When Advance Purchase need to be Made for Future Consumption – An Empirical Investigation of Consumer Choice under Bucket Pricing

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Abstract

Bucket pricing entails a prepaid price and a maximum consumption limit, which requires consumers to make advance purchase decisions before their consumption needs are fully revealed. We propose a dynamic model that involves how consumers form expectations of future consumption needs, learn to reduce uncertainty through experience, and make optimal advance purchase decisions. Applying the model to an online DVD rental history data, we examine how consumption uncertainty may drive advance purchase decisions. Consumers tend to overpurchase to cover the unexpected volatility of future consumption needs, avoid stockouts and switching costs. Over time, consumers learn to reduce uncertainty but only those with lower switching costs adjust their overpurchases to adapt to their reduced uncertainty. Bucket pricing could lead to greater profits if higher-level plans were more attractive, which would induce consumers to overpurchase more. By explicitly modeling advance purchase decision making and empirically investigating consumer decision processes, this article helps managers better understand the effects of price/quotas combinations on consumer choice.

Key words: service industry; flat fee and quota; two-part pricing; demand uncertainty; forward planning; Bayesian learning; dynamic consumer choice; optimal pricing; product design.
1. Introduction

In the past decade, companies increasingly have adopted a pricing structure defined by periodically pre-paid flat fees and corresponding quotas that restrict the maximum consumption levels. Consumers choose among several plans characterized by different combinations of prices and quotas, then prepay the price specified by the chosen plan and accept the limit of maximum consumption implied by the chosen quota. For example, AOL offers a 4-hour daily dial-up plan for $9.95 a month, a 10-hour plan for $14.95, and an unlimited usage plan for $25.90. If a consumer chooses the first plan, he or she prepays $9.95 a month (monthly price) and may use up to approximately 120 dial-up hours per month (monthly quota).

Because such optional plans defined by quotas and flat fees suggest alternative “buckets” of different sizes and prices, we term this type of pricing structure bucket pricing. Bucket pricing appears commonly in service and subscription industries in the form of access (e.g., health club memberships) or subscription (e.g., AOL service access) fees, and is increasingly emerging in telecommunication, cable and satellite television, online music, and software industries. Companies like Blockbuster and Microsoft also have altered their business models by shifting a significant part of their business to online subscription services with bucket pricing.

Bucket pricing differs from unit-rate pricing, whereby a consumer pays a uniform price for each unit of the product or service. Because prepaid prices are charged for different amounts of similar products or services, bucket pricing also differs from bundled pricing, which refers to a postpaid price for a combination of several different products. Finally, though the price of each bucket seems similar to the flat-rate component of two-part pricing, the two pricing formats are distinct in at least three ways. First, consumption is capped by a quota in bucket pricing, whereas two-part pricing allows for excessive usage for a variable fee. Second, bucket pricing demands prepayment, whereas two-part pricing allows at least the variable fee to be paid after usage. Third, with bucket pricing, consumers make choice decisions among alternative plans that differ in size and associated price, whereas with two-part pricing, consumers determine their own usage rate because the usage fee is paid after usage (e.g., Danaher 2002).

Bucket pricing entails consumer decisions that differ from those under the extensively studied unit-rate and two-part pricing structures. These distinctions are crucial because pricing structure has important implications for consumer decision process as well as companies’ profit maximization strategy (Bell, Ho, and Tang 1998). First, consumers must make their purchase
decisions long before the consumption occasions. Such a separation of purchase from consumption is termed *advance purchase* by Shugan and Xie (2000) and Xie and Shugan (2001). Advance purchases transform deal-by-deal transactional relationships into contractual relationships to which consumers must commit for a certain period. When making such a commitment, consumers are unsure about their future consumption needs and therefore make purchase decisions on the basis of their expectations. Thus, the design of bucket pricing introduces uncertainty into the consumer decision process.

Second, when making advance purchases to secure their uncertain future consumption needs, consumers’ *ex ante* optimal purchase decisions (i.e., choices of plan) might not be optimal *ex post*. When consumers overestimate their future consumption, they overpay for unrealized consumption, and when they underestimate, they face stockout situations. To make the appropriate purchase decision under uncertainty, a consumer trades off a lower financial outlay (lower price) with a higher risk of encountering stockout situations (lower quota).

Third, bucket pricing requires consumers to prepay, which separates payment from consumption and minimizes consumers’ attention to price because they do not need to make a plan choice for every consumption occasion. Some companies even mandate automated and periodic withdrawals of payments from consumers’ credit card or checking accounts. Thus, prepayment means consumers’ actual consumption may not be directly affected by price, as it would be for two-part pricing. In turn, this may introduce consumer inertia that causes stickiness to a service plan. Realizing their potential inertia and resultant long-term commitment to a plan, consumers may look beyond the current plan period and make choices to address their long-term consumption needs. Thus, consumer choice behavior with bucket pricing also features switching costs and forward-planning behavior.

Fourth, consumer choice behavior with bucket pricing has nontrivial implications for the profit-maximizing combinations of price and quota. Unlike other pricing formats, the purchased quota or consumption capacity that drives total revenue may not coincide with the actual consumption that drives total cost. It is the difference between purchased consumption capacity and actual consumption that contributes to total profits. Furthermore, cannibalization among different plans must also be considered. Thus, it remains unclear what is the best way to design a menu of price/quota combinations with appropriate distances between adjacent buckets to improve total profit.
In Table 1, we use an example to better illustrate the consumer choice behavior with buckets pricing and its non-trivial implications for profit. In the first two columns, we list the specification of monthly prices and maximum amounts of outstanding DVDs of six service plans offered by an anonymous on-line DVD rental company. From the maximum number of outstanding DVDs, we calculate the implied monthly quota or consumption capacity. We use information from 10,000 randomly selected consumers to calculate the purchase share of each plan, average actual number of movies consumed per month, total revenue, total variable costs, and total profit. According to these numbers, we note several interesting observations. First, when monthly quota increases, the monthly payment increases but at a slower rate, indicating that the company offers volume discounts to heavy users. Second, the Standard plan has the highest purchase share, followed by Premium and Lite; thus, the popularity of plans does not appear to increase with the volume discount. Rather, the fee and quota seem to play a joint role in determining the popularity of a service plan. Third, across all service plans, the average actual consumption rates are barely half of the purchased consumption capacities. This overpurchase implies an average price of $6–$8 per movie consumed, significantly higher than the average $3–$4 unit price charged by traditional DVD rental stores. Consumers thus appear to pay a significant price premium with bucket pricing. Fourth, the amount of overpurchase increases with the quota and price of the plan. Intuitively, profit may be improved by making popular plans more profitable and/or profitable plans more popular, but the current bucket pricing menu may not be optimal because the most popular plan is not aligned with the most profitable plan.

These observations indicate the need to investigate how consumers make their advance plan choices under the uncertainty introduced by prepaid bucket pricing, and to draw some implications for the design heuristics of this novel pricing approach. Extant literature focuses mainly on consumers’ brand choices of frequently purchased packaged goods with unit rate pricing. The booming telecommunication industry has led to recent research on nonlinear pricing.

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2 Consumption capacity of plan \( j \) is approximated by the quota of plan \( j \times \) (number of working days each month/(1 + company’s estimation of average number of days for two-way delivery)). This calculation assumes that it takes at least one day for consumers to watch a movie. The calculated consumption capacity is consistent with the maximum actual consumption we observe in the data.
but this stream either adopts an analytical approach to study the competitive conditions under which flat-rate pricing is optimal (Chen and Hitt 2005; Essegaier et al. 2002; Oi 1971; Wilson 1993) or provides empirical evidence to demonstrate and explain the existence of a bias for flat-fee over two-part pricing (Danaher 2002; Hobson and Spady 1988; Kling and Van der Ploeg 1990; Kridel et al. 1993; Mitchell and Vogelsang 1991; Train et al. 1987, 1989; Miravete 2002a, b; Lambrecht and Skiera 2004; Narayanan et al. 2005). The most closely related article in marketing literature is by Danaher (2002), who applies a bivariate probit model to field experimental data on consumer usage and the attrition history of a new telecommunication service. He finds that an access fee has a greater impact on retention rates, whereas a usage fee is more influential for intensity. Despite the increasing popularity of bucket pricing and its distinct consumer purchase decision calculus, there is lack of research considering how consumers make choices among competing plans represented by prepaid bucket pricing. More importantly, advanced purchase that catches the increasing attention of marketing researchers needs to be better understood. As stated in Shugan and Xie (2000) and Xie and Shugan (2001), research is needed to explicitly model consumer advance purchase decision process and study how consumer purchase decisions are driven by future uncertainty. Some interesting research questions thus remain open, such as

- How do consumers make advance purchase decisions under prepaid bucket pricing?
- Why do consumers overpurchase?
- How do consumers adapt their choices of service plan to the dynamics of their expected consumption needs?
- Is there a better design of bucket pricing that would improve profits?

