The Promise of Strategic Customer Behavior: On the Value of Click Tracking

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C lick tracking is gaining in popularity, and the practice of web analytics is growing fast. Whether strategic customers are willing to visit a website when they know their clicks may be tracked is an important yet complex problem, which depends on various factors. Using a newsvendor framework, we examine this problem by focusing on the *operational* factor: how product availability induces strategic customers to voluntarily provide advance demand information. We find that a strong Nash equilibrium exists where every customer is willing to click, and customer incentives to click are robust to noise. Hence, we demonstrate the promise of strategic customer behavior in the context of click tracking, contrary to the conventional wisdom that it is typically a peril for the firm. Notably, click tracking is typically advantageous to both the firm and its customers, compared with other strategies such as advance selling, quantity commitment, availability guarantees, and quick response. Lastly, we extend to two settings by including marketing decisions, price-sensitive demand and markdown pricing, and discuss how operations and marketing decisions interact in influencing the value of click tracking.

1. Introduction

Recent Internet click tracking technology has generated the fast growing practice of web analytics[1] and stimulated ongoing research in academia. This research paper, together with an accompanying empirical study (Huang and Van Mieghem 2011), is motivated by our interaction with a US manufacturer of industrial products, hereafter referred to as "the company." The company makes high-end roll-up doors that are customized for industrial and commercial buildings with regard to size, type of material, type of environment, etc. As do many others, the company provides current and potential customers with company, product, and contact information on its website. In contrast to e-commerce firms, however, the website is non-transactional, and the company sells its products offline, either directly or through dealers. The company faces the newsvendor problem because there is demand uncertainty and it has to procure and keep inventory for a "patented part" (required for assembling an end product) that is supplied from Europe to match with the uncertain demand. The company hires the services of a web analytics firm that specializes in click tracking to help demand forecasting, procurement, and inventory planning.

This paper studies the value of click tracking as a mechanism of advance demand information (ADI). Our companion paper reports on an empirical study of the company's clickstream and sales data to demonstrate the effectiveness of click tracking: The empirical study shows that clickstream data provide the company with ADI in terms of not only purchasing probabilities and amounts, but also purchasing timing. Our data suggest that the company can reduce the inventory holding and backordering cost by about 5% by using clickstream data for demand forecasting. The improvement is significant, given the noise in the clickstream data, and demonstrates how click tracking yields ADI.

While this empirical finding is of considerable value from the company's perspective, it may sound striking to "average" consumers (or customers): At present, would a significant number of consumers give any thought to how their *individual* clicking decision to visit a website would influence the company's production quantity decisions? Based on our interaction with the company, many customers are not aware of its usage in our setting of offline transactions with informational websites in contrast to e-commerce. Therefore, the company currently "infers" (Fay et al. 2009) future demand from clickstreams

without notifying customers of the click tracking, which we refer to as *passive* click tracking. Alternatively, the company could proactively reveal this tracking and "ask" customers to share their demand information. We are interested in whether this *proactive* click tracking where customers realize that their clicks are tracked is recommended. In other words, we are concerned about the value of click tracking technology assuming that *strategic* (or forward-looking) customers are aware that the firm is tracking their clicks and anticipate the firm's optimal actions.

Our research questions are: Will such strategic customers still be willing to click? What is the resulting value of click tracking technology from an operations management perspective; that is, how can it help production, inventory, and pricing decisions? And how does it compare with other "traditional" strategies? These questions are important for at least the following reasons: First, whether strategic customers are willing to share their information determines the value of click tracking. Second, answering these questions helps firms to decide on which strategy should be adopted. For example, well-known strategies such as pre-orders (i.e., advance selling) have been used to collect demand information. Click tracking is essentially an information sharing channel for the firm and its customers. How do they differ, and which one should be adopted? Our study in section 5.1 offers managerial insights.

To answer our research questions, we first analyze the impact of click tracking using a standard newsvendor model where customer valuation is certain and known to the price-taking firm. We demonstrate that a strong Nash equilibrium always exists where *all* strategic customers are willing to "click"[2] regardless of the small individual impact on the aggregate demand. In contrast to other settings, the presence of strategic customer behavior also makes the firm better off: In theory, it could gather *perfect* demand information from *strategic* customers. Second, we study noisy clicks in a more realistic setting where strategic customers have uncertain valuations. We find that customer incentives to click are fairly robust to noise.

In a unified framework, we compare click tracking to traditional operations and marketing strategies such as advance selling, quantity commitment, availability guarantees, and quick response that have been extensively studied in the literature. Different researchers have studied how these strategies improve a newsvendor firm's profit when selling to strategic customers. Our model allows a unified comparison of the strategies that can be used by traditional manufacturers/retailers with the new click tracking technology available to firms with Internet access. This comparison provides insights into the key drivers of these different strategies and provides a recommendation as to which strategy is more valuable in certain stylized settings. We first compare click tracking with advance selling (or pre-orders), and find that click tracking can be better than advance selling for the firm, especially when selling popular products. We also show that click tracking can bring *more value* to the firm than strategic instruments such as quantity commitment and availability guarantees. The reason is that the latter strategies provide incentives to affect strategic customer behavior, while click tracking also reduces demand-supply mismatches. Compared with all these conventional strategies, notably, click tracking is typically advantageous to both the firm and its customers.

Finally, as an extension to include marketing decisions, we investigate settings where pricing may impact customer incentives to click: price-sensitive demand and markdown pricing. We propose price commitment and product personalization to induce customers to click.

There are three main contributions of the paper. First, driven by both practice and empirical evidence, this appears to be the first study to explore the value of click tracking practice in operations management, to the best of our knowledge. Second, our comparisons of click tracking with other operations and marketing strategies provide managerial insights into which strategy should be adopted. Third, our study also contributes to the recent operations literature on strategic customer behavior. While strategic customer behavior is typically a peril for firms, we demonstrate its *promise* in the context of click tracking for demand forecasting.

The outline of this paper is as follows. After reviewing related literature in section 2, we present a simple model in section 3. In section 4, we model noisy clicks. In section 5, we compare click tracking with other operations and marketing strategies. In section 6, we investigate how price risk may impact customer incentives to click by extending the simple model to price-sensitive demand and markdown pricing settings. Finally, we provide discussion and point out limitations. All proofs are relegated to the Online Supplement.

2. Related Literature

Our paper is related to several branches of research in operations management, economics, marketing, and information systems literature.

2.1. Advance Demand Information and Inventory Management
There is a vast body of literature modeling perfect and imperfect ADI for production planning and

inventory control; see, for example, Hariharan and Zipkin (1995), Gallego and Özer (2001, 2003), Özer (2003), Özer and Wei (2004), Wang and Toktay (2008), and Gayon et al. (2009). All these papers assume that the firm has ADI and study how to use ADI in inventory management and thus quantify the value of ADI. An exception is the study by Boyacı and Özer (2010), who show how advance information can be acquired from advance selling to make a better capacity decision in both newsvendor and dynamic pricing settings. Sharing a similar theme with Boyacı and Özer (2010), we conduct a study complementary to this literature by focusing on how ADI is obtained and how the interaction between strategic customers and the firm affects the quality of ADI. We study whether strategic customers are willing to click, given our empirical validation that click tracking technology does provide ADI (Huang and Van Mieghem 2011).

