

**An Empirical Analysis of Consumer Purchase Decisions
under Price-Discrimination Bucket Pricing**

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Abstract

Price-Discrimination bucket pricing (PDBP) is a unique price format that usually involves monthly subscription fees and instantaneous quotas. We propose an empirical model in which consumers make dynamic purchase decisions under consumption uncertainty, accounting for the constraints imposed by the instantaneous quota. Applying the model to an online DVD rental data, we find that (1) consumers have a large disutility ($\sim \$8$) related to *stockout* (i.e., unmet consumption needs due to the quota limit), (2) such disutility drives the consumers' *overpurchase* of the service quota as a way to avoid potential stockout situations and (3) the dynamics of overpurchase are driven by the interplay between trends in consumption needs and the magnitude of consumers' plan-switching costs. We run counterfactual exercises to better understand how the instantaneous quota and stockout risk affect consumers' consumption rates, purchase decisions and firm profitability. We find that the company does not benefit from replacing the instantaneous quota with a monthly quota, or from allowing consumers to cover their stockout with a marginal fee. We further demonstrate that the company should recognize the drivers of the dynamics in overpurchase to balance the short- and long-term profitability - for example, by offering targeted discounts to customers with excess overpurchase.

Key words: Price-Discrimination bucket pricing, continuous subscription service; uncertainty; stockout; overpurchase; dynamic purchase decisions; optimal pricing; product design.

1. Introduction

The past decade has seen a novel price format gaining great popularity in many services, including online movie rentals (e.g., Netflix and Blockbuster Online), video game rentals (e.g., GameFly), book rentals (e.g., Bookswim), music downloads (e.g., eMusic), personal healthcare services (e.g., Lifestyle Family Fitness), and even car insurance (Allianz). Well known by its tagline “\$X per month for Y,” this price format involves a menu of “tiered” service plans. A representative service plan consists of a fixed monthly subscription fee (\$X) and a *quota* (Y). We refer to this price format as *Price-Discrimination bucket pricing* (PDBP) for two reasons. First, it is a new mechanism for second-degree price discrimination (e.g., Mussa and Rosen 1978, Rochet and Stole 2002): consumers self-select into different service plans that are vertically differentiated by quota. Second, the quota represents a fixed consumption capacity that cannot be exceeded in a given period, which has been metaphorically referred to as a “bucket” (e.g., Lovelock and Wirtz 2007). Table 1 lists additional popular examples of continuous subscription services using PDBP, along with their offerings. A salient example of PDBP service is Netflix: Figure 1 illustrates the purchase and consumption decision of a representative consumer. The consumer starts by paying a fixed monthly fee (e.g., \$15.99) and receives a fixed number of DVDs (e.g., 3) delivered by USPS. The consumer again uses USPS to return the movies in exchange for new movies that are sent to her next.

[Insert Table 1 and Figure 1 about Here]

Figure 2 plots the price structure of PDBP, along with other popular nonlinear price formats in the subscription-service industry: flat tariffs and two-part pricing (Train, McFadden, and Ben-Akiva 1987; Danaher 2002; Narayanan, Chintagunta, and Miravete 2007), increasing block pricing (Iyengar, Ansari, and Gupta 2007) and three-part tariffs (Lambrecht, Seim, and Skiera 2007).

[Insert Figure 2 about Here]

It is insightful to compare PDBP and the three-part tariff (3PT), which also incorporates a fixed subscription price and a quota. Both price formats require consumers to purchase in advance (Xie and Shugan 2001). Similar to 3PT (Lambrecht et al. 2007), PDBP requires the consumer to make plan choices based on expectations of future consumption. These two price formats, however, differ in two significant ways. First, 3PT gives the consumer the option to incur monetary costs (marginal fees) to cover excessive consumption (Lambrecht et al. 2007), and the quota of 3PT serves as a threshold above which the marginal fee is assessed. In contrast, the quota of PDBP serves as a limit for consumption, and the consumer incurs the costs from unmet consumption (referred to as *stockout*). Second, while 3PT (and other nonlinear price formats such as two-part pricing) sets the quota at the monthly level, the quota of PDBP is usually set at

the daily level. We refer to such a daily quota as the *instantaneous quota* because it restricts the number of rental products available for instantaneous consumption on any given day. The difference between monthly and instantaneous quotas has subtle, yet important implications for the consumer. Intuitively, a consumer who tends to bunch consumption on specific days is more likely to be restricted by the instantaneous quota, compared with the monthly quota, which gives her greater flexibility in matching the quota with her time-varying consumption needs. In other words, the monthly quota discriminates consumers based on mean consumption needs, while PDBP discriminates consumers based on both mean and peak consumption needs.

