CONSUMER-DRIVEN OPERATIONS: EMPIRICAL AND EXPERIMENTAL STUDIES IN DEMAND MODELS

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The new selling techniques enabled by information technologies in today's marketplaces, such as online sales channels, search portals, and review platforms, changed the consumer-driven demand in many ways. Unlike traditional retail competition, mostly driven by product attributes (e.g., quality, price, etc.), these selling techniques based on information technologies have become more important to consider customer behavior and its resulting effect in shaping demand, in order for firms to better plan their operational strategies. In this dissertation, we investigate different sources of demand uncertainty and obtain insights into operations of the firms competing in the current marketplace. We develop methods for more accurate estimations of demand in the presence of downstream customers' choice behavior or social interactions. We adopt the Markov Chain based model to understand customer demand and validate the model using human-subject experiment and field data. We also conduct empirical research to capture online browsing behavior of consumers and provide implications to operational managers.

This dissertation consists of three chapters.

- Chapter 1: The Effect of Social Information on Demand in Quality Competition. This is joint work with Professor Vishal Gaur and Professor Andrew Davis
- Chapters 2: Predicting Order Variability in Inventory Decisions: A Model of Forecast Anchoring. This is joint work with Professor Andrew Davis and Professor Li Chen

- Chapter 3: Predicting Purchase Propensity from Online Browsing Behavior. This is joint work with Professor Vishal Gaur

The three chapters are self-contained but are related to one another: Chapter 1 investigates the impact of social information on demand uncertainty using experimental work, Chapter 2 explores the sources of amplified demand uncertainty from the downstream buyers' inventory decisions, and Chapter 3 empirically explores the effect of online browsing behavior on demand prediction and is a work-in-progress. All these chapters commonly focus on the behavioral sources of demand endogeneity. Therefore, this dissertation aims to contribute to improve the accuracy of demand estimation by incorporating those behavioral factors into the models in Operations.

BIOGRAPHICAL SKETCH

Dayoung Kim received a Bachelor's degree in Business Administration and Master's degree in Management Science, from Seoul National University. She received her Master's and doctoral degree in Operations, Technology and Information Management from SC Johnson College of Business at Cornell University.

To my parents

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CHAPTER 1

THE EFFECT OF SOCIAL INFORMATION ON DEMAND IN QUALITY COMPETITION

1.1 Introduction

In the services industry where a firm's true quality is not explicitly known to consumers, social information generated through the interaction of people plays a critical role in determining which firm to visit. Often times, this social information is depicted to consumers in different ways. For instance, *Urbanspoon.com* lists the 'most popular' restaurants in town, whereas *Zocdoc.com* displays doctors according to 'quality ratings' by patients. In these examples, the overall popularity rankings and number of reviews contain market share-based information reflecting the choices of consumers, whereas the average product ratings and reviews contain quality-based information. This raises the question as to whether consumers respond differently to various aspects of social information, affecting a firms' demand characteristics in alternative ways. If so, it is important that firms understand these differing impacts on demand so that they can make better operational and planning decisions. Furthermore, it may also help a firm determine whether they should strategically choose which type of information to promote to their customers through their own social media outlets. In this study, we investigate the effects of different types of social information on consumers' choice between firms, and their resulting impact on the firms' market shares and demand uncertainties.

Empirical evidence suggests that social information plays a significant role in how consumers choose among firms. For example, periodic surveys conducted by Nielsen illustrate that consumers consider earned recommendations from friends and family as the most trustworthy source of information followed by information posted on brandmanaged (owned) websites and consumer opinions posted online as the most reliable source of information [55]. Additionally, a growing academic literature demonstrates that humans, when making decisions, learn and are influenced by information in different ways (e.g. [30, 16]). Thus, it is important for firms to understand the effect that social information has on consumers' choices for visiting firms, and how this then affects their demand characteristics for better operational decision making. However, in practice, it is difficult for firms to make this assessment for two reasons: (i) they often have access to only partial data, i.e., visits by customers to their stores, but not the visits to competitors' stores, and (ii) customers are presented with more than one type of social information simultaneously, so that their effects are difficult to disentangle. This chapter addresses this problem by conducting a controlled laboratory experiment in which different types of social information are presented to different treatment groups of subjects and their subsequent choice behavior is analyzed.

In the operations management literature, there has been recent work on the role of social information and its impact on consumers' choices (e.g. [74], [58], [39], and [69]). Additionally, fields such as economics and marketing have incorporated social learning into consumer choice models ([27, 5, 3]). The marketing literature collectively identifies the key dimensions of social communication that determine the effectiveness of social information as the source, the volume, and the valence: the source of information indicates where the information is coming from, the volume of information indicates how much information on the firm is available, and the valence indicates positivity or negativity of the contents delivered through social information. However, much of this work neglects to distinguish between different characteristics of firms disclosed by social information, such as the number of reviews for a firm versus the average quality rating of a firm.[1] Of the few select works that are an exception to this, Park et al. [60] take a

[1]Some papers in marketing distinguish between the volume of social information and consumers' observational learning on others' choices. We consider that both the volume of information and the

theoretical approach to investigating the impact of different types of social information on demand. They find that the market share of competing firms can change when a consumer's recency bias interacts with her weight on different types of social information. From an empirical standpoint, Chen et al. [22] investigate the effect of two types of social information using data from *Amazon.com*. Some other studies exhibit conflicting evidence on how the different types of information influence the performance of the firms, e.g., [33, 23] and [47]. We contributes to this literature by developing a behavioral Hidden Markov chain model of consumer choice and conducting a controlled human-subject experiment that permits us to tease out the effect of two common, but different, types of social information on consumers' choices. Markov-chain based choice models have been used recently in the revenue management problems when consumers make choices from product assortments [11]. A Hidden Markov Model (HMM) has also been used by [2] in modeling of individual consumer behavior based on the concept of a conversion funnel in online advertisements that captures a consumer's deliberation process. We apply our model to the data collected from the experiment to assess the usefulness of social information as well as differences in individual-level consumer behavior with and without social information.

We begin our study by developing a Markov chain-based choice model for a consumer choosing between two firms. The model yields theoretical predictions for the firms' demand characteristics, such as their expected market shares, and demand uncertainty in the steady state. These theoretical predictions then serve as a basis for our behavioral hypotheses for consumers' choices under social information, which we then directly test in our experiment. We then design a 2x3 between-subject experiment to represent two situations of quality competition and three scenarios regarding social information. Each participant acts as a consumer choosing between two firms offering

observational learning are derived from information related to the market shares of competing firms.

different service quality levels that are unknown to the consumer. In the first factor, we manipulate the difference in the average service quality levels between the two firms to represent a large or a small difference. In the second factor, we vary the type of social information provided to consumers. Specifically, in a baseline set of treatments, no social information is provided, and consumers learn strictly from their own decisions and outcomes. In a second set of treatments, we supplement this with 'share-based' social information, which illustrates the percentage of people that visited each firm in the previous round. And in a third set of treatments, we provide 'quality-based' social information, which depicts the percentage of people that received a satisfactory experience from each firm in the previous round. A novel aspect of our design is that consumers are divided into cohorts and all of the social information provided is based on all consumers' actual decisions in a particular cohort in a particular round, and displayed to each subject in real time.

Our main experimental result is that quality-based information and share-based information have contrasting effects on a firm's demand characteristics as well as consumers' realized satisfaction, depending on whether the difference in service quality competition is large or small. First consider the scenario where there is a large difference in service quality between the firms. Under quality-based information, a firm with higher service quality achieves a 22% increase in market share (from 70.0% to 85.6%), and further benefits from lower demand uncertainty, compared to the case without any social information. Furthermore, a high-quality firm can take advantage of the increased chance of providing positive consumer experiences. Our data show that consumers' dependence on social information affects average consumers' satisfaction rate, thus affecting the market share and profitability altogether. However, under share-based information, interestingly, there is almost no benefit to the higher quality firm, only increasing market share by 1% (from 70.0% to 70.8%). In contrast, for the scenario where there is a small difference in service quality, and quality-based information is provided, then the firm with (marginally) higher market share actually experiences a *decrease* of 9% in market share (from 56.7% to 52.1%), compared to when there is no social information. Given our duopoly setting, this last result implies that the firm with lower service quality, can actually benefit from providing quality-based social information to consumers.

We proceed to utilize our data to examine the mechanism for this outcome at an individual consumer level. We find that, for both levels of service competition between the firms, quality-based information leads to less switching by consumers (between firms) than share-based information. In fact, quality-based information leads to a higher percentage of 'loyal' consumers. Thus, quality-based social information can benefit both firms, from an operational standpoint, through generating more stable consumer behavior and more predictable demand. On the other hand, share-based social information leads to a more intense switching behavior and shorter sojourn times at firms. In short, consumers do react to share-based social information, but it does not improve the market share of the higher quality firm or satisfaction obtained by consumers.

Because our experiment is designed to present the two types of social information separately, we also conduct an experimental treatment that presents both types of social information to consumers simultaneously, when the service quality gap between the firms is large. We find that the behavior of consumers, and the corresponding firms' demand characteristics, are virtually identical to those observed when only quality-based information is provided. In particular, the market share for the higher quality firm is 85.7% when both types of social information are provided, whereas the market share under only quality-based information, as previously noted, is 85.6%. This preliminary evidence indicates that when both types of social information are displayed to consumers, quality-based social information may actually crowd out the effects of share-based information.

Our study provides a number of managerial implications. First, by understanding how different types of social information affect consumers' choices, firms are able to generate more accurate predictions of market share and demand uncertainty. This translates into improved operational planning decisions. A second implication stems from the fact that firms increasingly spend a sizable fraction of their marketing budgets in managing their own social media. For instance, Sephora has a social media budget of several million dollars, which it spends on its Facebook page as well as a network on its own home page [67]. Interestingly, the firm chooses to promote share-based information on its products on its Facebook page. Our work provides guidance to firms as to the type of social information that can be beneficial to them in increasing market share, decreasing demand uncertainty, and improving overall profitability, relative to their current competitive positions.

1.2 Model

We represent a consumer's learning and choice behavior in this problem as a Markov Chain. We use the model to test hypotheses on the individual-level consumer behavior and construct aggregate characteristics of the demand faced by firms.

1.2.1 Model Description

We consider a fixed population of N identical consumers choosing between two firms, $s \in \{1, 2\}$, in discrete time periods, $t = \{1, ..., \infty\}$. 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 *Bernoulli*(q_s).

We assume that: (1) There are only two firms in the market. We make this assumption for parsimony of the model and ease of design of the experiment. (2) The average service quality of firm 1 is higher than that of firm 2 ($q_1 > q_2$) without loss of generality. We use the terms 'firm' and 'store' interchangeably throughout the chapter. (3) 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 social information. (4) Consumers are ex-ante identical. As time evolves, they become heterogeneous through differences in experiences and choices. (5) Consumers use exponential smoothing to update their beliefs. In addition, they may suffer from recency bias when choosing which firm to visit.

Because consumers are ex-ante identical, we first model the choice behavior of a single representative consumer and omit the corresponding index. Let $\mathcal{S}_t = (A_t, Y_{1t}, Y_{2t})$ denote the state of the representative consumer at the start of time t, where A_t, Y_{1t}, and Y_{2t} are the binary variables. Through the first variable, A_t, we represent the consumer's overall belief about which firm is better at the beginning of period t based on her learning up to time $t - 1$. When $A_t = 1$, the consumer believes that firm 1 has better quality. In this case, we call the consumer's belief as the (G)ood state, because her perception is in line with the true average service level of the firms. When $A_t = 0$, the consumer believes that firm 2 has better quality, and we call this belief as the (B)ad state.

The second variable, Y_{1t}, denotes the most recent service outcomes experienced by the consumer from the firm 1. If the consumer visited firm 1 at $t - 1$ and was satisfied, then $Y_{1t} = 1$; if the consumer visited firm 1 at $t - 1$ and was dissatisfied, $Y_{1t} = 0$; and if the consumer did not visit firm 1 at $t-1$, $Y_{1t} = Y_{1,t-1}$. And Y_{2t} similarly denotes the most recent service outcome experienced by the consumer from firm 2. Y_{1t} and Y_{2t} together represent the consumer's most recent service outcomes from both firms. These three binary variables define the consumer's state at t, $(A_t, Y_{1t}, Y_{2t}) = \mathcal{S}_t \in \mathcal{S} = \{(G,1,1),(G,1,0),(G,0,1),(G,0,0),(B,1,1),(B,1,0),(B,0,1),(B,0,0)\}$. Since their values are undefined at $t = 1$, we initialize the model by assuming that the consumer is equally likely to be in one of the eight states at $t = 1$. Subsequently, Y_{1t} and Y_{2t} are observed from the data, but A_t is a latent (hidden) state variable. We will construct a maximum likelihood distribution of the consumer's latent state as a function of observed outcomes, social information, and own experience information available to her.

Also let $V_t \in \{1,2\}$ denote the visit choice made by the representative consumer at time t. This visit choice and outcome probability together determine the state $\mathcal{S}_{t+1}$. We specify how A_t evolves over time as a function of historical experiences in Section 2.1.1, explain how a consumer decides V_t given state $\mathcal{S}_t$ in Section 2.1.2, and define social information in Section 2.1.3.

2.1.1. Belief Formation

Let $\mathcal{P} = [p_{GG}\ ,\ p_{GB}\ ;\ p_{BG}\ ,\ p_{BB}]$ denote the transition probabilities from the belief states in one time period to the next. For instance, p_{GB} defines the probability of a consumer changing her belief from $A_t = 1$ to $A_t = 0$, i.e., (G)ood to (B)ad for firm 1. We use two types of information to update A_t: own experience and social learning. Thus, we decompose $\mathcal{P}$ into a weighted sum of two matrices, $\mathcal{P}_o$ and $\mathcal{P}_s$, which jointly allow the switching of beliefs via a consumer's *(o)wn* experience and *(s)ocial* information.

$$\mathcal{P} = \begin{bmatrix} p_{GG} & p_{GB} \\ p_{BG} & p_{BB} \end{bmatrix} = (1-\beta)\cdot\mathcal{P}_o + \beta\cdot\mathcal{P}_s, \tag{1.1}$$

Here, $\beta \in [0,1]$ captures the weight on social information compared to a consumer's own experience in forming her belief. We use subscripts o and s to denote own and social information, respectively, throughout the paper.

To define $\mathcal{P}_o$ and $\mathcal{P}_s$, we adopt leakage probabilities, h and $g \in (0, 1)$, that allow belief switching from one state to the other when new information is not aligned with the prior belief. We define h as the *own learning propensity*, i.e., the probability of switching belief via own experience, and g as the *social learning propensity*, i.e., the probability of switching belief via social information.

First, consider the belief update mechanism based on the consumer's own observations. If the consumer's experience at time t does not coincide with her belief, then she changes her belief with probability h, otherwise her belief remains unchanged. Mathematically,

$$\mathcal{P}_o = \begin{bmatrix} 1 - h\mathbb{I}_{\{B_o\}} & h\mathbb{I}_{\{B_o\}} \\ \\ h\mathbb{I}_{\{G_o\}} & 1 - h\mathbb{I}_{\{G_o\}} \end{bmatrix}, \tag{1.2}$$

where $\mathbb{I}_{\{\cdot\}} = 1$ when the consumer's experience at t is inconsistent with her prior belief at time t. $\mathbb{I}_{\{B_o\}} = 1$ and $\mathbb{I}_{\{G_o\}} = 0$ when (1) $V_t = 1$ and dissatisfied, or (2) $V_t = 2$ and satisfied. On the other hand, $\mathbb{I}_{\{B_o\}} = 0$ and $\mathbb{I}_{\{G_o\}} = 1$ when (1) $V_t = 1$ and satisfied, or (2) $V_t = 2$ and dissatisfied.

For example, suppose a consumer's prior belief at time t is G ($A_t = 1$) at the beginning of the period t. If she chooses to visit firm 1 and is satisfied or chooses to visit firm 2 and is dissatisfied, her experience at t reinforces her prior belief that firm 1 is better. Thus, her posterior belief is unchanged. On the other hand, if the customer chooses to visit firm 1 and is dissatisfied or chooses to visit firm 2 and is satisfied, her experience at t allows her belief to be switched to B ($A_t = 0$) with probability h. Thus, h represents an exponential smoothing parameter in belief formation.

The belief update mechanism through social information is defined in the same way as $\mathcal{P}_s$. Mathematically,

$$\mathcal{P}_s = \begin{bmatrix} 1 - g\mathbb{I}_{\{B_s\}} & g\mathbb{I}_{\{B_s\}} \\ \\ g\mathbb{I}_{\{G_s\}} & 1 - g\mathbb{I}_{\{G_s\}} \end{bmatrix}, \tag{1.3}$$

where $\mathbb{I}_{\{\cdot\}} = 1$ when the social information at t is inconsistent with the consumer's prior belief at time t. $\mathbb{I}_{\{B_s\}} = 1$ and $\mathbb{I}_{\{G_s\}} = 0$ when social information at time t favors firm 2. Likewise, $\mathbb{I}_{\{B_s\}} = 0$ and $\mathbb{I}_{\{G_s\}} = 1$ when social information favors firm 1. We define the modeling of social information in Section 2.1.3.

With these two probabilities, we rewrite the transition matrix (1.1) as follows:

$$\mathcal{P} = \begin{bmatrix} \beta(1 - g\mathbb{I}_{\{B_s\}}) + (1-\beta)(1 - h\mathbb{I}_{\{B_o\}}) & \beta g\mathbb{I}_{\{B_s\}} + (1-\beta)h\mathbb{I}_{\{B_o\}} \\ \\ \beta g\mathbb{I}_{\{G_s\}} + (1-\beta)h\mathbb{I}_{\{G_o\}} & \beta(1 - g\mathbb{I}_{\{G_s\}}) + (1-\beta)(1 - h\mathbb{I}_{\{G_o\}}) \end{bmatrix}. \tag{1.4}$$

Therefore, the consumer's overall belief update depends on the three behavioral parameters: β captures weight on social information over own information, h captures responsiveness to her own experience, and g captures responsiveness to social information. For example, consider a consumer with prior belief G at the beginning of period t who chooses to visit firm 2 and is satisfied. If she disregards social information ($\beta = 0$), then with probability h she switches her belief to B after that period. However, if this consumer gets more positive social information about firm 1 (i.e., better reputation than firm 2) and disregards her own experience ($\beta = 1$), then she sticks to her prior belief that firm 1 is better (G) with probability one. More likely is the case that the consumer gives weight to both her own experience and social information ($0 < \beta < 1$). Then the transition probability in our model becomes $\mathcal{P} = \beta \cdot \begin{bmatrix} 1 & 0 \\ g & 1-g \end{bmatrix} + (1-\beta) \cdot \begin{bmatrix} 1-h & h \\ 0 & 1 \end{bmatrix}$.