2.2. Strategic Consumer Behavior in Operations

There is a significant literature that explicitly considers strategic consumer behavior; see, for example, Besanko and Winston (1990), Cachon and Swinney (2009), Prasad et al. (2010), and Swinney (2011) and references therein. We study the willingness of strategic consumer to click and thereby provide ADI, which is a timely addition to this literature. While strategic consumer behavior typically hurts the firm in the literature, in our setting, it is a benefit.

2.3. Clickstream Research in Marketing

Empirical research on clickstream data is an ongoing active research area in marketing. Moe and Fader (2004), Van den Poel and Buckinx (2005), and Hui et al. (2009) provide a comprehensive literature review. This stream of research focuses mainly on how to model online consumer behavior to best "fit" the observed click behavior with purchase probabilities in e-commerce settings. Different from this empirical literature, our study is theoretical. We are interested in offline-transaction firms with informational websites as well e-commerce using click tracking to collect ADI. It is reported that e-commerce sales only account for 1.2% of all retail sales.[3] Hence, the vast majority of commerce still is executed offline, and thus our research setting addresses a larger part of the economy beyond e-commerce. In addition, given the offline ordering lag relative to clicking, we investigate how clicking can be used as ADI for better operations management. Clearly, in an e-commerce setting like Amazon, the time lag between clicks and orders could be on the order of minutes, too short to adjust operational plans. In that setting, our study prescribes that e-commerce firms should adopt proactive click tracking by preemptively asking customers to "click" before making its procurement or production

decisions. In contrast, the company we study observes click lead times on the order of weeks and even months. Using newsvendor models that incorporate customers who realize their clicks are tracked for collecting advance information, we provide complementary theory to analyze how strategic customer behavior and click tracking technology affect firms' production, inventory, and pricing decisions.

2.4. Information Systems

Our work is also related to the information systems literature. There are two bodies of research that are closely related to ours. The first is empirical study of using keyword search and social mentions to predict future events (e.g., box-office revenues), based on the idea that what people are searching for today is predictive of what they will do in the future (cf. Asur and Huberman 2010, Goel et al. 2010, Joo et al. 2011 and reference therein). Our research (both empirical and this theoretical study) shares the same theme in spirit in that we all demonstrate the promise of using online data to forecast future consumer demand. While their studies are typically at the aggregate level using public data, our study shows that an individual firm can actually exploit its private data from click tracking and directly translate it to profit.

The other research stream concerns the theoretical study of learning consumer preference online and customizing/personalizing accordingly. Aron et al. (2006) study the impact of intelligent agents on electronic markets with the features of customization, preference revelation, and pricing. Murthi and Sarkar (2003) present a literature review of personalization, and Yang and Padmanabhan (2005) survey the evaluation of online personalization systems. Gupta et al. (2009) provide an excellent review of the expanding research of e-business in operations management. Trust is often an issue in e-commerce. McKnight et al. (2002) propose and validate measures for a multidisciplinary, multidimensional model of trust in e-commerce. In our setting, we assume that information revelation is verifiable and trusted. While the focus of our work on operational issues is quite different from theirs, we propose personalization as a strategy to mitigate the negative effect of consumers' strategic behavior purely based on operations models.

3. Simple Model

Consider a firm (which can be either a manufacturer or a retailer) that features a product on its website, uses Internet click tracking technology, and sells a product with a per-unit production or procurement cost c at a fixed price p to a random number D of discrete customers. Following Deneckere and Peck (1995) and Dana (2001), these customers are randomly

drawn by nature from a large population (which we call "potential customers") of size $\overline{N}$ into the market. We assume that all potential customers are homogeneous: This implies that each potential customer faces the same probability of being selected by nature. After being selected and having entered the market, each customer is only informed of her own presence, but not of the aggregate market size realization N.

Customers and the firm are rational decision makers that maximize expected utility and expected profit, respectively. Customer homogeneity implies that each customer has the same utility function U. Specifically, each customer derives deterministic utility v (mnemonic for "valuation") from buying the product, and zero when not buying (the outside option). We assume that one customer buys at most one unit. To avoid trivialities, we assume $v > p$. Thus the total demand $D \equiv N$. The demand D is a non-negative discrete random variable with cumulative distribution function F, probability mass function f, and expectation $\mu = \mathbb{E}(D) < \infty$.

Before purchasing the product, each customer decides whether or not to provide information by visiting the firm's informational website. The firm tracks the number of visits (or "clicks") X to predict demand. Each customer incurs an inconvenience/hassle cost t (mnemonic for travel or time cost) by visiting the website to provide information. Similar to the "search cost" in Bakos (1997), this cost may include the opportunity cost of time spent in clicking process[4], the hassling involved in sharing identity information (e.g., sign up or provide email address, etc.), the associated (presumably trivial) expenditures in connecting and using the Internet service, etc. Following Ellison and Ellison (2005) and Fay et al. (2009), we assume that t is zero or close to zero (i.e., arbitrarily small).

3.1. Information Structure
The price p, production cost c, cost t, demand distribution F, and valuation v are common knowledge. Only X and production quantity q are private information to the firm. Every customer's presence in the market and her click decision are privately known by herself.

3.2. Timing
At the beginning of the sales season, all customers decide whether or not to visit the website (and click) *independently*. Upon observing the number of clicks X, the firm updates its demand distribution and then decides its production/procurement quantity q. After the firm's production/procurement decision has been made, each customer decides whether or not to purchase the product. If $D \leq q$, then all customers are served. Otherwise, the product is rationed anonymously and uniformly; that is, each customer

receives one unit with probability $\frac{q}{D} < 1$. *Ex ante*, after a customer enters the market but before clicking, she faces the availability probability $s(q) = \frac{\mathbb{E}\min\{D,q\}}{\mathbb{E}(D)}$, which is also called fill rate or service level, given that the firm produces/procures quantity q (cf. Deneckere and Peck 1995 for how Bayesian updating yields this expression and Dana 2001 for more discussion).

Throughout the paper, we assume that the firm can distinguish clicks coming from different customers (from IP addresses or other identity information provided by customers, such as email accounts, home address, etc.). We also assume that the production/procurement lead time, that is, the length of time required to produce/procure the product, does not exceed the click lead time, that is, the length of time between clicking and purchasing. In other words, the firm has sufficient time to produce/procure to satisfy demand after observing clicks. Notice that it is perfectly admissible for clicks to occur sequentially. Given that click decisions are private information, all we need is that the firm observes the cumulative number of clicks before its production/procurement.

Let $a_i = (\xi_i, \eta_i)$ be customer i's clicking and purchasing strategy profile, where $\xi_i \in [0,1]$ denotes the clicking probability and $\eta_i \in [0,1]$ denotes the purchasing probability. Let $\mathbf{a} = \prod_{i=1}^{D} a_i$ be the vector of all the customers' strategy profile. We denote $\mathbf{a}_{-i}$ as the customers' strategy profile other than customer i. Let $X_i \in \{0,1\}$ be the realized clicking decision of customer i. We denote $\Pi(q,\mathbf{a}) \equiv p\mathbb{E}\min\{q, D(\mathbf{a})\} - cq$ as the firm's expected profit function, where $D(\mathbf{a})$ represents the firm's demand forecast after observing the number of customers who click given customer strategy $\mathbf{a}$. Note that $\Pi(q,\mathbf{a})$ is concave in q. Let $U_i(q, a_i, \mathbf{a}_{-i}) \equiv (v - p)s(q) - a_i t$ denote customer i's expected utility function.

