaur and Park 2007). We vary the quality gap between firms and randomize the social

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<th>Service Competition</th>
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<td>Share-SI</td>
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network in each period similar to the theoretical model in Ellison and Fudenberg (1995). Finally, our participants see aggregate market-share and/or quality information from the experiences of others in their social network similar to Besbes and Scarsini (2018) and Allon and Zhang (2017), who study the sharing of aggregate statistics of experiences in social networks.

4. Model

In general, the consumer’s optimal strategy in this experiment is the solution to a two-armed bandit problem. However, in practice, consumers may use analytically tractable decision rules that are simple functions of the information available to them. Several articles in the literature have modeled consumers as using exponential smoothing to estimate the service level of each firm (Gans et al. 2007, Gaur and Park 2007, Allon and Zhang 2017, DeCroix et al. 2019). With a similar motivation, we represent a consumer’s learning and choice behavior as a Markov chain in which the states represent the consumer’s belief about which firm is better and transitions are functions of the state, the visit choice, and outcomes. This model shares characteristics with exponential smoothing. Whereas in exponential smoothing, the model specifies a rule for updating the consumer’s estimate of service level, our model gives a rule for updating the probability distribution of the consumer’s beliefs over the states of the Markov chain. From a theoretical perspective, the consumer’s beliefs about quality are latent (unobserved) variables in both models because neither the exponentially smoothed series nor the state of the Markov chain are revealed to the firm or the researcher. However, since our model explicitly specifies the probability distribution of beliefs, it is easy to estimate and allows us to incorporate correlations across consumers induced by social information.

4.1. Model Description

We consider a fixed population of $N$ identical consumers choosing between two firms, $s \in \{1, 2\}$, in discrete time periods, $t = \{1, \ldots, \infty\}$. The firms are price-takers and identical in all respects except their service quality. Let $q_s \in (0, 1)$ denote the true average service quality of firm $s$. When a consumer visits firm $s$, her experience is measured as a binary outcome of either satisfaction (1), or dissatisfaction (0) realized from $\text{Bernoulli}(q_s)$.

We assume that: (1) The average service quality of firm 1 is higher than that of firm 2 ($q_1 > q_2$) without loss of generality. We use ‘firm’ and ‘store’ interchangeably throughout the paper. (2) Consumers do not know the true average service qualities of the firms. Instead, they decide which firm to visit in each time period by forming beliefs based on prior experiences and SI. (3) Consumers are ex-ante identical. As time evolves, they become heterogeneous through differences in experiences and choices. (4) Consumers are not Bayesian decision-makers. In addition, they may suffer from recency bias when choosing which firm to visit.
Because consumers are ex-ante identical, we first consider the choice behavior of a single consumer and omit the corresponding index. Let \( V_{it} = 1 \) if the consumer visits firm \( i \) at time \( t \) and 0 otherwise. Each consumer must visit only one of the two firms in each period, thus, \( V_{it} = \nabla_{2t} \). Also let \( Y_{it} \) denote the most recent service outcome experienced by the consumer from firm \( i \). If the consumer visited firm 1 at \( t - 1 \) and was satisfied, then \( Y_{1t} = 1 \); if she visited firm 1 at \( t - 1 \) and was dissatisfied, \( Y_{1t} = 0 \); and if she did not visit firm 1 at \( t - 1 \), \( Y_{1t} = Y_{1,t-1} \). Thus, the values of \( V_{it} \) and \( Y_{it} \) represent the data collected from the experiment regarding the choices made and the service outcomes experienced by the consumer from both firms.

4.1.1. Belief Formation: We model the consumer’s belief at the beginning of each period as a categorical state variable. We call the consumer’s belief state as the (G)ood state if she believes that firm 1 has better quality, i.e., if her belief is in line with the true average service levels of the firms. If instead the consumer believes that firm 2 has better quality, we call this belief as the (B)ad state. Let \( A_t \in \{G, B\} \) denote the consumer’s belief state at the start of period \( t \).

Belief formation takes place in our model by updating the consumer’s probability distribution over \( A_t \) as a function of experiences and revealed information. Let \( P = [p_{GG}, p_{GB}, p_{BG}, p_{BB}] \) denote the matrix of transition probabilities from the belief states in one time period to the next. Here, \( p_{GB} \in [0,1] \) denotes the probability of a consumer changing her belief from \( A_t = G \) to \( A_t = B \), i.e., (G)ood to (B)ad for firm 1, and so on. We assume that at the start of the experiment, the consumer has equal probability of being in either state. Subsequent state transitions will be functions of visit decisions, own experience, and social information. Thus, as the experiment progresses, the consumer’s probability of being in state \( G \) or \( B \) captures the strength of her belief about the relative quality levels of the two firms. For this, we construct \( P \) as a weighted sum of three matrices, \( P_o, P_m, \) and \( P_q \), which specify the switching of beliefs via a consumer’s (o)wn experience, (m)arket share SI, and (q)uality SI, respectively.

\[
P = \begin{bmatrix} p_{GG} & p_{GB} \\ p_{BG} & p_{BB} \end{bmatrix} = (1 - \beta_m - \beta_q) \cdot P_o + \beta_m \cdot P_m + \beta_q \cdot P_q.
\] (1)

Here, \( \beta_m, \beta_q, 1 - \beta_m - \beta_q \in [0,1] \) capture the weights on the two types of SI and the weight on the consumer’s own experience in forming her belief. Allon and Zhang (2017) use a similar linear rule, but applied to a numeric value of the belief rather than a probability structure.

We first describe the belief update mechanism based on the consumer’s own observations. We say that if the consumer’s experience at time \( t \) does not align with her belief, then she changes her belief with a leakage probability \( h \in (0,1) \), otherwise her belief remains unchanged. For example, if the consumer is in state \( G \), then she moves to state \( B \) with probability \( h \) if she visits firm 1 and is
dissatisfied, or if she visits firm 2 and is satisfied. Collecting all the possibilities, mathematically, we get the complete definition of \( P_o \) as

\[
P_o = \begin{bmatrix}
1 - h(V_{1t}Y_{1t} + V_{2t}Y_{2t}) & h(V_{1t}Y_{1t} + V_{2t}Y_{2t}) \\
h(V_{1t}Y_{1t} + V_{2t}Y_{2t}) & 1 - h(V_{1t}Y_{1t} + V_{2t}Y_{2t})
\end{bmatrix}.
\]  

(2)

Here, \( V_{1t}Y_{1t} + V_{2t}Y_{2t} \) gives the events when the consumer visits firm 1 and is dissatisfied or visits firm 2 and is satisfied. The other events are defined similarly. We define \( h \) as the consumer’s own-learning propensity.

Example 1: This belief update mechanism is similar to exponential smoothing with parameter \( h \). To see this, suppose the consumer starts in any of the two states \( G \) or \( B \) at a given time and has a series of satisfactory visits to firm 1. Then, \( V_{1t} = 1, V_{2t} = 0 \), and \( Y_{1t} = 1 \) in the subsequent time periods \( t \). Using this and the definition (2), her state in each subsequent period can be computed using the powers of the transition matrix as follows:

\[
P_o^1 = \begin{bmatrix} 1 & 0 \\ h & 1 - h \end{bmatrix}, \quad P_o^2 = \begin{bmatrix} 1 & 0 \\ h + h(1 - h) & (1 - h) \end{bmatrix}, \quad P_o^3 = \begin{bmatrix} 1 & 0 \\ h + h(1 - h) + h(1 - h)^2 & (1 - h)^3 \end{bmatrix}, 
\]

According to these probabilities, if the consumer was in state \( G \) at the beginning, then she stays in state \( G \) with probability 1, whereas if she was in state \( B \) at the beginning, then her probability of staying in state \( B \) diminishes exponentially and her probability of transitioning to state \( G \) increases with each successful experience. In this way, recent experiences are weighted more heavily than older experiences when determining the consumer’s probability of being in each state.