2.1.2. Visit Decision

To define the visit probability, let $R_t = \frac{Y_{1t}-Y_{2t}+1}{2} \in \{0, 0.5, 1\}$ combine the recency variables Y_{1t} and Y_{2t} to represent 'which firm is better' from the most recent service encounter. Previous research in sequential learning shows that human decision makers are prone to recency bias, and respond to both their most recent experience and overall past experience [30, 43, 51]. Evidence also indicates that the past outcomes, except the most recent outcome, have a similar impact on future choices [28, 54]. Although exponential smoothing gives a higher weight to more recent experiences, it differs from recency bias. Therefore, we allow a consumer to associate a higher weight with her most recent experiences given her overall belief. Thus, we model the probability of visiting firm 1 in time period t given current state (A_t, Y_{1t}, Y_{2t}) as:

$$Pr(V_t = 1 \mid (A_t, Y_{1t}, Y_{2t})) = (1-\alpha) \cdot A_t + \alpha \cdot R_t, \tag{1.5}$$

where $\alpha \in [0, 1]$ 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.

Figure 1.1 shows the transition diagram between the belief states, the outcome (visit) probability, and the related behavioral parameters in this process.

If we alternatively, expand this to our eight-state Markov Chain, the consumer's decision process and learning can be captured as in figure 1.2 shows our that captures the consumer's decision process and learning.

Now, we show the complete transition matrix and store visit probabilities in this Markov chain. Expanding the consumer's visiting probability of firm 1 conditional on the state x, v_x^1 is defined as following.

$v_1^1 = Pr(\text{visit firm 1 } \mid (\text{G,1,1})) = (1-\alpha) \cdot 1 + \alpha \cdot \frac{1}{2} = 1 - 0.5\alpha$

$v_2^1 = Pr(\text{visit firm 1 } \mid (\text{G,1,0})) = (1-\alpha) \cdot 1 + \alpha \cdot \frac{1}{1} = 1$

Figure 1.1: Transition diagram: transitions between the hidden belief states and the visit probability

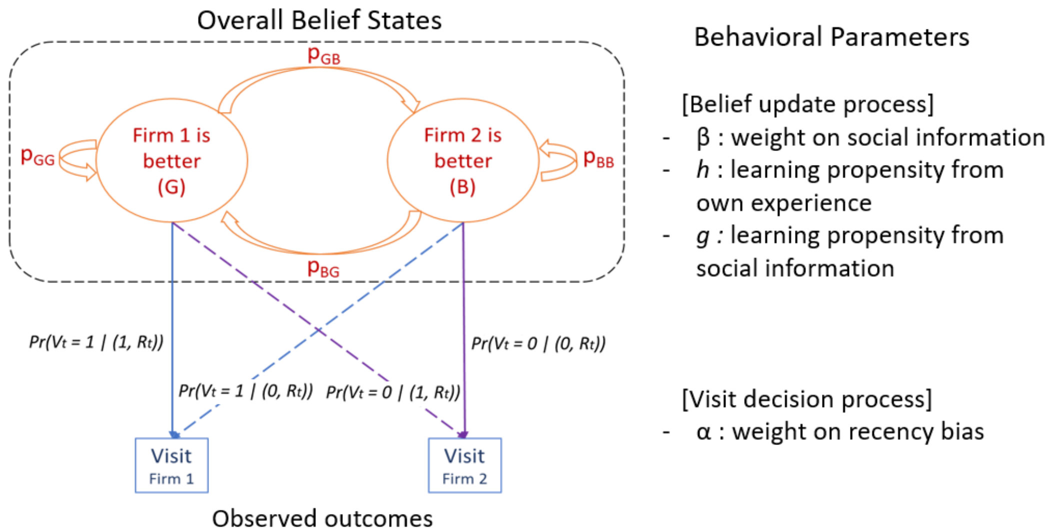


Figure 1.2: Transition diagram between the 8 states of $\mathcal{M}(S)$.

$v_3^1 = Pr(\text{visit firm 1 } \mid (\text{G},0,1)) = (1-\alpha)\cdot 1 + \alpha \cdot \frac{0}{1} = 1-\alpha$

$v_4^1 = Pr(\text{visit firm 1 } \mid (\text{G},0,0)) = (1-\alpha)\cdot 1 + \alpha \cdot \frac{1}{2} = 1-0.5\alpha$

$v_5^1 = Pr(\text{visit firm 1 } \mid (\text{B},1,1)) = (1-\alpha)\cdot 0 + \alpha \cdot \frac{1}{2} = 0.5\alpha$

$v_6^1 = Pr(\text{visit firm 1 } \mid (\text{B},1,0)) = (1-\alpha)\cdot 0 + \alpha \cdot \frac{1}{1} = \alpha$

$v_7^1 = Pr(\text{visit firm 1 } \mid (\text{B},0,1)) = (1-\alpha)\cdot 0 + \alpha \cdot \frac{0}{1} = 0$

$v_8^1 = Pr(\text{visit firm 1 } \mid (\text{B},0,0)) = (1-\alpha)\cdot 0 + \alpha \cdot \frac{1}{2} = 0.5\alpha$

Again, a consumer's visit probability of firm 2 given the state x, v_x^2, is $1 - v_x^1$. This structure in current configuration imposes a consumer's higher likelihood of revisiting the firm with satisfactory experience. For example, $v_3^1 = 1-\alpha$ renders that a consumer is not likely to choose firm 1 with certainty even if her prior belief is G, but with positive probability $1-\alpha$. The probability of visiting firm 1 decreases with the weight on the most recent experience, however, this decrease in probability is smaller in v_1^1, if her most recent experience from the firm 1 was also satisfactory.

It is notable that own learning propensity is embedded with probability h. For instance, if the consumer was dissatisfied from firm 1 while the belief being G, she switches her overall belief to B with probability h. This gives us 8×8 transition matrix $\mathcal{P}$ by combining the store visit probabilities and the switching propensity. Let $\mathcal{P} = [[P_{GG}, P_{GB}], [P_{BG}, P_{BB}]]$, where P_{GB} defines the transition sub-matrix from states G to B and P_{GG}, P_{BG}, and P_{BB} have analogous definitions. The values of the transition probabilities are:

$P_{GG} =$

$$\begin{bmatrix} v_1^1 q_1 + v_1^2 q_2(1-h) & v_1^2(1-q_2) & v_1^1(1-q_1)(1-h) & 0 \\ v_2^2 q_2(1-h) & v_2^1 q_1 + v_2^2(1-q_2) & 0 & v_2^1(1-q_1)(1-h) \\ v_3^1 q_1 & 0 & v_3^1(1-q_1)(1-h) + v_3^2 q_2(1-h) & v_3^2(1-q_2) \\ 0 & v_4^1 q_1 & v_4^2 q_2(1-h) & v_4^1(1-q_1)(1-h) + v_4^2(1-q_2) \end{bmatrix}$$

$P_{GB} =$

$$\begin{bmatrix} v_1^2 q_2 h & 0 & v_1^1(1-q_1)h & 0 \\ v_2^2 q_2 h & 0 & 0 & v_2^1(1-q_1)h \\ 0 & 0 & v_3^1(1-q_1)h + v_3^2 q_2 h & 0 \\ 0 & 0 & v_4^2 q_2 h & v_4^1(1-q_1)h \end{bmatrix}$$

$P_{BG} =$

$$\begin{bmatrix} v_5^1 q_1 h & v_5^2(1-q_2)h & 0 & 0 \\ 0 & v_6^1 q_1 h + v_6^2(1-q_2)h & 0 & 0 \\ v_7^1 q_1 h & 0 & 0 & v_7^2(1-q_2)h \\ 0 & v_8^1 q_1 h & 0 & v_8^2(1-q_2)h \end{bmatrix}$$

$P_{BB} =$

$$\begin{bmatrix} v_5^1 q_1(1-h) + v_5^2 q_2 & v_5^2(1-q_2)(1-h) & v_5^1(1-q_1) & 0 \\ v_6^2 q_2 & v_6^1 q_1(1-h) + v_6^2(1-q_2)(1-h) & 0 & v_6^1(1-q_1) \\ v_7^1 q_1(1-h) & 0 & v_7^1(1-q_1) + v_7^2 q_2 & v_7^2(1-q_2)(1-h) \\ 0 & v_8^1 q_1(1-h) & v_8^2 q_2 & v_8^1(1-q_1) + v_8^2(1-q_2)(1-h) \end{bmatrix}$$

This completes the description of the eight-state Markov chain model of consumer behavior in response to previous service experiences. Using the stationary distribution of this model, we can conduct preliminary simulation to generate the steady-state market share and the variance of the High-firm. Figure 1.3 and 1.4 show the impact of the α and h on predicted demand. Figure 1.3 shows that the long-term market share of High-firm decreases and the variance increases with more weight on recency bias (α). Figure 1.4 shows that the long-term market share of High-firm decreases and the variance increases with higher learning propensity (h).[2]

For instance, consider the transition probability from (G,1,0) to (B,1,1), which has a value of $Pr(\text{Visit Firm 2 } \mid \text{state } = (G,1,0)) \cdot q_2 \cdot h$. In order for this transition to occur,

[2]These simulation results display non-monotonicity due to the non-linearity of our model. Thus, we report only the reasonable range of parameters in the Figure 1.3 and 1.4.

Figure 1.3: Preliminary simulation result: Expected market share and the variance of High-firm with respect to the weight on recency bias α

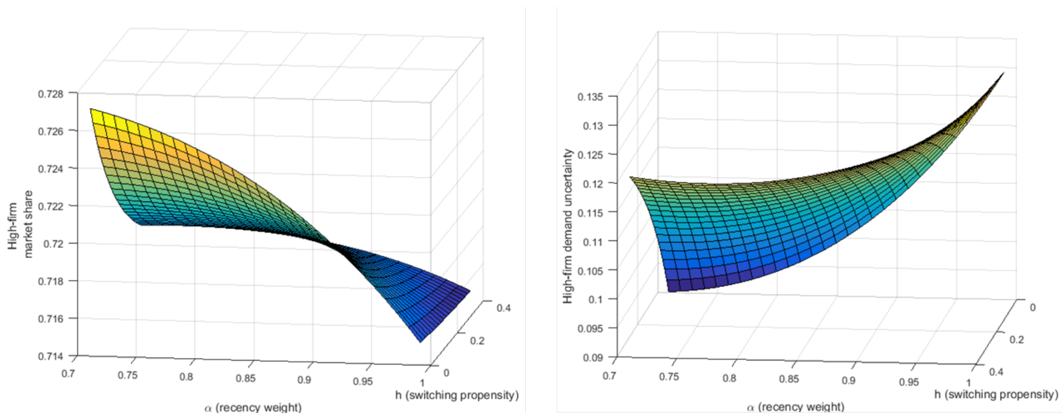
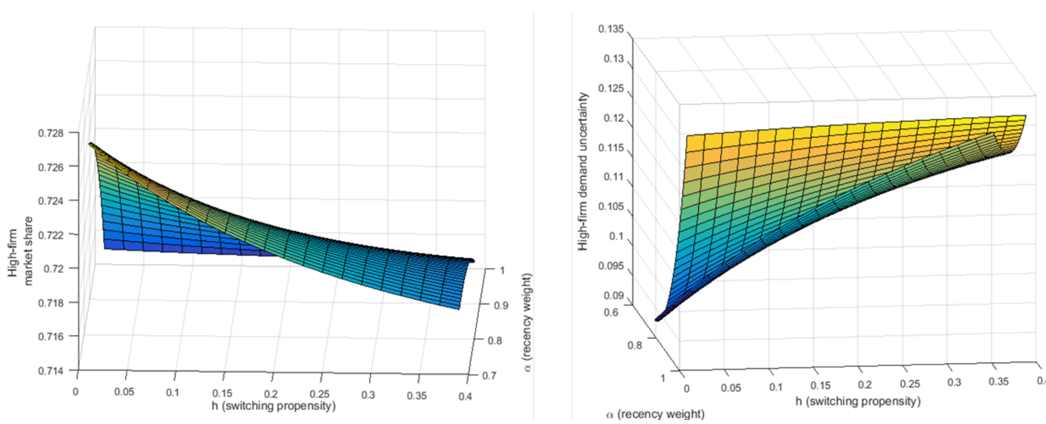


Figure 1.4: Preliminary simulation result: Expected market share and the variance of High-firm with respect to the own learning propensity h



the consumer must choose to visit firm 2 and experience satisfaction. This probability is $Pr(\text{visit the firm 2} \mid \text{state} = (G, 1, 0)) \cdot q_2$. 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. This characterizes the consumer's decision process 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.

2.1.3. Social Information

To model social information (SI, hereafter), we partition the N consumers into disjoint subsets that represent social networks. We retrieve two different types of social information from the network and provide them to consumers separately at the end of period t. The first type, 'share-based' SI, is defined as the percentage of consumers in a network who visit each firm. This information gives an estimate of market share of each firm in the network, or equivalently, the average of visit probabilities of consumers in the network, in period t. We say that share-based SI favors firm 1 (firm 2) if the observed market share of firm 1 (firm 2) is higher than that of firm 2 (firm 1), and is ambiguous if market shares are identical.[3] The second type, 'quality-based' SI, is defined as the percentage of consumers in a network who had satisfactory outcomes at the two firms. This information provides estimates of q_1 and q_2 from the experiences of consumers in the network in period t. Quality-based SI is undefined if no consumer in the network visited a firm in period t. Similar to share-based SI, we say that quality-based SI favors firm 1 (firm 2) if the observed average satisfaction from firm 1 (firm 2) is higher than that from firm 2 (firm 1), and is ambiguous if satisfaction rates are identical.[4] Thus, we incorporate these two different types of social information in the belief formation for each consumer.

Social information introduces a complexity that the transition matrix of a consumer is a function of the states and transitions of *all* consumers in her network. Thus, the states and transitions of consumers are correlated with each other. We simulate this correlation in our experiment by generating social information dynamically in each period using the

[3] We say that 50% visited firm 1 and 50% visited firm 2.

[4] We report the satisfactions from each firm as it is, so it does not matter when they are identical. If no consumers choose one firm, we just say no one visited that firm.

actual choices and visit outcomes of consumers. Thus, the experiment moves lock step from one time period to the next.

This completes the description of our model. It is a parsimonious model with only four parameters to be estimated. We considered alternative formulations of learning from historical experiences, but the state space of the model explodes quickly. Even a regression-based robustness test of our model (presented in Section 1.5.1) requires more parameters than the Markov chain model. The simplified binary states of belief of our model reflect the real-world where consumers often remember only the superiority/inferiority of a firm relative to its competitors rather than keeping track of each firm's quality level in absolute scales. By keeping the dimension of the state space minimal, our model is parsimonious, yet it predicts demand, and captures the salient aspects of a consumer's probability of visiting a store, namely, the overall beliefs about quality and the recency bias. Moreover, in forming the overall belief, two learning components from the consumer's own experience and social information are integrated into the latent state variable.

1.2.2 Hypotheses

Our first hypothesis tests the validity of the model. We hypothesize that consumers are susceptible to recency bias, but also form beliefs using own and social information, and utilize these beliefs in their store visit choice.

Hypothesis 1

(i) Consumers demonstrate moderate levels of recency bias ($\alpha > 0$), and own-learning propensity ($h > 0$).

(ii) Consumers respond to SI ($\beta > 0$), and demonstrate moderate levels of social-

learning propensity ($g > 0$).

Based on this hypothesized behavior of consumers, we can characterize demand by computing the following metrics from the estimated model: (1) the market share of each firm, (2) the variance of its demand, and (3) the speed of convergence of demand distribution to the steady state. We hypothesize that the availability of social information improves these metrics for the higher quality firm, i.e., firm 1.

Hypothesis 2

Comparing the marketplace under social information with the marketplace without social information, the High-firm

(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.

To set up this hypothesis, we reason as follows. When consumers are not exposed to SI, their learning is from own experiences alone. However, a consumer visits only one firm in each period, and thus, can update beliefs about one firm in each period. When they are exposed to SI, human subjects will utilize the increased availability of information ($\beta > 0$). Further, both types of social information are correlated with the true quality of the firms. Thus, consumers exposed to SI will learn at a faster rate that firm 1 is the higher quality firm. Moreover, their choices will be correlated with each other, which would lead to a higher market share for firm 1 and a lower variance of demand. Finally, when a consumer is exposed to SI, it may increase the relative weight on beliefs and decrease the extent of recency bias α. This factor would also result in higher market share and lower variance of demand for firm 1.

Besides testing these hypotheses, we assess the effect of social information by benchmarking our experimental results against outcomes from two models in the literature: the Wins-Stay-Lose-Shift (WSLS) model [63] and Bayesian learning [9, 31]. WSLS consumers, at one extreme, are fully myopic and respond to the most recent experience only. Bayesian learners, at the other extreme, utilize all previous experiences. Both these models are based on own experiences; they do not incorporate social information.

1.2.3 Parameter Estimation

We estimate the parameters of our model using maximum likelihood estimation (MLE). Our data set consists of the observed visit decisions, satisfaction outcomes, and social information for all consumers for all t. Thus, we compute the likelihood of observed visit decisions as a function of the model parameters and maximize it using the data set.

Let π_{it} be a vector denoting a probability distribution defined over the state space $\mathcal{S}$ of the Markov chain for consumer i in period t. We call π_{it} as 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 visit decisions and outcomes allow us to define $\mathbb{I}_{\{G_o\}}$, $\mathbb{I}_{\{B_o\}}$, $\mathbb{I}_{\{G_s\}}$, and $\mathbb{I}_{\{B_s\}}$ for all consumers in all periods. Using these values and the transition matrix defined in (1.4), the new belief-state probabilities can be computed iteratively in period $t + 1$ from π_{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 $\sum_{\mathcal{S}_{it} \in \mathcal{S}} \pi_{it}(\mathcal{S}_{it}) Pr(V_{it} = 1 \mid \mathcal{S}_{it})$. Likewise for the likelihood of visiting firm 2. Thus, the likelihood is also calculated iteratively as a function of the evolving belief-state probabilities, historical outcomes, and historical social information up to period $t - 1$. Next, we determine the parameters that jointly maximize the loglikelihood of observed visit choices.

$$\begin{aligned}\hat{\alpha}, \hat{\beta}, \hat{h}, \hat{g} &= \arg\max_{\alpha,\beta,h,g} \sum_{i,t} logL(\alpha, \beta, h, g; V_{it}, Y_{1it}, Y_{2it} \text{ for all } i, t) \\ &= \arg\max_{\alpha,\beta,h,g} \sum_{i,t} logPr(V_{it}|\alpha, \beta, h, g).\end{aligned}$$

We estimated the parameters using both a constrained non-linear optimization method and grid search. Both methods yielded consistent results. The estimated parameters are discussed in Section 1.4.1.