When making the click decision, each individual customer faces a trade-off: visiting the website may improve the firm aggregate demand information, which may subsequently increase product availability depending on the firm's quantity decisions; however, there is a small inconvenience cost of doing so. Given that the market demand D may be large, the influence of each individual customer's decision on the firm's quantity decision can be trivial. Hence, *a priori*, it appears unclear to a customer whether it is worthwhile for her to provide information. To investigate this trade-off, we use Bayesian Nash equilibrium as our solution concept and simply refer to it as Nash throughout the paper. Using this solution concept is consistent with the recent operations literature; see, Cachon and Swinney (2009) and Swinney (2011) and references therein, to name a few.

A Nash Equilibrium $(q^*, \mathbf{a}^*)$ of the game between the firm and customers satisfies the following:

1. The firm plays a best response given customer behavior: $q^* \in \arg\max_q \Pi(q, \mathbf{a}^*)$. The expected profit involves Bayesian updating of the demand distribution upon observing the number of clicks $X = \Sigma_{i=1}^{D} X_i$.
2. Each customer i plays a best response given firm behavior and other customers' behavior: $a_i^* \in \arg\max_{a_i} U_i(q^*, a_i, \mathbf{a}_{-i}^*)$.

Only for the sake of demonstrating the robustness of our equilibrium results, we will also occasionally use the concept of strong Nash equilibrium (Aumann 1959, Nessah and Tian 2009), which is a Nash equilibrium under which no coalition of players has any profitable deviation. In our setting, such a coalition can be formed as follows: Before potential customers are drawn into the market, they can freely discuss their strategies without making any binding commitments with each other. Furthermore, we even allow customers to discuss their strategies with the firm. The strong Nash concept is criticized as too "strong" in that it allows for unlimited private communication. For example, a strong Nash equilibrium has to be Pareto efficient. As a result of these stringent requirements, a strong Nash equilibrium rarely exists in general games. However, in our game played by the newsvendor firm and its customers, we will specify Nash equilibria that turn out to be also strong. Proposition 1 below characterizes the equilibria.

PROPOSITION 1. *(i) If and only if $t \leq \frac{v-p}{\mu}$, there exists a strong Nash equilibrium where $X^* = q^* = D$: All customers click with probability 1 and the firm produces the quantity that is equal to the number of observed clicks. In equilibrium, the firm's expected profit is $\Pi^* = (p - c)\mu$, and each customer's expected utility is $U^* = v - p - t$.*

(ii) There always exists a Nash equilibrium where $X^* = 0$ and $q^* = \min\{q \geq 0 : F(q) \geq \frac{p-c}{p}\}$: No customers click and the firm produces the newsvendor quantity. Furthermore, if $t \geq \frac{v-p}{\mu} \mathbb{E} \max\{0, D - q^*\}$, this equilibrium is a strong Nash equilibrium.

The key insight of Proposition 1 is that each customer is willing to click even if his own *individual* impact to the *aggregate* market appears small, for example, even if there may be infinitely many customers in the market. This is driven by the fact that $\frac{v-p}{\mu} > 0$ no matter whether demand D is unbounded or not. Hence, under our assumption that t is trivially small, there always exists a strong Nash equilibrium where the firm obtains *perfect* ADI provided by *strategic* customers.

4. Random Conversion and Noisy Clicks

In the simple model, every click necessarily leads to a purchase. However, in reality, some customers who click do not "convert," that is, they visit the website without purchasing the product eventually. This means that in practice the clicks data are *noisy* in that the firm cannot perfectly distinguish *buyers* from *non-buyers* who click without purchasing the product. Such noisy clicks provide the firm with *imperfect* ADI, which often results from customers' *valuation uncertainty* of the product when they click. Typically, customers search online or offline to learn more information about the product. At the time of clicking, they may only be interested in the product, but not sure whether they will purchase or not. Only if their valuation turns out to be higher than the price will they buy. In this section, we are interested in how the "noise" of clicks affects customer incentives to click.[5]

We continue with the simple model in section 3, but add valuation uncertainty. We distinguish between a population of a random number N of homogenous strategic customers with uncertain valuation V and the *actual* number of buyers D. Note that the N customers randomly selected into the market are homogenous *ex ante*, that is, when making clicking decisions. However, they are *heterogenous ex post*, that is, when making their purchasing decisions, their valuation realizations may be different. We assume that N is approximately normally distributed with mean μ_N and standard deviation σ_N. Using the continuous distribution for the number of discrete customers is an approximation for the sake of analytical tractability. Denote the coefficient of variation of N by $COV_N \equiv \frac{\sigma_N}{\mu_N}$. The prior valuation V has distribution function $G(.)$ and density $g(.)$ over the support $[v_L, v_H]$, where $p > v_L$.[6] Let the mean of V be μ_V and standard deviation be σ_V. After her valuation uncertainty is resolved, a customer buys if $v \geq p$ and does not buy otherwise.

The sequence of events is the same as before: At the beginning of the sales season, customers decide whether to click. Then the firm observes the number of clicks and uses Bayesian updating to forecast demand. In contrast to the simple model with deterministic valuation where $D = N$, the firm can no longer infer the exact number of realized demand D from clicks, but only the potential demand N due to valuation uncertainty.

While each individual customer's click indeed strictly improves the firm's quantity level in the simple model, it may not when there is noise. Intuitively, noise may dilute the informativeness of clicks, given that each click may not convert to real demand. To

investigate whether and when each customer is still willing to click in the presence of noise, we go through the following preliminary analysis.

If all customers click, then $X = N$ and the firm knows the market size (i.e., potential demand). Suppose $N = n$ clicks are observed; then the number of buyers D follows a binomial distribution with parameters $\overline{G}(p)$ and n. For a large n, this binomial distribution can be approximated by a normal distribution with mean $\mathbb{E}(D \mid n) = n\overline{G}(p)$ and variance $Var(D \mid n) = n\overline{G}(p)G(p)$. Note that the coefficient of variation is $COV(D \mid n) = \sqrt{\frac{G(p)}{n\overline{G}(p)}}$. If $G(p) = 0$, $COV(D \mid n) = 0$, and demand information is *perfect*. As $G(p)$ becomes larger, the demand information is *less informative* or *noisier*. Upon observing n clicks, the firm solves its newsvendor problem by stocking quantity $q^*_{D|n} = n\overline{G}(p) + z\sqrt{n\overline{G}(p)G(p)}$. The firm's expected profit is $\Pi = \mathbb{E}_N[\Pi(N)] = (p - c)\mu_N\overline{G}(p) - p\phi(z)\mathbb{E}_N \times \left[\sqrt{N\overline{G}(p)G(p)}\right]$.

