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

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

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Abstract. 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 in which 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 who visited each firm; (3) quality-based social information, which illustrates the percentage of people who received a satisfactory experience from each firm; or (4) full social information, which contains both share- 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.

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 more than $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, for example, 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 their 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 study a repeated two-armed Bernoulli bandit experiment in which human decision makers learn from their own previous choices and from the choices and experiences of others in their social network. We use the experiment design to create social networks as well as control the type of social information revealed to participants, considering two stylized kinds 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, retail store, bank, or airline lounge, the customer may share the location with the customer’s 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 in which participants do not receive any social information. Full-SI is the treatment in which participants receive both share-SI and quality-SI.

Our stylized setup follows the experimental approach of Gans et al. (2007), who study human decision makers learning from their own past choices in a bandit experiment. 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 comprise 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. A controlled experiment enables us to abstract away from these complexities and directly collect information within the experiment from the participants’ choices, experiences, and network and share it with them in real time. It then enables us to evaluate the resulting effect on their future choices.

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 an empirical question to determine how a consumer includes different kinds of information in a simple decision rule. Thus, we propose a general hidden Markov chain framework to analyze the experimental data and answer our research questions. 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—from own experiences and the social network—in a learning model, 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 also benchmark the results of the model against those obtained by applying rational Bayesian learning models with and without social information and a myopic win-stay-lose-shift (WSLS) model to our setup and data set.

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. When there is a large difference in service quality between the firms, the firm with the higher service quality achieves a market share of 70.7% in the case without any social information, 75.6% under share-SI, 81.0% under full-SI, and 86.2% under quality-SI. Thus, it gains a 22% increase in market share from quality-SI but a much smaller increase from share-SI or full-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. In contrast, 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 it 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 because of convergence in later periods under both large and small gaps in 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 different types of social information using a human-subject experiment. Its main contributions to the operations literature on social information are as follows: First, by conducting a controlled experiment, we are able to show differences across 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. However, our study is not without its limitations. One limitation stems from the absence of theory predicting the effects of different types of social information and quality differences between firms on consumer learning. Although we set up hypotheses based on the literature, we are unable to predict some of the empirical results, such as the reversal in the effectiveness of share-SI and quality-SI across quality competition settings. This raises questions of generalizability that can be addressed through theory building. A second limitation arises from experiment design, such as a limited number of treatments or binary choices, which can be overcome by studying different variations and field data. Although we limit this paper to two types of social information, our model can be easily expanded to incorporate a larger dimensionality of information and beliefs.

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 mainly drawing from the normative theory. However, we also cite relevant empirical and behavioral research and specify when it is or is not consistent with our hypotheses. In Section 4, we present an estimation model to test the hypotheses and relate its parameters to each hypothesis.

First, consider how individuals learn from their own decisions. Although the literature in this research field is vast (see Erev and Haruvy 2017 for a summary), the papers by Gans et al. (2007), Hall and Porteus (2000), and Gaur and Park (2007) 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 that coincide with a consumer’s limited memory or recency bias. Hall and Porteus (2000) and Gaur and Park (2007) formulate theoretical models of consumer response to own experience and study the implications for the firms’ demand and decisions. The former consider an extreme form of recency bias in which consumers’ future choices are fully determined by their most recent experience: they stay with the same firm if they have a successful experience and switch to a competing firm otherwise. The latter analyze learning using an exponential smoothing model. Given that we investigate a setting similar to these papers, we posit that consumers learn from their own service outcomes and also exhibit a recency bias. This motivates our first hypothesis:

Hypothesis 1 (Own Learning). The choices made by consumers are correlated with their own experiences in previous time periods independently of the presence of social information. Specifically, (i) consumers give a higher weight to the most recent experience (recency bias), and (ii) they update their beliefs about the quality levels of firms in the marketplace (learning); these beliefs then determine future choices.