After parameter estimation, we calculate the long-term market share, variance of demand, and rate of convergence towards steady state for each firm. With $\alpha, \beta, h, g > 0$, we have an irreducible, aperiodic, and regular Markov Chain on the finite state space. Therefore, there exists a stationary distribution $\pi = \lim_{t\to\infty} \pi_{it}$. This stationary probability of the hidden belief states and the visit probabilities (1.5) allow us to calculate the long-run market share and variance of demand for firm 1. Additionally, the convergence speed of π_{it} to π is determined by the size of the second-largest eigenvalue, λ_2, 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 social information compared to the scenario without social information. We compute the convergence speeds under different treatments in our model in Section 1.4.4 and we explain in Appendix 1.7.2 why the second-largest eigenvalue (SLE) determines the convergence speed.

1.3 Experimental Design

We design our experiment to replicate the setting defined in Section 1.2. Each subject plays the role of a consumer choosing among two stores competing through their service quality. In each round, after a subject 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 between-subject design. Each subject participates in one treatment among 2×3 possible combinations given by two different quality competition settings and three 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 investigate the effect of different types of SI, we use three information settings: (1) a control treatment with no SI (2) a *share-based* information treatment, and (3) a *quality-based* information treatment. In the share-based treatment, in each period, we provide subjects with the percentage of visitors to each firm as additional feedback, e.g., "For this period, 30% of your acquaintances visited store A, and 70% of your acquaintances visited store B." In the quality-based treatment, in each period, we display the satisfaction rate of consumers for each firm, e.g., "For this period, 60% of your acquaintances who visited store A experienced satisfaction, and 20% of your acquaintances who visited store B experienced satisfaction." Thus, we distinguish between two different kinds of social information that are typically available to consumers in practice.

As mentioned previously, in the SI treatments, we interactively collect the decisions made by the subjects in each period to provide information in the following period, instead of using pre-generated outcomes. Using real-time information of the actual subjects' choices/experiences better captures the true process of SI generation in practice. Moreover, we randomize the social network in each period. Specifically, each session of the experiment consists of 18 subjects, who are randomly placed into a group of nine in each period. In the treatments with SI, after each round, all of the decisions are collected from the eight other people in a subject's group and used as the SI for that subject. Thus, after each period of decision making, each subject is presented with not only her own service encounter but also certain social information regarding eight other subjects. We inform subjects 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.

There are 36 subjects in each of the six treatments. A subject's main 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 subjects (which is unknown to them). For the duration of the experiment, subjects can observe their history of choices, outcomes, and SI, when applicable. After completing 40 periods of decision making, we ask the subjects to provide their own estimate of service quality of each firm. To maintain incentive compatibility for this post-experiment question, we award subjects additional earnings if their answer lies within a certain range of the true average service quality.

Subjects 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 subject 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 [29]. Instructions, screen shots, and more details about our experimental design are available upon request.

1.4 Results

In this section we first report the parameters of our Markov chain model, estimated using the experimental data, in subsection 1.4.1, and conclude on Hypothesis 1. Then, we summarize our three demand characteristics of interest (market share, demand uncertainty, and convergence speed), in subsections 1.4.2, 1.4.3, and 1.4.4, and conclude on each component of Hypothesis 2.

1.4.1 Parameter Estimation

In Table 1.1, we first report the two-parameter model estimation results, without consideration of SI (i.e. $h = g = 0$). The behavioral parameters, all significant, demonstrate that consumers show moderate levels of recency bias and learning propensity under all treatments. Moreover, the presence of SI appears to create a difference in the amount of recency bias. For instance, for both levels of service competition, large-gap and small gap, α is lower under quality-based SI, indicating that consumers are less susceptible to a recency bias when quality-based SI is provided. Also, note that, when interpreting the magnitude of the estimates, only comparisons across different types of SI within a particular level of service competition are meaningful (since different values of q_1 and q_2 are used in different service competition treatments).

In Table 1.2, we report the estimate results using all four parameters. Note that the most striking effect of social learning exists under quality-based SI under large-gap competition. Under this treatment, consumers utilize quality-based SI significantly ($\beta = 0.58$), and display relatively low recency bias ($\alpha = 0.16$). We also observe higher own-learning ($h = 0.29$) and social-learning ($g = 0.17$) propensities than the other

Table 1.1: Two parameter model estimates

Parameter	Description	Large-gap (Control)	Large-gap Share-info	Large-gap Qual-info	Small-gap (Control)	Small-gap Share-info	Small-gap Qual-info
α	Recency	0.33	0.29	0.11	0.27	0.39	0.23
	bias	(0.046)	(0.044)	(0.055)	(0.042)	(0.038)	(0.041)
h	Own-learning	0.15	0.15	0.20	0.14	0.11	0.07
	propensity	(0.022)	(0.017)	(0.020)	(0.018)	(0.020)	(0.012)
	Log likelihood	-688.2	-738.6	-557.0	-865.8	-874.9	-897.2
	BIC	1390.7	1491.7	1128.2	1746.1	1764.3	1808.9

Note: All parameters are significant with $p < 0.01$. Standard errors from inverse Hessian matrix are in parentheses.

treatments, which means a consumer's overall belief transition is actively influenced by both learning from their own recent experience and via the social information about others' experiences.

In all four SI treatments, in Table 1.2, we continue to observe that consumers' belief switching is more influenced by their own experience than others ($h > g$). In addition, SI is utilized by consumers under share-based SI treatments ($\beta > 0$), despite the fact that this information does not directly signal the true service quality of the firms. However, when we compare the overall fit in Table 1.2 to that in Table 1.1, it would appear as though including the two SI-related parameters, β and g, only improves the fit in quality-based SI under large-gap competition, which is evidenced by the smaller BIC value. Furthermore, a series of Likelihood Ratio tests confirms that the four parameter model, which explicitly incorporates the impact of SI, is preferred in the quality-based SI treatment with large-gap competition ($p < 0.001$).

Before concluding on Hypothesis 1, it is important to note that we also estimated

Table 1.2: Four parameter model estimates

		Large-gap			Small-gap		
Parameter	Description	(Control)	Share-info	Qual-info	(Control)	Share-info	Qual-info
α	Recency bias	0.33	0.29	0.16	0.27	0.39	0.23
		(0.046)	(0.045)	(0.046)	(0.042)	(0.038)	(0.041)
β	Weight on SI		0.15	0.58		0.13	0.01*
			(0.068)	(0.077)		(0.085)	(0.147)
h	Own-learning propensity	0.15	0.17	0.29	0.14	0.11	0.07
		(0.022)	(0.021)	(0.055)	(0.018)	(0.021)	(0.012)
g	Social-learning propensity		0.10	0.17		0.10	0.01*
			(0.067)	(0.029)		(0.071)	(0.017)
	Log likelihood	-688.2	-736.6	-543.1	-865.8	-873.8	-897.2
	BIC	1390.7	1502.3	1114.7	1746.1	1776.7	1823.4

Note: *Parameters are not statistically significant. Standard errors from inverse Hessian matrix are in parentheses.

the model at an individual level. Unsurprisingly, there is some heterogeneity in the estimates among subjects, but the average values of the parameters do not deviate significantly from the aggregate-level estimates presented above. Therefore, to summarize, Hypothesis 1 -*(i)* is fully supported - subjects demonstrate moderate levels of recency bias and own-learning propensity, whereas Hypothesis 1 -*(ii)* is partially supported - consumers directly respond to quality-based SI when there is a large-gap in the level of service competition.

Prediction Accuracy of the Model

One important way in which firms can benefit from understanding the SI-induced change in consumer behavior is by improving their demand forecasting. Here, we report the predictive performance of our model by simulating the choice paths of consumers. Using the estimated parameters from Table 1.2, we generate the simulated choice paths of consumers, and thus, predict the market share.

Table 1.3: Prediction error in the hold-out samples (period 31-40)

	Large-gap			Small-gap		
	(Control)	Share-info	Qual-info	(Control)	Share-info	Qual-info
HMM model MAD	0.35	0.22	0.16	0.46	0.41	0.43
(% improvement)	(insig.)	(39.8%)	(48.5%)	(insig.)	(9.8%)	(11.3%)

Note: "% improvement" compared to the WSLS prediction (no improvement under control group).

In Table 1.3, we present the mean-absolute deviations (MAD) of the model's (HMM) prediction to the observations in periods 31-40. It also illustrates the percent improvement from the model's predictions compared to that of the WSLS consumers' simulated choice paths. One can immediately observe that the prediction errors are smaller under SI treatments, and that, with SI, the model better explains the choice behavior of consumers compared to the WSLS prediction. Particularly, the prediction accuracy of the model increases considerably with the presence of SI under large-gap competition.

1.4.2 Market Share

To understand the consequences of this behavior on the firms, we next turn to firm-level demand characteristics. Our first firm-level demand characteristic of interest is average market share. Given that the proportion of consumers choosing the High-firm and Low-firm sums up to one, for presentation purposes, we report only the High-firm's market share. In Table 1.4, we provide the average market share of the High-firm in each treatment, along with two benchmarks: the predicted market share if consumers followed a Win-Stay-Lose-Shift (WSLS) strategy ($\alpha = 1$), or behaved like perfect Bayesian consumers ($\alpha = 0$).[5] As seen in Table 1.4, under both competition levels, the market share of the High-firm in the control treatment falls between the predicted market share of WSLS and Bayesian consumers – human subjects chose the High-firm more frequently than WSLS consumers, but not as often as Bayesian consumers. Turning to the SI treatments, it is interesting to note that the average market share of the High-firm in the quality-based information treatment under large-gap competition (85.6%), is nearly identical to the Bayesian prediction (86.6%), whereas under small-gap competition, it is almost the same (52.1%) as the WSLS prediction (52.5%).

To conclude on Hypothesis 2 -*(i)*, we must compare the average market share of the High-firm under different types of SI (Table 1.4). Beginning with the share-based information treatments, one can see that the average market share of the High-firm is virtually identical to the control treatment, for both levels of competition. However, the average market share under quality-based information is significantly different compared to the control treatment, albeit in opposite directions, depending on the level of competition. In particular, under large-gap competition, the average market share with quality-based information is 85.6%, which is significantly higher than both the control and share-based SI conditions (t-tests, both $p < 0.01$). On the other hand, under small-gap competition, the market share of the High-firm under quality-based information is actually lower than the control treatment, weakly significantly so (t-test, $p < 0.10$). Note that this final result implies that the Low-firm, under small-gap competition may benefit from quality-based

[5] Please see Appendix 1.7.1 for details of these benchmarks.

Table 1.4: Market share of the High-firm under different SI treatments

SI treatment	Large-gap	Small-gap
(Control)	70.0%	56.7%
	(1.2%)	(1.0%)
Share-based info	70.8%	58.1%
	(2.0%)	(1.3%)
Quality-based info	85.6%***	52.1%**
	(1.4%)	(1.3%)
Bayesian benchmark	86.6%	62.9%
	(2.0%)	(0.8%)
WSLS benchmark	67.6%	52.5%
	(1.8%)	(1.7%)

Note: $^{**}p < 0.01$, $^{*}p < 0.1$ t-tests comparing SI treatments to Control. Standard errors over time in parentheses.

information, as a reduction in the High-firm's market share increases the market share of the Low-firm, from 43.4% (High-firm 56.7%) to 47.9% (High-firm 52.1%). Therefore, Hypothesis 2 -*(i)* is partially supported, for quality-based information under large-gap competition.

The contrasting market share results under large and small-gap competition in the quality-based information treatment warrants additional discussion, and can be understood by returning to the behavioral parameter estimates in Table 1.2. Specifically, recall that consumers' actively use quality-based SI under large-gap competition, but not small-gap competition. This implies that a firm's promotion of quality-based information can magnify the impact of the actual quality gap between the competitors with respect to their market share. Thus, quality-based information can overly detriment the

Low-firm under large-gap competition, but provide potential benefits under small-gap competition, relative to the firm's true quality difference with its competitor.

Consumer Satisfaction

Increased market share is clearly desired by firms, but with it comes an additional benefit when there is SI. That is, a higher market share allows a firm a better chance of providing a satisfactory experience for consumers, which not only impacts a consumer's willingness to revisit the same firm, but also re-generates positive social influence for others. Indeed, when positive information is naturally generated through satisfactory outcomes, as in our setting, the market share can further favor one of the competing firms.

Table 1.5: Average satisfaction rates of all subjects in each treatment, and the subjects visiting each firms

	Large-gap			Small-gap		
Description	(Control)	Share-info	Qual-info	(Control)	Share-info	Qual-info
Overall Satisfaction	69.8%	70.1%	74.4%*	54.0%	51.8%	50.8%
Satisfaction[a] from High-firm	76.0%	77.9%	79.2%*	53.3%	53.7%	48.4%*
Satisfaction from Low-firm	49.2%	44.9%	36.1%*	47.3%	43.2%	46.7%

Note: $^*p < 0.01$, significant difference with the subjects in other SI treatments.

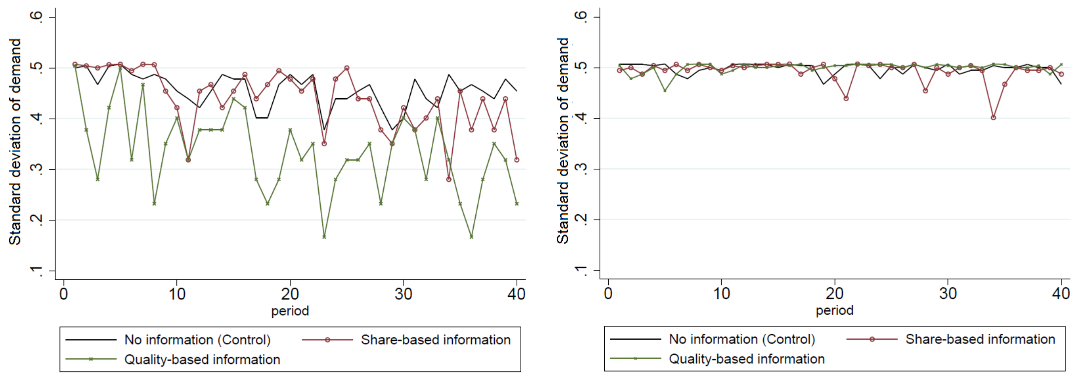
Table 1.5 depicts the overall satisfaction rates of consumers who visit each firm, by treatment. One interesting observation is that the satisfaction rates for each firm, which theoretically should be the same across different SI treatments, within the same level of quality competition, show systematic differences. Consider the second and third rows of numbers, which report the average satisfaction rate of from subjects from each firm. One might note that all of these numbers are below the firms' true average service qualities, and, in certain SI conditions, the Low-firm achieves an exceptionally low satisfaction rate. This is because consumers do not switch randomly between firms, rather, they may be more inclined to switch after a failed service (and depending on the SI). For example, in the quality-based information treatment in large-gap competition, the consumer satisfaction rate from the Low-firm is only 36.1%, and this is considerably lower than the consumer satisfaction under the control treatment in large-gap competition, 49.2%. Instead, the average satisfaction rate should be close to 50%. However, in general, when a consumer visits the Low-firm, there is a relatively higher likelihood of receiving a dissatisfactory experience. Combined with quality-based SI, the consumer may also receive positive information about the High-firm, causing the consumer to switch to the High-firm. Once at the High-firm, however, there is a lower likelihood of a dissatisfactory experience, and to see SI that would cause them to switch back to the Low-firm. The net result is that the High-firm can achieve an even greater advantage in terms of providing satisfactory experiences to consumers, under quality SI in large-gap competition.

This result is consistent with Park et al. [60], as a low estimate of service quality leads to longer time between a consumer's subsequent visits, and so, less occasion to learn the service quality offered by a firm. We conclude that under the circumstances where consumers are not well informed about the true service level offered by firms, their dependence on SI affects the chances for firms to provide satisfaction to consumers, thus affecting the market share and profitability altogether.

1.4.3 Demand Uncertainty

Our second firm level characteristic of interest pertains to the uncertainty of demand. Figure 1.5 plots the standard deviation of demand (market share) over time. One can see

Figure 1.5: Demand uncertainty under different types of SI (standard deviation) under Large-gap (left) and Small-gap (right) treatment



that demand uncertainty varies across SI treatments. In particular, under quality-based information, for all decision periods, we observe a significant reduction in demand uncertainty in large-gap competition (t-tests, across all $p < 0.01$). Combining this with our previous findings on average market share implies that, when the firm with significantly higher quality promotes quality-based information, it not only benefits from increased market share, but from reduced demand uncertainty as well. In such a case, the Low-firm will lose a significant portion of its consumers to its competitor, achieve considerably lower market share, and also face higher demand uncertainty. Therefore, like the impact of SI on market share, Hypothesis 2 -*(ii)*, which states that the variance of demand will be reduced with social information, is partially supported, under quality-based information with large-gap competition.

Switching Behavior

To further investigate demand uncertainty, we also looked into the individual consumers' choice behavior (since the variance of demand only captures the number of visitors rather than the composite of consumers). To this end, the left-hand side of Table 1.6 shows how frequently an average consumer switches between firms, and the right-hand side of Table 1.6 shows the average time each subject spends in one firm before switching, along with the predictions according to the Bayesian and WSLS benchmarks (the right hand side can be interpreted as the average *Sojourn time* between transitions among the states out of 40 total periods).

Table 1.6: Percentage of time switching and expected sojourn time over 40 periods

	% of time switching		$E_i(Sojourn\ time)$	
	Large-gap	Small-gap	Large-gap	Small-gap
(Control)	25.7%	31.3%	9.1	4.4
Share-based info	24.8%	34.6%	5.5*	3.5*
Quality-based info	18.4%	29.6%	10.8	5.0
Bayesian benchmark	11.5%	15.9%	11.3	8.4
WSLS benchmark	31.5%	45.6%	3.5	2.3

Note: $^*p < 0.01$ for t-tests with the control treatment.

Compared to the theoretical benchmarks, in Table 1.6, it appears that subjects stay in one firm longer than the WSLS consumers, but shorter than the Bayesian consumers, on average across all treatments. Comparing treatments to one another, under share-based information, average sojourn time is significantly lower than the other treatments, both in large-gap and small-gap competition. Furthermore, while not depicted, we find that all of the subjects in the share-based information treatment switched at least once, whereas some subjects never switched at all in the other treatments.