If none of the customers click, then the firm can only use its prior demand distribution. As the conditional random variable $D \mid N$ is approximately normally distributed and N is normally distributed, the unconditional demand D also approximately follows a normal distribution with mean $\mu_D = \mathbb{E}(D) = \mathbb{E}[\mathbb{E}(D \mid N = n)] = \mu_N\overline{G}(p)$ and variance $\sigma^2_D = \mu_N\overline{G}(p)G(p) + \sigma^2_N\overline{G}^2(p)$. The firm thus uses its optimal newsvendor stocking quantity $q^*_D = \mu_N\overline{G}(p) + z\sqrt{\mu_N\overline{G}(p)G(p) + \sigma^2_N\overline{G}^2(p)}$. The firm's expected profit is $\Pi_0 = (p - c)\mu_N\overline{G}(p) - p\phi(z)\sqrt{\mu_N\overline{G}(p)G(p) + \sigma^2_N\overline{G}^2(p)}$. Note that σ_N partially measures the imperfection of the ADI from noisy clicks. If $\sigma_N = 0$, then clicking or not would not make a difference for the firm. As σ_N becomes larger, clicking provides more demand information for the firm.

With a fixed price, customers are only concerned with availability. The fill rate when they all click is $s_C \equiv \mathbb{E}_N\{\frac{\mathbb{E}\min\{D|N,q^*_{D|N}\}}{\mathbb{E}(D|N)}\}$. The fill rate when none click is $s_N \equiv \frac{\mathbb{E}\min\{D,q^*_D\}}{\mathbb{E}(D)}$. Define $(V - p)^+ \equiv \max\{0, V - p\}$. Clicking is preferred to none clicking *only if* $U = s_C\mathbb{E}(V - p)^+ - t \geq U_N = s_N\mathbb{E}(V - p)^+$. As t is close to zero, the *necessary* condition becomes equivalent to $U > U_N$. We are interested in whether sufficient and necessary conditions exist under which each individual customer has an incentive to click given other agents' strategies and that no coalition of agents has profitable deviations. Proposition 2 below characterizes the existence condition.

PROPOSITION 2. *If and only if*

$$\sqrt{\frac{1}{\mu_N} + \frac{\overline{G}(p)}{G(p)}COV^2_N} > \mathbb{E}\sqrt{\frac{1}{N}} \qquad (1)$$

does a strong Nash equilibrium exist, in which all customers click, and the firm produces quantity $q^*_{D|X} = X\overline{G}(p) + z\sqrt{X\overline{G}(p)G(p)}$ upon observing X clicks. Furthermore, in equilibrium, the value of noisy clicks is strictly positive,

$$\Delta\Pi = \Pi - \Pi_0$$
$$= p\phi(z)\sqrt{\overline{G}(p)G(p)}\left[\sqrt{\mu_N + \frac{\overline{G}(p)}{G(p)}\sigma^2_N} - \mathbb{E}\sqrt{N}\right] > 0.$$
$$(2)$$

Condition (1) highlights the key factors that induce strategic customers to click: Jensen's inequality yields $\sqrt{\frac{1}{\mu_N}} = \sqrt{\frac{1}{\mathbb{E}(N)}} < \mathbb{E}\sqrt{\frac{1}{N}}$ as the function $\sqrt{\frac{1}{x}}$ is strictly convex. Therefore, the population size N needs to be highly uncertain (large coefficient of variation COV_N), or the purchasing probability $\overline{G}(p)$ needs to be high for strategic customers to click. However, it appears unclear whether and "how likely" condition equation (1) is going to hold.

To investigate the parameter regimes where this inequality holds, we conduct a numerical study. As detailed in Table 1, when $\mu_N > 5000$, strategic customers are always willing to click. Even when μ_N is small, in more than 97% cases they are willing to click. The few cases in which they are not willing to click are when μ_N, COV_N, and $\overline{G}(p)$ are *all* extremely small.

In conclusion, if clicks are noisy but the total population is large and volatile and the customers' purchasing probability is not too small, then strategic customers are still willing to click. The resulting noisy clicks always provide strictly positive benefit for the firm. The main finding from this section is that *customer incentives to click are fairly robust to noise*.

5. Value of Strategic Clicks: Comparing to Other Strategies

One essential part of our study involves evaluating the value of click tracking of strategic customers, especially when compared to conventional operations and marketing strategies that have been extensively studied in the literature. For fair comparisons, we distinguish two different settings based on whether customers' valuation is certain or uncertain when they make their clicking decisions. The aim of this comp-

Table 1 Numerical Experiments of Noisy Clicks

μ_N	COV_N	$\overline{G}(p)$	Percentage of cases where strategic customers will click
30	0.001:0.001:0.3	0.001:0.001:0.99	97.28%
50	0.001:0.001:0.3	0.001:0.001:0.99	98.38%
100	0.001:0.001:0.3	0.001:0.001:0.99	99.21%
200	0.001:0.001:0.3	0.001:0.001:0.99	99.62%
300	0.001:0.001:0.3	0.001:0.001:0.99	99.77%
500	0.001:0.001:0.3	0.001:0.001:0.99	99.88%
1000	0.001:0.001:0.3	0.001:0.001:0.99	99.99%
2000	0.001:0.001:0.3	0.001:0.001:0.99	99.99%
4000	0.001:0.001:0.3	0.001:0.001:0.99	99.99%
5000	0.001:0.001:0.3	0.001:0.001:0.99	100%
10,000	0.001:0.001:0.3	0.001:0.001:0.99	100%
60,000	0.001:0.001:0.3	0.001:0.001:0.99	100%
100,000	0.001:0.001:0.3	0.001:0.001:0.99	100%
1,000,000	0.001:0.001:0.3	0.001:0.001:0.99	100%
10,000,000	0.001:0.001:0.3	0.001:0.001:0.99	100%

For each value of μ_N, there are 297,000 parameter cases.

arison is to further understand how well this click tracking technology performs relative to other conventional strategies. We first compare with advance selling, given that advance selling receives considerable attention in both operations and marketing.

5.1. Comparison with Advance Selling

Advance selling (also called pre-order strategy) is the marketing practice of selling a product at a time preceding consumption (Boyacı and Özer 2010, Shugan and Xie 2000, 2004, Xie and Shugan 2007). Xie and Shugan (2007) argue that offering advance sales can improve profit because advance selling separates purchase from consumption. This creates buyer uncertainty about their future product/service valuation and removes the seller's information disadvantage (caused by the buyer knowing more about their own valuation than the seller does).

From an operations perspective, advance selling is another mechanism of ADI and thus allows the firm to better match supply with demand. Given that both advance selling and click tracking can provide a firm ADI, how do they compare?

We build a stylized model of advance selling capturing both the valuation uncertainty feature and ADI feature as in section 4. Consistent with the literature (cf. Gundepudi et al. 2001, Prasad et al. 2010, Shugan and Xie 2007, Yu et al. 2007 and references therein), suppose there are two time epochs: The first period is the advance selling period, which is equivalent to the time when strategic customers have to decide whether or not to click (recall the model in section 4). The second period is the regular selling (consumption) period. For brevity, we assume that the regular selling price $p_2 = p$ is exogenously given, but the advance-selling price p_1 is a decision variable for the firm. Strategic customers must decide whether to commit to purchase in the advance selling period or delay to the regular period. Based on how many pre-orders are received, the firm determines its production/procurement quantity.