We next consider consumer learning from social information. 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 nonzero 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 payoff 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 modeled the effect of social information on consumer learning, markets, and operational decisions under sequential visits. Ifrach et al. (2019) examine asymptotic learning and optimal dynamic pricing by a monopoly seller in a market in which 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. Predicated on consumer response to social information, many applications of social information for firm-level decisions have also been studied, including stocking policies (Hu et al. 2016), design of quality attributes (Zhang et al. 2017), demand forecasting (Cui et al. 2018), healthcare offerings (Xu et al. 2016), 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. 2019).

If consumers respond to social information, then social information should be a valuable determinant of demand. This factor has been empirically tested 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, Chen and Xie 2008, Goh et al. 2013). Other research papers have analyzed the characteristics and implications of online reviews, ratings, and ranking systems (see, for example, Dellarocas 2003 and Ghose et al. 2012). 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两种 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 behavioral operations literature, Kremer and Debo (2015) conduct experiments to investigate whether the number of consumers in a queue can act as a signal of quality for a firm, and Çelen and Hyndman (2012) test a theory of social learning through endogenous information acquisition in experiments in which subjects can observe others’ decisions by forming links at a cost.

Our paper considers the belief evolution of consumers in a repeated-interaction setting with both own and social learning, which is most closely related to Allon and Zhang (2017) and DeCroix et al. (2019). The former study a model in which the consumer takes a weighted average of the consumer’s friends’ service quality outcomes and forms a new belief as a linear combination of the consumer’s past belief and influence from the consumer’s social network. The latter focus on own learning in a similar model structure and also investigate the implications of social information. Whereas Allon and Zhang (2017) focus on the optimal service differentiation strategy for a monopoly firm under this behavior and DeCroix et al. (2019) study dynamic pricing, we focus on empirically characterizing the decision rules used by consumers and their implications for firms.

Thus, the literature on observational and social learning provides considerable motivation for consumer learning from social information, which leads to our second hypothesis:

**Hypothesis 2** (Social Learning). The choices made by consumers are correlated with the social information received by them in previous periods. Specifically, consumers learn from social information by updating their beliefs about the quality levels of firms in the marketplace. These beliefs then determine the future choices they make.

Our third hypothesis compares the distribution of demand under social information with that under no social information. Although different types of social information have not been combined together in a normative model, we explain the rationale for this hypothesis by developing on the insights from the normative models cited earlier. Hypothesis 1 (own learning) posits that consumers learn from their own
experience and outcomes. Further, Hypothesis 2 (social learning) states that, when exposed to social information, consumers 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 learn at a faster rate as to which firm has a higher average service quality. This likely leads to a higher market share for the better firm, lower variance of demand, and faster convergence to steady state. Indeed, several papers in the social learning literature show the occurrence of asymptotic learning rather than herding, that is, consumers converge to the highest payoff choice; examples include Ellison and Fudenberg (1995), Banerjee and Fudenberg (2004), and Ifrach et al. (2019). Thus, we test the following hypothesis:

**Hypothesis 3 (Demand).** Comparing the marketplace under social information with the marketplace without social information, the firm with the higher average service quality realizes (i) a higher market share, (ii) a lower rate of demand, and (iii) a faster convergence of its market share to the steady-state value.

i. A higher market share.
ii. A lower variance of demand.
iii. A faster rate of convergence of its market share to the steady-state value.

In the fourth hypothesis, we distinguish the effects 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). From Bayesian reasoning, quality-SI is generated from other consumers’ actual service outcomes. Thus, it is likely to play an informative role for 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, we expect quality-SI to benefit the higher quality firm more than share-SI.

This reasoning is also supported by the behavioral literature. According to Simonsohn and Ariely (2008), learning from others’ choices requires observers to make correct attributional inferences about the behaviors they observe. However, consumers often misinterpret the causality of others’ choices. Thus, drawing quality inferences from the preceding choices of others may lead to a systematic bias because of irrational herding. Zhang and Liu (2012) distinguish between rational and irrational herding and show that the results of the herding momentum can vary in loan markets. In our setting, if only share-SI is provided, a subject may not be able to infer whether the other consumers’ visit decisions are due to an exploration of a new firm or an exploitation of their private signals, especially in early periods, so that share-SI would provide a noisy signal for updating beliefs. Thus, we formulate the following hypothesis:

**Hypothesis 4 (SI Type).** The firm with higher average service quality has more favorable demand characteristics, that is, 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, we investigate how consumers’ choices and firms’ demand characteristics are impacted when both types of SI are presented simultaneously. This hypothesis can also be motivated through Bayesian learning. A rational consumer can use the perfect information regarding the visits and experiences of others and update beliefs on the firms’ true average service quality levels. Therefore, we hypothesize that, compared with the cases in which 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 has 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 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 the consumer’s decisions. Schroder et al. (1967) were the first to refer to the relationship between information and decision accuracy as an inverted U-curve (see Edmunds and Morris 2000 for a review of the literature on information overload). Further, when people face multiple sources of information, they may not be able to utilize all information because of 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 shows 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 setup; we can design the social network, control the types of information revealed to each participant, and 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, in which the mean service quality levels of each firm, \( q_1 \) and \( q_2 \), are unknown to the consumer.

The experiment follows a 2 \( \times \) 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 the market shares of the two firms under Bayesian learning are statistically different from each other in both large- 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, for example, “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, for example, “For this period, 67% of your acquaintances who visited store A experienced satisfaction, and 20% of your acquaintances who visited store B experienced satisfaction.”

Finally, 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, we randomize the social network in each period to reduce correlations across participants and prevent potential learning of a session’s group characteristics. 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 the participant’s 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 to better capture the true dynamic process of SI generation and market evolution in practice. We inform participants that they are randomly matched into a group of nine people in every period and 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.

Although the real-time choices made by participants and their outcomes are used to generate social information, the entire panel of service realizations for the 18 participants across both firms is generated ex ante from a Bernoulli distribution using the average service level of each firm. We then use this same panel across sessions so that the only sources of any differences are the treatments themselves and the choices made by participants.

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 the high- or 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.

Table 1. Experimental Design and Number of Participants

<table>
<thead>
<tr>
<th>Service competition</th>
<th>Large gap</th>
<th>Small gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social information</td>
<td>No-SI</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>Share-SI</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>Quality-SI</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>Full-SI</td>
<td>36</td>
</tr>
</tbody>
</table>

Participants in our experiment were recruited from a university located in the northeast United States.
The average total compensation was approximately $20 per participant. Each time a participant received “satisfaction” from the 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 multifaceted, 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. In many papers, quality outcomes are modeled as binary (Banerjee 1992, Gans et al. 2007, Gaur and Park 2007, Acemoglu et al. 2011, 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, DeCroix et al. 2019, Ifrach et al. 2019) or duopoly (Gans et al. 2007, Gaur and Park 2007). We vary the quality gap between firms and randomize the social 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 can be compared 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, because 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, \( t = \{1, \ldots, T\} \). 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 \( s \), the consumer’s experience is measured as a binary outcome of either satisfaction (one) or dissatisfaction (zero) realized from 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 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 \( V_{st} = 1 \) if the consumer visits firm \( s \) at time \( t \) and zero otherwise. Each consumer must visit only one of the two firms in each period; thus, \( V_{1t} + V_{2t} = 1 \). Also let \( Y_{st} \) denote the most recent service outcome experienced by the consumer from firm \( s \). If the consumer visited firm 1 at \( t = 1 \) and was satisfied, then \( Y_{11} = 1 \); if the consumer visited firm 1 at \( t = 1 \) and was dissatisfied, \( Y_{11} = 0 \); and if the consumer did not visit firm 1 at \( t = 1 \), \( Y_{11} = Y_{1j, t-1} \). Thus, the values of \( V_{st} \) and \( Y_{st} \) 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 the (G)ood state if the consumer believes that firm 1 has better quality, that is, if the consumer’s 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 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 \( \mathcal{A}_t \) as a function of experiences and revealed information. Let \( \mathcal{P} = [p_{CG}, p_{CB}, p_{BG}, p_{BB}] \) denote the matrix of transition probabilities from the belief states in one time period to the next. Here, \( p_{CG} \in [0, 1] \) denotes the probability of a consumer changing belief from \( \mathcal{A}_t = G \) to \( \mathcal{A}_t = B \), that is, \((G)ood \rightarrow (B)ad\) 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 are 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 the consumer’s belief about the relative quality levels of the two firms. For this, we construct \( \mathcal{P} \) as a weighted sum of three matrices, \( \mathcal{P}_o, \mathcal{P}_m, \) and \( \mathcal{P}_q \), which specify the switching of beliefs via a consumer’s (o)wn experience, (m)arket share SI, and (q)uality SI, respectively.