We propose a dynamic model that involves consumption uncertainty, learning, and forward-looking consumers; specifically, we allow forward-looking consumers to form expectations of their future consumption needs, learn about their future consumption pattern to reduce their uncertainty through consumption experiences, and make optimal purchase decisions to maximize their long-term utility. Because realized consumption is endogenously driven by the quota and variance in expected consumption needs, the model allows us to investigate how
consumers make advance purchase decisions under consumption uncertainty and how overpurchases are driven by the volatility of future consumption needs.

Applying the proposed model to a unique panel data of consumer purchase and usage history of an online DVD rental service, we offer a rational explanation of the seeming “mistake” of overpurchase made by consumers: they over-purchase to cover future consumption volatility. We show that the amount of overpurchase is driven by consumers’ sensitivity to stockouts, risk attitude, and switching costs. Furthermore, consumers learn through experience to reduce uncertainty, but are heterogeneous in adapting their plan choices to the dynamics of their expected consumption needs. Consumers with low switching costs adjust their plan choices more frequently to match the evolution of their expected consumption needs, whereas those with higher switching costs tend to stick with the same plan. We further study the competitive relationship among alternative plans and find that companies could increase their profits by inducing consumers to switch to higher-level plans and overpurchase more.

We contribute to marketing literature by empirically investigating the consumer choice process with bucket pricing. We are one of the early papers to formulate consumer advance purchase decisions as a forward-looking model with demand uncertainty and consumer learning. Our results offer empirical evidences for a better understanding of the economic functions of bucket pricing and their impact on consumers’ plan choices, which can help managers improve the design of their bucket pricing.

The remainder of this article is organized as follows: In the next section, we give a brief description of the industry and data we study. We then establish the model and discuss the empirical findings. We conclude with summary, managerial implications, and directions for future research.

2. Industry Background and Data Description

Online DVD Rental Industry

Since the founding of Netflix.com in 1998, the online DVD rental industry has grown at a breathtaking pace (E-Business Strategies, 2002). The biggest player, Netflix alone serves more than 3 million consumers, earns more than $600 million annual revenue, and hopes to expand its consumer base to 20 million in the next several years (Netflix 2005). With the entry of Wal-Mart,
Blockbuster, and Amazon.com to the market, online DVD rentals now serve more than 6.3 million users who generated $1 billion revenues in the United States and Europe in 2005. It is a fast booming sector in the $10 billion home-video industry (Jayalath and Wood 2005; Mortimer 2004a, b; Knox and Eliashberg 2005).

The online DVD rental business innovatively integrates DVD rental, Internet technology, and postal services, as depicted in Figure 1. Consumers choose among alternative plans defined by different price/quota combinations and furnish credit card information so the company can automatically debit the monthly payments from their accounts. Once the account is established, consumers can log onto the company’s web site and create queues of movie titles in the order of their viewing preference. The company then sends them the number of movies specified by their chosen plan via first-class mail. Consumers can keep the movies as long as they like without paying any late fees. To return the DVDs, consumers mail the DVDs in a postage-paid envelope provided by the company. When it receives the returned DVDs, the company mails the next movies on the queue, limited to the total number of outstanding movies allowed by the chosen plan. The same process continues until the subscription is terminated. During this process, consumers may switch plans at any time by clicking on the “change” link on the company’s web site. Usually, no refunds or credit are given for partial periods or unused rentals.

The increasing popularity of online DVD rentals stems from the convenience the business model creates. Compared with their patronage of traditional DVD rental stores, consumers enjoy the convenience of continuous service and automatic monthly payments, as well as the mental comfort to keep the DVDs without worrying about late fees. Because the two-way, door-to-door delivery is included in the subscription price, consumers avoid both shipping costs and the hassle of visiting a brick-and-mortar store. In addition, the low inventory cost enables the company to maintain a much larger selection of DVDs from which consumers may select. Furthermore, the consumer-managed movie queues enable the company to predict consumer demand better.

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3 If the number of requests for a movie exceeds inventory, the company determines to whom to send the DVDs on the basis of a priority score calculated according to a consumer segmentation rule. Consumers who have to wait are informed of the wait time, which ranges from “very short” to “very long.” The company sends the next preferred DVDs on the queue that is available.
maneuver DVDs more efficiently, and send consumers their preferred DVDs in a more timely fashion. 

Other than the standard overhead costs and copyright fees paid to obtain a stock of DVDs, the main variable cost faced by online DVD rental companies is postage; for the rental company we study, such cost is $.45 for each one-way shipment.

Data
The online DVD rental company we investigate targets family-oriented viewers by providing content-edited movies in which sexual and violent scenes or offensive language have been removed. This company offers us a consumer panel data containing the purchase, payment, and shipment history of 10,000 registered consumers during a 33-month observation period from August 2002 to May 2005. For the purchase and payment histories, we observe the date when service was initiated, changes in plan choices over time, monthly payments, and date of termination if it occurs. The shipment history contains titles of movies, date movies were dispatched, expected arrival dates, and dates movies were received by the company. In addition, we have product- and consumer-specific information, including the genre of each movie, consumer-constructed movie queues, consumer priority scores, whether the consumer resides within the same state as the company, and the company estimated turnaround time. On the basis of the shipment information, we approximate actual monthly consumption as the total number of movies dispatched, adjusted by the number of movies not returned at the end of month. Our calibration sample consists of 333 randomly selected consumers, and the holdout sample contains an additional 316 randomly selected consumers.

In Table 2A, we provide some sample statistics of the variables we use. As we show in Table 1, the dominant purchase share rests with the Standard plan, whereas the Elite plan has the lowest purchase share. The average plan price is approximately $20.68, and price discounts, averaging $.50, are offered in approximately 2.57% of all cases. The average actual movie consumption per month is 2.71, with a standard deviation of 2.37. During our study period,
consumers stayed with the company for an average of 17.68 months. Finally, 93% of the consumers live in different states and don’t pay sales tax.

In Table 2B, we provide a switching matrix that demonstrates the frequency and direction of plan switches among the six service plans during the observation period. We find that most switches involve a move to adjacent higher- or lower-level plans. For the Standard plan and up, more consumers switched down to lower-level plans. In contrast, for the Economy and Lite plans, more consumers switched up to the Standard or beyond.

To illustrate how consumers’ purchases and actual consumption evolve over time, we plot the average purchased consumption capacity and average number of DVDs actually consumed per month over observed consumer tenure in Figure 2. Purchased consumption capacity is always significantly higher than actual consumption. Both actual consumption and purchased consumption capacity decrease as the consumer’s tenure increases. This decrease in consumption capacity is consistent with our observation from Table 2B that more consumers switch from higher- to lower-level plans than vice versa and reflects that consumers may learn about their consumption needs and adjust their purchase decisions accordingly.

We run various analyses to determine whether actual consumption is driven directly by flat fees and payment dates and find empirically that neither coefficient is significant. This is consistent with Miravete (2002b) that telephone usage is not price sensitive when only a prepaid flat tariff is offered.

3. Model Setup

For an advance purchase, consumers must make purchase decisions to address their future consumption needs. Suppose the company offers \( j = 0, \ldots, J \) products or services with prepaid bucket pricing, which can be represented by \((P_j, QT_j)\). There are \( i = 1, \ldots, I \) consumers who make periodical choice decisions among the \( j = 0, \ldots, J \) competing service plans at the end of periods \( t = 1, \ldots, T \) to secure their consumption during the next period (and beyond). Choice \( j = 0 \) denotes no purchase of any of the service plans, which we include to allow consumers to stop
the service. We define time periods as months since purchase decisions are made monthly. We use a dummy variable $D_{ijt}$ to represent consumer $i$’s plan choice:

$$D_{ijt} = \begin{cases} 1, & \text{if choice } j \text{ is chosen by consumer i at time } t, \\ 0, & \text{otherwise} \end{cases}$$

The bucket pricing of service plan $j$ chosen by consumer $i$ at time $t$ is represented by $(P_{ijt}, QT_{ijt})$, where $P_{ijt}$ denotes the periodic price and $QT_{ijt}$ denotes the maximum consumption allowed.