Taking this analysis a step further, we label the subjects who stay in one firm more than 10 consecutive periods on average, i.e., individuals with $E(Sojourn\ time) > 10$, as 'Loyal consumers,' and subjects who switch frequently, i.e., with $E(Sojourn\ time) < 2$, as 'Frequent switchers.' We present the percentage of these subjects in each treatment in

Figure 1.6: Percentage of frequent switchers and loyal consumers under different SI treatments

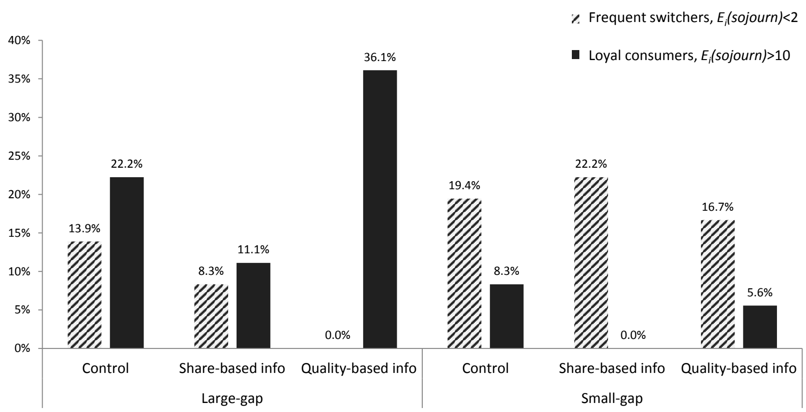


Figure 1.6. As one can see, in the quality-based information treatment under large-gap competition, more than 35% of subjects behave like loyal customers, on average. On the other hand, in the share-based information treatment, the proportion of loyal customers is the lowest, for both levels of competition (11% under large-gap, 0% under small-gap). This evidence suggests that quality-based information boosts loyalty for the High-firm under large-gap competition, whereas share-based information reduces loyal customers and promotes switching regardless of the level of competition.[6]

[6]To test whether the deviation from Bayesian choice can be explained by subjects' most recent experience and by SI, we use a Logit model with $P(Deviation\ from\ Bayes\ Choice = 1|X_i)$ as a dependent variable, which captures only (unnecessary) switching of subjects to a firm with lower estimate of service quality each period. We observed that the exploration to the Low-firm decreases with the most recent satisfaction from the High-firm, and increases with the recent satisfaction from the Low-firm. More interestingly, both of the SI types significantly affected the result: share-based information increases this exploration to the firm with the lower estimate of service quality, whereas positive quality-based information from the High-firm decreases unnecessary switching. This evidence confirms that overall deviations from the Bayesian choices increase under share-based information, whereas the valence of quality-based information directly impacts the switching of the consumers.

1.4.4 Convergence Speed

We now consider our third demand characteristic, by analyzing the convergence speed of the transition probability (between the unobserved belief states of our model).

Table 1.7 reports the convergence measures based on our current model assumption where the demand is formed by unobserved belief states (G or B). In the long run, how the overall belief states of aggregate consumers settles to its equilibrium determines the market share convergence speed.

Table 1.7: Stationary probability (π) of the belief transition matrix $\mathcal{P}$ and the convergence speed measures

Competition treatment	SI treatment	Stationary dist. $\pi = [\pi_G, \pi_B]$	Minimum periods for $\mathcal{P} \in \{\pi \pm 0.01\}$	SLE λ_2
Large-gap	(Control)	[0.666 , 0.334]	26 periods	0.847
	Share-based info	[0.717*, 0.283]	25 periods	0.843
	Quality-based info	[0.791*, 0.209]	18 periods	0.782
Small-gap	(Control)	[0.531 , 0.469]	28 periods	0.864
	Share-based info	[0.562 , 0.438]	35 periods	0.889
	Quality-based info	[0.512 , 0.488]	54 periods	0.929

Note: *Limit probability of overall belief being G, π_G, is significantly higher than $E(R_t)$ observed from data. SLE represents "second-largest eigenvalue."

First, in Table 1.7 note that the stationary distribution of the overall belief being G, for large-gap competition, is highest in quality-based SI ($\pi_G = 0.791$), and in small-gap competition, is highest in share-based SI ($\pi_G = 0.562$). With the behavioral parameter estimates in Table 1.2, and the different information set of each subject, we reconstructed the belief-transition probabilities $\mathcal{P}$ uniquely under different treatments, such that the limit probabilities and the convergence speed to equilibrium vary across treatments. A higher stationary probability of the overall belief being G leads to a frequent visit to the High-firm. In short, the results here are consistent with our previous observations that the market share is highest in quality-based SI under large-gap competition, and highest in share-based SI under small-gap competition (recall Table 1.4, which illustrated average market share by treatment).

Second, continuing in Table 1.7, consumers' overall belief status converges to its stationary probability quickest in quality-based SI under large-gap competition. In particular, within 18 periods, belief switching probabilities converge within the bound of 0.01 from the limit probabilities. The second-largest eigenvalue (SLE) is also smallest in this treatment ($\lambda_2 = 0.782$), providing further support for fastest convergence to stability, making the demand forecast easier in earlier periods (please see Appendix 1.7.2 for a further discussion and technical details).

Third, in Table 1.7, note that the speed of the belief converging to equilibrium is significantly slower with SI treatments under small-gap competition. This is due to the average quality being similar between firms, under small-gap competition, and thus, the SI generated based on consumers' experience naturally exhibits relatively higher variance. Therefore, this potentially leads to non-informative SI, and does not improve consumer learning and the settlement of beliefs.

In sum, our convergence analysis allows us to conclude that Hypothesis 2 -*(iii)* is supported under quality-based information in the large-gap competition treatment, but not across all SI treatments. Faster convergence speed is driven by the fact that, in our analyses on market share, the presence of quality-based information significantly favors the High-firm, which is compounded by a moderated recency bias and increased learning propensities, particularly under large-gap competition.

1.5 Robustness Checks

Here we report two robustness checks for our study, each which differ in their focus. The first serves as a robustness check for our Markov chain-based model and its estimates, where we build an alternative Logit model. The second pertains to our experiment, where we report results from an additional experimental treatment which provided both share-based and quality-based information to subjects, under large-gap competition.

1.5.1 Supporting Alternative Logit Model

For our Logit model, we express the probability of a customer choosing the High-firm as a function of hypothesized state variables, such as the consumer's weight on the most recent experience, the consumer's weight on the past experiences, and the numerical values of each type of SI presented to subjects. Let $\rho = p(V_t = 1 \mid (A_t, R_t))$ in (1.5), then

$$\log(\frac{\rho}{1-\rho}) = \beta_0 + \beta_{recent} * Exper_{i,t-1} + \beta_{cumulative} * Exper_{i,1:t-2} + \beta_{SI} * SI + \beta_p * Period + \nu_i + \epsilon_{i,t}.$$

We run this model with random effects, where the probability of a consumer choosing the High-firm at time t becomes equivalent to E(Market share of the High-firm at t). Note that we include dummy variables for the most recent experience, $Exper_{i,t-1}$, from both firms, and also include average past experience $Exper_{i,1:t-2}$ from all previous trials of each firm to represent overall learning. In order to determine whether we included a sufficient number of recent experiences in the model, we ran an AR(n) test. Our tests proved that an AR(1) model best explains our experimental data, which is consistent with our Markov model setting. For SI, $ShareInfo_{i,t-1}$ captures the actual proportion of the High-firm visitors displayed to a subject i at the end of period $t-1$, $QualityInfo1_{i,t-1}$ captures the proportion of satisfied visitors at the High-firm at the end of each period

$t-1$, and $QualityInfo2_{i,t-1}$ captures the proportion of satisfied visitors at the Low-firm at the end of each period $t-1$ displayed to each subject i.

Table 1.8: Logit regression on the choice of the High-firm by each treatment

Variable	Description	Large-gap			Small-gap		
		(Control)	Share-info	Qual-info	(Control)	Share-info	Qual-info
Constant	Intercept	0.571	0.127	-1.874*	-0.048	-0.552	-0.639
		(0.493)	(0.577)	(0.883)	(0.303)	(0.394)	(0.414)
$Experience1_{i,t-1}$	Recent satis from High-firm	0.833**	1.108**	0.993**	1.076**	0.913**	0.862**
		(0.171)	(0.172)	(0.218)	(0.163)	(0.156)	(0.167)
$Experience2_{i,t-1}$	Recent satis from Low-firm	-0.711**	-0.513*	-0.870**	-0.939**	-0.919**	-0.970**
		(0.210)	(0.216)	(0.304)	(0.172)	(0.176)	(0.176)
$Experience1_{i,1:t-2}$	Cumulative satis from High-firm	1.329**	1.769**	2.300**	1.764**	1.708**	2.541**
		(0.506)	(0.519)	(0.817)	(0.381)	(0.418)	(0.408)
$Experience2_{i,1:t-2}$	Cumulative satis from Low-firm	-2.208**	-2.491**	-1.736**	-1.651**	-1.379**	-1.545**
		(0.523)	(0.451)	(0.438)	(0.369)	(0.405)	(0.429)
$ShareInfo_{i,t-1}$	Market share-info of High-firm		-0.173			0.474	
			(0.473)			(0.387)	
$QualityInfo1_{i,t-1}$	Quality-info of High-firm			2.833**			0.590*
				(0.622)			(0.273)
$QualityInfo2_{i,t-1}$	Quality-info of Low-firm			-1.625**			-0.605*
				(0.229)			(0.268)
Period	Period	0.008	0.030**	0.024*	0.006	0.011*	0.013*
		(0.008)	(0.008)	(0.010)	(0.007)	(0.007)	(0.007)
	n	32	36	31	36	36	35
	$Prob > \chi^2$	0.000	0.000	0.000	0.003	0.000	0.000

Note: $^{**}p < 0.01$, $^{*}p < 0.05$. Standard errors are in parentheses.

Table 1.8 presents the regression results. As one can see, the results are consistent with our earlier results from the Markov chain model. In particular, both the most recent and cumulative experience significantly affect choices, which we observed in Tables

1.1 and 1.2. Additionally, in the "Qual-info" columns, it appears as though positive quality-based information on the High-firm itself (or negative quality-based information on the Low-firm) significantly encourages people to choose the High-firm, especially under large-gap competition (see the significant coefficients of $QualityInfo1_{i,t-1}$ and $QualityInfo2_{i,t-1}$). However, in terms of share-based information, the effects of this type of SI are not significant. In sum, both of these results, with respect to the types of SI and their impact on choices, are consistent with our earlier estimations in our Markov model.

1.5.2 Treatment with Both Types of Social Information

While our objective in this work is to take a first step towards understanding how different types of SI affect consumer choices and firms' demand characteristics, we also ran an additional experimental session which provided both share-based and quality-based information to subjects under large-gap competition, which we refer to as "full information." While we omit the detailed results for brevity, our data from this treatment suggest that consumers having access to full information behave very similar to those with only quality-based information. For instance, the average market share of the High-firm is 85.7% under this full-info treatment, which is almost identical to the market share of 85.6% in the quality-based information treatment. Furthermore, we also observe that the switching behavior of subjects under full information resembles the behavior of subjects under only quality-based information. For example, the average number of choices deviating from Bayesian choices under full information is close to the number in the quality-based information treatment: under large-gap competition, subjects deviate from Bayesian choices 5.7 times in the quality-based information treatment, and 6.1 times in the full information treatment over 40 periods.

Table 1.9: Average of subjects' elicited estimate of service quality (%) for the High and Low-firm

Competition treatment	SI treatment	$E_i(\hat{q}_1)$ (RMSE($\hat{q}_1$))	$E_i(\hat{q}_2)$ (RMSE($\hat{q}_2$))
Large-gap $(q_1, q_2) = (0.8, 0.5)$	(Control)	73.9% (12.3%)	51.7% (15.2%)
	Share-based Info	75.3% (11.2%)	45.1% (20.6%)
	Quality-based Info	78.3% (6.1%)	48.9% (17.9%)
	Full-info*	75.3% (11.4%)	50.0% (19.8%)
Small-gap $(q_1, q_2) = (0.55, 0.5)$	(Control)	56.8% (16.6%)	50.2% (15.7%)
	Share-based Info	59.5% (16.2%)	45.3% (15.0%)
	Quality-based Info	54.1% (15.6%)	56.2% (12.5%)

Note: *Number of subjects under Full-info treatment was 18.

The results from the full information treatment suggest that even when both dimensions of SI are available to a firm, firms should make strategic decisions in which social information to disclose, since quality-based information appears to potentially crowd out the effect of share-based information. For instance, consider the case where the firm can promote both types of information. When the quality gap between the competitors is large, the Low-firm can benefit from promoting share-based information, but should not try to reveal the true quality level at the same time. More specifically, positive share-based information promotes consumers to visit the Low-firm, providing a short-term benefit in increased market share. However, when quality-based information is displayed to consumers at the same time (i.e. full information), consumers quickly learn to behave like Bayesian decision makers and shift to the High-firm quickly.

Lastly, recall that, in all of our treatments, we asked subjects to state their belief on the service quality of each firm at the end of each experiment. Their average elicited belief is reported in Table 1.9. First, observe that subjects tend to have better estimates of service quality, i.e., estimates (78.3% or 48.9% under large-gap) closer to the true q_1 or q_2, under quality-based information, with lower root mean squared error (RMSE) as well. Also, no significant difference is present between the quality-based information and full-info treatments, which suggests that quality-based information itself has high informativeness. Overall, the elicited estimates by subjects under share-based information treatment are the least accurate, which is consistent with the notion that share-based information has reduced informativeness.

1.6 Conclusion

In this study, we investigate the impact of different types of social information on consumers' choices and firms' demand characteristics. Unlike utility-based models under social learning, our proposed Markov-chain based model assumes that consumers do not go through a sophisticated utility evaluation process for available options. Instead, we assume that consumers form their private beliefs about which firm is the 'better' option, and visits the firm that seems more likely to give a satisfactory experience in the next period, i.e., chooses a firm with higher likelihood of satisfaction. Therefore, our current setting is directly applicable in the service industry where the outcomes of the service quality are rather simple. For example, consumers tend to get either satisfaction (problem solved), or dissatisfaction (not solved), from visiting a doctor to hiring a plumber.

Further, when consumers make repeated visits to such service providers, they may be affected by social information.

Our experimental results yield a number of managerial implications. When the quality gap between the competitors is large, promotion of quality-based information is greatly beneficial for the firm with superior quality. In this setting, when provided quality-based social information, consumers behave similar to Bayesian decision makers, so that the High-firm can dominate by achieving higher market share and profit. Further, since the consumers quickly converge to the High-firm under quality-based information, both firms in the market can benefit from more accurate demand forecasting. On the other hand, promoting share-based information is not necessarily favorable to the High-firm, especially in the early periods. Instead, our data illustrate that the lower quality firm can use share-based information to induce an early adoption of consumers and achieve short-term benefits.

When the quality gap between the competitors is marginal, neither type of social information can dramatically help consumers converge to one of the firms. However, when a firm has marginally lower quality than its competitor, quality-based information allows the firm to attract variety-seeking consumers, and portions the market share reflecting the true quality levels. This shows that the direction of market share bias under quality-based information depends on the intensity of competition because consumers' responsiveness to service quality differs based on their perceived quality gap between competing firms. Conversely, a firm with marginally higher quality can do better with intentional vagueness on quality, or promotion of share-based information. This is because the quality signal itself is not strong enough to differentiate the higher quality firm from its competitors unless it exerts effort to decrease the noise in social information. Particularly, share-based information promotes over-switching and decreases the number of loyal consumers, thus, it can play a role to increase the market share, especially when the difference in quality ratings is hard to distinguish. Considering that our share-based information treatment creates a natural environment where people can see what others do, but not know what they know, firms can use the idea of 'information cascade' to attempt to get a 'visit cascade' in a new service initiation.[7] If the firm can attract an initial set of consumers with share-based information, then those who make decisions later may also try visiting the firm even if its quality is no better than its competitor [26, 65]. Thus, for firms whose service quality is the key factor for competition, our work can help guide their information disclosure policies (through which types of social information to promote), better demand forecasting, and improved capacity planning decisions. A summary of some of these implications regarding different social information and their affect on firm performance is provided in Table 1.10.

Table 1.10: SI promotion strategy recommended to the firms with different quality in competition

Competition level	Large-gap	Small-gap
High-firm	Quality-based Info (significant benefit)	Share-based Info (benefit from cascade)
Low-firm	Share-based Info (short-term benefit)	Quality-based Info (insignificant impact)

[7]From Banerjee [6], people pay attention to external information because they think others' decisions may reflect information that they do not have. This can happen especially when there is high uncertainty in private information. The consequence is that people follow what everyone else is doing, even when their private information suggests doing something quite different, and this is called information cascade.

1.7 Appendices

1.7.1 Technical Details in Bayesian and WSLS Benchmark

We find Equation (1.5) useful to represent the heterogeneity in consumers' information utilization by varying the values of A_t and α. Also, we note that one can apply this visit choice probability to $s \in \mathbb{N}$ firms competing, where the consumers have complex sets of valuation structure. In such case, the generalized state space $S = \{(A_t, R_t) \mid 1 \leq t \leq T\}$ for some $T \in \mathbb{N}$ is defined to capture the consumer's belief status. Then, A_t can be any function of the consumer's entire history of service experiences, measurable on $\sigma(V_1, V_2, ..., V_t, X_1, ..., X_t)$, and R_t can be a function of the consumer's recent service experiences, measurable on $\sigma(Y_{1t}, ..., Y_{st})$. The state space S can have varying dimensions to represent different types of choice rules as in Gans et al. [30]. If we let α fixed over time as in our model, and assume that A_t is equal to $A_{(t-1)}$ in a recursive manner, it becomes an exponentially discounted memory model as in Park et al. [60]. Or, if we want to incorporate a Bayesian updating scheme, we impose $\alpha = 0$ and $A_t = \mathbb{I}_{\{v_{st} \geq v_{s't}\}}$, where the valuation v_{st} is updated and recalculated with all historical outcomes (e.g., [75], [31]). Another extreme example could be the myopic decision maker who only considers the most recent experience with $\alpha = 1$. In such case, we can think of the Win-Stay-Lose-Shift (WSLS) benchmark. Further details on the how we bench-marked Bayesian and WSLS consumers are described in the following.

Bayesian Consumer Benchmark

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., $X_{1t} \sim \text{Ber}(q_1), X_{2t} \sim \text{Ber}(q_2)$. 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, $\sum_{j=1}^{k} X_{1t_j}$, follows Binom(k, q_1) and her accumulated satisfaction from the firm 2, $\sum_{j=1}^{t-k} X_{2t_j}$, follows Binom$(t-k, q_2)$. Since the Beta distribution is conjugate for 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 [31]. 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., 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 Beta$(1+\sum_{j=1}^{k} X_{1t_j}, 1+k-\sum_{j=1}^{k} X_{1t_j})$ 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 v_{st}, i.e.,

$$v_{1t} = E(\hat{q}_{1t}) = \frac{1+\sum_{j=1}^{k} X_{1t_j}}{2+k}, \qquad v_{2t} = E(\hat{q}_{2t}) = \frac{1+\sum_{j=1}^{t-k} X_{2t_j}}{2+t-k}. \tag{1.6}$$

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 v_{st} among the two firms every time t.