For convenience, denote the coefficient of variation of the demand D by $COV_D = \frac{\sigma_D}{\mu_D} = \sqrt{\frac{\mu_N \overline{G}(p)G(p) + \sigma_N^2 \overline{G}^2(p)}{\mu_N^2 \overline{G}^2(p)}}$ and the value of advance selling over regular selling (i.e., selling in a single period with price p) by $\Delta\Pi_A$. While using click tracking never hurts, the firm can lose profit by using advance selling, as the advance-selling price p_1 charged has to induce strategic customers to purchase in advance (Prasad et al. 2010). Based on Lemma A-1 in the Online Supplement, we can compare the value of click tracking and advance selling to the firm as follows.

PROPOSITION 3. *If inequality equation (1) holds, then* $\Delta\Pi > \Delta\Pi_A$ *if and only if*

$$\mu_V < p\overline{G}(p) + cG(p) + s_N \int_p^{v_H} (v - p)g(v)dv$$
$$- \frac{p\phi(z)}{\mu_N}\sqrt{G(p)\overline{G}(p)}\mathbb{E}\sqrt{N}.$$

Otherwise, $\Delta\Pi > \Delta\Pi_A$ *if and only if*

$$\mu_V < p\overline{G}(p) + cG(p) + s_N \int_p^{v_H} (v - p)g(v)dv$$
$$- p\phi(z)\sqrt{\frac{\overline{G}(p)G(p)}{\mu_N} + \overline{G}^2(p)COV_N^2}.$$

When $G(p) = 0$ and consumers are *certain* about their own valuation (which exceeds the price p), it is always optimal for the firm to adopt advance selling, and customers are always willing to purchase in advance to eliminate any stockout risk. This special case essentially reduces to the simple model in section 3. This suggests that, in the absence of valuation uncertainty, advance selling and strategic clicks are equivalent; that is, they yield the same benefit for the firm *ceteris paribus*.

When $G(p) > 0$ and there is *valuation uncertainty*, strategic clicks and advance selling differ in profitability. Proposition 3 states that when customers' expectation of the valuation is low, strategic clicks outperform advance selling; otherwise, advance selling can outperform strategic clicks by exploiting the benefit of the high expectation and gaining ADI.

To gain intuition about Proposition 3, we let

$$
\overline{\mu}_V(\overline{G}(p), \mu_N, \sigma_N) \equiv p\overline{G}(p) + cG(p)
$$

$$
+ s_N \int_p^{v_H} (v - p)g(v)dv - \frac{p\phi(z)}{\mu_N} \sqrt{G(p)\overline{G}(p)} \, \mathbb{E}\sqrt{N} \quad (3)
$$

be the *expectation threshold* of customer valuation below which click tracking is preferred over advance selling. We are interested in how this threshold depends on the purchasing probability $\overline{G}(p)$ and the variation of the potential demand, that is, the customer population, measured by COV_N. We performed a numerical study fixing μ_V and μ_N while varying other parameters, and one representative example is shown in Figure 1. The numerical example suggests that $\overline{\mu}_V(\overline{G}(p), \mu_N, \sigma_N)$ is increasing in the purchasing probability $\overline{G}(p)$, but not necessarily monotone in the coefficient of variation COV_N. We observe that $\overline{\mu}_V(\overline{G}(p), \mu_N, \sigma_N)$ is increasing in COV_N when $\overline{G}(p)$ is small while decreasing in COV_N when $\overline{G}(p)$ becomes large. This observation suggests the following: As each customer is more likely to buy the product in the regular-selling period, click tracking is more likely to be preferred. However, more uncertainty of potential demand favors strategic clicks when $\overline{G}(p)$ is small, while it favors advance selling when $\overline{G}(p)$ is large. Indeed, both click tracking and advance selling reduce demand uncertainty, but which demand uncertainty reduction of the two strategies is more beneficial crucially depends on the purchasing probability $\overline{G}(p)$. From Figure 1, we notice that the expectation threshold is

Figure 1 The Expectation Threshold $\overline{\mu}_V$ ($p = 10, c = 7, \mu_V = 8$, $\mu_N = 80,000$, V is uniformly distributed in $[v_L, v_H]$, where $v_L = \mu_V + \frac{p - \mu_V}{2\overline{G}(p) - 1}$, $v_H = 2\mu_V - v_L$)
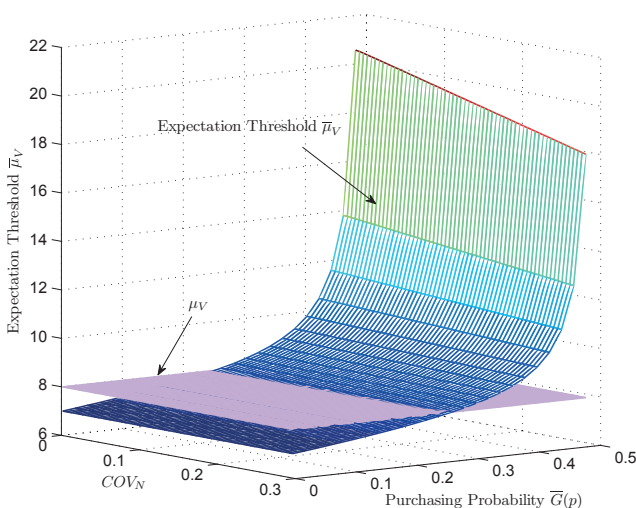
more sensitive to the purchasing probability than to the coefficient of variation of the population. This suggests that, for any given expected valuation of the product μ_V, when customers are more likely to purchase the product in the regular period, click tracking tends to be more valuable to the firm than advance selling.

We offer an intuitive explanation of the difference between click tracking and advance selling as follows. Advance selling mostly benefits from consumers' valuation uncertainty. One necessary condition to reap the benefits is that consumers have sufficiently high expectation about their valuation and thus have incentives to *commit* to purchase early to secure availability (and thus eliminate stockouts). In contrast, click tracking benefits from taking advantage of consumer strategic behavior in that stockouts are costly for both firms and consumers. Click tracking does not rely on consumers to commit to purchase early; hence, high expectation of valuation on the part of consumers is not necessary. When consumer expectation of product valuation is fixed, higher purchasing probabilities make click tracking more desirable. This appears to suggest that click tracking is better than pre-orders when selling popular products. However, higher variation of potential demand can favor either strategy depending on customer purchasing probabilities.

Another notable advantage of click tracking over advance selling is that *ex ante* consumer welfare is *strictly* improved when click tracking is used while it remains unchanged with advance selling. Each customer's expected utility in equilibrium under advance selling is $U_A \equiv \mu_V - p_1^* = s_N \mathbb{E} \max\{V - p, 0\}$, while her expected utility under click tracking is $U = s_C \mathbb{E} \max\{V - p, 0\} - t$. We have $U > U_A$ as the cost t is sufficiently small. Therefore, click tracking brings "win-win" outcomes for both the firm and its customers, while advance selling can *only* benefit the firm. Furthermore, the *ex post* consumer welfare can be negative (due to low valuation realizations) under advance selling, while it can *never* be negative under click tracking.