**Expected Future Consumption Needs and Learning**

To make advance purchase decisions, consumers must predict their intrinsic consumption needs for the next period (and beyond). Let $C^*_t$ represent consumer $i$’s consumption need for service during any time $t$, which we assume has two components. One component can be determined by observable variables, such as past consumption, tenure, and seasonality, and the other is random shock. The log of consumption need, or $\log(C^*_t)$, follows a modified first-order Markov process,

$$\log(C^*_t) = \alpha_0 + \alpha_i \log(C^*_{t-1}) + \alpha_2 TENURE_t + \sum_{s=1}^{8} \alpha_{2+s} T_s + e_t.$$

Variable $\log(C^*_{t-1})$ is the log of non-zero realized past consumption with subscript $t_c$ representing the most recent period when consumption happens. We include this variable to reflect the influence of past (non-zero) consumption on current consumption needs, because consumers have been shown to establish their consumption habits over time on the basis of their prior experiences (Becker and Murphy 1988; Chaloupka et al. 2002). $TENURE_t$ represents the number of months since consumer $i$ first established a relationship with the company and thereby encompasses the possibility that the longer the consumer’s tenure with the company, the fewer unseen movies he or she will have as choices. With fewer favored movies from which to choose, the consumer may decrease his or her consumption need. We also include dummy variables $T_s$. 
for $s = 1, 2, 3$ to capture the effect of seasonality, such that $T_1$ represents January–March, $T_2$ covers April–June, and $T_3$ stands for July–September.

The other component $e_{it}$ is the random shock that represents all unobserved factors that affect consumption needs at time $t$. Random shocks cause consumers to experience greater uncertainty about their future consumption needs. Following Danaher (2002), we assume that the random shock has two parts: consumer-specific and both consumer- and time-specific, or

$$
e_{it} = \eta_i + \zeta_{it} \quad \text{and} \quad \zeta_{it} \sim N(0, \sigma_\zeta^2).$$

Consumer-specific shock $\eta_i$ is a summary statistic of both tangible and intangible consumption preferences of consumer $i$, which we term the true consumption type. Consumers may not have perfect information about their consumption type $\eta_i$ because they may not keep track of their past consumption or are unsure about their preference for this new on-line DVD rental service. In contrast, random shock $\zeta_{it}$ is temporary, and we assume it is i.i.d normally distributed across time and consumers.

At $t = 0$, we assume all consumers have prior information about their true consumption type. We define $\mu_{\eta_0}$ as the prior expectation of their true type and $\sigma_{\eta_0}^2$ as the prior variance. It is normally distributed as

$$\eta_i \sim N(0, \sigma_{\eta_0}^2).$$

Recent research has provide ample evidence on consumer learning when making decisions under demand uncertainty (e.g. Erdem and Keane 1996; Courty 2003). As time goes by, consumers learn about their true types and thus improve the accuracy of their predicted future consumption needs. We capture this possibility by allowing consumers to learn and reduce uncertainty about their true type through their consumption experience. This is consistent with Erdem, Keane and Sun (2005), who found past consumption experience serves as one of the most important information source of consumer learning. We define the information set available to consumer $i$ at time $t$ as $I_{it} = \{C_{i1}^*, C_{i2}^*, ..., C_{i(t-1)}^*\}$. Starting at period $t = 1$, consumer $i$ starts to update his or her true type on the basis of previous consumption experience. Then, we define
consumer $i$’s expectation of his or her true type at time $t$ as $\mu_{\eta_i} = E[\eta_i \mid I_{it}]$ and the variance of expected mean type as $\sigma_{\eta_i}^2 = Var[\eta_i \mid I_{it}] = E[(\eta_i - \mu_{\eta_i})^2 \mid I_{it}]$. We define $DC_{i(t-1)}$ as the dummy variable for consumption experience at time $t - 1$, such that $DC_{i(t-1)} = 1$ if consumption occurs and 0 if it does not during period $t - 1$. At time $t$, the expectation of $\eta_i$ is updated as follows:

$$
(5) \quad \mu_{\eta_i} = \mu_{\eta_i(t-1)} + D_{i(t-1)}(\eta_{i(t-1)} + \xi_{i(t-1)} - \mu_{\eta_i(t-1)}) \frac{\sigma_{\xi}^2}{\sigma_{\eta_i(t-1)}^2 + \sigma_{\xi}^2}.
$$

Intuitively, when a consumer experiences consumption during time $t - 1$, his or her perceived true type is updated with new information $(\eta_{i(t-1)} + \xi_{i(t-1)} - \mu_{\eta_i(t-1)})$, weighted by information precision $\frac{\sigma_{\xi}^2}{\sigma_{\eta_i(t-1)}^2 + \sigma_{\xi}^2}$. Accordingly, the update of the variance of perceived true type is given by

$$
(6) \quad \sigma_{\eta_i}^2 = \frac{1}{\sigma_{\eta_i(t-1)}^2 + \sigma_{\xi}^2}.
$$

Thus, although consumers cannot observe their true consumption needs when they make advance purchase decisions, they can use the available information set $I_{it}$ to create an expectation of those consumption needs. The expected mean of the log consumption needs can be written as follows:

$$
(7) \quad \mu_{\log C_{it}} = E[\log(C_{it}^*) \mid I_{it}] = \alpha_{0i} + \alpha_{1i} \log(C_{it-1}) + \alpha_{2i} \text{TENURE}_{it} + \sum_{s=1}^{S} \alpha_{2+si} T_s + \mu_{\eta_i}.
$$

The variance of the log consumption need is given by

$$
(8) \quad \sigma_{\log C_{it}}^2 = Var[\log(C_{it}^*) \mid I_{it}] = \sigma_{\eta_i}^2 + \sigma_{\xi}^2.
$$
Thus, the expected time $t$ consumption need is

$$E[C_i^* \mid I_{it}] = \exp(E[\log(C_i^*) \mid I_{it}] + \frac{1}{2} Var[\log(C_i^*) \mid I_{it}]).$$

Its variance is given by

$$Var[C_i^* \mid I_{it}] = (E[C_i^* \mid I_{it}])^2 - E[C_i^{*2} \mid I_{it}]$$

where $E[C_i^{*2} \mid I_{it}] = \exp(2E[\log(C_i^*) \mid I_{it}] + 2Var[\log(C_i^*) \mid I_{it}]).$

This learning process reflects that consumers can improve the accuracy of their predictions about their future consumption needs over time. The learning mechanism thus enables us to examine whether reducing the perceived volatility of future consumption needs drive consumers’ plan choices.

**Stockout Probabilities and Expected Realized Consumption**

When making plan choices, consumers also choose the associated quota. When their consumption needs exceed that quota, consumers encounter stockout situations, which means their realized consumptions are defined by the purchased consumption capacity rather than their consumption needs. Otherwise, they can consume up to their consumption needs. Thus, consumers evaluate the chance of stockout situations associated with each plan choice $j$. We define the consumption that could be realized when plan $j$ is chosen as $C_{ijt}$, which is given by

$$C_{ijt} = \begin{cases} C_i^* & \text{if } C_i^* \leq QT_{ijt}, \\ QT_{ijt} & \text{otherwise.} \end{cases}$$

Note that we include a plan subscript for realized consumption $C_{ijt}$ because realized consumption is affected by the quota of choice $j$ chosen by consumer $i$ at time $t$.

Thus, we obtain the probability of a stockout situation at time $t$ when consumer $i$ chooses plan $j$. Using $\rho_{ijt}$ to denote the stockout probability of plan $j$, we obtain
\begin{equation}
\rho_{ijt} = 1 - \Pr(ob(C_{ijt}^* \leq QT_{ijt}) = 1 - \Phi\left(\frac{\log QT_{ijt} - \mu_{\log C_{ijt}^*}}{\sigma_{\log C_{ijt}^*}}\right).
\end{equation}

From Equation (12), we know that the stockout probability is also a function of the quota, such that the higher the quota, the lower is the probability that consumer \( i \) will face a stockout situation. Similarly, the lower the mean of consumption needs and/or the lower the variability of consumption needs, the lower is the probability of a stockout.