Bayesian benchmark choice paths generation Without SI, 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

$$\lim_{k\to\infty} E(\hat{q}_{1t}) = q_1, \quad \lim_{(t-k)\to\infty} E(\hat{q}_{2t}) = q_2. \tag{1.7}$$

Thus, if infinite explorations to both firms is possible for all satisfaction-maximizing consumers, the long-run market share eventually should become dominated by the firm with higher quality, q_s. However, when a Bayesian consumer keeps choosing a firm $s = \arg\max_{s\in 1,2} E(\hat{q}_{st})$ for all t, the challenge is to guarantee that she explores both of the firms 'often' 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 [70, 32], 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 that successively choosing the firm with higher posterior estimate of service quality can be considered optimal to a reasonable extent [18].Therefore, we first collect what actual subjects 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.'

WSLS Consumer Benchmark

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

$$X_t = \begin{cases} 1, & \text{if a consumer visits store 1 at time t} \\ 2, & \text{if a consumer visits store 2 at time t} \end{cases} \tag{1.8}$$

and the transition probability is given as $P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} q_1 & 1-q_1 \\ 1-q_2 & q_2 \end{bmatrix}$.

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

$$\pi_1 = \lim_{t\to\infty} P(X_t = 1) = \frac{1-q_2}{(1-q_1)+(1-q_2)}, \quad \pi_2 = \lim_{t\to\infty} P(X_t = 2) = \frac{1-q_1}{(1-q_1)+(1-q_2)} \tag{1.9}$$

WSLS benchmark choice paths generation To generate one-to-one comparable individual benchmark paths for an experimental data, we again use the same fixed set of service outcomes designed for the experiment. Then, we start from the initial choice of the subjects and generate individual choice paths by WSLS consumers, and aggregate and average the individual choice paths to generate the 'WSLS market share path'.

1.7.2 Technical Details on Convergence Speed Test

We build the 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. This simpler setting where we only take into account the most recent experience allows us to compare how human behavior gets closer to Bayesian or WSLS consumers under SI. 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 satisfied(S) or dissatisfied(D) at her latest service encounter of that firm.

In the general theory of convergence of transition matrix P with $0 < a_{i,j} < 1$, one of the indicators on how fast P converges to its steady-state is to look into its eigenvalues. As we have an irreducible, aperiodic, and regular Markov Chain on the finite state space S, there exist stationary distribution, s.t. $\pi = \pi P$, where $\lim_{t\to\infty} P_{ij}^{(t)} = \pi_j, \quad \forall i, j \in S$, and the convergence speed of P^n to π is dominated by the size of second-largest eigenvalue, λ_2, of each transition matrix. This can be an indicator of how quickly the switching probability, i.e. likelihood of switching in response to the most recent experience, becomes stabilized over time. Our estimated $P \in \mathbb{R}_{4\times4}$ had all positive entries, under different treatments. This makes the Markov chain regular, and then, has a unique largest eigenvalue $\lambda_1 = 1$, because all row sums of the transition matrices P are 1. See Perron-Frobenius theory in Behrends [8] for details. Then, there exists a unique distribution vector π such that $\pi P = \pi$.

Since all eigenvalues of P, $\lambda_1, ..., \lambda_4$, are real and distinct, we know that by eigenvalue decomposition, $\exists$ invertible U, s.t.

$$U \cdot P \cdot U^{-1} = \Lambda = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & & 0 \\ \vdots & & \ddots & 0 \\ 0 & 0 & \dots & \lambda_4 \end{bmatrix}.$$

In this case, $U^{-1} = V$ are precisely the right eigenvectors corresponding to the eigenvalues $\lambda_1, ..., \lambda_4$.

$$P^n = V \cdot \Lambda^n \cdot U^T = \sum_{i=1}^{4} \lambda_i^n v_i u_i^T$$

$$|P^n - \lambda_1^n v_1 u_1^T| \leq |\sum_{i=1}^{4} \lambda_i^n v_i u_i^T| \leq \sum_{i=2}^{4} |\lambda_i^n||v_i||u_i^T|$$

Since P has a unique largest eigenvalue $\lambda_1 = 1$ and the other eigenvalues can also be ordered so that $1 = \lambda_1 > |\lambda_2| \geq \dots \geq |\lambda_n|$, when $n \to \infty$,

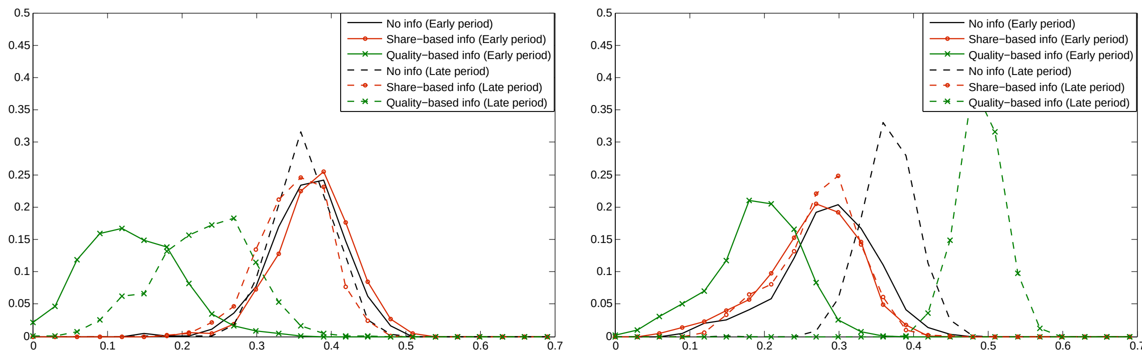
$$P^n = V \begin{bmatrix} 1 & & \dots & 0 \\ 0 & \lambda_2^n & \dots & 0 \\ \vdots & & \ddots & 0 \\ 0 & 0 & \dots & \lambda_4^n \end{bmatrix} U^T = V \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & & \ddots & 0 \\ 0 & 0 & \dots & 0 \end{bmatrix} U^T = \begin{bmatrix} v_{11}u_1 \\ v_{12}u_1 \\ \vdots \\ v_{14}u_1 \end{bmatrix} = \begin{bmatrix} \pi \\ \pi \\ \pi \\ \pi \end{bmatrix}$$

The second last equation holds because the unique left eigenvector associated to eigenvalue 1 is the stationary distribution π, and the corresponding unique right eigenvector is $\mathbf{1} = (1, 1, 1, 1)$ up to normalization. If the first row of U is normalized to π, then the first column of V must be normalized to $\mathbf{1}$ because $UV = UU^{-1} = I$, and $(UV)_{11} = u_1 v_1 = \pi v_1 = 1$. Hence, if we let $\Pi = \begin{bmatrix} \pi \\ \pi \\ \pi \\ \pi \end{bmatrix}$,

$\exists$ positive M s.t. $|P^n - \Pi| \leq (\sum_{i=2}^{4} |v_i||u_i^T|)|\lambda_2|^n \leq (n-1) \cdot \mathbf{1} \cdot \mathbf{1}^T \cdot |\lambda_2|^n = M \cdot |\lambda_2|^n$

Thus, $P^n = \Pi + O(|\lambda_2|^n)$, and the convergence speed of P^n is dominated by the size of λ_2.

Figure 1.7: Bootstrapped probability distribution of second-largest eigenvalues of estimated transition matrices: Solid lines are from the transition matrices estimated using the first 15 periods, dashed lines are from the transition matrices estimated using the latter 25 periods.



This result is further supported by Boyd et al. [17], where they show that the Markov chain reaches its equilibrium faster with the smaller SLEM (Second Largest Eigenvalue Modulus), which is defined by $max\ \{\lambda_2, -\lambda_n\}$. 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. Then, we captured the convergence speed, i.e., measured second-largest eigenvalues (SLE), of the transition probability under both time blocks to see how the learning speed under different SI treatment evolves.

Figure 1.7 shows the bootstrapped probability distributions of estimated SLEs of transition matrices under all six treatments. Note that horizontal axis represents the SLE values. We had different transition probabilities P estimated under different treatments, and therefore different convergence speeds to equilibrium. Again, a smaller second-largest eigenvalue implies faster convergence to stability. Learning speed under the share-based info treatment does not significantly vary in early and later periods of time;

however, note that SLEs of estimated transition matrices under quality-based information treatment are significantly lower, implying faster convergence to the stable status. Since fast convergence to equilibrium occurs in the early periods, i.e., quick learning, under quality-based information, the convergence speed is estimated to be slower in the latter periods.

CHAPTER 2

PREDICTING ORDER VARIABILITY IN INVENTORY DECISIONS: A MODEL OF FORECAST ANCHORING

2.1 Introduction

A prevalent supply chain phenomenon, known as the bullwhip effect, is that demand variability tends to amplify as it propagates from a downstream stage to an upstream stage [44]. Amplified demand variability can lead to excessive inventory investment, poor customer service, and lost revenues for companies. For instance, a recent study suggests that the suppliers of consumer packaged goods hold an excessive 42 days of average inventory on hand [71], which is largely due to the order volatility coming from downstream buyers. In addition, in the automotive industry, upstream suppliers can be fined up to $4,000 per minute if they fail to provide a component/product and cause production downtime[1]. Excessive order variability of the bullwhip effect can be a result of rational decision making with limited information in a decentralized supply chain [44], but it can also be a result of human decision errors such as under-reaction to lead time, over-stocking to avoid potential supply shortage, and mis-accounting for inventory carryover/backorders [24, 25, 12].[2]

In this chapter, we seek to reveal further insight into the behavioral causes of the excessive order variability by isolating the effects of lead time, supply shortage, and inventory carryover/backorders. To this end, we consider a multi-period newsvendor problem with stationary demand and constant cost parameters, where lead time, supply shortage, and inventory carryover/backorders do not play a role in one's order decisions.

[1]Refer to the archived article on March 10, 2016 from *https://www.forbes.com/sites/stevebanker*.

[2]Recent developments in the study of the bullwhip effect can be found in a comprehensive review by Chen and Lee [19].

For such a problem, a rational decision maker would order at a constant level across periods, and the resulting order variability would be zero. Yet, a number of experiments (e.g., [64, 13]) have shown that human decision makers not only deviate from the profit-maximizing order quantity in average orders, but also exhibit significant order variability from period to period.

A number of behavioral models have been proposed to explain and predict the deviation in *mean* order quantities (e.g., [38, 56]), but few exist to predict the *variability* of order quantities. In fact, the observed order variability is often simply left as unexplainable residual noise. For example, Ho et al. [38] assume and estimate the order variability as a form of treatment-specific residual noise (p. 1900), which does not have predictive power across treatments. In this chapter, we develop a behavioral model that can predict both the mean and variability of order quantities.

Our model, referred to as the *forecast anchoring* model, is a generalization of the mean anchoring model suggested by Schweitzer and Cachon [64]. As the name indicates, it is based on the anchoring-and-adjustment heuristic [41]. Specifically, we posit that human decision makers anchor their order decisions on the (random) point forecast instead of the (constant) mean demand in each period. In the multi-period newsvendor problem, the decision maker is primed to make sequential demand forecasts from period to period. It is known that human subjects may fall victim to probability matching for such a task with binary predictions [73]. We build on this behavioral tendency by assuming that the point forecast mentally drawn by the decision maker in each period follows a certain distribution, according to the simulation heuristic [41]. Therefore, the random point forecast represents a possible cause for order variability. In addition, recognizing possible individual heterogeneity in employing the anchoring-and-adjustment heuristic, we further assume that the heuristic adjustment level in each period could also vary, representing another possible cause of order variability.

In summary, we model the newsvendor decision as a two-step process: subjects first mentally draw a demand forecast as an anchor point and then adjust toward the profit-maximizing quantity to arrive at the order decision. Under this model framework, we derive formulas for the mean and variance of order quantities for estimation and prediction purposes. As a result, the order variability prediction is parameterized under the forecast anchoring model.

To test and validate our forecast anchoring model, we obtain data from two past newsvendor experiments: Bolton and Katok [13] and Ockenfels and Selten [56]. The study of Bolton and Katok [13] is also used in the estimation of the bounded rationality model of Su [68]. Among the existing models that focus on predicting newsvendor behavior, Su's (2008) model is particularly relevant to our study, as it is the only one, to our knowledge, that provides the prediction formulas for the mean and variance of order quantities. With the same data set, we utilize his bounded rationality model estimates as an important benchmark for our forecast anchoring model. The data set from Ockenfels and Selten [56] is a rich one as it consists of 11 different critical fractile conditions. We use it for *cross-study* out-of-sample testing to further validate our model.

We first apply the generalized method of moments (GMM) to generate parameters of our forecast anchoring model and fit them to the data set of [13]. We then compare these results to the bounded rationality model predictions and observe that the forecast anchoring model yields significant improvements (see Figure 2.1 in §2.4). The bounded rationality model is found to bias the mean order estimate toward the optimal quantity and also overestimate the order variability. To further validate our model, we take our model estimates from the [13] data, and use them to generate predictions for ordering decisions in the data set from [56]. We evaluate how these cross-study out-of-sample forecasts compare to actual decisions, and find that they predict both mean and variability of order quantities well in the high critical fractile conditions, but with a moderate bias in the low critical fractile conditions. We hypothesize that this is due to a shift in demand distributions (by design) across the two studies under these conditions, and subsequently show that this bias goes away when fitting the forecast anchoring model with the (pooled) within-study data from [56]. This within-study estimation further demonstrates that our model can predict the mean and variability of order quantities well for specific critical fractile conditions, even with parameters estimated from data pooled across different critical fractile conditions (which is not possible with the existing models, such as [38]).

We further demonstrate that our model is flexible enough to fit the individual order behavior using the data from [13] and [56]. We find that most subjects do not exhibit variability in their adjustment levels across periods, but the adjustment level differs significantly across subjects. This explains why we need to account for variable adjustment levels in cross-subject estimates.

The two experimental data sets used in our model validation are based on a continuous, uniform demand distribution, which is symmetric around the mean demand. Such symmetric demand distributions (e.g., the uniform or normal distribution) have been used in a vast majority of previous experimental newsvendor studies. To determine whether our forecast anchoring model is robust in settings beyond these distributions, we investigate the order behavior in the context with asymmetric two-point demand (the same as the binary prediction game studied in the probability matching literature). We conduct our own experiments and continue to observe that the forecast anchoring model predicts the mean and variability of order quantities well. Moreover, this asymmetric two-point demand experimental study enables us to test the validity of alternative models, such as utility-based models and other anchoring models. Interestingly, we find that these alternative models are not robust enough to fit the data in this unique setting.

Across the different data sets (i.e., [13], [56], and our own two-point demand experiments), we find a consistent pattern that subjects tend to anchor heavily on their demand forecast when the newsvendor critical fractile is high (that is, when the product profit margin is 50% or more). This finding suggests that managers need to pay extra attention to the forecast anchoring tendency in high profit margin products. Overall, our forecast anchoring model provides a new perspective for explaining and predicting order variability observed in behavioral inventory decisions. From our study, we identify random point forecasts and variable adjustment levels as two possible causes of excessive order variability. Specifically, the main cause of order variability at the individual level is random point forecasts across periods. Nevertheless, the order variability at the aggregate level is driven by both random point forecasts and variable adjustment levels across individual decision makers.

The rest of the paper is organized as follows. First, we begin by presenting a summary of the relevant literature in §2.2. In §2.3 we provide the theoretical details of our forecast anchoring model for continuous demand. Following this, in §2.4, we validate the model through a series of estimations and predictions. In §**??**, we further check the robustness of the model under a setting with discrete, asymmetric demand. Finally, §2.5 provides a conclusion and managerial implications from our study.

2.2 Literature Review

Behavioral operations management investigates how human decision makers act in operational settings, and attempts to understand what behavioral biases may account for any observed outcomes. Within this field, a considerable amount of attention has been spent on the newsvendor problem. The seminal experimental paper on this topic is Schweitzer and Cachon [64], where they observe that order quantities deviate from the normative predictions in two key ways. First, decision makers exhibit a pull-to-center effect, in that mean order quantities are between the mean of the demand distribution and the normative prediction. Second, there is a considerable amount of variability in order quantities from period to period, despite all price, cost, and demand parameters remaining constant. A number of studies have subsequently illustrated the robustness of these two results. For instance, they have been shown to persist with additional decisions, more feedback relating to foregone options, higher payoffs, lower decision frequency, multi-location correlation, experienced managers, mental accounting, and task decomposition [13, 15, 49, 38, 14, 20, 45]. For a summary of the experimental literature on the newsvendor, please see the work of Becker-Peth and Thonemann [7] and references therein.

With respect to the first anomaly, the pull-to-center effect for mean orders, researchers have identified a number of behavioral models that can account for it, which generally follow one of three approaches. The first, broadly speaking, relies on a more traditional expected utility (or expected profit) approach. For instance, Schweitzer and Cachon [64] posit that decision makers may attempt to minimize ex post inventory regret. In their model, they assume that a newsvendor's expected utility function is comprised of the standard expected profit function, plus a disutility term which is increasing in the absolute deviation between the observed demand and order quantity. In another study, Ho et al. [38], extend this ex post inventory regret model by incorporating reference dependence. That is, they assume that the newsvendor's expected utility function is the standard expected profit function plus two disutility terms, one which is increasing in the number of units stocked above actual demand, and one which is increasing in the number of units stocked below actual demand. Ockenfels and Selten [56] develop an impulse-balanced equilibrium (IBE) concept for predicting mean order quantities, by proposing an expected utility function that relies on the empirical observation that people tend to weight losses roughly twice that of gains. Lastly, Long and Nasiry [48] demonstrate that prospect theory can account for mean newsvendor orders when the reference point is not a payoff of zero.[3]

Still within this first category, there are papers which also assume that people are biased in developing a demand distribution, to which they then apply the standard critical fractile solution (which is based on maximizing expected profit). For example, Ren and Croson [62] propose that decision makers underestimate the variance of the forecast distribution (i.e. exhibit overconfidence), which is then used in conjunction with the standard critical fractile solution, and find that it can explain mean orders well. Similarly, Tong and Feiler [72] claim that bounded cognition and representativeness, which states that a decision maker relies on a small sample of outcomes and that this sample is representative of the population, can also bias a newsvendor's estimated demand distribution and lead to ordering decisions that coincide with the pull-to-center effect. Another perspective regarding the biases in developing a demand distribution is the tendency of overreacting to forecast errors in time-series forecasts. For instance, Kremer et al. [42] find that people overreact to forecast errors in relatively stable time series, but underreact to errors in relatively unstable time series. In most newsvendor experiments including the ones we analyze here, however, the demand distribution is a simple uniform distribution, and the demand chasing behavior is found to be largely negligible [64]. For this reason, we assume that people's point forecast is drawn from the same uniform distribution as the demand.