While advance selling has been practiced for quite some time, click tracking is fairly new. Our comparison suggests that click tracking is promising, yet both practices can co-exist. Indeed, Figure 2 provides an example from Amazon.com where the company takes pre-orders (i.e., advance selling) for some products while inviting customers to be notified for others, such as "Want us to e-mail you when this item becomes available?" and "Sign up to be notified when this item becomes available." This practice is akin to click tracking. We may call this practice *proactive* click tracking, as opposed to *passive* click tracking without explicitly

Figure 2   Advance Selling vs. Click Tracking: A Casual Observation
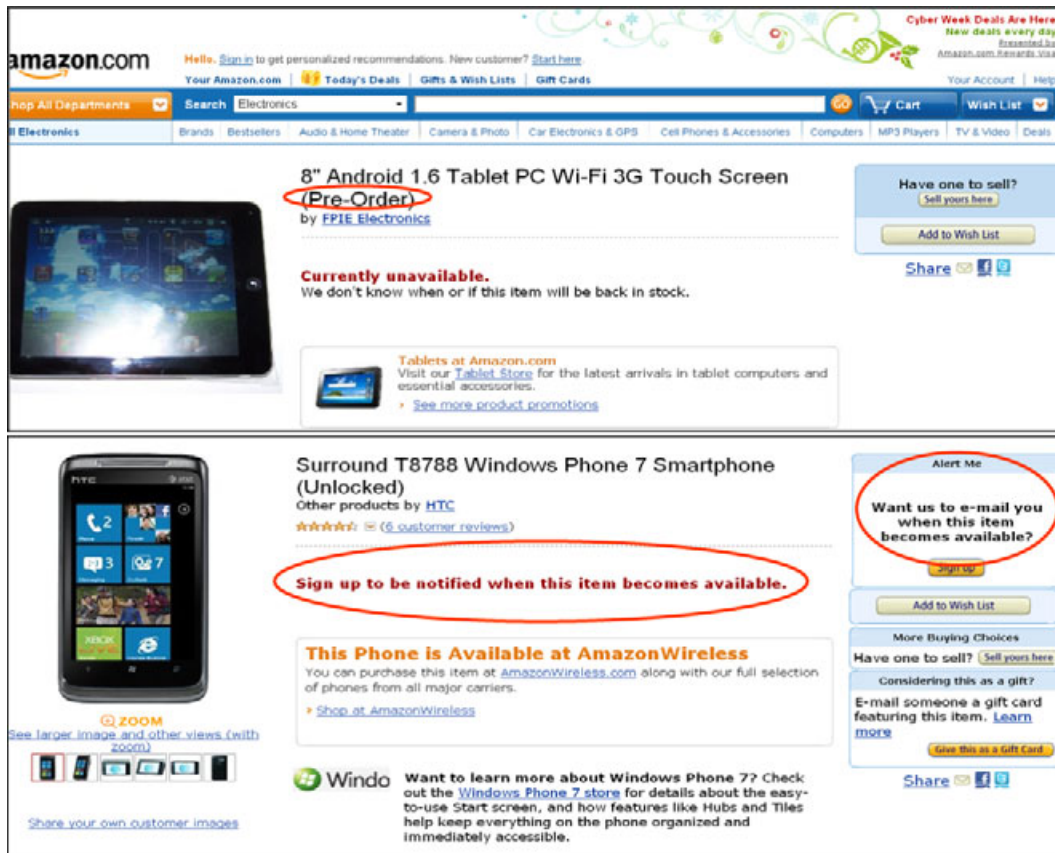
notifying customers (e.g., the setting of the B2B company). Observing Figure 2, one may tend to claim that the Smartphone is more "popular" than the Tablet PC touch screen; then Amazon's practice is by chance already aligned with our suggestion that click tracking is preferred when selling popular products. Clearly, rigorous empirical validation is needed and is left for future research.

5.2. Comparison with Quantity Commitment, Availability Guarantees, and Quick Response

When customers' valuation is certain, we compare click tracking with quantity commitment and availability guarantees, studied in Su and Zhang (2009), and quick response studied extensively in the literature (cf. Fisher and Raman 1996, Cachon and Swinney 2009, Iyer and Bergen 1997, Lin and Parlaktürk 2012, and references therein). We refer the reader to the Online Supplement 2 and 3 for detailed analysis. The main finding is that click tracking outperforms all the other strategies studied in the literature given that click tracking provides perfect demand information from strategic customers. A presumably more realistic evaluation is conducted below when customer valuation is uncertain.

When customer valuation is uncertain, we conduct an analytical study, as detailed in the Online Supplement 4. We use a numerical study to compare the value of different strategies. A subset of representative results is shown in Table 2, where c_2 is the quick-response production cost, h is the physical hassle cost, and w is the cost of compensation when using availability guarantees. These numerical examples suggest that the results from the certain-valuation case are robust: in the majority of the cases, noisy clicks outperform the traditional strategies. This implies that the *efficiency effect* (meaning reducing the supply–demand mismatches) dominates the *strategic effect* (meaning merely relying on commitment power to influence customer behavior). Only when the premium cost of quick response is sufficiently small can quick response outperform noisy clicks. Only when the demand variation is extremely low, for example, the coefficient of demand is <0.001, can the strategic effect dominate the efficiency effect. (Obviously, when demand is certain, there is no value/need in using any of these strategies.)

Table 2   Comparison of Values (in % Increment) of Different Practices with Uncertain Valuation

Parameters $(u = h, t = 0, w = 0, c = 0.1, \overline{v} = 1, \mu_N = 10^5)$	COV_N	Quantity commitment	Availability guarantees (upper bound)	Quick response	Noisy clicks
$c_2 = c + 0.06, h = 0.01$					
$\mathbb{P}(\overline{v}) = 0.45$	0.20	0.0073%	0.0118%	2.73%	4.09%
$\mathbb{P}(\overline{v}) = 0.30$	0.20	0.0049%	0.0119%	2.78%	4.12%
$\mathbb{P}(\overline{v}) = 0.20$	0.20	0.0129%	0.0122%	2.83%	4.18%
$\mathbb{P}(\overline{v}) = 0.10$	0.20	0.0103%	0.0129%	3.02%	4.38%
$\mathbb{P}(\overline{v}) = 0.45$	0.10	0.0081%	0.0116%	1.35%	1.97%
$\mathbb{P}(\overline{v}) = 0.20$	0.10	0.0064%	0.0000%	1.38%	1.98%
$\mathbb{P}(\overline{v}) = 0.10$	0.10	0.0115%	0.0127%	1.49%	2.05%
$c_2 = c + 0.06, h = 0.02$					
$\mathbb{P}(\overline{v}) = 0.55$	0.25	0.0109%	0.0361%	3.49%	5.25%
$\mathbb{P}(\overline{v}) = 0.50$	0.25	0.0132%	0.0363%	3.53%	5.29%
$\mathbb{P}(\overline{v}) = 0.55$	0.02	0.0117%	0.0116%	0.28%	0.36%
$c_2 = c + 0.001, h = 0.02$					
$\mathbb{P}(\overline{v}) = 0.40$	0.20	0.0130%	0.0243%	4.26%	4.23%
$c_2 = c + 0.001, h = 0.01$					
$\mathbb{P}(\overline{v}) = 0.30$	0.005	0.0064%	0.0000%	0.15%	0.0426%
$\mathbb{P}(\overline{v}) = 0.30$	0.002	0.0067%	0.0000%	0.11%	0.0079%
$\mathbb{P}(\overline{v}) = 0.30$	0.001	0.0067%	0.0000%	0.11%	0.0020%
$\mathbb{P}(\overline{v}) = 0.30$	0.0005	0.0068%	0.0000%	0.10%	0.0005%

6. Extensions

One essential feature of the simple model and the model of noisy clicks is that the demand distribution does not depend on price. We treated price as an external parameter, which allows us to focus on the *operational* decisions. A natural extension is to introduce price effects, the marketing aspect. In this section, we extend our posted-price and one-period model in section 3 to price-sensitive and two-period settings to understand how the marketing decision interacts and influences the operational concern.