4.1.2. Social Information: We define \( P_m \) and \( P_q \) analogous to \( P_o \). Let \( g_m \in (0,1) \) denote the consumer’s social learning propensity from market share-SI. Belief formation in share-SI occurs as follows: if the consumer is in state \( G \) at the start of a period and the observed market share of firm 2 in her social network in that period is higher than that of firm 1, then the consumer stays in state \( G \) with probability \( 1 - g_m \) and transitions to state \( B \) with probability \( g_m \). In this case, we say that share-SI favors firm 2 in that period. On the other hand, if share-SI favors firm 1, then the consumer stays in state \( G \). If the realized market shares of both firms are identical, then the consumer changes state with probability \( 0.5g_m \). The transitions from state \( B \) are symmetric, and this gives us the matrix \( P_m \). Likewise, let \( g_q \in (0,1) \) denote the consumer’s social learning propensity from quality-SI. The definition of \( P_q \) follows in the same manner as for \( P_m \), but using quality-SI.
Example 2: In the previous example, we illustrated $P_o$ when a consumer has satisfactory visits to firm 1. Additionally, suppose this consumer receives both share-SI and quality-SI favoring firm 2. Then, the transition matrix for the consumer corresponding to this social information is given by:

\[ P_m = \begin{bmatrix} 1 - g_m & g_m \\ 0 & 1 \end{bmatrix}, \quad P_q = \begin{bmatrix} 1 - g_q & g_q \\ 0 & 1 \end{bmatrix}, \quad \text{and} \quad P = (1 - \beta_m - \beta_q)P_o + \beta_m P_m + \beta_q P_q. \]

4.1.3. Visit Decisions: We now describe how the consumer decides which store to visit as a function of her beliefs and the information at her disposal. Previous research in sequential learning shows that human decision makers are prone to recency bias, and may place extra weight on their most recent experience compared to earlier outcomes (Kremer et al. 2011, Meyer and Shi 1995). Evidence also indicates that outcomes, prior to the most recent, have a relatively equal impact on future choices (Erev and Roth 1998, Nevo and Erev 2012). Therefore, we allow a consumer to associate a higher weight with her most recent experiences given her overall belief.

Let $R_t = Y_{1t} - Y_{2t} + 1 \in \{0, 0.5, 1\}$ combine the recency variables $Y_{1t}$ and $Y_{2t}$ to represent ‘which firm is better’ from the most recent service encounter. By this definition, $R_t = 1$ if $Y_{1t} > Y_{2t}$, $R_t = 0$ if $Y_{1t} < Y_{2t}$, and $R_t = 0.5$ if $Y_{1t} = Y_{2t}$. We model the consumer’s probability of visiting firm 1 in time period $t$ given current state $(A_t, Y_{1t}, Y_{2t})$ as:

\[
Pr(V_{1t} = 1 \mid A_t, Y_{1t}, Y_{2t}) \equiv (1 - \alpha) \cdot I(A_t = G) + \alpha \cdot R_t,
\]

where $I(x)$ equals 1 if $x$ is true and 0 otherwise, and $\alpha \in [0, 1]$ measures the extent of recency bias. If $\alpha = 0$, the consumer’s visit decision is driven purely by her overall belief (that is updated through own and social learning), if $\alpha = 1$, the choice is purely myopic, and if $0 < \alpha < 1$, the consumer is influenced by her overall belief, yet exhibits recency bias at the same time.

In summary, the consumer’s beliefs at the start of any time period $t$ are given by a probability distribution over the states $S_t = (A_t, Y_{1t}, Y_{2t})$ where $A_t$ is a latent variable; and the visit choices, outcomes and social information from other consumers determine the transition matrix from one period to the next. This Markov chain is irreducible, aperiodic, and recurrent on a finite state space, thus it converges to a stationary distribution. Figure 1 shows the decision process and learning for one consumer, which is affected by a two-fold memory structure with (1) an (unobserved) overall belief formed by past experiences up to time $t$, and (2) the most recent experience (observed) from a consumer’s visit to each firm. For instance, consider the transition probability from $(G, 1, 0)$ to $(B, 1, 1)$. In order for this transition to occur, the consumer must choose to visit firm 2 and experience satisfaction. Further, the consumer, who previously believed that firm 1 had better
quality, changes her belief from $G$ to $B$ with probability $h$. Combining these steps of the decision process gives us the transition probability $Pr(V_2 = 1 \mid (G, 1, 0)) \cdot q_2 \cdot h$.

Our model has six parameters: the recency bias $\alpha$, the weights on share-SI and quality-SI $\beta_m$ and $\beta_q$, and the learning propensities from own, share-SI, and quality-SI, $h, g_m$, and $g_q$, respectively. We estimate these parameters to test Hypotheses 1 and 2, and then compute the aggregate characteristics of demand to test Hypotheses 3-5.

It is important to note that when learning takes place from own experiences only, then the belief states of consumers in this model are independent of each other. However, the introduction of social information in the repeated experiment induces dependencies across consumers, so that the state of the system must now be represented as a Cartesian product of the states of all consumers in the social network. If there are $n$ consumers, then a complete specification of the system has $8^n$ states. Thus, to estimate the model, we will compute a joint likelihood of the observed sample path of all participants in a session, then maximize the likelihood with respect to the model parameters.

4.2. Estimation and Benchmarks
As noted above, we estimate the parameters of the model using maximum likelihood estimation (MLE). We also compare the demand characteristics of participants in the experiment against three benchmarks: a no-SI Bayesian model based on learning from own experiences alone, a full-SI Bayesian model based on learning from own experiences and full-SI, and a myopic Win-Stay-Lose-Shift (WSLS) model. We compute the benchmarks on the same data set as used in the experiment. Note that this is possible because the entire set of sample paths of probabilistic outcomes was generated prior to the experiment. Thus, for this purpose, we simulate the decisions of consumers under each benchmarking model for the same random service outcomes that were used in our experiment, and then evaluate demand characteristics. These three benchmarks allow us to determine where human consumers’ choices fall relative to normative predictions. In particular, WSLS
consumers represent one extreme by being fully myopic and only responding to the most recent experience; Gans et al. (2007) call this the Last-1 model. Bayesian learners (Behrens et al. 2007, Gelman et al. 2013) with full-SI represent the other extreme because they utilize all previous own and others’ experiences, with equal weights and without bias, to update their beliefs.

We describe the MLE estimation procedure in Appendix A and the benchmark models in Appendix C.

5. Results

In this section we report our experimental results. We begin by discussing the behavioral parameters of our model in Section 5.1. We then summarize the aggregate-level demand characteristics in Section 5.2 and investigate the behavioral dynamics behind those results in Section 5.3. All hypotheses tests are two-sided t-tests.

It is important to note that our results characterize how consumers combine different types of own and social information and the resulting effect on the firms’ demand distributions, but do not delve into why consumers interpret different types of information in different ways. We provide plausible explanations where possible, and leave a full investigation of consumer behavior with respect to social information for future research.

5.1. Differences in Learning: Parameter Estimation

Tables 2 and 3 present the estimation results of our behavioral model for the large-gap and small-gap settings. We estimated parameters using the entire data set as well as using data for different sub-periods because the rate of learning varies over time and this additional analysis helps us better understand learning in early periods. Thus, we report parameters estimated using periods 1-15 and 1-40; results from periods 1-20 and 1-25 are similar to those from 1-15.