[3]Note that, technically, prospect theory uses a "value" function, but this value function is essentially the same as the expected utility approach of models like Ho et al. [38], in that the value function is comprised of the standard expected profit function, in addition to some additional terms which account for biases such as loss aversion and reference dependence.

The second approach to explain the pull-to-center effect is to assume that a decision maker's utility evaluation is subject to random (Gumbel) noise.[4] [68] proposes this framework for the newsvendor problem, demonstrating that a newsvendor may not always select the expected-profit maximizing quantity, but instead, choose better order quantities more often. He then illustrates that it fits the data better than the normative prediction. [15] also incorporate random utility into their model, combined with a memory and reinforcement bias, and show that it too coincides well with mean order quantities.

The third way to account for the pull-to-center effect for mean order quantities relies on decision heuristics. For example, Schweitzer and Cachon [64] mention that anchoring and insufficient adjustment can explain mean orders. In particular, they hypothesize that a decision maker may select an anchor for their quantity and then adjust away from this, where there are two likely anchors in the newsvendor problem, mean demand or demand in the prior period. Our forecast anchoring model is a generalization of the mean anchoring model, where we assume the anchor is the random point forecast in each period.

In short, we contributes to this rich literature by developing a model that can accurately predict the mean and variability of order quantities as well as help identify possible behavioral causes for excessive order variability.

[4][50] propose such a random utility model for normal form games (termed the "quantal response equilibrium") and apply it to various experimental game data. Successful applications of the model have been reported in coordination games [4], auction games [34], pricing contracts [46, 37], newsvendor experiments [68], and capacity allocation games [21].

2.3 Forecast Anchoring Model

Consider a newsvendor problem for a single product. The demand in a period, denoted by D, is a random draw from a probability distribution. Let $f(\cdot)$ denote the demand distribution density and $F(\cdot)$ be the cumulative distribution function. Let $[a, b]$ be the support of the demand distribution ($a = -\infty$ and $b = \infty$ if the demand follows a normal distribution). Let $m = E\{D\}$ denote the mean demand. The demand across different periods is independent and identically-distributed (i.i.d.).

The unit purchase cost for the product is c and the unit selling price is p, with $0 < c < p$. The unit salvage value for any leftover inventory is assumed to be zero. It can be shown that the order quantity that maximizes the expected profit is

$$q^* = F^{-1}\left(\frac{p-c}{p}\right), \tag{2.1}$$

where $F^{-1}(\cdot)$ is the inverse function of $F(\cdot)$. The ratio $\gamma = (p-c)/p$ is commonly referred to as the critical fractile in the newsvendor problem. Following the convention in the literature, we use q^* as our normative benchmark.

When a human decision maker attempts to make repeated order decisions for the newsvendor problem under i.i.d. demand, we posit that she would start her decision process by first forecasting the demand in a period. The demand forecast is then used as a decision anchor, based on which she adjusts her order quantity in the direction toward the normative benchmark. Thus, the decision process consists of two stages: the first stage involves demand forecast generation, and the second stage involves an anchoring-and-adjustment heuristic to arrive at the final order decision.

Suppose that a point forecast for demand, denoted by X, is mentally drawn by the decision maker in a period. Assume that X is i.i.d. and follows a distribution with density $g(x)$. It is quite plausible that $g(\cdot) \equiv f(\cdot)$, that is, the demand forecast is drawn from the same demand distribution $f(\cdot)$. For example, when the demand distribution is a two-point distribution, the well-documented probability matching tendency in human judgment [73] implies $g(\cdot) \equiv f(\cdot)$. In general, however, $g(\cdot)$ may be different from $f(\cdot)$, as there could be errors and noise when an individual mentally draws a random sample from a, potentially complex, demand distribution. Nevertheless, it is reasonable to assume that $g(\cdot)$ is statistically close to $f(\cdot)$. For example, if the decision maker knows the mean of the demand distribution, it is reasonable to assume that the mean of the point forecast would be the same as the mean of demand, i.e., $E\{X\} = E\{D\} = m$. In other words, the point forecast is unbiased, which we shall assume throughout the chapter.[5] Given a random point forecast $X = x$ in a period, we assume that the decision maker anchors on the point forecast and then adjusts in the direction toward the normative benchmark to reach the final order decision Q [41]. Specifically, the heuristic can be written as

$$Q = x + \Lambda(q^* - x), \tag{2.2}$$

where q^* is the target for adjustment and Λ is the level of adjustment from the forecast anchor x toward the target. For generality, we assume that Λ is a random variable with mean and variance given by

$$E\{\Lambda\} = \lambda, \quad \mathrm{var}\{\Lambda\} = \sigma_\Lambda^2.$$

The noise around the adjustment level captures the decision maker's cognitive limitation in precisely determining the magnitude of adjustment. When the decision maker uses a constant adjustment level, we have $\sigma_\Lambda = 0$.

Given the above heuristic specification (2.2), we can derive the following conditional

[5]Note that we assume that the decision maker is informed of the underlying demand distribution, which is the case in most experimental newsvendor studies such as [13] and [56]. When this information is not available, there may exist biases in the decision maker's point forecast due to the loss function pull [45].

expectation and variance expressions:

$$
\begin{aligned}
E\{Q|X = x\} &= x + \lambda(q^* - x), \\
\mathrm{var}\{Q|X = x\} &= (q^* - x)^2\sigma_\Lambda^2.
\end{aligned}
$$

Thus, we can obtain the unconditional expected order quantity as follows:

$$
E\{Q\} = E\{E\{Q|X\}\} = m + \lambda(q^* - m), \tag{2.3}
$$

where, as mentioned previously, we use the assumption that the demand forecast is unbiased, i.e., $E\{X\} = E\{D\} = m$. We note that the above mean order prediction is the same as those from the mean anchoring models [64, 13, 15]. Nevertheless, our forecast anchoring model can further predict the order variance. Following the law of total variance, we have

$$
\begin{aligned}
\mathrm{var}\{Q\} &= E\{\mathrm{var}\{Q|X\}\} + \mathrm{var}\{E\{Q|X\}\} \\
&= \left[(q^* - m)^2 + \mathrm{var}\{X\}\right]\sigma_\Lambda^2 + (1 - \lambda)^2\mathrm{var}\{X\}. \qquad (2.4)
\end{aligned}
$$

where $\mathrm{var}\{X\}$ depends on the forecast distribution $g(x)$ in general (not necessarily the same as the demand distribution).

To summarize, our forecast anchoring model builds on two well-documented psychological effects: the probability matching behavior in sequential predictions [73] and the anchoring-and-adjustment heuristic [41]. Because the model relies on pure decision heuristics, there is no need to assume the decision maker capable of evaluating a non-trivial newsvendor profit and/or utility function on the fly. The model can be used to predict not only the mean but also the variance of order quantities, and can also help identify possible causes of excessive order variability in inventory decisions.

2.4 Model Estimation and Validation

In this section we test and validate our model through the use of two external newsvendor experimental data sets from [13] and [56]. For ease of reference, we shall refer to Bolton and Katok [13] as "BK," and Ockenfels and Selten [56] as "OS." In the BK data, the observed variances of order quantities are 289.71 in the low critical fractile condition, and 341.06 in the high critical fractile condition. In the OS data, the observed variance of the order quantities range from 114.67 to 377.40 (for the critical fractile conditions from 0.1 to 0.9). In short, the observed order variances are all significantly greater than the normative prediction of zero.

We first estimate the parameters of our model using the BK data. We then take these estimates and use them to generate predictions for the mean and standard deviation of order quantities in the setting employed by OS, and compare the predictions to the OS data. We also fit individual order decisions in both data sets.

2.4.1 Parameter Estimation

Both BK and OS uses the uniform demand distribution in their studies. Below we first derive our forecast anchoring model predictions under this distribution. Given that the demand distribution is uniformly distributed in $[a, b]$, the mean demand and the normative benchmark order quantity are given by

$$m = \frac{b-a}{2}, \quad q^* = a + (b-a)\gamma,$$

where $\gamma = (p-c)/p$ is the critical fractile.

Because the uniform distribution is relatively intuitive, we assume that the point forecast distribution $g(\cdot)$ is the same as the demand distribution for simplicity, i.e., $g(x) =$

$1/(b-a)$ over $[a,b]$.[6] Plugging the uniform density function into (2.3) and (2.4), we obtain

$$\begin{aligned} E\{Q\} &= m+\lambda(q^*-m), & (2.5)\\ \mathrm{var}\{Q\} &= \left[(q^*-m)^2+\frac{(b-a)^2}{12}\right]\sigma_\Lambda^2+\frac{(b-a)^2}{12}(1-\lambda)^2. & (2.6)\end{aligned}$$

We shall use the above two prediction equations to estimate the parameters of our forecast anchoring model.

In the experiment of BK, under the high critical fractile condition ($\gamma = 0.75$), the demand distribution is uniformly distributed between $[0, 100]$, with an optimal order quantity $q^* = 75$. Under the low critical fractile condition ($\gamma = 0.25$), the demand distribution is uniformly distributed between $[50, 150]$, with an optimal order quantity $q^* = 75$. Thus, equations (2.5) and (2.6) give the predictions of the mean and variance of order quantity for each period. Specifically, the expected order quantities of each critical fractile condition are

$$E\{Q\}_{(\gamma=0.75)} = 50+25\lambda,$$

$$E\{Q\}_{(\gamma=0.25)} = 100-25\lambda,$$

and the variance is identical for both conditions:

$$\mathrm{var}\{Q\}_{(\gamma=0.75)} = \mathrm{var}\{Q\}_{(\gamma=0.25)} = \left(25^2+\frac{100^2}{12}\right)\sigma_\Lambda^2+\frac{100^2}{12}(1-\lambda)^2.$$

We use the order quantities across subjects in each of the 100 rounds from BK to calculate the sample mean and standard deviation. Based on these 100 observations of each of the two moments, we estimate the model parameters λ and σ_Λ by applying the iterative GMM method [36]. The GMM iteration is terminated when the successive

[6] A more precise approach is to use an empirically estimated forecast distribution for $f(x)$, which is not available from the BK and OS data sets.

estimate differences are less than 0.005 for both parameters. We choose the iterative GMM method because the resulting estimates are invariant with respect to the scale of the data and to the initial weighting matrix [35].

Table 2.1: Estimated Parameters and Prediction Results for the BK Data

Critical Fractile Condition	Parameter Estimates		Observation from the Data		Model Prediction	
	λ	σ_Λ	Mean	Std Dev	Mean	Std Dev
$\gamma = 0.75$	0.43 (0.001)	0.20 (0.001)	60.76	18.47	60.76	18.13
$\gamma = 0.25$	0.49 (0.001)	0.21 (0.003)	87.81	17.02	87.77	16.72

Note: Standard errors of the estimated parameters are in the parentheses.

The estimation results as well as the predictions of the mean and standard deviation of order quantities are reported in Table 2.1.[7] From the table, the estimated parameters of λ and σ_Λ are similar under both critical fractile conditions, with the level of adjustment from the forecast anchor x to the normative benchmark q^* being lower under the high critical fractile condition ($\lambda_{(\gamma=0.75)} = 0.43 < \lambda_{(\gamma=0.25)} = 0.49$). The adjustment toward the normative benchmark is clearly insufficient under both conditions: the average level of adjustment stops short of half way toward the normative benchmark. According to our model specification in equation (2.2), lower adjustment level implies stronger anchoring effect on the demand forecast. Thus, the results suggest that subjects tend to anchor heavily on their demand forecast when the critical fractile is high. Moreover, there exists a significant amount of noise (estimates of σ_Λ) around the adjustment level. This aggregate level variability in adjustment level can be a result of two potential causes: the variable adjustment levels across periods of individual decision makers, or

[7] We also checked the robustness of the results by using the pooled sample mean and standard deviation of each successive five periods and find the similar results.

heterogeneous (constant) adjustment levels of individual decision makers. In §2.4.3, we conduct an individual analysis to further test which cause is at work here.

Table 2.1 also shows that the forecast anchoring model predicts the mean and standard deviation of order quantities well. As a comparison, we note that the bounded rationality (BR) model of Su [68] also predicts the mean and standard deviation of order quantities. Because the same data set from BK is used in Su [68], we can compare the bounded rationality model's predictions of the mean and standard deviation with our model's predictions. According to Su [68], the order quantity under bounded rationality follows a truncated normal distribution. Therefore, we take the estimates of τ in Table 2 of his paper (p. 576) for high and low critical fractile conditions of the BK study, and plug them into the formula of a truncated normal distribution (p. 573) to obtain predictions for the mean and standard deviation of order quantities. Figure 2.1 depicts the predicted values from the BR model compared with our forecast anchoring (FA) model predictions. As one can see, in Figure 2.1, the BR model estimates the mean order quantity with a bias toward $q^* = 75$ relative to the observed mean order quantity, and over-estimates the standard deviation of the order quantity, whereas our forecast anchoring model yields an accurate prediction of both metrics.

2.4.2 Cross-Study Out-of-Sample Validation

We now test how well the model parameter estimates obtained from the BK data can predict the mean and standard deviation of order quantities in a separate newsvendor experiment. To this end, Ockenfels and Selten [56] provide a rich data set for cross-validation purposes. Specifically, their experiment is conducted under a uniform demand distribution over $[0, 100]$ with critical fractile levels $\gamma = 0$, 0.1, 0.2, ..., 1 (the

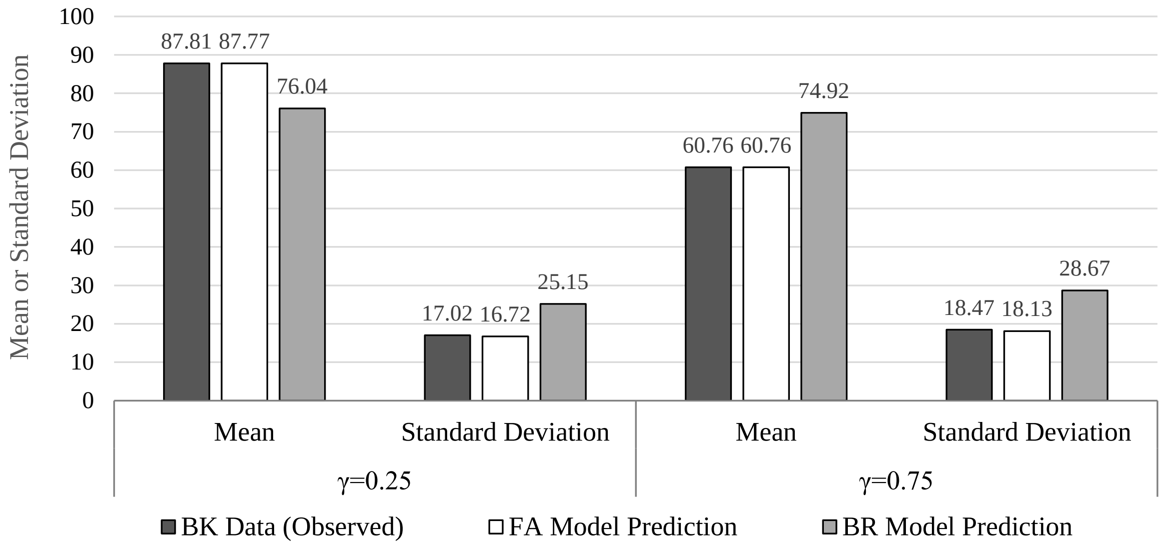


Figure 2.1: Observations from BK and Predictions by the Forecast Anchoring (FA) and Bounded Rationality (BR) Models

corresponding $q^* = 0, 10, 20, ..., 100$), and 200 rounds of decisions.[8]

To conduct this out-of-sample test, for the OS data with critical fractile greater than or equal to 0.5, we generate the predictions of the mean and standard deviation of order quantities using the parameters of the high critical fractile condition, $(\lambda, \sigma_\Lambda)_{(\gamma=0.75)} = (0.43, 0.20)$, estimated from the BK data. For the OS data with critical fractile less than 0.5, we generate the predictions using the parameters of the low critical fractile condition, $(\lambda, \sigma_\Lambda)_{(\gamma=0.25)} = (0.49, 0.21)$, estimated from the BK data (see Table 2.1). Thus, we provide a fairly rigorous cross-study test of the model.

Figure 2.2 illustrates the observed mean and standard deviation of order quantities from the OS data as well as the forecast anchoring (FA) predictions based on the BK estimates. In both plots, beginning with the high critical fractile cases ($\gamma \geq 0.5$), the parameters estimated from the BK condition $\gamma = 0.75$ generate fairly accurate predic-

[8]In reporting our cross-validation results, we omit the extreme cases with critical fractile being zero and one.

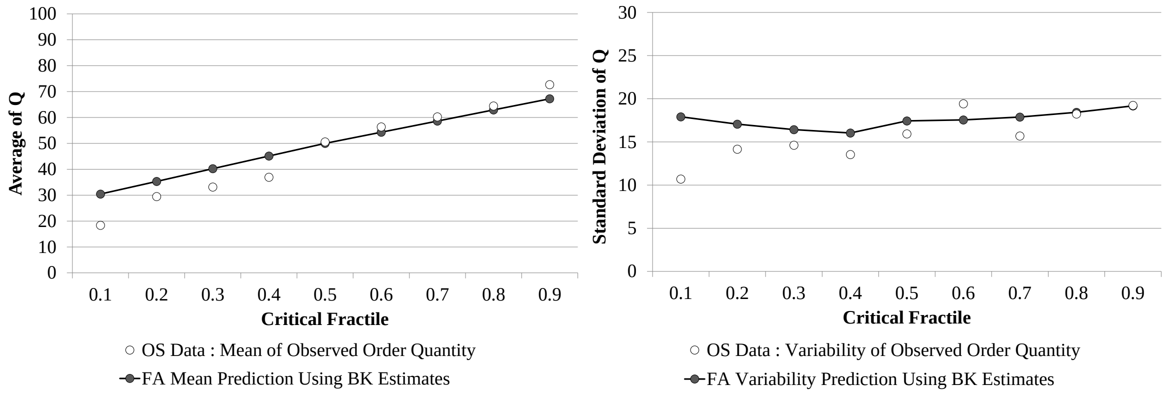


Figure 2.2: Cross-Study Out-of-Sample Validation: Mean (left) and Variability (right) Fit of OS Data using the BK Estimates

tions for the mean and standard deviation of order quantities. However, turning to the low fractile cases ($\gamma < 0.5$), some biases appear to exist in the predictions generated by the parameters estimated from the BK condition $\gamma = 0.25$. Recall that in the condition $\gamma = 0.25$ of the BK study, the demand range was shifted from $[0, 100]$ to $[50, 150]$, so that the normative benchmark quantity was the same ($q^* = 75$) across both critical fractile conditions. In contrast, in the OS study the demand range is fixed at $[0, 100]$ for all critical fractile cases. Thus, the less accurate predictions in the low critical fractile cases are likely due to the different demand ranges used in the BK and OS experiments, which we further investigate below.