\[
\mathcal{P} = [p_{CG}, p_{CB}, p_{BG}, p_{BB}] = (1 - \beta_m - \beta_q) \cdot \mathcal{P}_o + \beta_m \cdot \mathcal{P}_m + \beta_q \cdot \mathcal{P}_q. \tag{1}
\]

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 a 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 the consumer’s belief, then the consumer changes belief with a leakage probability \( h \in (0, 1) \); otherwise, the consumer’s belief remains unchanged. For example, if the consumer is in state \( G \), then the consumer moves to state \( B \) with probability \( h \) if the consumer visits firm 1 and is dissatisfied or if the consumer visits firm 2 and is satisfied. Collecting all the possibilities, mathematically, we get the complete definition of \( \mathcal{P}_o \) as

\[
\mathcal{P}_o = \begin{bmatrix} 1 - h & h \left( V_{11} Y_{11} + V_{21} Y_{21} \right) \\ h \left( V_{11} Y_{11} + V_{21} Y_{21} \right) & 1 - h \left( V_{11} Y_{11} + V_{21} Y_{21} \right) \end{bmatrix}.
\]

(2)

Here, \( V_{11} Y_{11} + V_{21} Y_{21} \) gives the events when the consumer visits firm 1 and is dissatisfied or visits firm 2 and is satisfied. The other events are defined. 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, \( V_{11} = 1, V_{21} = 0 \), and \( Y_{11} = 1 \) in the subsequent time periods. Using this and the definition (2), the consumer’s state in each subsequent period can be computed using the powers of the transition matrix as follows:

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

\[
\mathcal{P}_o^3 = \begin{bmatrix} 1 & 0 \\ h + h(1 - h) + h(1 - h)^2 & (1 - h)^3 \end{bmatrix}, \ldots
\]

According to these probabilities, if the consumer was in state \( G \) at the beginning, then the consumer stays in state \( G \) with probability one, whereas if the consumer was in state \( B \) at the beginning, then the consumer’s probability of staying in state \( B \) diminishes exponentially, and the consumer’s 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 \( \mathcal{P}_m \) and \( \mathcal{P}_q \) analogous to \( \mathcal{P}_o \). 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 the consumer’s social network for 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 \( 0.5 g_m \). The transitions from state \( B \) are symmetric, and this gives us the matrix \( \mathcal{P}_m \). Likewise, let \( g_q \in (0, 1) \) denote the consumer’s social learning propensity from quality-SI. The definition of \( \mathcal{P}_q \) follows in the same manner as for \( \mathcal{P}_m \) but using quality-SI.

**Example 2.** In the previous example, we illustrated \( \mathcal{P}_o \) 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

\[
\mathcal{P}_m = \begin{bmatrix} 1 - g_m & g_m \\ 0 & 1 \end{bmatrix}, \quad \mathcal{P}_q = \begin{bmatrix} 1 - g_q & g_q \\ 0 & 1 \end{bmatrix},
\]

and \( \mathcal{P} = (1 - \beta_m - \beta_q)\mathcal{P}_o + \beta_m \mathcal{P}_m + \beta_q \mathcal{P}_q. \)
4.1.3. Visit Decisions. We now describe how the consumer decides which store to visit as a function of the consumer’s beliefs and the information at the consumer’s 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 with earlier outcomes (Meyer and Shi 1995, Kremer et al. 2011). 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 the consumer’s most recent experiences given the consumer’s overall belief.