Given the definition of realized consumption when plan \( j \) is chosen, as in Equation (11), we obtain an expectation of realized consumption and its squared term as follows:

\begin{equation}
E[C_{ijt} | I_{it}] = \left\{ QT_{ijt}[1 - \Phi\left(\frac{\log QT_{ijt} - \mu_{\log C_{ijt}^*}}{\sigma_{\log C_{ijt}^*}}\right)] + \exp(\mu_{\log C_{ijt}} + \frac{\sigma_{\log C_{ijt}}^2}{2})\Phi\left(\frac{\log QT_{ijt} - \mu_{\log C_{ijt}^*} - \sigma_{\log C_{ijt}^*}^2}{\sigma_{\log C_{ijt}^*}}\right)\right\},
\end{equation}

and

\begin{equation}
E[C_{ijt}^2 | I_{it}] = \left\{ QT_{ijt}^2[1 - \Phi\left(\frac{\log QT_{ijt} - \mu_{\log C_{ijt}^*}}{\sigma_{\log C_{ijt}^*}}\right)] + \exp(2\mu_{\log C_{ijt}} + \sigma_{\log C_{ijt}^*}^2)\Phi\left(\frac{\log QT_{ijt} - \mu_{\log C_{ijt}^*} - \sigma_{\log C_{ijt}^*}^2}{\sigma_{\log C_{ijt}^*}}\right)\right\}.
\end{equation}

The variance of realized consumption \( \sigma_{C_{ijt}}^2 \) is given by

\begin{equation}
Var[C_{ijt} | I_{it}] = E[C_{ijt}^2 | I_{it}] - (E[C_{ijt} | I_{it}])^2.
\end{equation}

**Expected Utility Function**

We assume that consumers make plan choices on basis of their consumption utility, that is determined by the benefit from realized consumption \( C_{ijt} \) and costs that include price paid for the chosen plan \( P_{ijt} \), stockout possibilities, and switching cost. Without uncertainty, we specify the utility function associated with plan \( j \) for consumer \( i \) at time \( t \) as
for $j = 0, \ldots, J$. The variable $C_{ijt}$ represents the realized consumption for consumer $i$ during period $t$ when plan $j$ is chosen. We include the squared term of $C_{ijt}$ to take into account risk aversion with respect to consumption. It allows for the possibility that consumption utility may not increase linearly with consumption. Furthermore, $P_{ijt}$ represents the periodic price paid by consumer $i$ for plan $j$ at time $t$. Although the listed price of each plan $P_j$ at a given time is identical across consumers, the actual paid prices $P_{ijt}$ vary across consumers because the company occasionally offers small price discounts. In addition, a 6.6% sales tax is charged to those consumers who reside in the same state as the company. Thus, we calculate the actual price paid by consumer $i$ for the $j$th plan at time $t$ as

$$P_{ijt} = P_j - \lambda_i DSCT_{ijt} + D_{TAX_i} \times 0.066 \times P_j,$$

where $P_j$ is the listed monthly price for plan $j$, $DSCT_{ijt}$ is the price discount received by consumer $i$ in period $t$ for plan $j$, and $D_{TAX_i}$ is a dummy variable that equals 1 if the consumer pays sales tax and 0 otherwise. We also include a coefficient $\lambda_i$ to allow the possibility that the effect of discount may differ from that of price. $D_{SC_{ij}}$ is a dummy variable that indicates whether a stockout occurs if plan $j$ is chosen, which equals 1 when desired consumption exceeds purchased consumption and 0 otherwise. $D_{SW_{ij}}$ is a dummy variable that indicates whether choosing plan $j$ at time $t$ implies a switch; it is 0 if consumer $i$ chooses to stay with his or her current plan and 1 if he or she chooses a different plan. We include this dummy variable to take into account the significant time and mental efforts required to switch to another plan. Finally, $\varepsilon_{ijt}$ represents the random errors related to consumption, observable to consumers but not researchers.

With the uncertainty introduced by advance purchase, consumers make purchase decisions on the basis of their expected utility, given by

$$U_{ijt} = \beta_{0i} + \beta_{1i} C_{ijt} + \beta_{2i} C_{ijt}^2 + \beta_{3i} P_{ijt} + \beta_{4i} D_{SC_{ij}} + \beta_{5i} D_{SW_{ij}} + \varepsilon_{ijt},$$
\[
E[U_{ijt} | I_n] = \beta_0 + \beta_1 E[C_{ijt} | I_n] + \beta_2 E[C_{ijt}^2 | I_n] + \beta_3 P_{ijt} + \beta_4 E[D_{Sij} | I_n] + \beta_5 D_{Sij} + \varepsilon_{ijt}.
\]

(18)

Since \( E[C_{ijt} | I_n] \), \( E[C_{ijt}^2 | I_n] \), and \( \rho_{ijt} \) (as defined in Equations (13), (14), and (12)) are functions of quota and the mean as well as variance of consumption needs, consumer purchase decisions are also driven by the mean and variance of expected consumption needs, the quota and price of the plan, the probabilities of a stockout situation, and the costs of switching plans. Parameter \( \beta_{0i} \) captures consumer’s intrinsic preference for on-line DVD rental service due to factors such as convenience and flexibility. \( \beta_{1i} \) measures the unit benefit of movie consumption, \( \beta_{2i} \) represents the degree of risk aversion, or whether marginal consumption benefit decreases with excessive movie viewing. \( \beta_{3i} \) measures consumer sensitivity to price, \( \beta_{4i} \) measures consumer sensitivity to stockouts, and \( \beta_{5i} \) is the switching cost.

We also note several points regarding the expected utility function. First, because the realized consumption and stockout probabilities are determined by quota, expected utility is also a function of quota. Thus, the consumer purchase decision is determined directly by both components of bucket pricing (i.e., price and quota). Second, in addition to quota, the utility function is also driven by the mean and variance of expected future consumption needs. The volatility of these needs influence consumer purchase decisions. Third, if the results show the consumers we study are risk averse with respect to consumption, the volatility of realized consumption will decrease their expected utility because, compared with risk-neutral consumers who always value the consumption of additional movie consumption the same as the previous movie, risk-averse consumers attach smaller utilities to additional movie consumption and are less sensitive to their realized consumption being limited by the quota. In line with this argument, given other things equal, risk-averse consumers may be more likely to choose lower-level plans.

**Forward-Looking Consumers**

A purchase decision at time \( t \) implies a possible commitment to a service plan, so consumers must look beyond the current period to ensure their long-term consumption needs are...
met. Therefore, we model consumers as forward-looking decision makers who make advance plan choices to maximize their total discounted future expected utilities:

\[
\text{Max}_{D_{ijt}} \left\{ E \left[ \sum_{\tau=t}^{T} \delta^{\tau-t} U_{ijt} \mid I_{ijt} \right] \right\},
\]

where \( U_{ijt} \) is the single-period utility function, and \( \delta \) is a discounting factor that measures the trade-off between current and future expected utilities. We follow convention and set the utility discount rate at .995 (Erdem and Keane 1996; Gonul and Srinivasan 1996; Sun 2005).

Given this one-period expected utility function, we obtain the following Bellman equation for the optimal plan choice:

\[
V_{ijt}(I_{ijt}) = \max_{\delta E} \left\{ E[U_{ijt} \mid I_{ijt}] + \delta E[\text{max}_{i(t+1)}(I_{i(t+1)} \mid I_{ijt})] \right\}.
\]

In the Bellman equation, the concurrent expected utility function is given by Equation (18) and the optimal plan choice is given by

\[
D_{ijt} = \arg \max \left\{ \sum_{j=0}^{J} D_{ijt} V_{ijt}(I_{ijt}) \right\}.
\]

According to this setup of the model, the decision variable is the plan choice. The endogenous state variables are the two components of bucket pricing (\( P_{ijt} \) and \( QT_{ijt} \)), and the mean and variability of future consumption needs (\( E[C^*_{ijt} \mid I_{ijt}] \) and \( \text{Var}[C^*_{ijt} \mid I_{ijt}] \)).

The dynamic programming problem of advance purchases under demand uncertainty is as follows: At the end of time \( t-1 \), consumers form expectations about their future consumption needs during \( t \) and beyond. They calculate the probability of a stockout situation on the basis of the mean and variance of future consumption needs, as well as the quota associated with each plan. Consumers then choose the service plan that maximizes the sum of their discounted future utilities by optimally balancing a lower periodic payment and the higher cost of stockouts in the future, which results in a sequence of optimal plan choices. The choices are intertemporally
related because, when they realize the switching cost, forward-looking consumers may sacrifice their current utility by choosing a plan that will secure their consumption in the future. In addition, consumers’ plan choices in the current period affect their future realized consumption which in turn affect future plan choices.

**Heterogeneity and Estimation**

Ignoring unobserved consumer heterogeneity leads to biased parameter estimates (Gonul and Srinivasan 1993). Therefore, we employ a latent class approach developed by Kamakura and Russell (1989) to control for unobserved consumer heterogeneity. Suppose there are \( m = 1, \ldots, M \) segments of consumers, and each consumer has a probability of \( 0 \leq \pi(m) \leq 1 \) of belonging to segment \( m \). We use a vector \( \Theta \) to represent all parameters to be estimated; that is, \( \Theta = (\beta_{0j}(m), \beta_1(m), \beta_2(m), \beta_3(m), \beta_4(m), \beta_5(m), \lambda(m), \pi(m)) \) for all \( m \) and \( j \).