For comparison purposes, we estimate the model parameters directly based on the 200 rounds of the OS data. Let $\gamma = 0.1, 0.2, ..., 0.9$ be the critical fractile. With the demand uniformly distributed over $[0, 100]$, we have $q^* = 100\gamma$. From (2.5) and (2.6), we can derive the following estimation equations for the average and the variance of order quantity for each period:

$$\begin{aligned} E\{Q\}_\gamma &= 50 + \lambda(100\gamma - 50), \\ \text{var}\{Q\}_\gamma &= \left((100\gamma - 50)^2 + \frac{100^2}{12}\right)\sigma_\Lambda^2 + \frac{100^2}{12}(1 - \lambda)^2. \end{aligned}$$

Based on the above equations, we pool the data for conditions with $\gamma \geq 0.5$ and again use the iterative GMM method described earlier to estimate λ and σ_Λ for the high critical fractile condition. We repeat the same procedure by pooling data with $\gamma < 0.5$ for the low critical fractile condition. The estimation results from this exercise are shown in Table 2.2. In addition, Figure 2.3 plots the observed mean and standard deviation of order quantities from OS as well as the predictions based on the parameter estimates shown in Table 2.2.

Table 2.2: Estimated Parameters of FA Model from Pooled OS Data using the OS Estimates

Critical Fractile Condition	Parameter Estimates λ	σ_Λ
$\gamma = 0.5, ..., 0.9$ (pooled)	0.53 (0.000)	0.29 (0.000)
$\gamma = 0.1, ..., 0.4$ (pooled)	0.76 (0.000)	0.26 (0.000)

Note: Standard errors of the estimated parameters are in the parentheses.

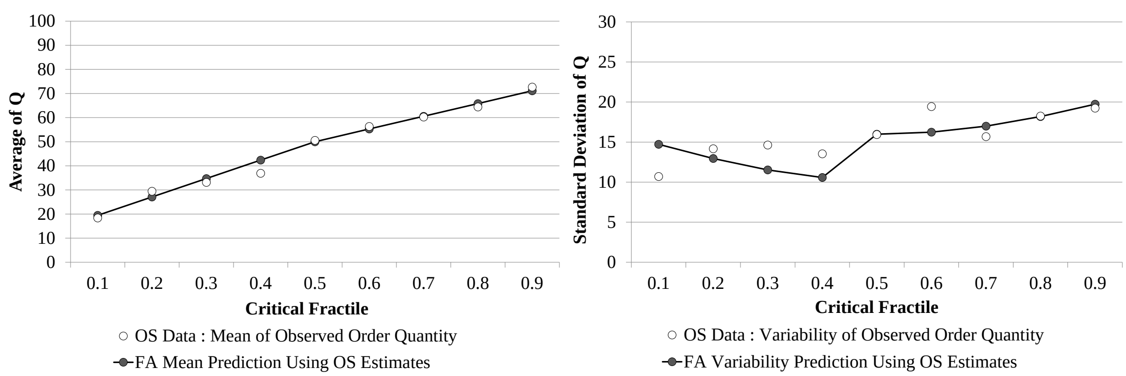


Figure 2.3: Within-Study Validation of the Estimates: Mean (left) and Variability (right) Fit of OS Data

From Figure 2.3, it is clear that the within-study predictions are more accurate than the cross-study predictions shown in Figure 2.2 (note that the within-study predictions are based on pooled data across different critical fractile conditions as shown in Table

2.2). This is especially true in the low critical fractile cases, where the bias is no longer present. Turning back to Table 2.2, it appears that the pattern of lower adjustment level in high critical fractile cases is consistent with that observed in the BK data. Thus, the OS data support the earlier finding that subjects tend to anchor heavily on their demand forecast when the critical fractile is high. Moreover, the within-study estimate of λ is significantly higher than the cross-study estimate of λ in the low critical fractile cases (0.76 versus 0.49). This explains the prediction bias observed in Figure 2.2 and suggests that the demand range may have an impact on the average adjustment levels. In addition, the noise levels of σ_Λ are moderately higher in the within-study analysis, relative to the BK estimates in Table 2.1. This is due to data pooling across the different critical fractile conditions in the OS within-study estimation.

Finally, recall that Ockenfels and Selten [56] propose an IBE model that explains the mean of order quantities observed in their data. The predicted mean by the IBE model displays significant downward bias when the critical fractile is 0.5 (see Figure 1, [56] p. 240). Figures 2.2 and 2.3 show that the forecast anchoring model does not have such a bias at critical fractile 0.5. In addition, Figures 2.2 and 2.3 demonstrate that our forecast anchoring model has the ability to predict the order variability present in their data with fairly reasonable accuracy both within and across studies.

2.4.3 Individual Heterogeneity

It is well-known that there is considerable heterogeneity in newsvendor experiments. Therefore, in this section, we fit our model to individual order decisions, which effectively captures the heterogeneity in each subject's adjustment level. We use the order quantities of each subject's 20 rounds from both BK and OS to calculate the sample means and standard deviations of individual orders. Based on these within-subject level observations of each of the two moments, we estimate the model parameters λ and σ_Λ by applying the iterative GMM method for each subject.

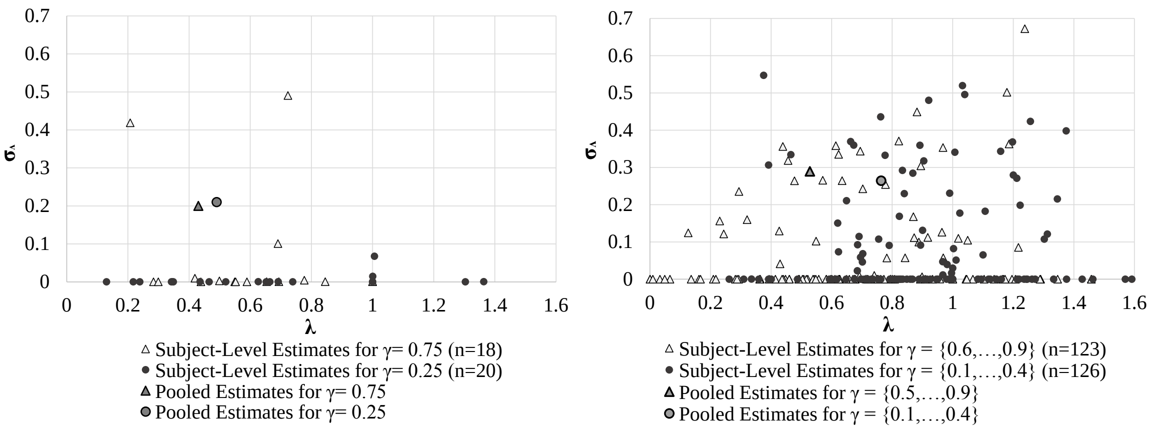


Figure 2.4: Scatter Plots of Estimates: Subject-Level λ and σ_Λ Distribution of BK (left) and OS (right) data

Figure 2.4 shows the distribution of subject-level estimates (along with the aggregate estimate values from earlier estimations for reference). Although subjects from both the BK and OS experiments display considerable heterogeneity, the distribution of individual estimates display a similar pattern across both high and low critical fractile conditions. The aggregate estimates, marked with thicker points in Figure 2.4, reflect the distribution of individual estimates and capture the dispersion in individual adjustment levels.

Note in Figure 2.4 that most individuals do not exhibit variability in Λ across periods, while there is significant variability in Λ across subjects. Interestingly, at least two-thirds of subjects in every condition have a constant adjustment level, i.e., σ_Λ=0. This indicates that the main cause of order variability for many subjects is due to their random point forecasts, rather than variable adjustment levels, and that their order quantities can be fit parsimoniously using a single parameter λ. However, these individual λ values are considerably dispersed across subjects. This explains why we need to account for variability in Λ in the aggregate level estimation. In summary, while the main cause of order variability at the individual level is random point forecasts across periods, the order variability at the aggregate level is driven by both random point forecasts and variable adjustment levels across individual decision makers. Moreover, individual heterogeneity in adjustment levels can largely account for the aggregate level variability in adjustment level (σ_Λ) as hypothesized in §2.4.1, especially with the BK data shown in Figure 2.4 (a).

Figure 2.4 also shows that some subjects over-adjust their forecasts to q^* (with $\lambda > 1$). This tendency is stronger under the low critical fractile conditions in both the BK and OS data. In Figures 2.4 (a) and (b), subjects in the high critical fractile conditions tend to have smaller λ than those in the low critical fractile conditions, suggesting that more subjects anchor heavily on their demand forecast when the critical fractile is high. This observation is consistent with the cross-subject aggregate level estimation results reported earlier.

2.5 Conclusion

In this chapter, we propose a forecast anchoring model that can predict the variability of order quantities when the effects of lead time, inventory carryover/backorders, and the four causes of the bullwhip effect [44] are isolated. In such a setting, a rational decision maker should set a constant profit-maximizing order in every period. However, human decision makers have been shown to set quantities in a way that exhibit considerable order variability from period to period. Our model relies on a simple decision heuristic, which is grounded in two well-known behavioral tendencies: probability matching [73] and anchoring-and-adjustment [41]. Essentially, we attribute the cause of order variability to random point forecasts as well as variable adjustment levels in each period.

We conduct a series of estimations and predictions to validate the forecast anchoring model both within and across studies. First, with the experimental data set from [13], we find that our model can predict the mean and variability of order quantities well. We then compare the predictions with those obtained by the bounded rationality model of [68], and find that the forecast anchoring model leads to more accurate predictions, especially the order variances. We also conduct an out-of-sample test where we take the estimates from the data of Bolton and Katok [13], and use them to predict ordering decisions in a separate data set from Ockenfels and Selten [56] and validate the fit of our model. Across the different data sets, we also find a consistent pattern of subjects tending to anchor heavily on their demand forecast when the product has high profit margin. This finding suggests that managers need to pay extra attention to the forecast anchoring tendency in the high profit margin products. Moreover, we conduct an individual heterogeneity analysis and find that the order variability at the individual level is largely a consequence of random point forecasts. Nevertheless, at the aggregate level, order variability across periods is due to both random point forecasts and variable adjustment levels across individual decision makers.

From a managerial standpoint, our work provides upstream firms with the ability to develop more accurate forecasts of order quantities from downstream parties, resulting in reduced costs and improved profitability. In addition, by fitting our model to several experimental data sets, we are able to identify that random point forecasts and variable adjustment levels are two main causes of excessive order variability in inventory decisions. Thus, to mitigate the adverse effect of excessive order variability, one strategy is to reframe the problem to induce the decision maker to focus on profit maximization, instead of relying on her point forecasts.

We believe that there are several exciting opportunities for future work in this area. In particular, now that the field has developed a well established set of theories that can account for the mean ordering behavior in inventory decisions, future work can leverage this body of work, in conjunction with models such as ours that aim to predict order variability, and extend them to several settings such as nonperishable products, limited capacity, multiple products with substitution, or multiple buyers. In addition, the general notion of formulating simple decision heuristics in a model, and using them to predict behavior, can be applied to a variety of other operational settings, such as in service operations or procurement.

CHAPTER 3

PREDICTING PURCHASE PROPENSITY FROM ONLINE BROWSING BEHAVIOR

3.1 Introduction

Customers' series of visit events, such as how frequently and how long they visit the store, and the items they browse and purchase, can provide useful information to estimate demand in advance. Retail stores have traditionally used sales data for making various operational decisions; however, recent growth of online retail[1] and clickstream tracking technology has provided retailers an extremely rich set of information on customers' pre-purchase browsing behavior, which can help facilitate a firm's operational tasks such as demand forecasting, estimation of choice and substitution behavior [10], and product assortment, promotion, and presentation decisions. Moreover, utilizing the online clickstream data provides advance demand information well before customer ordering, which is a major advantage over classic inventory management models where the information is provided at the time of ordering [40]. For a comprehensive literature review of modeling advance demand information in OM, see Özer [57].

Although tremendously useful, there are potential challenges to investigate online customer behavior using clickstream data. First, firms can only capture visits to their own retailing website and cannot track other websites the consumer is browsing or buying from. Competing firms do not share data with one another and limit their information sharing with web analytics firms with specialized/silo-ed contracts. Therefore, it is still difficult to fully observe consumer behavior with respect to complementary and substi-

[1] The National Retail Federation (https://nrf.com) expects that online retail will grow 8-12% in 2017, up to three times higher than the growth rate of the wider industry.

tute products available in outside market places. Second, online customers often access the site from different devices. Although the membership and log-in policy mitigate this issue to a certain extent, it is still nontrivial to fully match the consumer-specific characteristics, such as demographics, purchasing history, and sensitivity to prices/deals across different devices. Third, customers can easily keep the web pages on, not paying attention. If a consumer makes a subsequent click to move to a specific page or go back, the following URL page is recorded as a part of the clickstream data; however, if the customer leaves the page upon doing something else, it may seem as if the customer is still viewing the page. Therefore, it is not obvious whether the customer ended the active engagement, and we have censored exit time. Fourth, browsing data are not linked with product attributes and purchases. Since scraping all page information increases the size of data exponentially, clickstream tracking companies often use URLs to infer on-page product information.

Acknowledging this, we collaborated with a search marketing analytics company aiming to build the most useful information from the customers' clickstream data in online retailing sites. Our research objective is twofold. First, we investigate which aspect of, and to what extent, the traffic aspect of clickstream data, or the 'timing of visit,' can be used as advance demand information. Second, we further aim to build the demand estimation model that can improve forecasting by categorizing on-page information and identifying the customers' stage of purchase.

In order to describe our data and conduct predictive analysis, we define time-related variables and terms as follows. First, 'page' or 'page-viewing' refers to the rendering of a page in the user's browser window. Usually, when a customer arrives at the retailers' website, she views multiple pages. 'Session' is defined as a sequence of page viewings or a period of sustained web browsing and starts with the arrival, or the 'visit', to the retailing site. If a user has been dormant for more than 60 minutes on one page, we assume that the session has ended and that the next page viewing marks the beginning of a new session. Session also ends with the purchase, in which 'purchase' is defined as any page view during which a purchase occurred. Sessions include all of a user's page viewings on the retailing website. We call the session that ends with purchase a 'converting session' and the customer who made any purchase during the window of data collection a 'buyer'. From the perspective of individual consumers, 'buyers' may have multiple non-converting sessions with at least one converting session, whereas 'non-buyers' only have non-converting sessions within the data collection period.

It took us several rounds of data revision request to obtain the data set that fits our research objective, while the analytics firm used their clickstream tracking technologies across various clients' websites. The data we obtained through these interactions consist of three different sets. The first set is collected from August 1, 2013 to July 31, 2014 and includes the customers' access time to the retailing site and their order information from three different companies in online retailing. These data contain the buyers' landing time to the websites and the shopping cart information. The second data set spans from April 29, 2015 through August 31, 2015, capturing the history of all customer interactions with the sites. Unlike the first data set where only the buyers' footsteps are captured, this data set includes the clickstream of all visitors regardless of their purchase decisions and contains every within-session click, i.e., the sequences and timing of all pages viewed during the four-month period. The third data set is currently being collected, since May 2017, across multiple retailing sites. This batch of data provides the most comprehensive and unique information for the estimation of customer preferences and the heterogeneity across different companies. It includes all of the timing information as well as the product-specific information collected from every page viewed. Therefore, it contains information, such as how long a customer stayed on the search page, which products were viewed, and whether the product was purchased. In this data set, we match the browsed item information displayed on the page view with the purchased item information and effectively resolve the challenges from the mismatches between product attributes and URL information; however, since the data collection is still in process, we use the first two batches of data to meet our first research objective in this chapter. We explore the impact of the timing of visit and the following sequences of page views as advance demand information in this chapter.

By analyzing a series of visits to an online store by individual customers over a time period, we aim to examine online purchasing propensity by identifying its potential predictors. This study is related to prior research on online customer conversion behavior and dynamic models of time duration. Although customer browsing behavior linked with purchasing conversion has been extensively studied by researchers in both operations and marketing (e.g., [40, 53, 52, 66]), many of these studies focus on one aspect of clickstream: either within-session or across-session analysis. For example, Montgomery et al. [53] focuses on the within-session sequence of pages viewed and studies the purchasing behavior given visit conditional on a customer's arrival. On the other hand, Moe and Fader [52] address the cumulative effects of visits across-sessions between purchase conversions. In a recent study, Park and Park [59] utilize different patterns, considering both within session clicks and across-session visits at the individual level to study the conversion rate. They also find that repeated purchases increase sales probability significantly. Our study contributes to the literature in clickstream modeling by studying the impact of the time duration variables within-session (or shopping dynamics given a visit), combining the effect of cross-session visits by individual consumers over time (or the past visit history). Moreover, we contribute to the study by Huang and Van Mieghem [40] by using the clickstream data from multiple firms. We report the econometric analyses results, using the timestamp data and identifying customer's visit patterns and page-view duration as important sources of predictive information about their purchase behaviors.

With the first data set, we confirm that the customer conversion rate does not have a linear relationship with time duration variables. Expected time to purchase, revenue, basket size, and the types of product vary with the time between the first landing to order and the number of revisits. Moreover, our finding suggests that the impact of latency[2] varies across different retailers. This suggests that it is more important to understand industry characteristics and build tactics to impact the customer purchase effectively, rather than focus on minimizing the latency, as online retailers often do.

With the second data set, we conduct predictive analyses at both the user level and the session level. When we predict whether a customer is likely to buy, we conduct a user-level analysis, and when we predict whether a session is likely to be a 'converting session,' we conduct a session-level analysis. Our main finding is that customer engagement intensity plays a more significant role in predicting a purchase. We find that rather than the frequency of different page views, repeated cumulative visits and the longer (but active) page-view duration increase the conversion rate. We analyze the frequency and the duration of visits altogether to find that active engagement in a session significantly predicts the purchase.

We first describe our data characteristics in detail in the next section. We then present our preliminary findings and propose an econometric model that can provide a foundation to estimate demand utilizing the clickstream data. Since we are still in the process of collecting the product information on the viewed page and data from multiple other retailers, we briefly discuss the design of the model but omit the estimation results from

[2]Latency in the retail sense is defined as the time between two customer events, such as a first and second purchase. In our study, latency measures the length of the time between the first access (after the previous session is over) to the purchase.

the third dataset in this chapter.