From the first two rows of Tables 2 and 3, we find that nearly all of the estimates for recency ($\alpha$) and own-learning propensity ($h$) are positive and significant. The estimate of $\alpha$, when significant, varies between 0.02 and 0.38, showing that participants place this weight on their most recent experience and the remaining weight of 0.62-0.98 on their latent beliefs $A_t$ in the visit choice Equation (3). Moreover, the weight on recency generally declines with quality-SI and full-SI compared to the no-SI control treatment, and in fact, is zero under full-SI with large-gap competition (in the last column of Table 2). This reduction in bias shows a benefit of social information. The estimate of $h$ is significant in all cases regardless of SI treatment, ranging between 0.11 and 0.48. This means that when forming their beliefs from own experience, participants give a weight of 0.11-0.48 to the most recent experience and the remaining weight of 0.51-0.89 to accumulated past experience. Note
that values of $h$ close to 1 would be indicative of a WSLS model in which participants ignore earlier experiences, whereas values of $h$ close to zero would imply that own experience is not informative. Our estimates largely support Hypothesis 1—consumers display a recency bias in their choices but also learn from their own past experiences.

Turning to social information, we find that the social-learning propensity parameters ($g_m$ and $g_q$) and weights on share-SI and quality-SI ($\beta_m$ and $\beta_q$) are almost all positive and significant. Consider the example of share-SI under large quality gap. The estimates imply that participants give a weight of $\beta_m = 0.24$ to share-SI and the remaining weight of $1 - \beta_m = 0.76$ to own beliefs. Moreover, the estimate of $g_m = 0.23$ shows that when they update their beliefs of share-SI, they give a weight of 0.23 to the most recent information and 0.77 to accumulated information. Altogether, the value of $g_m$ ranges between 0.03 and 0.32 when significant, $\beta_m$ ranges between 0.02 and 0.41, $g_q$ between 0.06 and 0.52, and $\beta_q$ between 0.23 and 0.68. A combination of these results largely supports Hypothesis 2—consumers display social learning propensity and place positive weight on SI when it is available. Thus, consumers utilize both types of social information, whether quality or share, along with their own experience for learning and choice.

It is insightful to compare the estimates of $\beta_m$ and $\beta_q$ across treatments. Consider again large-gap estimates from 1-40 periods. Under share-SI, consumers give a weight of 0.24 to social information (since $\beta_m = 0.24$) and 0.76 to own experience in forming the latent beliefs $A_t$. Under quality-SI, the weights on social information and own experience are divided equally as 0.5 each. Under full-SI, $\beta_m$ and $\beta_q$ add up to 0.41, showing a weight of 0.41 on social information and of 0.59 on own

---

**Table 2** Parameter estimates in the large-gap treatments

<table>
<thead>
<tr>
<th>Large-gap Parameter</th>
<th>Description</th>
<th>(No-SI)</th>
<th>Share-SI</th>
<th>Quality-SI</th>
<th>Full-SI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Period</td>
<td>All</td>
<td>Period</td>
<td>All</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1-15</td>
<td>1-40</td>
<td>1-15</td>
<td>1-40</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Weight on recency bias</td>
<td>0.10</td>
<td>0.31***</td>
<td>0.15**</td>
<td>0.23***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.069)</td>
<td>(0.037)</td>
<td>(0.055)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>$h$</td>
<td>Own-learning propensity</td>
<td>0.27***</td>
<td>0.16***</td>
<td>0.34***</td>
<td>0.18***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.029)</td>
<td>(0.017)</td>
<td>(0.036)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>$\beta_m$</td>
<td>Weight on share-SI</td>
<td>0.37**</td>
<td>0.24***</td>
<td>0.18**</td>
<td>0.23***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.084)</td>
<td>(0.038)</td>
<td>(0.057)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>$g_m$</td>
<td>Learning propensity from share-SI</td>
<td>0.20***</td>
<td>0.23***</td>
<td>0.20***</td>
<td>0.26***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.037)</td>
<td>(0.033)</td>
<td>(0.037)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>$\beta_q$</td>
<td>Weight on quality-SI</td>
<td>0.20***</td>
<td>0.23***</td>
<td>0.20***</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.037)</td>
<td>(0.033)</td>
<td>(0.037)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>$g_q$</td>
<td>Learning propensity from quality-SI</td>
<td>0.20***</td>
<td>0.23***</td>
<td>0.20***</td>
<td>0.52***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.037)</td>
<td>(0.033)</td>
<td>(0.037)</td>
<td>(0.033)</td>
</tr>
</tbody>
</table>

Note: Standard errors from inverse Hessian matrix are in parentheses. *** $p<0.01$, ** $p<0.05$, and * $p<0.10$. 

---


experience. Thus, it is interesting to observe that consumers weigh social information the most when quality-SI is presented, the least when share-SI is presented, and in between when both types of social information are presented. This pattern changes slightly under small gap. In a normative model, we would expect a consumer provided with quality-SI or full-SI to give equal weight to own experience and social information, or to give a higher weight to social information since it is an aggregation of a larger number of data points, for any values of the quality levels of firms. Instead, we find that the weights placed by consumers on social information vary across the quality gap treatments. This is surprising. It shows that consumers’ usage of social information varies with the quality levels of firms. We see in the next section that this behavior has implications for the market shares of firms.

### Table 3 Parameter estimates in the small-gap treatments

<table>
<thead>
<tr>
<th>Small-gap Parameter</th>
<th>Description</th>
<th>(No-SI)</th>
<th>Share-SI</th>
<th>Quality-SI</th>
<th>Full-SI</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>Weight on recency bias</td>
<td>0.17**</td>
<td>0.26***</td>
<td>0.00</td>
<td>0.02***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.062)</td>
<td>(0.034)</td>
<td>(0.049)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( h )</td>
<td>Own-learning propensity</td>
<td>0.26***</td>
<td>0.14***</td>
<td>0.35***</td>
<td>0.26***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.033)</td>
<td>(0.015)</td>
<td>(0.035)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( \beta_m )</td>
<td>Weight on share-SI</td>
<td>0.00</td>
<td>0.22***</td>
<td>0.02***</td>
<td>0.40***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.143)</td>
<td>(0.043)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( g_m )</td>
<td>Learning propensity from share-SI</td>
<td>0.00</td>
<td>0.13**</td>
<td>0.03***</td>
<td>0.04***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.062)</td>
<td>(0.033)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( \beta_q )</td>
<td>Weight on quality-SI</td>
<td>0.59***</td>
<td>0.39***</td>
<td>0.49***</td>
<td>0.36***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.058)</td>
<td>(0.072)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>( g_q )</td>
<td>Learning propensity from quality-SI</td>
<td>0.08*</td>
<td>0.02</td>
<td>0.24***</td>
<td>0.06***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.031)</td>
<td>(0.022)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-485.73</td>
<td>-1300.2</td>
<td>-496.07</td>
<td>-1304.3</td>
<td>-521.54</td>
</tr>
</tbody>
</table>

Note: Standard errors from inverse Hessian matrix are in parentheses. *** \( p < 0.01 \), ** \( p < 0.05 \), and * \( p < 0.10 \).

It is also interesting that the weights on share-SI and quality-SI change in magnitude over time under full-SI. Specifically, the last two columns of Tables 2 and 3 illustrate that the impact of share-SI (\( \beta_m \)) becomes more salient over time, whereas the weight on the quality-SI (\( \beta_q \)) decreases over time, becoming zero under full-SI large-gap treatment. We discuss the individual-level behavioral dynamics that lead to this outcome in Section 5.3.1. Overall, this discussion and earlier observations lead to our first result:

**Result 1 (Own and Social Learning).** Consumers demonstrate own-learning propensity and social-learning propensity in all scenarios, except under full-SI when quality-SI parameters
become insignificant in later periods under large-gap competition. Their weight on social information varies across treatments. Moreover, they demonstrate moderate levels of recency bias in addition to the learning model.