We define \( V_{ijt}^* = V_{ijt} - \epsilon_{ijt} \) as the deterministic part of the utility function in Equation (18), which is observable. Assuming the error term \( \epsilon_{ijt} \) is independently and identically extreme value distributed, we obtain the probability of consumer \( i \) choosing plan \( j \) at time \( t \), conditional on \( \Theta \):

\[
\Pr(\text{ob}(D_{ijt} = 1 \mid \Theta)) = \sum_{m=1}^{M} \pi(m) \frac{e^{V_{ijt}^*(m)}}{\sum_{j=0}^{J} e^{V_{ijt}^*(m)}}.
\]

The log-likelihood function is given by

\[
\log L = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j=0}^{J} D_{ijt} \log \Pr(\text{ob}(D_{ijt} = 1 \mid \Theta)).
\]

To estimate the model, we use simulated maximum likelihood, which employs Monte Carlo methods to simulate the integrals rather than evaluating them numerically (Keane 1993; McFadden 1989). Because state variables are continuous, we encounter the problem of a large state space. We adopt the interpolation method developed by Keane and Wolpin (1994) and calculate the value functions for a few state space points, which we then use to estimate the
coefficients of an interpolation regression. The interpolation regression function provides values for the expected maxima at any other state points for which values are needed in the backward recursion solution process.

In our proposed dynamic model, we assume that consumers form expectations about their future consumption needs as described in Equations (2–11). We need to know the values of the coefficients in these equations to parameterize consumers’ formation of expectations about their future consumption needs before we can estimate the proposed dynamic model. Because $\xi_{\nu}$ is normally distributed, we estimate a right-censored (nonnegative probability mass at $QT_{ij\nu}$) regression model, in which realized consumption is the observable dependent variable. When we estimate the proposed model, we assume that consumers forecast their consumption needs according to the same process.

4. Empirical Results
Model Comparison

To see whether our proposed model, which incorporates uncertainty, learning, and forward-looking consumers, better explains consumer advance purchase behavior, we estimate three benchmark models. The first (Model 1) is our proposed model without uncertainty, learning, or forward-looking consumers and thus is very similar to most existing models used to study consumer plan choices in the telecommunication industry (e.g., Danaher 2002). The second benchmark model (Model 2) is our proposed model with uncertainty but without learning or forward-looking consumers. By introducing uncertainty, this model recognizes consumer decision making with imperfect knowledge for advance purchases. The third benchmark model (Model 3) includes both uncertainty and learning but not forward-looking consumers, such that consumers may learn to reduce the uncertainty of their future consumption needs but only plan for consumption in the current period. The fourth model (Model 4) is our proposed model with uncertainty, learning, and forward-looking consumers.

Because we use the latent class approach to take into account consumer heterogeneity for the four models, we must determine how many segments best fit the data for each of the model. To address this empirical question, we estimate the four competing models with various segments ($m = 1, 2, 3, \text{ and } 4$). The results suggest that Model 1 with 3 segment, Model 2 with 3
segments, Model 3 with 2 segments, and Model 4 with 2 segments are the best fitting models. For example, the log-likelihood, Akaike information criterion (AIC), and Bayesian information criterion (BIC) of our proposed model are, respectively, -2265.5, 4544.9, and 4555.3 for one segment, -2216.8, 4465.5, and 4489.7 for two segments, and -2210.4, 4468.7 and 4504.6 for three segments.

[Insert Table 3 About Here]

In Table 3, we report the log-likelihood, AIC, and BIC of all the four competing models with the chosen numbers of segments. The comparison of model fit statistics for both the calibration sample and the holdout sample shows that our proposed model significantly outperforms all three benchmark models; thus, it is important to allow for uncertainty, learning, and forward-looking consumers when modeling consumer advance purchase decisions with prepaid bucket pricing. This finding comes at no surprise, given our proposed model is more consistent with consumer decision processes in advance purchase. The comparison further suggests that adding the uncertainty surrounding future consumption needs contributes the most to improving data fit, following by forward-looking consumers. Allowing consumers to learn to reduce their uncertainty also improves model performance. Because Model 4 is the best-fitting model, our subsequent discussion focuses on this model.

**Parameter Estimates**

[Insert Table 4A and 4B About Here]

We first report the parameter estimates and t-statistics for the expected consumption needs process in Table 4A. The coefficient of realized consumption in the prior period is positive and significant, which indicates that realized prior period consumption increases current period consumption needs. This result confirms findings in the literature that consumers establish consumption habits over time on the basis of their prior experiences. In addition, tenure has a negative effect on consumption needs, which implies that cumulative consumption may exhaust the consumer choice set and reduce the need to consume movies. The coefficients of $T_1$ and $T_3$
are positive and that of $T_2$ is negative, which suggests consumption needs are higher during the winter and summer and lower during the spring. We estimate the initial variability of consumption to be 1.68, which implies consumers have high uncertainty about their true consumption type at the beginning of the observation period. Furthermore, their experience variability is approximately 2.48, so experience provides noisy information about true consumption type.

In Table 4B, we report the parameter estimates of our proposed model (Model 4). Latent class estimates indicate that there are two consumers segments. 83.3% of consumers belong to the first segment and 16.7% belong to the second segment. As we expected, the unit consumption benefit coefficients are positive and significant for both segments, and the risk aversion coefficients are negative. That is, consumers’ consumption utility decreases with the variance of realized consumption. The price coefficients are negative and significant, but the coefficients of the price discount are not significant. This shows that consumers are not affected by price promotions to switch plans. Stockout costs are significantly negative for both segments, which means consumers are sensitive to the negative utility caused by stockout situations when their consumption needs are capped by a quota. Consumers also demonstrate significant switching costs. As we discussed previously, other than the time and effort required to switch plans, the mandatory automated payment using credit cards might have introduced additional switching costs. Realizing this cost, consumers may plan beyond the current period and make a purchase decision that will cover the unexpected variability of their long-term consumption needs.

In comparing the coefficients between the two segments, we find that consumers in the first segment have higher intrinsic preference for on-line DVD rental service (4.39 vs. 1.24) and higher switching costs (-1.63 vs. -1.18), are less price sensitive (-0.098 versus -0.109) and more risk averse (-0.05 versus -0.035), and have higher stockout costs (-5.60 vs. -1.45).

**Overpurchase**

Since we observe consumers purchase more than they actually consume in advance purchase situations, we are interested in finding out what affects overpurchases and how overpurchases differ between the two consumer segments. We define overpurchase at time $t$ as the extra
consumption capacity purchased by consumers above the mean of their expected consumption needs. Because all alternative plans are offered by the same company, we calculate consumer $i$’s total demand for consumption capacity from the company as the sum of the quota of each plan weighted by the corresponding purchase probabilities, or $\sum_{j=1}^{J} QT_{ijt} \Pr(ob(D_{ijt} = 1|\Theta)).$ The expected mean consumption needs at time $t$ are given by $E[C_{it}^*|I_{it}]$, as defined in Equation (9).

In Figure 3A, we illustrate the percentage of consumer overpurchases $(\sum_{j=1}^{J} QT_{ijt} \Pr(ob(D_{ijt} = 1|\Theta)) - E[C_{ijt}^*|I_{it}]) / E[C_{ijt}^*|I_{it})$ compared with their corresponding perceived variance of future consumption needs ($Var[C_{it}^*|I_{it}]$), as defined in Equation (10). It is shown that the higher the volatility of future consumption needs, the higher is the demand for consumption capacity. This implies that consumers are willing to increase their demand for capacity as the volatility of future consumption needs increase. This is because the consumers need to purchase more to reduce stockout situations caused by random shocks in their consumption needs. Thus, consumers overpurchase when demand uncertainty is introduced by bucket pricing to avoid future stockout risks.