3.2 Data Description

The first set of data includes the clickstream from three retailers but captures the converting customers' paths only due to the data size restriction. This data consists of all the access times to the retail site, the order time, shopping cart information such as price, quantity, and item SKU number, and the consumer's information such as IP address and location. This data validates the presence of customer heterogeneity across different industries, and motivates the estimation of time-duration parameters separately across industries. We collect the data from the three retailing companies with similar sizes: company S in stationary supplies, F in food retailing, and P in pet supplies. The data collection period ranges from August 1, 2013 to July 31, 2014. During this one year, the total number of orders is 8,122 from company S, 18,812 from company F, 37,788 from company P. Total revenue sizes are similar across these retailers: $2.5 million for company S, $3.3 million for company F, and $2.8 million for company P. The average revenue per order, price per ordered item, and the time until the order from the first landing are summarized in Table 3.1.

Comparing the relationship between customer latency and the revenue across different retailers in Table 3.1, note that the relationship is not linear. In company F, for example, customers spend longer average time until purchase, but the revenue per order is smaller than company S. Furthermore, we observe that the average number of sessions before the purchase are 1.8 for company S, 1.7 for company F, and 2.3 for company P. This shows that average customers of company S or F stays longer in the website until purchase than company P. In case of company P, the median and mean of latency has

Table 3.1: Summary statistics of the purchase data from three companies

		Company S	Company F	Company P
Revenue per order	Mean	\$270	\$174	\$73
	Median	\$137	\$132	\$47
Price per item	Mean	\$32	\$85	\$26
	Median	\$16	\$71	\$12
Latency*	Mean	89 hrs	53 hrs	59 hrs
	Median	1.2 hrs	2.4 hrs	0.5 hrs

Note: * In our study, latency measures the length of time from the first landing of the page until purchase.

big gap (in Table 3.1, latency median is 30 minutes and the mean is 59 hours), and the average number of sessions before the purchase are higher. This implies the presence of frequent visitors without often making purchases.

We further segment the customers based on their number of repeated sessions until purchase, and calculate the average quantity and the revenue size of the basket for each segment. We omit the description of details here; however, we observe that the revenue generation is not linearly trended with the repeated visits. This result implies that minimizing latency simply does not lead to higher revenue directly, and motivates us to identify the factors that can predict the purchasing decisions. We also acknowledge the importance of (1) incorporating abandonment rate by including non-converting sessions, and (2) breaking down the time-related variables into specific quantitative measures of engagement in order to accurately predict the purchasing probability.

Therefore, in the second data set, we collect the clickstream data for every visitor including within-session clicks from multiple companies. For analysis, we select a retailing company that sells a broad range of products in arts and crafts, such as cross-stitch and needlework, general craft, knit and crochet, scrapbooking, and stamped stitchery product. The company provides products through its factory outlet store and mail catalogs, as well as online. The data spans from April 29 through August 31, 2015, capturing the history of all customer interactions with a website. The sequence and timing of all pages viewed by both buyers and non-buyers are recorded. Therefore, the data includes time stamps of entry to website and subsequent clicks, pages viewed, and purchases made. We observe 198 unique visitors during the data collection periods with 14,621 unique active sessions. Among 198 unique visitors, 96 visitors at least have purchased once, and we call them 'buyers'. Among those 96 buyers, 78 buyers revisited, indicating that 81% of buyers are repeated buyers. Among 14,621 unique active sessions, 657 sessions are the converting sessions.

Table 3.2: Summary Statistics of the sessions

	Converting session paths					Non-converting session paths				
	Mean	SD	Min	Max	Median	Mean	SD	Min	Max	Median
Session length (min)	8.7	15.0	0	199.9	2.8	10.0	16.8	0	249.2	3.6
Page-view duration (sec)	27.7	14.5	0.9	223.6	25.7	24.9	8.8	4.8	56.7	23.8
Page-views per session	19.1	35.2	0	523	7	25.6	81.3	0	5880	9
Total sessions*	9.7	12.9	0	81	5	90.7	51.9	3	265	80
Total page-views*	72.7	73.8	0	523	53	317.6	621.5	45	5880	204
Purchase history	4.5	4.9	1	32	3	-	-	-	-	-

Note: * The numbers are counted until a purchase happens, a customer exits, or the data is censored.

Among the customer engagement measures, Peterson and Carrabis [61] defines the quantitative indices of clickstream, such as click depth, duration, recency, and loyalty index. In their definition, click depth represents the number of page views, duration index is the time spent, and the recency is the rate at which users return to the site over time, and the loyalty index is the level of long-term interaction the user has with the site (total frequency of revisits). In this dataset, all measures are defined.

Table 3.2 summarizes the visiting and purchasing dynamics at this retail site (in the second data set) during the four months of data collection. In our study, 'session length' measures the minutes spent from the visit through the purchase or the exit. Again, we truncate the session if the page view activity is dormant for more than an hour, and consider it as exit. 'Page duration' measures the time spent on the page viewed, 'page-views per session' measures the number of clicks within the session. This summary statistics show that the average session length and the number of pages viewed of converting session paths are not necessarily higher than non-converting session paths. We conduct econometric analysis to better understand this data in the following section.

3.3 Empirical Analyses

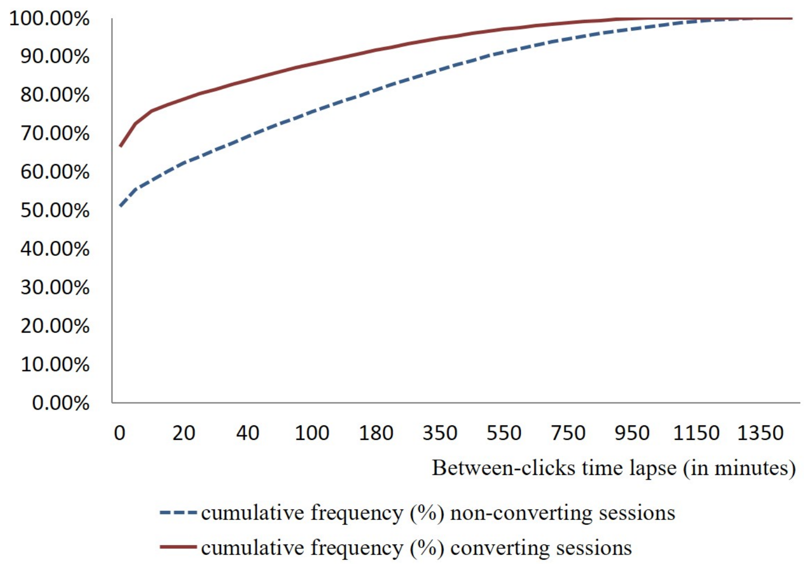
In this section, we empirically examine which aspect of clickstream data is useful to estimate the purchasing probability using our second data set.

Table 3.3: Length of Active Engagement

		Converting sessions	Non-converting sessions
Longest idle time per day	≥5min lapse	34%	49%
	≥20min lapse	22%	41%
Active sessions per day	≤ 1min lapse	61%	65%
	1-5min lapse	37%	31%
	1-20min laspe	38%	32%
	≥30min lapse	1%	2%

We first compare the pattern of customers' engagement time between the converting and non-converting sessions. In Table 3.3, we measure the average of dormant (idle) time and active time per day. First, note that non-converting session paths have a higher percentage of idle time per day. For example, more than 40% of the time, the non-

Figure 3.1: CDF of Time Between Clicks



converting sessions stay dormant, while less users ($< 22\%$) in converting sessions stay dormant on the web for prolonged time. Second, converting sessions have a higher percentage of 1-5 minute-length or 1-20 minute-length page views than non-converting sessions. We consider that customers are actively engaging in the page if the time between the clicks are greater than a few seconds but smaller than a few minutes. Figure 3.1 also shows the cumulative distribution of the between-click time lapse, and shows that between-click time is more dispersed in case of non-converting session. That is, if we consider the pages with no click more than an hour (up to a day) as inactive page, non-converting sessions have higher frequency of dormant sessions. These observations suggest the higher density of active engagement for converting sessions, and motivates us to conduct econometric analyses.

Now, we report the Logit regression results. We conduct this analysis in order to test which time variables can predict the conversion.

First, in order to conduct a user-level and session-level prediction, we express the probability of a session ending with conversion as a function of hypothesized within-session time variables, such as the session length, page duration, and the number of clicks. We also incorporate the across-session variables, such as past history of purchase and the total minutes elapsed from the beginning of the very first session up to the current session. In Table 3.4, we first regress the conversion rate at the user level and the session level.

Table 3.4: User- and Session- level Logit Regression on the Conversion

	User level	Session level	
Intercept	27.088 **	-3.801 **	-3.295 **
	(10.341)	(0.092)	(0.123)
Session length	0.008	0.007 **	0.009 **
	(0.279)	(0.002)	(0.001)
Page duration	-0.527	0.361 **	0.618 **
	(4.605)	(0.114)	(0.126)
Number of clicks	-0.017 **	0.000	0.000
	(0.006)	(0.000)	(0.000)
Purchase history			0.179 **
			(0.016)
Total sessions	-0.009		-0.055 **
	(0.020)		(0.005)
Pseudo R^2	0.927	0.020	0.189
$Prob > \chi^2$	0.000	0.000	0.000
log likelihood	-9.93	-1868.95	-1254.19
N	195	12126	11601

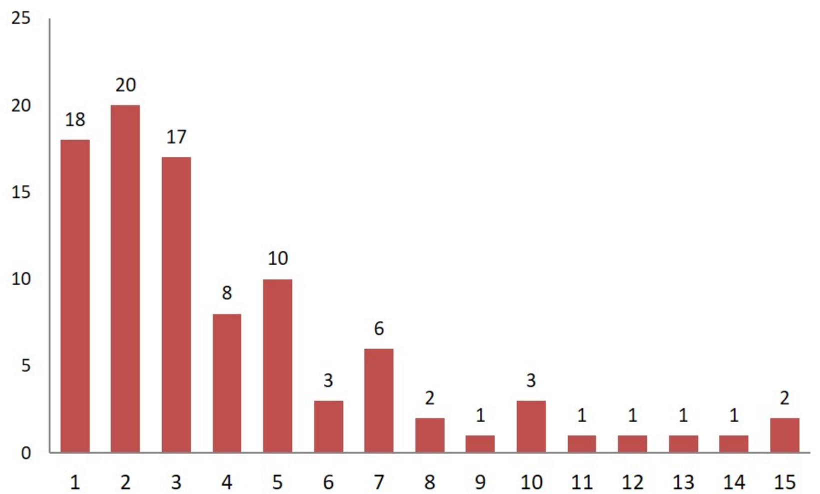
Note: $^{**}p < 0.01$. Standard errors are in parentheses.

In the first column of Table 3.4, the dependent variable in the user-level analysis is the probability of the session belonging to buyer. Note that only the number of clicks can explain the buyer and non-buyer difference. Here, the number of clicks at user level indicates the total number of clicks during the data collection period. Recall that the site-wise conversion rate is 4.5% (657 converting sessions among 14,621 active sessions). Moreover, the summary statistics in Table 3.2 suggest that non-converting sessions have a large number of total clicks over four months. Since there are too many non-converting sessions which increases the total number of clicks of non-buyers significantly, this prediction result with negative sign on the total number of clicks is understandable. This result itself does not signal much about the relationship between the time duration variables. On the other hand, in the session level analysis on the second column of Table 3.4, the session length and page duration both increases the probability of the session being the converting session. The dependent variable for these columns is the probability of the session ends up with conversion. The total number of clicks becomes insignificant in predicting the converting session, but instead, the longer page-view duration significantly predicts the conversion. Page duration measures the minutes between the subsequent clicks only within the active sessions. This result is consistent with our previous descriptive statistics that converting sessions display higher active engagement.

We further observe that there is a large number of repeated buyers in this retailing site. Figure 3.2 shows the distribution of the number of repeated buyers. It shows that out of 96 visitors who have previously purchased, 78 visitors revisited, and among them, 58 visitors revisited, and so on. Past studies (e.g., [52, 40]) support that customers who have purchased previously are more likely to buy again. We incorporate this cross-session information into our model, and confirm that number of past purchase has positive effect on conversion rate.

Next, we conduct Logit analysis at the page-level, in order to investigate the engagement dynamics within the session. In other words, this model can be used to predict the conversion given the customer's arrival. In this analysis, the dependent variable

Figure 3.2: The Number of Repeated Buyers



is the purchase probability at the page view level. Here, the session length measures the minutes elapsed from the beginning of the current session, page duration measures the minutes lasted for that specific page, number of clicks measures the within-session accumulated number counts of the page views, purchase history is the number of past purchases, total sessions measures the total minutes elapsed from the beginning of the session up to the most recent page.

We report the results in Table 3.5. The main finding from the page-level analyses is that within-the session, the longer the page view and the longer lapse time of session predict the conversion. That is, as long as the session is active, customers who spend more time to engage in the page views are more likely to make purchasing decision. Specifically, notice that session length has positive correlation to conversion, whereas the number of clicks has negative correlation to conversion. Although the results are omitted here, we found that if we consider only the converting sessions, the number of clicks is positively associated with conversion. That is, given the session started, the more the number of pages viewed, the more likely is the conversion happen. On the

Table 3.5: Click (Page) level Logit Regression on the Conversion

	Page level conversion		
Intercept	-2.936 **	-3.623 **	-2.352 **
	(0.010)	(0.015)	(0.015)
Session length	0.007 **	0.006 **	0.009 **
	(0.000)	(0.000)	(0.000)
Page duration	0.131 **	0.165 **	0.143 **
	(0.011)	(0.012)	(0.012)
Number of clicks	-0.003 **	0.006 **	-0.003 **
	(0.000)	(0.000)	(0.000)
Purchase history			0.201 **
			(0.003)
Total sessions			-0.050 **
			(0.001)
Num click ^{2}		-0.0004 **	
		(0.003)	
Pseudo R^2	0.012	0.102	0.166
$Prob > \chi^2$	0.000	0.000	0.000
log likelihood	-73444.26	-66720.04	-61998.84
N	340940	340940	340940

Note: $^{**}p < 0.01$. Standard errors are in parentheses.

other hand, the Table 3.5 shows that when we consider the clicks from all sessions, a higher number of clicks is associated with a lower conversion rate (in column 1 and 3). However, the column 2 of the table suggest that this result is an artifact of the dominance of non-converting sessions in our data. In column 2, when we add the quadratic term to add the curvature in the model, the conversion probability increases and then decreases with the number of the clicks. We have tried several different configurations of the model with squared terms, and report the models with good fit only in Table 3.5. Also, note that the purchase history significantly explains the conversion rate, supporting that repeated buyers are more likely to buy again.

3.4 Implication in Operations

Our preliminary analyses suggest that time-related variables can be used for the conversion prediction. We analyze the frequency and the duration of visits altogether to find that active engagement in a session significantly predicts the purchase. For instance, our main finding that *repeated cumulative visits and the longer active page-views increase the conversion rate* can be directly applied to estimate users' probability of conversion. This advance information can be used for targeted marketing or real-time inventory planning.

First, our Logit analysis shows that within the active session, a five minute increase of page-view increases the conversion rate by more than 10%. In table 3.4, an increase in average time spent in page-view is highly correlated with high conversion probability. An increase of 10% in probability is significant, considering that only about 4% of the sessions are converting out of all sessions. Therefore, from the retailer's perspective, this information is useful to set the threshold of timing of targeted marketing, such as providing promotions. It can take many different forms, which include advertisements, free-shipping deals, or price promotions on the specific items in the user's shopping cart, but the retailer can select when the best timing for this intervention is.

Second, instead of stocking the inventory with no consideration for future demand, if the firm can identify the shopping cart information of those sessions with longer active page views, the firm can be responsive in inventory planning. If we compare sessions with an average page-view duration of one minute to those of five minutes, our analysis result implies that the conversion probability is approximately 40% higher for sessions with a five minute average page-view duration. Therefore, the firm can use the shopping cart information from those sessions with longer page-views and focus on forecasting the demand for that group to reduce demand uncertainty. For an accurate robustness check of actual operational value, we would need to make assumptions on the inventory cost parameters and run the simulations.

Third, compared to the users with no purchase history, our result shows that the users with one purchase history are about 2% more likely to purchase, and the likelihood increases with further accumulated purchases. By stratifying the user groups with the number of repeated visits, firms can more efficiently forecast the demand with low cost.

3.5 Conclusion

In this chapter, we identify the predictors of purchase propensity given the history of customer interaction with a website. Our main findings suggest that converting session paths differ from non-converting session paths: they have higher intensity of successive engagement. We also find that previous purchases are strong predictors of future purchases. Moreover, utilizing the data from multiple retailing sites that vary in industry and size, we find that the revenue and the customers' frequency/duration of visits have a complex relationship. Not only do the optimal latency and the number of clicks vary across different firms, but expected time to make purchase, revenue, basket size, and the types of the product also vary with latency and number of visits.

Because we are still in the process of collecting product information on the viewed pages from the multiple other retailers, we briefly sketch the idea of our future model. In order to capture the individual heterogeneity across sessions, as well as online shopping dynamics within sessions, we can utilize a modified survival model. Let the time between the subsequent clicks, or the latency, be the random variable T representing the time duration. Hazard rate is the rate at which this T is completed after duration t, given that they last until at least t. Since standard hazard rate models are limited to capture the duration of 'active' customer engagement, customer latency can be better modeled if we incorporate the customer specific covariates. Therefore, we define the state variable as the individual consumer's stage towards the purchase or like the concept of a conversion funnel in Abhishek et al. [1]. We can construct four states: disengaged, active, engaged, and conversion. Among the disengaged, active, and engaged states, we assume a static rate of decay or revisit, which can be estimated from data; however, our preliminary analyses suggest that we need to consider the predictive role of engagement measures once the session becomes active. When defining the purchase rate, we posit a survival function conditioned on the individual specific effects, such as the session length, page duration, number of clicks, and purchase history.

Then, we can build the Markov-chain using the proportional hazard model: we set the initial hazard rate at the beginning of the session as a function of purchase history and then incorporate the rest of the within-session time covariates as explanatory variables. By doing so, we can predict the survival rate at a given time t, which is the timing of purchase. This advance demand information can reduce inventory cost, since it will further enhance the operational managers to predict the timing of order.

Our study in this chapter has limitations: it only identifies the potential predictors of conversion using the data and leaves the hazard model to be built for future work. We also did not observe (nor estimate) the session ending time. We still have remaining questions, such as what firms should do to identify non-converting paths and turn them into converting paths and how customers make decisions on what to buy.

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