5.2. Impact of Differences in Learning: Demand Characteristics

To understand how alternative types of SI ultimately impact firms, we now turn to demand characteristics: market share, demand uncertainty, and convergence speed.

5.2.1. Market Share Table 4 presents the average market share of the High-firm in each treatment along with the three benchmarks. It is calculated as the percentage of decisions in which participants chose to visit the High-firm in the observed data across periods 1-40. We also include the High-firm’s market share for periods 31-40 to illustrate results closer to steady state.

Table 4 Average market share of the High-firm in all periods and in the last ten periods

<table>
<thead>
<tr>
<th>Treatment</th>
<th>All Periods</th>
<th>Last 10 Periods</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Large-gap</td>
<td>Small-gap</td>
</tr>
<tr>
<td>(No-SI)</td>
<td>70.7%</td>
<td>56.4%</td>
</tr>
<tr>
<td></td>
<td>(1.1%)</td>
<td>(0.9%)</td>
</tr>
<tr>
<td>Share-SI</td>
<td>75.6%***</td>
<td>60.0%**</td>
</tr>
<tr>
<td></td>
<td>(1.5%)</td>
<td>(1.1%)</td>
</tr>
<tr>
<td>Quality-SI</td>
<td>86.2%***</td>
<td>55.8%</td>
</tr>
<tr>
<td></td>
<td>(1.3%)</td>
<td>(1.2%)</td>
</tr>
<tr>
<td>Full-SI</td>
<td>81.0%***</td>
<td>57.8%</td>
</tr>
<tr>
<td></td>
<td>(1.0%)</td>
<td>(1.3%)</td>
</tr>
<tr>
<td>Bayesian benchmark (with Full-SI)</td>
<td>97.6%</td>
<td>80.7%</td>
</tr>
<tr>
<td></td>
<td>(0.4%)</td>
<td>(1.0%)</td>
</tr>
<tr>
<td>Bayesian benchmark (with no-SI)</td>
<td>80.6%</td>
<td>63.3%</td>
</tr>
<tr>
<td></td>
<td>(1.0%)</td>
<td>(1.3%)</td>
</tr>
<tr>
<td>WSLS benchmark (with no-SI)</td>
<td>68.1%</td>
<td>51.8%</td>
</tr>
<tr>
<td></td>
<td>(1.2%)</td>
<td>(1.3%)</td>
</tr>
</tbody>
</table>

Note: *** p < 0.01, ** p < 0.05, * p < 0.10; t-tests comparing SI treatments to No-SI; Standard errors over time in parentheses.

First consider the average market shares across all periods. As seen in Table 4, the market share of the High-firm in the No-SI treatment falls between the predicted market shares for WSLS and Bayesian consumers in each column. More importantly, the market shares in the SI treatments are markedly different from one another. Beginning with large-gap competition, the average market share of the High-firm under quality-SI is even higher than the Bayesian prediction with no-SI (86.2\% versus 80.6\%). This suggests that quality-SI under large-gap competition enables consumers to make decisions much like rational (Bayesian) decision makers (without SI) and yields a significantly higher market share under large-gap competition compared to the control No-SI treatment.
Figure 2  Cumulative market share of the High-firm over time

(a) Large-gap

(b) Small-gap

Note: The plot shows the average of accumulated visits to High-firm from the second to the last period. Each point represents the average market share of High-firm up to a time period and treatment, and is computed across the choices made by all consumers in that period and treatment.

(86.2% versus 70.7%, $p < 0.01$). Share-SI under large-gap competition also results in a higher market share of the High-firm than the No-SI treatment (75.6% versus 70.7%, $p < 0.05$), but is inferior to quality-SI.

The relative ordering of share-SI and quality-SI flips under small-gap competition—share-SI results in a market share that is larger than the control treatment and is closer to the Bayesian benchmark with no-SI, whereas quality-SI results in a market share that is slightly worse than the control No-SI treatment. It is worth noting that if consumers were Bayesian, the relative ordering of quality- and share-SI should be the same in both quality gap treatments. Moreover, the average market share with quality-SI should be at least as high as the Bayesian no-SI benchmark in not only large-gap but also small-gap. Instead, we observe that the quality levels of the firms matter to the effectiveness of social information.

Another interesting result emerges under full-SI. Theoretically, more information should help consumers identify and visit the High-firm more frequently. However, the market share of the High-firm under full-SI falls between quality-SI and share-SI in both large-gap competition (81.0%) and small-gap competition (57.8%). We also find that this result persists over time for accumulated market share, as shown in Figure 2. We will discuss potential explanations for this difference in Section 5.3.2. Overall, the market share statistics support Hypothesis 3(i) except under small-gap competition for quality-SI. They support Hypothesis 4 under large-gap SI, but not under small-gap SI. Finally, they do not support Hypothesis 5. We state our summary observations as follows:

Result 2 (Market Share with Social Information). Under large-gap competition, all
three types of SI lead to significantly higher market share for the High-firm, with quality-SI achieving the highest. Under small-gap competition, share-SI leads to higher market share for the High-firm. Lastly, the market share of the High-firm under full-SI falls between the share-SI and quality-SI treatments.

5.2.2. Demand Uncertainty Our second firm level characteristic of interest pertains to the uncertainty of demand. Figure 3 illustrates our results for Hypothesis 3(ii) by plotting the standard deviation of demand over time for each treatment. Each point is computed across the choices made by all participants in a treatment in that particular time period. Note that if consumers have equal probability of choosing each firm, then the standard deviation would be \( \sqrt{0.5(1 - 0.5)} = 0.5; \) this gives an upper bound on all points. Beginning with large-gap competition in Figure 3(a), we find that all three SI treatments lead to statistically significant lower standard deviations compared to the No-SI treatment (all \( p < 0.01 \)). We also observe that quality-SI generates the greatest reduction in demand uncertainty compared to No-SI (the standard deviation is actually lower than the control treatment in 38/40 periods). Under small-gap competition, in Figure 3(b), the only significant difference is between share-SI and the No-SI treatment (\( p < 0.01 \)). Therefore, Hypothesis 3(ii), which states that the variance of demand will be reduced with SI, is supported for all SI types under large-gap competition, but only for share-SI under small-gap competition. We explain these findings further in Section 5.3.3 by examining the switching behavior and sojourn time of consumers.

5.2.3. Convergence Speed Our Markov chain model allows us to better understand how fast the consumers’ (hidden) belief state converges to its limit. In Table 5, we report three quantities:
the stationary distribution of the states \( \{G, B\} \), an upper bound on the number of periods needed for the belief distribution to converge to within 0.01 of the stationary distribution, and the second largest eigenvalue (SLE) of the transition matrix (smaller values indicate faster convergence). We compute these values by constructing the transition matrix of the Markov chain using the estimated parameters from Tables 2 and 3 (see Appendix B for details).\footnote{The stationary distribution and convergence speed thus computed are approximations because we ignore correlations across consumers to make this computation tractable.}

| Competition | Treatment | Stationary dist. \( \pi = [\pi_G, \pi_B] \) | Number of periods (upper bound) \( |P^n - \pi I| \leq 0.01 \) | SLE \( |\lambda_2| \) |
|-------------|-----------|--------------------------------|---------------------------------|--------|
| Large-gap   | (No-SI)   | [0.688, 0.312]                | 25 periods                      | 0.841  |
|             | Share-SI  | [0.767*, 0.233]               | 21 periods                      | 0.809  |
|             | Quality-SI| [0.780*, 0.220]               | 14 periods                      | 0.728  |
|             | Full-SI   | [0.817*, 0.183]               | 17 periods                      | 0.770  |
| Small-gap   | (No-SI)   | [0.528, 0.472]                | 26 periods                      | 0.857  |
|             | Share-SI  | [0.587*, 0.413]               | 34 periods                      | 0.884  |
|             | Quality-SI| [0.532, 0.468]                | 43 periods                      | 0.910  |
|             | Full-SI   | [0.555, 0.446]                | 30 periods                      | 0.875  |

Note: *Limit probability of overall belief being \( G, \pi_G \), is significantly higher than \( E(R_t) \) in the data. SLE represents second-largest eigenvalue.