Whereas consumption uncertainty causes consumers to overpurchase, the amount by which they overpurchase is also affected by other factors such as their sensitivity to stockout costs, switching costs, and risk attitude. In Figure 3B–3D, we provide the percentages of overpurchase with varied multipliers of stockout cost sensitivity (0–2), switching cost (0–3), and risk aversion (0–4). The higher a consumer’s sensitivity to stockout costs, the higher is his or her overpurchase. Similarly, the higher the switching cost, the higher is the overpurchase; foreseeing the high cost of switching in the future, consumers tend to consider beyond the current plan period and over-purchase more to avoid long-term consumption shocks. However, overpurchase decreases as consumers’ risk attitudes increase. As we discussed previously, risk-averse consumers tend to attach smaller utilities to additional movie consumption and have less negative utility associated with stockouts; thus, they may overpurchase less.
We next examine the relative strength of the factors affecting overpurchase. Because the effects of consumption volatility, stockout costs, switching costs, and risk aversion are neither additive nor separable, we study their relative strength by comparing the simulated percentages of overpurchase when setting each factor to 0 and keeping the others the same. In Table 5, we report these percentages and compare them with that suggested by the current model. In the current model, on average consumers are shown to overpurchase by 136.85%. Their purchased consumption capacity more than doubles what they need. When consumption uncertainty disappears, consumers decrease their overpurchases from 136.85% to 87.06%. When consumers are assumed to have zero sensitivity to stock-out situations or zero switching cost, they decrease their overpurchases to 110.63% and 131.11%, respectively. However, when assumed to be risk neutral with respect to consumption, consumers increase their overpurchases to 155.89%. Thus, with current bucket pricing designs, consumption uncertainty represents the fundamental driver of overpurchase, followed by sensitivity to stockouts and risk attitude towards consumption and then switching costs. Note that even when all the four factors are set to 0, we may still observe a positive level of overpurchase, due to factors such as convenience and the discrepancy between consumption needs and available quotas. For example, if the ideal monthly consumption for a consumer is 20 movies, but the available Advantage plan offers 16 and the Elite plan allows 22.5 DVDs. If she chooses the Elite, she overpurchases because of the difference between her needs and the available quota choice.

In general, overpurchases stem from the uncertainty due to the separation between purchase and consumption. Overpurchases also increase with greater sensitivity to stockout and switching costs but decreases with risk attitude. In our framework, apparent mistakes by consumers (i.e., they could have saved money by choosing a different plan) appear actually to be rational behavior. When consumers make advance purchase decisions, they are uncertain about their future consumption needs and overpurchase to cover their future consumption volatility. This finding confirms the analytical and preliminary empirical results offered by Miravete (2002a, b), namely, that with the available knowledge they have about future consumption needs, consumers make *ex ante* optimal purchase decisions to avoid stockouts even though that decision appears to be a mistake *ex post*. This rational explanation is different from existing behavioral...
and theoretical explanations that attribute overpurchasing to irrational behaviors, such as an explicit preference for a flat fee or the insurance, and taxi meter (Lambrecht and Skiera 2004; Mitchell and Vogelsang 1991).

Overpurchase implies that consumers are willing to pay a price premium with on-line DVD rental service. This risk premium contributes to the company’s profit. Thus, we provide additional support for advance selling: They can be leveraged as effective tools to extract greater profit, in addition to their flatter demand curve and reduced demand uncertainty, as proposed by Shugan and Xie (2000).

Learning and Choice Dynamics

To demonstrate how learning affects overpurchasing, we depict the evolution of average variance of expected consumption type ($\sigma^2_{\eta}$) in Figure 4A and corresponding average overpurchases in Figure 4B for both segments. The variances of expected consumption type decrease over time for both segments, in support of consumer learning to reduce uncertainty through consumption experience. Consumers in the first segment overpurchase more than those in the second segment because with a higher sensitivity to stockout situations and higher switching costs, they are more willing to sacrifice current utility by overpurchasing more to decrease the potential for stockout situations in the future. In addition, higher switching costs prevent consumers in the first segment from adapting their plan choices to their updated knowledge about their consumption needs. Given that the mean of their consumption needs decreases more than the adjustment of purchase for consumers in the first segment, we observe an increase in the percentages of overpurchase over time. In contrast, with a lower sensitivity to stockout situations and lower switching cost, consumers in the second segment are more tolerant of the risk of stockouts. They constantly adjust their plan choices to make their purchased consumption capacity consistent with their evolving expected consumption needs. As a result, they decrease their overpurchase over time.

The above discussion is consistent with our observation from Figure 2 that on average, consumers learn to improve the accuracy of their predictions and adjust their purchases
accordingly. On the basis of these observations, we would like to refer to consumers in the first
segment as “convenience consumers” and those in the second segment as “value seekers.”

**Competition among Alternative Plans**

[Insert Table 6 About Here]

The six plans offered by the company with bucket pricing compete with each other,
because the combinations of price and quota affect the attractiveness of each plan relative to the
others. To better understand the cannibalizing relationship among the plans, we report in Table 6
the simulated percentage changes of purchase probabilities ($Prob(D_{yt} = 1|\Theta)$) of the six plans
when we increase the price of each plan by 5% but maintain the same quotas. The diagonal
elements in the switching matrix offer a means to calculate self-price elasticities, and the off-
diagonal elements can provide cross-price elasticities.

We find several interesting results. First, according to the diagonal elements, consumers
are more sensitive to price changes in the higher-level plans and less sensitive for lower-level
ones. This is not surprising because the services offered by various plans only differ in quantity.
Consumers are expected to be more sensitive to the price change of higher-level plans. Second,
when the price of the Lite and Standard plans increases, the impact is higher on the purchase
shares of their lower adjacent plans than on those of the higher adjacent plans. However, when
the price of the Premium and Advantage plans increases, it has higher impact on the purchase
shares of their higher adjacent plans. Third, when the price of Standard and higher-level plans
increases, consumers are most likely to opt out, but surprisingly, when the price of the Economy
and Lite plans increases, consumers are least likely to do so. The reason for this pattern may be
that consumers choosing higher plans are likely to be those with either higher consumption needs
or higher switching cost (because they overpurchase more). Realizing a higher price to pay in the
future, these consumers may not want to switch to a lighter plan and experience higher stockout
opportunities in the future. They choose to leave the company and look for other offers that can
satisfy their consumption needs. On the contrary, consumers who choose Economy or Lite plans
are either those with lower consumption needs or those with lower switching cost. They are also
much less sensitive to price changes in the lower-level plans.
Optimal Product Design under Bucket Pricing

Preceding discussion focused on consumer demand. However, an important feature that differentiates bucket pricing from other pricing formats is that demand can differ from actual consumption. Although demand drives the total revenue, actual consumption drives total cost. Given the novelty of this pricing approach, we next study whether current bucket pricing designs can be improved to increase profit.

To identify optimal bucket pricing, we need to solve for monthly price and quota by solving the optimization problem that maximizes total long-term profit. The net present value of total profit is given by

\[
\text{max}_{P_j, Q_{T_j}} \text{PROFIT} = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j=0}^{J} \delta^t (\Pr ob(D_{ji} = 1|\Theta)P_j - C_j mc),
\]

where \( mc \) is the marginal cost of providing the online rental service for each DVD, approximated by the two-way postage fee. \[^4\] \( \delta \) is the same discount rate as in the consumer model. This optimization problem takes into account consumers’ reactions to the pricing policy through \( \Pr ob(D_{ji} = 1|\Theta) \). We first solve for the best pricing \( P^*_j \) for the current set of quotas. Then we vary the quotas near the current quota specifications and solve for the corresponding best prices. This is because it is more practical for a company to consider alternative quota specifications that are modified only marginally from the current design. Thus, we offer local optimization instead of global optimization.

[Insert Table 7 About Here]

In Table 7, we report several alternative bucket pricing designs \( (P_j, QT_j) \) for all \( j \) and compare them with the existing design. We also calculate the resulting average purchase shares,

\[^4\] For the purpose of demonstrating whether the current design of bucket pricing can be improved, we only consider the two-way shipment cost. This is the only cost information we have from the company. It will be interesting to study how price agreement with the movie providers and capacity constraint affect optimal pricing. That is beyond the scope of this paper. We leave it for future research.
consumption, total revenue, variable cost, and profit. The first alternative design shows the profit-maximizing prices for the current quota specifications. It is shown that to improve profit, the company should decrease the prices of the Advantage and Elite plans and increase those of the Economy, Lite, and Standard plans. With these adjustments, the six plans are less spread out in terms of price. The purchase shares of the higher-level plans (Premium, Advantage, and Elite) increase, whereas those of the lower-level plans (Economy, Lite, and Standard) are only marginally affected. Consumers switch out of the lower-level plans that become more expensive and to higher-level plans that have become more affordable. Most switches are initiated by consumers in the Standard plan. Given the relatively stability of consumers’ actual consumption needs, the shift to higher-level plans implies greater overpurchase rates among these switching consumers.