Let \( R_t = (Y_{1t} - Y_{2t} + 1)^{1/2} \in \{0, 0.5, 1\} \) 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

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

where \( \mathbb{I}(x) \) equals one if \( x \) is true and zero otherwise and \( \alpha \in [0, 1] \) measures the extent of recency bias. If \( \alpha = 0 \), the consumer’s visit decision is driven purely by the consumer’s overall belief (which 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 the consumer’s 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 \( Y_t = (A_t, Y_{1t}, Y_{2t}) \), 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 twofold 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 belief from \( G \) to \( B \) with probability \( h \). Combining these steps of the decision process gives us the transition probability \( \Pr(V_{2t} = 1 | (G, 1, 0)) \cdot q_2 \cdot h \).

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, \( h_g \), \( g_m \), and \( g_q \), respectively. We estimate these parameters to test Hypothesis 1 using \( \alpha \) and \( h \) and Hypothesis 2 using \( \beta_m \), \( \beta_q \), \( g_m \), and \( g_q \). Then, we 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^{th} states. Thus, to estimate the model, we compute a joint likelihood of the observed sample path of all participants in a session and then maximize the likelihood with respect to the model parameters.

4.2. Estimation and Benchmarks
As noted, 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 Bayesian no-SI model based on learning from own experiences alone, a Bayesian full-SI model based on learning from own experiences and full-SI, and a myopic 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) 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 Online Appendix A and the benchmark models in Online 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 unless otherwise noted.

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 when 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- and small-gap settings. We estimate parameters using the entire data set as well as using data for different subperiods 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 (α) and own-learning propensity (h) are positive and significant. The estimate of α, 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 θt in the visit choice Equation (3). Moreover, the weight on recency generally declines with quality-SI and full-SI compared with 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 one 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: (i) consumers display a recency bias in their choices and also (ii) learn from their own past experiences and update their beliefs about quality level of firms to determine future choices.

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 (β_m and β_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 β_m = 0.24 to share-SI and the remaining weight of 1 − β_m = 0.76 to their 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, β_m ranges between 0.02 and 0.41, g_q between 0.06 and 0.52, and β_q between 0.23 and 0.68. A combination of these results largely supports Hypothesis 2: consumers place positive weight on SI when it is available and display social learning propensity. Thus, consumers utilize both types of social information, whether quality or share, for updating their beliefs to determine the future choices they make.
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 (because $\beta_m = 0.24$) and 0.76 to their 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 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 a small gap. In a normative model, we would expect consumers provided with quality-SI or full-SI to give equal weight to their own experience and social information or to give a higher weight to social information.

### 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>$\alpha$</td>
<td>Weight on recency bias</td>
<td>0.10 (0.069)</td>
<td>0.15** (0.055)</td>
<td>0.13** (0.046)</td>
<td>0.00 (0.118)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.31*** (0.037)</td>
<td>0.23*** (0.036)</td>
<td>0.10** (0.038)</td>
<td>0.00 (0.047)</td>
</tr>
<tr>
<td>$h$</td>
<td>Own-learning propensity</td>
<td>0.27*** (0.029)</td>
<td>0.34*** (0.036)</td>
<td>0.48*** (0.044)</td>
<td>0.30*** (0.052)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.16** (0.017)</td>
<td>0.18*** (0.020)</td>
<td>0.25*** (0.038)</td>
<td>0.23*** (0.015)</td>
</tr>
<tr>
<td>$\beta_m$</td>
<td>Weight on share-SI</td>
<td>0.37*** (0.084)</td>
<td>0.24*** (0.038)</td>
<td>0.20** (0.070)</td>
<td>0.41*** (0.026)</td>
</tr>
<tr>
<td>$\gamma_m$</td>
<td>Learning propensity from share-SI</td>
<td>0.18** (0.057)</td>
<td>0.23*** (0.029)</td>
<td>0.32** (0.115)</td>
<td>0.26*** (0.033)</td>
</tr>
<tr>
<td>$\beta_q$</td>
<td>Weight on quality-SI</td>
<td>0.00 (0.143)</td>
<td>0.22*** (0.043)</td>
<td>0.02** (0.070)</td>
<td>0.40*** (0.026)</td>
</tr>
<tr>
<td>$\gamma_q$</td>
<td>Learning propensity from quality-SI</td>
<td>0.00 (0.062)</td>
<td>0.13** (0.033)</td>
<td>0.03** (0.033)</td>
<td>0.04** (0.033)</td>
</tr>
</tbody>
</table>