There are three important observations in Table 5. First, with respect to Hypothesis 3(iii), belief convergence speed improves with any type of SI under large-gap competition, but slows down with any type of SI under small-gap competition. Second, this contrast between large-gap and small-gap treatments is the most striking with quality-SI (14 periods in large-gap versus 43 in small-gap). Third, the stationary distribution of the overall belief being \( G \) is significantly higher than the No-SI treatment for any kind of SI under large-gap, and for share-SI under small-gap competition. This means that, in these settings, social information enables a larger fraction of consumers to converge to the long-term belief that ‘the High-firm has higher quality’ the actual average of ‘which firm provided a higher recent experience.’

To summarize, our experiment results regarding Hypotheses 3 and 4 vary across the two quality gaps. These results imply that the High-firm should invest in quality-SI under large-gap competition and in share-SI under small-gap competition. Thus we have:

**Result 3 (Variance and Convergence Rate with Social Information).** Under large-gap competition, all three types of SI lead to significantly lower variance of demand, with quality-SI
achieving the greatest improvement. Under small-gap competition, only share-SI leads to a significantly lower variance of demand. Lastly, when consumers have SI available, their beliefs converge to steady-state faster under large-gap competition and slower under small-gap competition.

5.3. Dynamics under Different Types of Social Information

In this section, we use consumer behavior dynamics to explain some of the results of Sections 5.1 and 5.2, namely, why the weight on quality-SI, $\beta_q$, goes to zero in the later periods in the full-SI large-gap treatment, why the market-shares under full-SI fall in between the other two SI treatments, and why social information results in lower demand uncertainty in the large-gap but not in the small-gap treatment.

5.3.1. Estimate of $\beta_q$ under full-SI We first consider the estimate of $\beta_q$ under full-SI in the last column of Table 2. In Figure 4, we show for each SI treatment, how often the SI provided in a period favors the High-firm and the percentage of participants visiting the High-firm. Beginning with large-gap competition under share-SI (Figure 4(a)), 89% of the time share-SI indicates that more people visit the High-firm than the Low-firm across all time periods. As convergence to the High-firm takes place, share-SI becomes increasingly favorable to the High-firm, leading to 96% of positive share-SI over the last 20 periods. On the other hand, quality-SI signals are independent across time because each quality experience is i.i.d. Under large-gap competition (Figure 4(c)), quality-SI favors the High-firm 81% of the time, and this rate is time-invariant. Likewise in full-SI under large-gap competition (Figure 4(e)), share-SI favors the High-firm 95% of the time, whereas quality-SI favors the High-firm 69% of the time. But over the last 20 periods, share-SI increases and favors the High-firm 100% of the time whereas quality-SI remains steady and favors the High-firm only 70% of the time. Overall, in later periods under large-gap competition with SI, consumers often choose the High-firm even after observing a conflicting SI signal from previous periods, since their accumulated belief has converged. This convergence creates more positive share-SI for the High-firm, but does not change the signal of the quality-SI (especially from the less-visited firm). A similar reasoning applies under small-gap competition as well, but the rate of convergence is slower, and consumers continue to utilize the most recent quality-SI. To summarize, as consumers identify the High-firm in earlier periods under large-gap competition, they keep revisiting the High-firm in later periods even when the quality-SI contradicts those beliefs. Meanwhile, for share-SI, as convergence happens the SI becomes more favorable for the High-firm, reinforcing consumers’ choices. Hence, the coefficients of quality-SI become non-informative under full-SI in later periods.
Figure 4  % of social information favoring High-firm and the market share of High-firm

(a) Large-gap, Share-SI

(b) Small-gap, Share-SI

(c) Large-gap, Quality-SI

(d) Small-gap, Quality-SI

(e) Large-gap, Full-SI

(f) Small-gap, Full-SI

Note: % of participants receiving positive SI for High-firm counts the % of participants observing more favorable SI for the High-firm during that period. This reflects the frequency of SI sign aligned with the true quality difference in direction because the (unknown) true quality of High-firm is superior to Low-firm. % of High-firm visit counts the percentage of participants choosing High-firm during that period, representing the High-firm market share.

5.3.2. Value of full-SI When both types of SI are available, theoretically, rational consumers can use the perfect information regarding the number of other visitors and satisfaction rates from each firm and update their beliefs in accordance with the firms’ true average service quality levels.
While we did not expect consumers to act like perfect Bayesian learners in our experiment, in Hypothesis 5 we reasoned that full-SI would dominate quality- or share-SI as it would enable consumers to update their estimates of service quality faster and more accurately when provided with both types of SI rather than only one. However, the results in Table 4 do not support this hypothesis under either large- or small-gap competition.

In order to understand consumer choices under full-SI, we investigate the visit decisions conditional on observing a certain type of SI signal. Specifically, we measure the demand of the High-firm following a positive (favoring the High-firm) or negative (favoring the Low-firm) SI signal in each SI treatment. Figure 5 presents the results obtained. For example, under large-gap with full-SI, 82.9% of consumers choose the High-firm after observing positive quality SI for the High-firm and 75.8% choose the High-firm after observing negative quality SI for the High-firm (a difference of 7.1%). In comparison, under the large-gap quality-SI treatment, 18.3% (=89.2%-70.9%) more consumers visit the High-firm when they observe positive quality SI over negative quality SI. This suggests that consumers are significantly more responsive to quality SI when only quality-SI is presented than when full-SI is presented. Under small-gap competition, consumers are also more responsive to quality SI under quality-SI versus full-SI (11.5% versus 6.4% differences, respectively). This pattern is also sustained under share-SI in small-gap in Figure 5(b), whereas there is no statistically significant difference under share-SI in large-gap.

Lower responsiveness to a specific type of SI in the full-SI treatment may be driven by mixed signals between quality-SI and share-SI. To examine this, we compute the percentage of consumers choosing the High-firm conditional on the valence of quality-SI and share-SI provided from the previous period in the full-SI treatment. Table 6 shows the results obtained. For example, under
Table 6  % of High-firm choices after observing different types of SI under full-SI treatments

<table>
<thead>
<tr>
<th>Valence of quality-SI</th>
<th>Valence of share-SI</th>
<th>Large-gap</th>
<th>Small-gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Positive</td>
<td>83.2%**</td>
<td>61.4%**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.2%)</td>
<td>(1.8%)</td>
</tr>
<tr>
<td>Positive</td>
<td>Negative</td>
<td>73.5%*</td>
<td>56.6%*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7.7%)</td>
<td>(3.5%)</td>
</tr>
<tr>
<td>Negative</td>
<td>Positive</td>
<td>76.6%**</td>
<td>52.9%**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.2%)</td>
<td>(2.4%)</td>
</tr>
<tr>
<td>Negative</td>
<td>Negative</td>
<td>0.0%</td>
<td>57.1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0%)</td>
<td>(5.2%)</td>
</tr>
</tbody>
</table>

Note: ** $p < 0.05$, * $p < 0.10$; Standard errors in parentheses. The cases with both SI negative were observed very rarely, leading to insignificance.

large-gap competition, if both quality- and share-SI signals are positive (more favorable for the High-firm), 83.2% of consumers choose the High-firm in the subsequent period, but if the two types of SI send conflicting signals, the choice of the High-firm decreases (73.5% and 76.6%). Thus, the response to full-SI is diluted compared to quality-SI alone due to mixed signals. Furthermore, note that even when both quality-SI signals are positive, the rate of consumers choosing the High-firm (83.2%) is lower than the rate of consumers choosing the High-firm under only quality-SI and a positive signal (89.2% in Figure 5). These patterns are weakly supported under small-gap competition.