Comparing across several possible alternative designs in which we report the best prices for various quota specifications, we find that our second alternative design results in the highest overall profit. The quotas of the three lighter plans stay the same, but those of the Advantage and Elite plans decrease by 1 and 2 outstanding DVDs, respectively. This implies the monthly quotas decrease from 16 and 22.5 to 12.4 and 16 for these two plans. Compared to the first alternative design, the prices of the Advantage and Elite plans are further decreased (with their lower quota). In terms of both quota and prices, the six plans are even less spread out under this optimal design. In comparing consumer purchase probabilities from the first alternative design with the optimal design, we find that more consumers are induced to switch up to higher-level plans, such that the purchase share of the Economy plan drops by a quarter and that of the Standard plan drops by 5%. Meanwhile, the purchase shares of the Premium and Advantage plans are almost doubled. The purchase share of Elite plan increase from 0.1% to 0.49%.

Because of the migration of consumers from lower- to higher-level plans, total revenue increases, but total costs increase only marginally. As a result, the total profit increases by 6.17% from the current design to the first alternative design and by 9.17% from the current design to the optimal design. We suggest several explanations for why the optimal design improves total profit. First, the decrease in the quotas of the higher-level plans make the consumption limit of these plans more aligned with expected consumption needs. The decrease in prices further makes these plans more attractive. This induces consumers to purchase higher-level plans. The company can obtain more revenue from the increased overpurchases. Second, because consumers are least
likely to opt out when the prices of the Economy and Lite plans increase, increasing these prices has the smallest impact on total demand. Similarly, decreasing the prices of the higher-level plans encourages more consumers to purchase the company’s product. Thus, profit improves through attracting more heavy users. Third, even though consumer switching increases average actual consumption, this increase is only marginal compared with the monthly payment increases contributed by increased overpurchases. Overall, by making the lower-level plans more expensive and the higher-level plans more affordable and decreasing the quotas of the Premium and Elite plans, this optimal pricing design encourages more consumers to self-select into the Premium and Elite plans, in which they overpurchase more and contribute more to total profits. Profit improves because the volume effect (increase of total overpurchase) dominates the price effect (decrease of prices) and the consumption effect (slight increase of actual consumption).

In summary, our investigation of consumer advance purchase decision making under prepaid bucket pricing indicates that

- For advance purchases, consumers’ purchase decisions are driven by uncertainty about their future consumption needs, such that they overpurchase to address volatility.
- Overpurchasing increases with greater sensitivity to stockout situations and switching costs and decreases with risk aversion.
- Consumers are heterogeneous with respect to overpurchase, such that those who are looking for convenience overpurchase more than those who are looking for value.
- Consumers learn to reduce uncertainty over time, and those with lower switching costs are more likely to adjust their overpurchases to adapt to their evolving consumption needs.
- Consumers’ advance purchase decision processes are better approximated by a forward-looking model under demand uncertainty.

5. Conclusions, Managerial Implications, and Further Research

The bucket pricing adopted by industries such as the booming online DVD rental asks consumers to make advance purchase decisions when they are uncertain about their future consumption needs. Although some previous studies examine how consumers make choices
between flat-rate and two-part pricing (e.g., Danaher 2002; Miravete 2002a, b), no existing research evaluates how they choose among a menu of optional plans priced as alternative combinations of flat fees and quotas. Because of its recent increasing popularity, research is needed to understand how consumers respond to this innovative pricing structure and how companies can improve the design of bucket pricing to increase profits.

In this paper, we propose a dynamic structural model with consumption uncertainty and consumer learning to study how consumers make advance purchase decisions. More specifically, we allow forward-looking consumers to form their expectations of future consumption needs, learn to reduce uncertainty about such needs, and make optimal purchase decisions to maximize their long-term utility. Because the realized consumption rates are endogenously driven by the quota and volatility of future consumption needs, this model enables us to explicitly study how consumers’ advance purchases are driven by the uncertainty of future consumption needs.

In applying the proposed model to an online DVD rental history data, we find that the uncertainty of future consumption needs plays an important role in determining consumer purchase decisions. Consumers overpurchase to cover the unexpected volatility of their future consumption needs and do so to a greater extent when they have greater sensitivity to stockout situations and higher switching costs. On the other hand, consumers learn to reduce uncertainty over time, but only those with lower switching costs are likely to adjust their overpurchases to adapt to their evolving consumption needs. We also find that the current design of bucket pricing could be improved by making higher-level plans more attractive to induce consumers to overpurchase more.

The empirical results help managers better understand how consumers make choices among the competing alternative plans, as well as how to improve the design of their bucket pricing for the purpose of increasing overall profitability. For example, marketing managers should understand that by adopting pricing structures that mandate advance purchase, uncertainty can be introduced to consumer decision process and profit may be increased due to the resulting overpurchase. Since the amount of overpurchase is driven by the level of uncertainty, stockout costs, risk aversion, and switching cost, creative product and pricing can be designed on these aspects to induce higher overpurchase. In addition, profit may be improved when the popularity of plans are more aligned with their profitability. Furthermore, given some consumers adapt their purchases according to the reduced uncertainty, product and pricing decisions can be made to
recognize the dynamics of individual consumer demand. Finally, the managers should understand the substantial heterogeneity among consumers, which forms the basis for segmented and targeted marketing.

We contribute to the marketing literature by providing empirical analysis on consumer purchase decision process with innovative bucket pricing, a timely issue that may be of interests to marketing managers considering adopting this increasingly popular pricing structure and/or advance selling. Our research is in line with the emerging analytical research that shows sellers can leverage such uncertainty by advance selling (Shugan and Xie 2001) or strategically inducing an excess demand (Degraba 1995). Methodologically, our study is the first that structurally models consumer advance purchase decisions using a forward-looking model under demand uncertainty. We empirically establish that it is important to incorporate uncertainty, learning, and forward-looking consumers when modeling consumer advance plan choices under prepaid bucket pricing. Although our discussion focuses on online DVD rentals, our model can be extended to study consumer advance purchase behavior in other industries and/or introduced by other marketing mechanisms.

Our research is subject to several limitations that provide avenues for further research. First, due to the company’s data collection process, we don’t have demographic variables. Additional research can include such information in order to better explain heterogeneous purchase and consumption patterns. Second, the company under study specializes on offering family-oriented movies to a niche market, for which ignoring competition among companies may not affect the major results. Further research can examine the advance purchase behavior when competition plays a more significant role and explore how bucket pricing affects consumer attrition. Third, some existing behavioral explanations of overpurchases, such as persistent misperceptions of actual consumption, could be incorporated in the proposed rational model. Fourth, because price and quota jointly define a service plan, research can be developed to further evaluate the differential effects of these two components on consumer choices. Fifth, for demonstration purpose, we only consider variable cost when deriving optimal pricing. It will be interesting to take into account fixed cost, price agreement with movie providers, and capacity constraint in order to explicitly study optimal pricing designs.
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Table 1. Prices and Quotas of Alternative Plans and Profit Contribution

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<th>Average Actual Consumption&lt;sup&gt;3&lt;/sup&gt;</th>
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<td>8.02</td>
<td>$51,402</td>
<td>$14,226</td>
<td>$37,176</td>
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1. The total monthly consumption limit of the Economy plan is limited to two.
2. Consumption capacity is approximated by the quota of plan $j \times \frac{\text{number of working days each month}}{1 + \text{average number of days for two-way delivery estimated by the company}}$. This calculation assumes that it takes at least one day for consumers to watch a movie. The calculated consumption capacity is consistent with the maximum actual consumption we observe in the data.
3. Average actual consumption is the total number of DVDs shipped to the consumer each month, adjusted by the DVDs not shipped back at the end of that month.
4. Variable cost is approximated as the sum of postage cost, or $.45 for one-way delivery and an estimated $1.1 for overhead costs.
Table 2A Sample Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Explanation</th>
<th>Mean</th>
<th>Standard Deviation</th>
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<tr>
<td>Purchase share $D_{ijt}$</td>
<td>Purchase probabilities of each service plan</td>
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<td></td>
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<td>NA</td>
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<td>.056</td>
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<tr>
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<td>Advantage</td>
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<td>Elite</td>
<td>.0075</td>
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<tr>
<td>$P_{ijt}$</td>
<td>Monthly payment including tax</td>
<td>20.68</td>
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<tr>
<td>DSCT$_{ijt}$</td>
<td>Amount of discount off monthly payment</td>
<td>.50</td>
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<td>2.71</td>
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<tr>
<td>Tenure</td>
<td>Number of months with the company</td>
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<td>6.25</td>
</tr>
<tr>
<td>T1</td>
<td>January–March</td>
<td>.25</td>
<td>.43</td>
</tr>
<tr>
<td>T2</td>
<td>April–June.</td>
<td>.20</td>
<td>.40</td>
</tr>
<tr>
<td>T3</td>
<td>July–September.</td>
<td>.23</td>
<td>.42</td>
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<tr>
<td>$D_{iTAX}$</td>
<td>Dummy variable equal to 1 if the consumer resides outside the state and 0 otherwise.</td>
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Table 2B Patterns of Plan Switching