6.1. Price-Sensitive Demand

As argued in Petruzzi and Dada (1999), the newsvendor model where stocking quantity and selling price are set simultaneously provides an excellent vehicle for examining how operational problems interact with marketing issues to influence decision-making at the firm level. We now investigate what happens if demand is price sensitive: When clicking, customers now must trade-off the benefit of stockout elimination with the risk of contingent pricing.

Demand now is a random function of price: $D(p,\varepsilon)$, where ε is a random variable with support $[A,B]$. Let $F(x,p)$ denote the probability that $D \leq x$ for a price p. The demand–price relationship $D(p,\varepsilon)$ is used commonly in the economics and operations literature to represent the market demand at an aggregate level. Meanwhile, we study customer purchasing behavior at an individual level, where customers are *heterogeneous*. Specifically, we assume customer i has a deterministic valuation v_i, for $i = 1,2,\ldots,D(p,\varepsilon)$. We

refer readers to Deaton and Muellbauer (1980) and Petruzzi and Dada (1999) for how to link the aggregate level demand with the individual level.

The game is the same as before, except that price now is the firm's decision variable, and it sets the stocking quantity and price simultaneously. Following Petruzzi and Dada (1999), we investigate two extensively used forms of the demand function $D(p,\varepsilon)$: the additive demand and the multiplicative demand.

6.1.1. Additive Demand. Demand is defined as $D(p,\varepsilon) = y(p) + \varepsilon$ in the additive case (Mills 1959), where $y(p)$ is a decreasing function that captures the dependency between demand and price. In particular, let $y(p) = a - bp$, $a > 0, b > 0$, which represents a linear demand curve commonly used in the economics literature. The demand parameters a and b must be estimated from experience and may not be known to the customers. However, to isolate the role of the demand functional form, we ignore the information asymmetry here.

Petruzzi and Dada (1999, p. 185) offer us the optimal stock quantity q^* and price p^* of the firm in the absence of ADI and the optimal price p_ϵ in the presence of perfect ADI. Let $p^0 = \mathbb{E}(p_\epsilon)$ be the expected price when demand uncertainty is resolved before the firm makes decisions. Let $x^* = q^* - y(p^*)$ and $\Theta(x^*) = \int_{x^*}^B (u - x^*) f(u) du$. We can actually invoke a natural refinement of strong Nash equilibrium, the strong perfect equilibrium (Rubinstein 1980) in this game. Clearly, all the equilibria found here are both Nash and strong Nash without using this refinement. Proposition 4 below characterizes the equilibria.

PROPOSITION 4. *With linear demand functions:*

1. *There is a strong Nash equilibrium where all customers click, and the firm sets price p_ϵ and stocks the number of clicks $q_\epsilon = X(p_\epsilon, \epsilon)$. However, this equilibrium is not a strong perfect equilibrium if*
$1 - [1 + \frac{\Theta(x^*)}{2b(v_i - p^0)}] \frac{\mathbb{E}\min\{D(p^*,\epsilon),q^*\}}{\mathbb{E}[D(p^*,\epsilon)]} \leq 0$ *for each customer i.*

2. *There is a strong perfect equilibrium where no customers click, the firm sets price p^* and stock quantity q^* on the equilibrium path, but sets price p_ϵ and stocks the number of clicks $q_\epsilon = X(p_\epsilon, \epsilon)$ off the equilibrium path, if* $1 - [1 + \frac{\Theta(x^*)}{2b(v_i - p^0)}]$ $\frac{\mathbb{E}\min\{D(p^*,\epsilon),q^*\}}{\mathbb{E}[D(p^*,\epsilon)]} \leq 0$ *for each customer i.*

It is indeed possible that the condition in Proposition 4 is satisfied as $p^* \leq p^0$, in which case not all customers are willing to click in a strong perfect equilibrium. The trade-off is about whether availability improvement outweighs price increment or not.

6.1.2. Multiplicative Demand.
Demand is defined as $D(p,\varepsilon) = y(p)\varepsilon$ in the multiplicative case (Karlin and Carr 1962), where $y(p) = ap^{-b}$, $a > 0$, $b > 1$. Then Theorem 2 in Petruzzi and Dada (1999, p. 186) specifies the optimal stock quantity q^* and price p^* of the firm. As before, define $p^0 = \mathbb{E}(p_\epsilon)$. Note that in this multiplicative demand case, we have $p^* \geq p^0$, *opposite* to the result for the additive cases. We have the following result.

PROPOSITION 5. *With multiplicative demand functions, there is a strong perfect equilibrium in which all customers click, and the firm sets price p_ϵ and stocks the number of clicks $q_\epsilon = X(p_\epsilon, \epsilon)$.*

The explanation follows from comparing the prices that the firm charges to certain-demand cases. The demand variance and coefficient of variation are increasing in p for the additive case but decreasing in p for the multiplicative case. Hence, for the additive case, the firm is willing to charge a lower price to decrease demand variability when demand is uncertain, while for multiplicative case, the firm prefers to charge a higher price to decrease demand variability when demand is uncertain. Thus, in the former case, consumers may not be willing to click, while they will in the multiplicative case. The firm should adopt a *price commitment* strategy to induce strategic customers to click in case they are not willing to (Huang 2011).

In sum, we have the following managerial insights from the two models of price-sensitive demand: Strategic customers face the trade-off between *availability improvement* and *price increment* when making their clicking decisions. Whether strategic clicks are valuable critically depends on the *functional form* of the demand function. Thus, the firm must carefully investigate how uncertainties enter into the price-dependent demand function, possibly using historical data. Driver and Valletti (2003) discuss which demand form is more realistic. They suggest that the multiplicative demand model seems more appropriate, as the price elasticity of demand is constant regardless of the demand realization in the multiplicative case. Their discussion favors the click tracking technology here.

6.2. Markdown Pricing
When markdown pricing is possible or frequent, customers may strategically wait for the markdown period to enjoy a lower price. In that case, customers may prefer the firm to have a poor forecast of demand so that the chance of overstocking for the firm is high. The key trade-off faced by customers now is the *stock-out loss* vs. *overstock benefit*: Providing ADI becomes a "double-edged sword," as it improves the availability while reducing the markdown probability. Hence, it is not clear whether strategic customers are willing to provide ADI. The following model extending the simple model in section 3 to two periods formalizes this intuition.