This evidence explains why the market share of the High-firm under full-SI lies between the market shares under quality-SI and share-SI in both large- and small-gap competition. It is interesting to ask why consumers are more responsive when only one type of SI is presented to them. Although this question is beyond the scope of this paper, we believe that there are a few plausible explanations. First, this could be due to limited attention (Kahneman 1973) when consumers face multiple sources of information. Another explanation is that accumulated belief likely exacerbates this problem. Accumulated belief under full-SI as a result of this repeated process may be weaker than that under only one type of SI, so that consumers do not respond fully to social information even when both types of SI provided in a given period are positive. Managerially, these results suggest that even when both dimensions of SI are available to a firm, it should carefully choose which type of SI to disclose. Thus we have:

RESULT 4 (Informativeness of Partial-SI vs. Full-SI). Providing only one type of SI to consumers can be more helpful to the High-firm than providing full-SI. Under full-SI, human consumers do not take full advantage of the increased amount of SI, and the benefits of one type of SI may decrease with the presence of the other type of SI.
5.3.3. Switching and Herding Behavior  Observed differences in demand uncertainty can be traced to the switching behavior of consumers between firms. To this end, Table 7 shows the average frequency of consumers switching between firms and the percentage of loyal consumers in each treatment. We label a consumer as loyal if her average sojourn time at one of the two firms is greater than 10. For comparison, we include the Bayesian and WSLS benchmarks. The Bayesian benchmarks yield the lowest frequency of switching and the highest percentage of loyal consumers across all treatments, whereas the WSLS benchmark yields the opposite extreme.

<table>
<thead>
<tr>
<th></th>
<th>% of time switching</th>
<th>% of loyal consumers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Large-gap Small-gap</td>
<td>Large-gap Small-gap</td>
</tr>
<tr>
<td>(No-SI)</td>
<td>26.8% 30.7%</td>
<td>20.4% 5.6%</td>
</tr>
<tr>
<td>Share-SI</td>
<td>20.1%* 31.9%</td>
<td>20.4% 0.0%</td>
</tr>
<tr>
<td>Quality-SI</td>
<td>17.3%*** 29.3%</td>
<td>29.6% 7.4%</td>
</tr>
<tr>
<td>Full-SI</td>
<td>17.6%** 31.1%</td>
<td>30.6% 11.1%</td>
</tr>
<tr>
<td>Bayesian (with full-SI)</td>
<td>2.0% 9.5%</td>
<td>100.0% 55.6%</td>
</tr>
<tr>
<td>Bayesian (with no-SI)</td>
<td>3.4% 5.7%</td>
<td>83.3% 77.8%</td>
</tr>
<tr>
<td>WSLS</td>
<td>30.5% 45.3%</td>
<td>0.0% 0.0%</td>
</tr>
</tbody>
</table>

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. T-tests with the No-SI treatment.

We observe that under large-gap quality-SI and full-SI, switching frequency reduces significantly and the proportion of loyal consumers is the highest. On the other hand, share-SI yields the lowest proportion of loyal customers for both large- and small-gap competition (20.4% in large-gap and 0% under small-gap), although it does decrease the frequency of switching compared to no-SI in the large-gap treatment. This evidence explains why social information, especially quality- and full-SI, results in a significant reduction in the standard deviation of demand under large-gap competition, but not under small-gap competition. It suggests that quality-SI and full-SI boost loyalty for the High-firm under large-gap competition (which is expected), whereas share-SI reduces loyal customers regardless of the level of competition.

6. Conclusion
Our paper finds that the type of social information that a firm should promote depends on its average service quality relative to the competition in the marketplace. When the quality gap between the competitors is large, the firm with superior quality benefits from the presence of SI, particularly the most significantly by promoting quality-SI. However, when the quality gap between the competitors is small, quality-SI does not work the same way. Instead, share-SI help consumers choose the firm with marginally higher quality more often, thus, the high-quality firm can increase
its market share by promoting share-SI rather than quality-SI. When full-SI is provided, human consumers fail to take full advantage of the increased amount of information, and the resulting market share and uncertainty under full-SI falls between those under quality-SI and share-SI. Therefore, when the high-quality firm has significantly superior quality than the low-quality firm, the high-quality firm may be better off with promoting quality-SI only. In practice, there are many tools available to enable firms to signal their quality versus market share. For example, firms can signal quality through promoting ratings from Yelp or Zagat, and can signal market share through sales rank, number of reviews, and making the waiting line more visible.

Our results show that the differences in the effects of quality-, share- and full-SI occur because of variations in consumer response. Although consumers respond to both quality- and share-SI, their response to quality-SI manifests in their behaving similar to Bayesian decision-makers especially when the quality signal is clearly favorable to one firm over the other, whereas their response to share-SI encourages switching behavior. Thus, in both large- and small-gap settings, the presence of quality-SI decreases consumer switching behavior and increases the portion of loyal consumers, but share-SI promotes switching particularly under small-gap competition. Compared to these treatments, the availability of full-SI does not serve as the best for helping consumers choose the higher quality firm, under any service competition level. This counter-intuitive insight may be particularly valuable to managers, especially at higher quality firms, who may presume that promoting social information is unconditionally beneficial and may incorrectly invest their resources.

We believe that there are a number of opportunities for future research in this area. First, our setting could be extended to include a “do not visit either store” option to allow the market size to shrink or to include more than two firms, e.g., two high-quality and one low-quality, to differentiate between the effects of quality level and competition. Second, asymmetric strategies could be studied where one type of social information (or none) is provided for one firm and a different type is provided for the other firm. Third, customers’ willingness to consume different types of social information could be studied by endowing them with budgets to purchase social information. Finally, while we considered two types of social information with two firms, our model could be extended to allow a larger set of attributes and combined with field data to assess the value of social information to a firm.

Acknowledgments
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References


Appendix A: Estimation of Model Parameters

We compute the likelihood function for our model over the sample path of the observed visit decisions, satisfaction outcomes, and SI for all consumers for all $t$ because the consumers’ latent beliefs evolve over time as a correlated process. Let $\pi_{it}$ be a vector denoting a probability distribution defined over the state space $S$ of the Markov chain for consumer $i$ in period $t$ and $\pi$ denote the stationary distribution. We call $\pi_{it}$ the belief-state probabilities. To initialize the model, we assume that each consumer has an equal probability of being in any of the eight states at $t = 1$, and moreover, she has an equal probability of visiting either firm. Subsequently, the new belief-state probabilities can be computed iteratively in period $t + 1$ from $\pi_{it}$. The next step is the setting up of the likelihood function. The likelihood of consumer $i$ visiting firm 1 in period $t$ is given by $\sum_{S_{it} \in S} \pi_{it}(S_{it}) Pr(V_{it} = 1 | S_{it})$ and the probability distribution of the consumer’s state in period $t + 1$ is given by $\pi_{i,t+1}(S_{i,t+1}) = \sum_{S_{it} \in S} \pi_{it}(S_{it}) P(S_{it}, S_{i,t+1})$. Thus, the likelihood is calculated iteratively as a function of the evolving belief-state probabilities, historical outcomes, and historical SI. Finally, we determine the parameters that jointly maximize the log-likelihood (LL) of observed visit choices over the duration of the experiment.