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<th>Standard</th>
<th>Premium</th>
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<th>Elite</th>
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<td>11.43%</td>
<td>77.14%</td>
<td>8.57%</td>
<td>2.86%</td>
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<tr>
<td>Lite</td>
<td>23.62%</td>
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<td>66.14%</td>
<td>7.87%</td>
<td>2.36%</td>
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<tr>
<td>Standard</td>
<td>16.87%</td>
<td>32.70%</td>
<td>--</td>
<td>30.15%</td>
<td>17.05%</td>
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<tr>
<td>Premium</td>
<td>0.91%</td>
<td>7.55%</td>
<td>65.56%</td>
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<td>24.17%</td>
<td>1.81%</td>
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<td>0.00%</td>
<td>2.86%</td>
<td>50.71%</td>
<td>34.64%</td>
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<td>11.79%</td>
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<td>Elite</td>
<td>2.30%</td>
<td>2.30%</td>
<td>37.93%</td>
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Table 3 Model Comparisons

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<tr>
<th></th>
<th>Model 1 Myopic Model without Uncertainty or Learning</th>
<th>Model 2 Myopic Model with Uncertainty but without Learning</th>
<th>Model 3 Myopic Model with Uncertainty and Learning</th>
<th>Model 4 Proposed Model</th>
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<tr>
<td><strong>Calibration Sample</strong></td>
<td>-3024.98</td>
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<td>Log-likelihood</td>
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<td>6079.96</td>
<td>5128.82</td>
<td>4931.6</td>
<td>4465.54</td>
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<td>AIC</td>
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<tr>
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<td>6102.64</td>
<td>5153.012</td>
<td>4955.792</td>
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<td>BIC</td>
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<tr>
<td>Holdout Sample</td>
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<td>-2188.34</td>
<td>-2127.52</td>
<td>-2005.42</td>
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<td>-2188.34</td>
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<td>5323.583</td>
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### Table 4A Results from Censored Regression

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Estimates (t-values)</th>
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<tbody>
<tr>
<td>Constant ( \alpha_{0i} )</td>
<td>0.688 (114.61)</td>
</tr>
<tr>
<td>( \log(C_{it-1}+1) ) ( \alpha_{1i} )</td>
<td>0.395 (109.49)</td>
</tr>
<tr>
<td>TENURE ( \alpha_{2i} )</td>
<td>-0.0065 (-18.56)</td>
</tr>
<tr>
<td>T1 ( \alpha_{3i} )</td>
<td>0.407 (7.51)</td>
</tr>
<tr>
<td>T2 ( \alpha_{4i} )</td>
<td>-0.024 (-4.41)</td>
</tr>
<tr>
<td>T3</td>
<td>0.000 (0.12)</td>
</tr>
<tr>
<td>Initial variability ( \sigma_{\eta_0} )</td>
<td>1.68</td>
</tr>
<tr>
<td>Experience variability ( \sigma_{\xi} )</td>
<td>2.48</td>
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</table>

### Table 4B Estimation Results of the Proposed Model

<table>
<thead>
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<th>Parameters</th>
<th>Estimates (t-values)</th>
<th>Segment 1</th>
<th>Segment 2</th>
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</thead>
<tbody>
<tr>
<td>Estimated segment size</td>
<td></td>
<td>83.3%</td>
<td>16.7%</td>
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<tr>
<td></td>
<td></td>
<td>(9.72)</td>
<td>(9.57)</td>
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<tr>
<td>Constant ( \beta_{0i} )</td>
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<td>4.39</td>
<td>1.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(11.96)</td>
<td>(2.06)</td>
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<tr>
<td>Consumption ( \beta_{1i} )</td>
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<td>0.28</td>
<td>0.65</td>
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<tr>
<td></td>
<td></td>
<td>(3.91)</td>
<td>(4.65)</td>
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<td>Squared consumption ( \beta_{2i} )</td>
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<td>-0.035</td>
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<tr>
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<td></td>
<td>(-9.18)</td>
<td>(-10.22)</td>
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<td>Price ( \beta_{3i} )</td>
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<td>-0.109</td>
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<td>(-7.10)</td>
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<td>Stockout ( \beta_{4i} )</td>
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<td>-5.60</td>
<td>-1.45</td>
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<tr>
<td></td>
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<td>(-7.12)</td>
<td>(-2.52)</td>
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<tr>
<td>Switching cost ( \beta_{5i} )</td>
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<td>-1.18</td>
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<tr>
<td></td>
<td></td>
<td>(-2.60)</td>
<td>(-2.55)</td>
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<tr>
<td>Price discount ( -\lambda_i )</td>
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<td>0.048</td>
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<td></td>
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<td>(1.23)</td>
<td>(0.163)</td>
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### Table 5 Percentages of Overpurchases

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<tr>
<td>136.85%</td>
<td>87.06%</td>
<td>110.63%</td>
<td>131.11%</td>
<td>155.89%</td>
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### Table 6 Demand Elasticities with Regard to Price

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<tr>
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<th>Standard</th>
<th>Premium</th>
<th>Advantage</th>
<th>Elite</th>
<th>Demand for Consumption Capacity</th>
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<td>0.03%</td>
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<tr>
<td>Standard</td>
<td>1.95%</td>
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<td>2.17%</td>
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<td>1.78%</td>
<td>1.38%</td>
<td>1.21%</td>
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<tr>
<td>Premium</td>
<td>0.83%</td>
<td>0.76%</td>
<td>0.84%</td>
<td>0.61%</td>
<td>-6.45%</td>
<td>0.70%</td>
<td>0.63%</td>
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<tr>
<td>Advantage</td>
<td>1.22%</td>
<td>1.30%</td>
<td>1.42%</td>
<td>1.20%</td>
<td>1.74%</td>
<td>-7.58%</td>
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<tr>
<td>Elite</td>
<td>1.12%</td>
<td>1.40%</td>
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<td>1.50%</td>
<td>2.23%</td>
<td>3.80%</td>
<td>-10.86%</td>
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1 Estimated with a hypothetical price increase of 5%.
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<th>Std</th>
<th>Pre</th>
<th>Adv</th>
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<th>Total Revenue</th>
<th>Total Cost</th>
<th>Total Profit</th>
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<td>1</td>
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<td>5</td>
<td>7</td>
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<tr>
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<td>$18.95</td>
<td>$23.55</td>
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<td>$43.72</td>
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<td>$14125.1</td>
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<td>1.04%</td>
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<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>6</td>
<td>$64563.3</td>
<td>$14909.5</td>
</tr>
<tr>
<td>Best Price</td>
<td>$0.0</td>
<td>$15.93</td>
<td>$18.94</td>
<td>$24.87</td>
<td>$34.95</td>
<td>$42.97</td>
<td>$62.43</td>
<td>$62458.2</td>
<td>$13518.9</td>
</tr>
<tr>
<td>Purchase Share</td>
<td>26.6%</td>
<td>1.53%</td>
<td>1.45%</td>
<td>68.35%</td>
<td>1.36%</td>
<td>0.56%</td>
<td>0.07%</td>
<td>$62458.2</td>
<td>$13518.9</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.0%</td>
<td>0.9%</td>
<td>1.16%</td>
<td>93.62%</td>
<td>2.63%</td>
<td>1.43%</td>
<td>0.25%</td>
<td>$62458.2</td>
<td>$13518.9</td>
</tr>
</tbody>
</table>
Figure 1 How Online DVD Rental Works

- Consumer creates online preference queue
- Company sends the most preferred (and available) DVD to consumer
- Consumer returns the DVD to company for a new one from the queue.
- Consumer watches DVD

Source: Netflix.com.

Figure 2 Evolution of Purchased and Realized Consumption over Tenure
Figure 3A Overpurchase Increases with Uncertainty of Consumption Needs

Figure 3B Overpurchase Increases with Sensitivity to Stockout

Figure 3C Overpurchase Increases with Switching Cost

Figure 3D Overpurchase Decreases with Risk Aversion Coefficient
Fig 4A Evolvement of Learning

Fig 4B Evolvement of Percentages of Over-purchase