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

### 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** (0.062)</td>
<td>0.23** (0.058)</td>
<td>0.00 (0.049)</td>
<td>0.02*** (0.000)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.26*** (0.034)</td>
<td>0.38*** (0.030)</td>
<td>0.02** (0.000)</td>
<td>0.19*** (0.000)</td>
</tr>
<tr>
<td>$h$</td>
<td>Own-learning propensity</td>
<td>0.00 (0.143)</td>
<td>0.23*** (0.043)</td>
<td>0.35*** (0.035)</td>
<td>0.23*** (0.000)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.14*** (0.015)</td>
<td>0.11*** (0.022)</td>
<td>0.13*** (0.015)</td>
<td>0.36*** (0.000)</td>
</tr>
<tr>
<td>$\beta_m$</td>
<td>Weight on share-SI</td>
<td>0.00 (0.062)</td>
<td>0.00 (0.033)</td>
<td>0.03** (0.000)</td>
<td>0.04** (0.000)</td>
</tr>
<tr>
<td>$\gamma_m$</td>
<td>Learning propensity from share-SI</td>
<td>0.59*** (0.058)</td>
<td>0.39*** (0.072)</td>
<td>0.49** (0.000)</td>
<td>0.36*** (0.000)</td>
</tr>
<tr>
<td>$\beta_q$</td>
<td>Weight on quality-SI</td>
<td>0.08* (0.031)</td>
<td>0.02 (0.022)</td>
<td>0.24** (0.000)</td>
<td>0.06** (0.000)</td>
</tr>
<tr>
<td>$\gamma_q$</td>
<td>Learning propensity from quality-SI</td>
<td>0.00 (0.062)</td>
<td>0.13** (0.033)</td>
<td>0.00 (0.000)</td>
<td>0.00 (0.000)</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td></td>
<td>–485.73</td>
<td>–496.07</td>
<td>–521.54</td>
<td>–353.14</td>
</tr>
</tbody>
</table>

**Note.** Standard errors from inverse Hessian matrix are in parentheses. $*** p < 0.01$, $** p < 0.05$, and $* p < 0.10$. 
weight to social information because 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.

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 quality-SI ($\beta_q$) decreases over time. 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).** Under large-gap competition, (1) consumers demonstrate own- and social-learning propensity, (2) SI reduces the amount of recency bias, and (3) consumers place the most weight on quality-SI followed by full-SI and then share-SI. Under small-gap competition, (1) consumers demonstrate own- and social-learning propensity (except in share-SI in early periods), (2) quality-SI and full-SI reduce the amount of recency bias, and (3) consumers place similar weight on quality-SI and full-SI followed by share-SI.

### 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:

<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>(1.7)</td>
<td>(1.3)</td>
</tr>
<tr>
<td>Bayesian benchmark (with full-SI)</td>
<td>98.2</td>
<td>83.9</td>
</tr>
<tr>
<td></td>
<td>(1.3)</td>
<td>(1.2)</td>
</tr>
<tr>
<td>Bayesian benchmark (with no-SI)</td>
<td>78.9</td>
<td>57.6</td>
</tr>
<tr>
<td></td>
<td>(1.6)</td>
<td>(0.8)</td>
</tr>
<tr>
<td>WSLS benchmark (with no-SI)</td>
<td>67.9</td>
<td>52.3</td>
</tr>
<tr>
<td></td>
<td>(1.8)</td>
<td>(1.7)</td>
</tr>
</tbody>
</table>

**Note.** Standard errors in parentheses.

**p < 0.01, **p < 0.05 for T-tests comparing SI treatments to no-SI.

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5.2.1. Market Share. In Table 4, we present the average market share of the high firm in each treatment and in the three benchmarks. The all-periods average market share is calculated as the percentage of decisions in which participants chose to visit the high firm in the observed data across periods 1–40, and the last 10 periods’ market share is calculated for periods 31–40 to illustrate results closer to steady state. Additionally, in Figure 2, we present the results of pairwise comparisons of market shares across the treatments and benchmarks. Complete details of the statistical tests that yield these results are described in Online Appendix D.