The first-period price p is exogenously given and fixed, but the second-period markdown price is endogenously determined by the firm (Cachon and Swinney 2009). There are homogeneous strategic customers whose second-period valuation of the product is $\overline{v}$ (commonly known) and whose first-period valuation is v_1 (commonly known), where $\overline{v} \leq p \leq v_1$. There are a random number D of strategic customers in the first period. For analytical tractability, we assume that D is approximately uniformly distributed over $[0,b]$, where $b > 0$. In the second period, the firm has to salvage its remaining inventory at value $v_L < c$. To explicitly account for inventory salvaging in the second period, we introduce bargain-hunting customers who only purchase the product when it is on sale in the second period, having valuation $v_L < c$. There are infinitely many of them in the market, and they do not click at all. Consistent with the literature, we assume that the strategic customers are satisfied first when both types of customers request a unit. The timing of the game is shown in Figure 3. For analytical tractability, we focus on the symmetric pure-strategy equilibrium where all strategic customers choose the same pure strategy. We characterize the Nash equilibrium as follows.

PROPOSITION 6. *(i) If $\overline{v} \in (c + \frac{v_1 - p}{v_L}, p)$, then there exists an equilibrium in which no strategic customers are willing to click; (ii) if $\overline{v} \in (c, c + \frac{v_1 - p}{v_L}]$, then there exists*

Figure 3 Sequence of Events
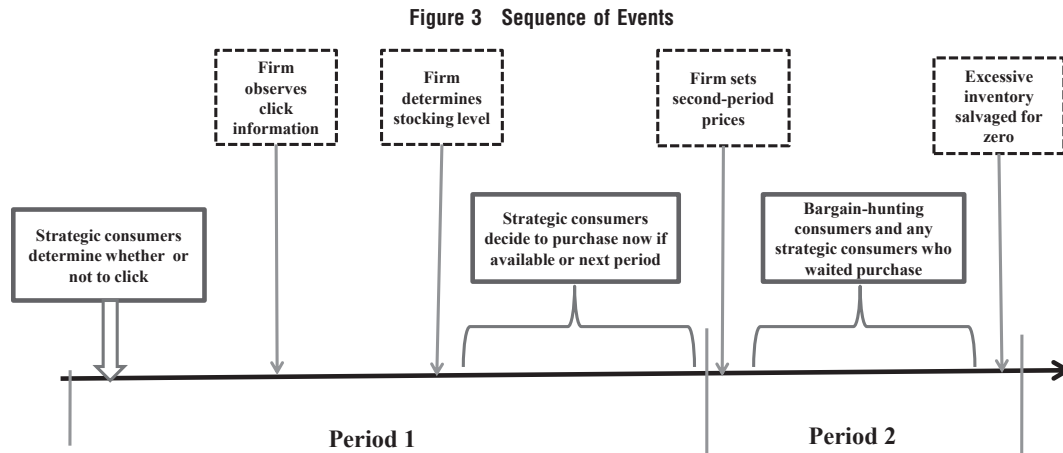
an equilibrium in which all strategic customers are willing to click.

Proposition 6 can be put as follows: The strategic customers whose second period valuation is lower than the valuation threshold $c + \frac{v_1 - p}{v_L}$ would purchase in the first period if click tracking were not used. They are willing to click if the technology is used, as the availability benefit outweighs the markdown benefit. The strategic customers whose second period valuation is higher than the valuation threshold $c + \frac{v_1 - p}{v_L}$ would wait for the markdown season if click tracking were not used. They are not willing to click if the technology is used, as markdown benefit outweighs availability benefit.

In sum, the two-period model suggests that in the settings when markdown pricing is possible and frequent (for instance, when selling nondurable/perishable or fashion goods), using click tracking is not always recommended. If many customers wait for second-period selling, then click tracking technology may be of little value. We propose that the firm can use *product personalization* to induce them to click (Huang 2011).

7. Discussion

We found that click tracking of strategic customers can be of great value to the firm. This technology can provide a better match of supply with demand than other operations and marketing strategies and brings win-win outcomes for both firm and customers. Contrary to the conventional wisdom that strategic customer behavior is typically a peril for firms, we demonstrate its *promise* in the context of click tracking.

Obviously, this theoretical result must be put in perspective: In practice, implementing click tracking may be difficult for traditional brick-and-mortar

retailers who can more easily adopt quantity commitment and availability guarantees. No strategy fits all settings. Click tracking can be implemented in manufacturing and retailing by firms facing newsvendor problems. Wherever advance selling is used to reduce supply–demand mismatches, proactive click tracking (i.e., proactively asking customers to "click" as opposed to passively collecting clickstream data) can be used. For example, it can be used when selling products in short seasons, such as new product releases and retailing of new novels, DVDs, and video games. Click tracking can also be used for products that require customers to search online to collect or learn more information in advance or specify a certain level of customization. In these settings, our findings suggest that the firm should inform customers that click tracking is used to collect advance demand information and explain its benefits, that is, *train* its customers to be strategic.

Like other economic models, our models are stylized and do not account for many practical and implementation issues. For example, while clear identification of customers in the B2B setting where we conducted our empirical study (that motivates this game-theoretic study) is not an issue, it becomes more difficult in B2C (i.e., business to consumers) settings. One person may use different computers, so identification from IP addresses becomes unreliable. What makes it even worse is that competitors may purposely generate fraud clicks. However, we suggest that B2C firms should proactively *ask* customers to reveal more reliable information of their identities (e.g., email address, home address, or even credit card information) rather than passively inferring. Our study shows that strategic customers are typically *willing* to share their demand information (in terms of their interest in the product), and it could be better than traditionally used pre-orders for both the firm and its customers.

Acknowledgments

Notes

[1]Forrester forecasts that US businesses will spend $953 million on web analytics software in 2014 with an average compound annual growth rate of 17% (http://www.forrester.com/Research/Document/Excerpt/0,7211,53629,00.html, Retrieved on Oct 18, 2011).

[2]Throughout the paper, we shall interpret "click" at an abstract level as "visit the website to provide information," which may involve clickstreams or a process of sharing identity information or interest in the product.

[3]http://www.ecommercetimes.com/story/19145.html?wlc=1292379670, retrieved on Oct. 22, 2011.

[4]Assuming an opportunity cost of time of roughly $20/hour, the inconvenience cost t can be on the order of (1 second to 1 minute)×$20/hour = $0.005 to $0.33.

[5]To isolate this effect, we will assume that customer valuation uncertainty is resolved even without clicking (e.g., time itself and alternative learning channels can resolve this uncertainty). The impact of preference learning from clicking is studied in the Online Supplement 5.

[6]Note that section 3 includes the case when $p \leq v_L$.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Online Supplement 1: Proofs.
Online Supplement 2: Clicks with Endogenous Pricing.
Online Supplement 3: Comparing Strategic Clicks to Other Operations Strategies.
Online Supplement 4: Comparing Strategic Clicks with Other Operations Strategies with Uncertain Customer Valuation.
Online Supplement 5: Preference Learning.

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