We note one nuance in the estimation procedure. In quality-SI treatments, when everyone in a group chooses the same firm, quality-SI for the other firm does not exist. This occurred 36.5% of the time in large-gap and 1.0% of the time in small-gap. To account for this in our estimations when quality-SI is unavailable, we replace missing values with the average value of the quality-SI provided for that particular firm up to that time period. We also ran all estimations with two additional approaches that are standard in the econometrics literature for missing values: (1) by replacing the missing quality-based SI with the most recent period’s quality-based SI, and (2) by replacing the missing quality-based SI with 0. All three approaches yield similar results.

We estimated the parameters using both a constrained non-linear optimization method and grid search. Both methods yielded consistent results. After parameter estimation, we calculate the stationary distribution and rate of convergence towards steady state for each consumer using the transition matrix of the eight-state Markov chain of each consumer. (In this computation, we ignore the dependencies across consumers for simplicity.) The stationary probability of the hidden belief states and the visit probabilities in Equation (3) allow us to estimate the long-run market share and variance of demand for each firm, and the convergence speed of $\pi_{it}$ to $\pi$ can be similarly estimated by the size of the second-largest eigenvalue of the transition matrix. This metric shows how quickly a consumer’s belief-state probability converges to its stationary distribution. It thus indicates how fast a firm benefits from SI compared to the scenario without SI. We present the convergence speeds under different treatments in our model in Section 5.2 and discuss convergence further in Appendix B.

Appendix B: Estimation of Convergence Rate of Consumer Learning

In the theory of convergence of an ergodic Markov Chain with transition matrix $P$, one of the indicators of how fast the sequence of probability distributions over states $\{\pi_t\}, t = 0, 1, ...$ converges to a stationary
distribution $\pi$ is provided by the eigenvalues of $P$. The stationary distribution $\pi$ exists due to ergodicity. Let $\lambda_1, \ldots, \lambda_n$, where $n$ is the number of states, denote the eigenvalues of $P$. There is a unique largest eigenvalue $\lambda_1 = 1$. The convergence speed of $\pi_t$ to $\pi$ is dominated by the size of the second-largest eigenvalue. We explain this as follows.

Since all eigenvalues of $P$ are real, we know that by eigenvalue decomposition, $\exists$ an invertible matrix $U$ such that

$$U \cdot P \cdot U^{-1} = \Lambda = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix}.$$  

Let $V = U^{-1}$. Since $P$ has a unique largest eigenvalue $\lambda_1 = 1$ and the other eigenvalues can be ordered so that $1 = \lambda_1 > |\lambda_2| \geq \ldots \geq |\lambda_n|$, by taking the powers of the transition matrix and computing its limit as $t \to \infty$, we get

$$\lim_{t \to \infty} P^t = \lim_{t \to \infty} P^t V = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix} U^T = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} v_{11} u_1 \\ v_{12} u_1 \\ \vdots \\ v_{1n} u_1 \end{bmatrix} = \begin{bmatrix} \pi \\ \pi \\ \vdots \\ \pi \end{bmatrix}.$$  

The second last equation holds because the unique left eigenvector associated to eigenvalue 1 is the stationary distribution $\pi$, and the corresponding unique right eigenvector is $1 = (1, 1, 1)$ up to normalization. If the first row of $U$ is normalized to $\pi$, then the first column of $V$ must be normalized to 1 because $UV = UU^{-1} = I$, and $(UV)_{11} = u_1 v_1 = \pi(v_1) = 1$. Hence, if we let $\Pi = [\pi, \pi, \ldots, \pi]$, then there exists a positive constant $M$ such that $|P^t - \Pi| \leq (\sum_{i=2}^n |v_i| |u_i'|) |\lambda_2|^t \leq (t-1) \cdot 1 \cdot 1^t \cdot |\lambda_2|^t = M \cdot |\lambda_2|^t$. Thus, $P^t = \Pi + O(|\lambda_2|^t)$, and the convergence speed of $P^t$ is dominated by the size of $\lambda_2$. This result is further supported by Boyd et al. (2004), where they show that the Markov chain reaches its equilibrium faster when the SLEM (Second Largest Eigenvalue Modulus), defined by $\max \{ \lambda_2, -\lambda_n \}$, is smaller. This quantity is widely used to bound the asymptotic convergence rate of the Markov chain to its stationary distribution.
Since we noticed that the learning speed of the first and the latter half of the experiment are distinct from each other, we partitioned the first 15 periods and latter 25 periods of data and used them separately to compute the transition matrix and its eigenvalues. Then, we captured the convergence speed of the transition probability under both time blocks to see how the learning speed under different social information treatment evolves.

To further test the convergence speed, we build a simpler Markov chain to test the demand predictability by incorporating the first-order auto-regressive relationship (AR(1)) of each consumer’s most recent experience and the choice of the following period. We represent a consumer’s most recent visit and experience with four states, $S = \{1S, 1D, 2S, 2D\}$. The first number in each state denotes which firm a consumer chooses to visit, indicating the High-firm as 1 and the Low-firm as 2. The second letter denotes whether a consumer is (S)atisfied or (D)issatisfied at her latest service encounter of that firm. This simpler setting where we only take into account the most recent experience allows us to compare whether human behavior gets closer to Bayesian or WSLS consumers under social information.

Figure 6 shows the bootstrapped probability distributions of the estimated second largest eigenvalues (SLEs) under the No-SI, share-SI, and quality-SI treatments in our experiment. We compute these values by first estimating the transition matrix for each consumer, then computing the SLE for each consumer. A smaller value of the second-largest eigenvalue implies a faster rate of convergence to stationary distribution. We observe that the learning speed under the share-based info treatment does not significantly vary in early and later periods of time; however, the SLEs of estimated transition matrices under quality-based information in large-gap competition treatment are significantly lower, implying faster convergence. Further, since convergence occurs faster in the early periods under quality-based information, we observe that the estimated convergence speed is slower in the latter periods; in other words, quality-SI enables consumers to be quick learners.

Appendix C: Definitions of Bayesian and WSLS Benchmarks

In this appendix, we define our three benchmarking models, the Bayesian model with own learning, the Bayesian model with social learning, and the Wins-Stay-Lose-Shift (WSLS) model.