First consider the average market shares of the high firm across all periods. As seen in Table 4, the market share is the highest in the Bayesian full-SI benchmark and the lowest in the WSLS benchmark. Beginning with large-gap competition, the market shares in the SI treatments are markedly different from one another. The quality-SI treatment yields a significantly higher market share compared with the control no-SI treatment (86.2% versus 70.7%, p < 0.01) and compared with the share-SI treatment (86.2% versus 75.6%, p < 0.01). In fact, it is higher than even the Bayesian no-SI benchmark (86.2% versus 78.9%, p < 0.05) and is second only to the Bayesian full-SI benchmark. This suggests that quality-SI under large-gap competition enables consumers to make decisions much like rational (Bayesian) decision makers (with no-SI). The market share under share-SI is also higher than the no-SI treatment (75.6% versus 70.7%, p < 0.05) but is inferior to quality-SI. We find that all four large-gap
Experimental treatments are significantly different from one another (six tests, all $p < 0.05$, as shown in Figure 2).

The relative ordering of share-SI and quality-SI flips under small-gap competition: share-SI results in a market share that is significantly higher than the control treatment ($60.0\%$ versus $56.4\%, p < 0.05$) and is also higher than the Bayesian benchmark with no-SI ($57.6\%$), whereas quality-SI yields a market share of $55.8\%$ that is slightly worse than the control no-SI treatment and is significantly worse than share-SI. Figure 2 shows which of the differences between treatments are statistically significant. Moreover, note that the average market share with quality-SI is significantly higher than the Bayesian no-SI benchmark only under large gap. Thus, we observe that the effectiveness of different types of social information reverses depending on the quality gap between the firms.

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 3. We discuss potential explanations for this difference in Section 5.3.2.

Finally, we note that the high firm’s market share increases over time in all of our treatments, demonstrating that learning takes place. Comparing the average market shares for the last 10 periods under large-gap competition, we find that all differences are statistically significant except between full-SI versus share-SI and full-SI versus quality-SI (see Online Appendix D for additional details). Under small-gap competition, the only statistically significant difference during the last 10 periods is between share-SI and No-SI ($p = 0.033$). 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,

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**Figure 2.** (Color online) Pairwise Comparisons of the Average High Firm Market Share (All Periods)

<table>
<thead>
<tr>
<th>No-SI</th>
<th>Share-SI</th>
<th>Quality-SI</th>
<th>Full-SI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WSLS</td>
<td>Bayesian</td>
<td>Bayesian</td>
</tr>
<tr>
<td>Share-SI</td>
<td></td>
<td>no-SI</td>
<td>full-SI</td>
</tr>
</tbody>
</table>

Notes. Left and right boxes in each column denote large and small quality gaps, respectively. Solid filled boxes indicate market shares are significantly different at $p < 0.05$, vertical lines indicate when the benchmark market share is significantly higher than the treatment, cross-hatch shows benchmarks that are significantly lower than the treatment, and unfilled boxes indicate no statistical significance. See Online Appendix D for details.

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**Figure 3.** (Color online) Cumulative Market Share of the High Firm over Time

(a) Large-gap

(b) Small-gap

Notes. The plot shows the average of accumulated visits to the high firm from the second to the last period. Each point represents the average market share of the high firm up to a time period and treatment and is computed across the choices made by all consumers in that period and treatment.
share-SI leads to higher market share for the high firm. Finally, 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 4 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 4(a), we find that all three SI treatments lead to statistically significant lower standard deviations compared with the No-SI treatment (all \( p < 0.01 \)). We also observe that quality-SI generates the greatest reduction in demand uncertainty compared with No-SI (the standard deviation is actually lower than the control treatment in 38/40 periods). Under small-gap competition, in Figure 4(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 is reduced with SI, is supported for all SI types under large-gap competition and 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 Online Appendix B for details).

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- and small-gap treatments is the most striking with quality-SI (14 periods in large 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” than 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 the following:

**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. Finally, 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- 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 5, 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 5(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 independent and identically distributed. Under large-gap competition (Figure 5(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 5(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 because 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 noninformative under full-SI in later periods.

#### 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. Although 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
Notes. (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. The % receiving positive share-SI for the high firm and % receiving positive quality-SI for the high firm counts the percentage 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 the high firm is superior to the low firm. % of the high firm visit counts the percentage of participants choosing the high firm during that period, representing the high firm market share.
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 6 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 6(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. For example, under 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 with quality-SI alone because of 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 6). 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 the following:

**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.

![Figure 6. Effect of Quality-SI, Share-SI, and Full-SI on the High-Firm Choice in a Subsequent Period](image-url)
and full-SI boost loyalty for the high firm under large-gap competition (which is expected), whereas share-SI reduces loyal consumers 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 helps 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. 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.

Table 6. Percentage 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>

Notes. Standard errors in parentheses. Both SI negative rarely occurred, leading to insignificance.
**p < 0.05, *p < 0.10.

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 the consumer’s 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.

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 consumers 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 with 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

Table 7. Frequency of Consumers Switching Between Firms and Percentage of Loyal Consumers

<table>
<thead>
<tr>
<th>Percentage of time switching</th>
<th>Percentage of loyal consumers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Large gap</td>
</tr>
<tr>
<td>No-SI</td>
<td>26.8</td>
</tr>
<tr>
<td>Share-SI</td>
<td>20.1*</td>
</tr>
<tr>
<td>Quality-SI</td>
<td>17.3***</td>
</tr>
<tr>
<td>Full-SI</td>
<td>17.6**</td>
</tr>
<tr>
<td>Bayesian (with full-SI)</td>
<td>2.0</td>
</tr>
<tr>
<td>Bayesian (with no-SI)</td>
<td>3.4</td>
</tr>
<tr>
<td>WSLS</td>
<td>30.5</td>
</tr>
</tbody>
</table>

Note. T-tests with the no-SI treatment.
**p < 0.01, **p < 0.05, *p < 0.10.
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 counterintuitive 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.

Our paper takes a first step toward studying different types of social information and has some limitations that may be examined in future research. For instance, in practice, it may be difficult to recognize when a small- or large-gap setting applies. Also, the binary nature of our experiment, although consistent with the literature, may not reflect the richness of service and retail environments. One direction of future research is toward theory building to understand different attributes of social information, their effects on consumer learning, and their interaction with quality levels of firms. Such theory would be useful for validating the generalizability of our results regarding the inferiority of full-SI or the reversal of the relative ordering of market shares under quality- and share-SI. Another direction of future research is to enrich empirical and experimental evidence for different variations of our experiment. In particular, 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, for example, two high and one low quality, to differentiate between the effects of quality levels and competition. Asymmetric strategies could be studied in which firms provide different types of social information (or some provide none). Customers’ willingness to consume different types of social information could be studied by endowing them with budgets to purchase social information. Finally, our model could be extended to allow a larger set of attributes and combined with field data on social information as well as quality differences between firms.

Acknowledgments

The authors thank seminar participants at the University of Michigan, University of Wisconsin, Clemson University, Boston University, Emory University, Baruch College, and the Workshop on Empirical Research in Operations Management at the University of Pennsylvania for their comments.

Endnotes

1 In reality, social information can be biased because of the self-selection process of consumers, for example, extremely negative/positive opinions more often are expressed or shared than moderate opinions. In our controlled laboratory experiment, we rule out this potential of bias by collecting and reporting the information to participants directly.

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, for example, “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.

3 The stationary distribution and convergence speed thus computed are approximations because we ignore correlations across consumers to make this computation tractable.

References