C.1. Bayesian Model with No-SI

Let the service outcomes from firm $s$ at time $t$, $X_{st}$ for $s = 1, 2$, be sampled from the true service quality level of each firm, i.e., $X_{1t} \sim Bernoulli(q_1), X_{2t} \sim Bernoulli(q_2)$. Assume that a consumer chose $k$ times to visit firm 1, and $t - k$ times to visit firm 2 until time $t$. Then, her accumulated satisfaction from the firm 1, $\sum_{j=1}^{k} X_{1tj}$, follows $\text{Binom}(k, q_1)$ and her accumulated satisfaction from the firm 2, $\sum_{j=1}^{t-k} X_{2tj}$, follows $\text{Binom}(t - k, q_2)$. Since the Beta distribution is conjugate for the Binomial probability mass function, if a consumer updates the posterior distribution of $q_s$ with Bayes rule, the posterior has the same distributional family form with its prior (Gelman et al. 2013). Assume that the initial prior of the service quality of firm $s$, $\hat{q}_{s0}$, is drawn from the Uniform distribution on $[0,1]$, i.e., $\text{Beta}(1, 1)$ for both firms. At the end of time $t$, the updated estimate of service quality of the firm 1, $\hat{q}_{1t}$, is assigned with $\text{Beta}(1 + \sum_{j=1}^{k} X_{1tj}, 1 + k -$}
\( \sum_{j=1}^{k} X_{1t_j} \) distribution, with the initial prior Beta\( (1, 1) \). Note that \( \sum_{j=1}^{k} X_{1t_j} \) corresponds to the number of total satisfaction experienced from firm 1 up to time \( t \), and \( k - \sum_{j=1}^{k} X_{1t_j} \) is the number of dissatisfaction experienced from firm 1 up to time \( t \). Likewise, the updated estimate of service quality for firm 2, \( \hat{q}_{2t} \), is assigned with Beta\( (1 + \sum_{j=1}^{t-k} X_{2t_j}, 1 + (t-k) - \sum_{j=1}^{t-k} X_{2t_j}) \) distribution. Hence, if a consumer updates her service quality estimate in this Bayesian manner, she obtains a unique posterior estimate of service quality \( \hat{q}_{st} \) for each firm \( s \) at the end of every period \( t \). Then, she uses the expectation of posterior probability of getting satisfaction from each firm as the valuation of the firm \( \nu_{st} \), i.e.,

\[
\nu_{1t} = E(\hat{q}_{1t}) = \frac{1 + \sum_{j=1}^{k} X_{1t_j}}{2 + k}, \quad \nu_{2t} = E(\hat{q}_{2t}) = \frac{1 + \sum_{j=1}^{t-k} X_{2t_j}}{2 + t-k}.
\]

Each time, the expectations of service quality estimate on both firms are updated in this manner, and a consumer chooses the firm with highest expected reward to maximize her utility. Therefore, a Bayesian consumer under this setting chooses the firm with higher \( \nu_{st} \) among the two firms every time \( t \).

### C.2. Bayesian Model with SI

Assume the same Bayesian consumer is given full information about how others made decisions and she assigns equal weights to her own observation and others’ experiences to update her own estimate of service quality. Assume that among those \( n \) people, \( n_1 \) people visited firm 1 and \( n_2 \) people visited firm 2 at period \( t \), \( (n_1 + n_2 = n) \), where a consumer herself chose to visit firm 2. With SI, a consumer gets to know that among \( n_1 \) people who visited firm 1, \( n_1' (\leq n_1) \) people experienced satisfaction, and at the end of period \( t \), her estimate of service quality distribution on firm 1 is updated to Beta\( (\alpha_1 + n_1', \beta_1 + n_1 - n_1') \), and becomes the prior distribution of firm 1 for the following period \( t+1 \), i.e., \( \alpha_{t+1} = \alpha_1 + n_1', \beta_{t+1} = \beta_1 + (n_1 - n_1') \). Likewise, her posterior estimate of firm 2 is updated with more information. If she experienced satisfaction from her visit to firm 2, the parameters for the following period distribution is updated to \( \alpha_{t+1} = \alpha_2 + (n_2' + 1), \beta_{t+1} = \beta_2 + n_2 - (n_2' + 1) \). Thus, expected value on the estimate of service quality of firm \( s \) at the end of the period \( t \) can be summarized as following.

\[
\nu_{st} = E(\hat{q}_{st}) = \frac{\alpha^*_s + \text{Total number of satisfiers from firm } s}{\alpha^*_s + \beta^*_s + \text{Total number of visitors to firm } s}
\]

The assumption behind this update process is that a consumer counts her own experience equivalently with the experiences of others. By doing so, a Bayesian consumer utilizes \( n \) more observations of binary service outcomes to update her expectation on estimate of service quality, and can easily choose the firm with the higher expectation in reward.

**Bayesian benchmark choice paths generation:** Without social information, assume that a consumer can explore both firms infinitely often. Then, by the Law of Large Numbers, the long-run expected value of posterior estimate of service quality of firm \( s \) in Equation (1) becomes

\[
\lim_{k \to \infty} E(\hat{q}_{1t}) = q_1, \quad \lim_{(t-k) \to \infty} E(\hat{q}_{2t}) = q_2.
\]

Thus, if infinite explorations to both firms is possible for all satisfaction-maximizing consumers, the long-run market share should eventually become dominated by the firm with higher quality, \( q_s \). However, when a
Bayesian consumer keeps choosing a firm \( s = \arg\max_{s \in \{1, 2\}} \mathbb{E}(\hat{q}_{st}) \) for all \( t \), the challenge is to guarantee that she explores both of the firms sufficiently enough, i.e., with large enough \( k \) and \( t - k \) until time \( t \), to obtain an accurate enough estimate. Because of this so-called “exploration-exploitation dilemma” in sequential choices (Sutton and Barto 1998, Gittins 1979), we face a challenge that many individual Bayesian choices we generated fail to choose the firm with higher-quality consistently.

Note that given our assumptions on the initial prior, the subsequent decision rule of selecting the firm with the highest expected reward is equivalent to the Gittin’s index policy, which is known to be an optimal policy for the multi-armed bandit problem. The Gittin’s index measures the reward that can be achieved by a random process bearing a termination state and evolving from its present state onward. In our (simple) special case of a two-armed Bernoulli bandit problem, the Bayesian choice paths of successively choosing the firm with higher posterior estimate of service quality can be considered optimal to a reasonable extent (Bradt et al. 1956). Therefore, we first collect what actual participants experienced in our laboratory experiments. Then, based on their observations from every visit, we generate the Bayesian benchmark choice paths ex post. This is because our intent of developing this Bayesian benchmark path is to see how and when a consumer deviates from the choice that maximizes her expected reward. Thus, a Bayesian consumer in our model follows a choice path selecting the firm with the highest expected service quality each time, based on what corresponding subject observed through her own visits in the experiment. After generating the individual choice path of a Bayesian consumer, we aggregate and average the individual paths to generate the Bayesian market share path.

C.3. WSLS Consumer Benchmark

Under the WSLS setting, if a consumer \( i \) is satisfied at her visit of firm \( s \) at time \( t \), she chooses firm \( s \) again at time \( t + 1 \); otherwise, she switches to firm \( \bar{s} \) with probability 1. This immediate response to service failure allows our original Markov chain to collapse to two states defined solely based on a consumer’s visit choice as

\[
S_t = \begin{cases} 
1, & \text{if a consumer visits store 1 at time } t, \\
2, & \text{if a consumer visits store 2 at time } t,
\end{cases}
\]

and the transition probability is given as \( P = \begin{bmatrix} p_{11} & p_{12} \\
p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} q_1 & 1 - q_1 \\
1 - q_2 & q_2 \end{bmatrix} \) where \( q_1 \) and \( q_2 \) are the average service levels provided by the two firms.

Then, the long-run market share of two competing firms with WSLS consumers become

\[
\pi_1 = \lim_{t \to \infty} P(S_t = 1) = \frac{1 - q_2}{(1 - q_1) + (1 - q_2)}, \quad \pi_2 = \lim_{t \to \infty} P(S_t = 2) = \frac{1 - q_1}{(1 - q_1) + (1 - q_2)}
\]

**WSLS benchmark choice paths generation:** To generate one-to-one comparable individual benchmark paths for our experimental data, we again use the same set of service outcomes designed for the experiment. Then, we start from the initial choice of the participants and generate individual choice paths by WSLS consumers, and aggregate the individual choice paths to generate the WSLS market shares.