PDBP has become a very popular price format for rental services that specialize in movies (Netflix), video games (Gamefly), designer handbags (BagBorroworSteal), toys (BabyPlays), artwork (Turning Art) and dresses (RentTheRunway). For example, Netflix.com, the market leader of the online movie rental industry, has delivered more than 2 billion movies (SeekingAlpha 2011) and serves 33.1 million subscribers in United States, and more than 50 million users globally (Wikipedia). Despite the increasing popularity of PDBP and its unique structure described above, it has garnered little academic attention. This is in sharp contrast with the recent surge of research on nonlinear pricing in the telecommunications industry. Current research on nonlinear pricing has studied the competitive conditions under which flat-rate pricing is optimal (Chen and Hitt 2005; Essegai, Gupta, and Zhang 2002; Oi 1971; Wilson 1993) and has provided empirical evidence of a bias for flat-fee over two-part pricing (Danaher 2002; Hobson and Spady 1988; Kling and van der Ploeg 1990; Kridel, Lehmann, and Weisman 1993; Mitchell and Vogelsang 1991; Train, Ben-Akiva, and Atherton 1989; Train et al. 1987; Miravete 2002a, b; Lambrecht and Skiera 2006; Narayanan et al. 2007).

To our best knowledge, the only two existing studies on PDBP are Iyengar (2010) and Schlereth and Skiera (2012). Iyengar (2010) conducted a conjoint study to estimate consumers' willingness to pay for digital songs priced via pay-per-use pricing and PDBP. He finds that by offering both a BP plan and a pay-per-use plan, the company earns more profit than by offering a pay-per-use plan only. Applying a Bayesian model to the survey data, Schlereth and Skiera (2012) estimate consumers' plan-specific preferences and then use simulations to compare the performance of PDBP and two pay-per-use (linear) plans, a two-part tariff and 3PT. The authors find that the optimal PDBP is as profitable as other nonlinear price formats. Our empirical investigation differs from Iyengar (2010) and Schlereth and Skiera (2012) in two important ways. First, both papers consider monthly-level consumption, but not daily-level consumption that accounts for the constraint of the instantaneous quota. Second, both studies used survey data rather than transactional data, and both focused on eliciting the consumers' willingness to pay in a *static* context. However, PDBP services (e.g., Netflix) are usually continuous subscription services; thus, it is natural to

examine consumers' purchase decisions in a *dynamic* decision framework, which we adopt. Our empirical model is informed by the fact that consumers purchase prior to their use. As a result, we expect that various factors – such as the dynamics of consumers' consumption needs (e.g., Lambrecht et al. 2007), uncertainty in usage, and switching costs (e.g., Goettler and Clay 2011) – will give rise to interesting dynamics in consumers' plan choice and retention decisions. These dynamics, in turn, have important implications for companies wishing to balance short- and long-term profits.

To summarize, the unique PDBP design entails a new decision calculus for consumers and strategic implications for the company. Specifically, several interesting research questions arise:

- What is the effect of the instantaneous quota on consumers' consumption?
- What drives consumers' purchase decisions in PDBP?
- Do consumers dynamically change their purchase decisions over time?
- How can the company improve its PDBP design in order to increase long-term profitability?

To answer these questions, we propose an empirical model encapsulating the key aspects describing consumers' dynamic decision process under PDBP: uncertainty about future consumption, the instantaneous quota, the potential risk of stockout, and switching costs. To realistically capture the design of the instantaneous quota, we combine a daily-level consumption model with a monthly purchase decision model. The model allows consumers to form expectations of their future consumption needs based on their idiosyncratic consumption patterns, and recognizes the disutility when consumption needs are capped by the instantaneous quota. The proposed model explains several empirical regularities emerging from the unique panel data of consumer purchases and consumption history from a real online DVD rental service. First, on average, consumers substantially overpay for the unused quota (referred to as *overpurchase*), resulting in a high effective price per movie rental. Using our model, such overpurchase can be rationalized by the high disutility from unmet consumption needs, or stockout (approximately \$8 per stockout). Therefore, overpurchase can be viewed as “insurance” bought to ensure that future consumption is met. Second, we also find strong support for *lock-in*, evident from persistent and high overpurchase. Many consumers do not adjust their plan choices frequently enough, and consequently forgo opportunities to save money. Third, across consumers, there are interesting differences in the dynamics of overpurchase. Such dynamics can be explained by the interplay between switching costs and the change in consumption needs over time: some consumers exhibit a “fatigue” effect, i.e., their consumption needs decrease with accumulated consumption; while others exhibit an opposite, “reinforcing” effect. We find that consumers with low switching costs overpurchase more early and adjust their plan choices more frequently to match the evolution of their expected consumption needs so that their overpurchase diminishes over time. Consumers with higher switching costs realize the possible long-term financial expenditure induced by

switching costs, such that they overpurchase less early, but then seldom adjust purchases and end up with more overpurchase. The retention rate for low-switching-cost customers, however, is much higher than that for high-switching-cost consumers.

Based on the parameter estimates from the empirical model, we conduct counterfactual analyses to better understand the two key design components of PDBP: the daily-level quota and the stockout risk it induces. We find that given consumers' high risk aversion to stockout, PDBP allows the firm to charge high subscription fees and generate high profit. The focal company would rather not charge the marginal fee and would instead prefer to deny consumers the opportunity to cover stockout with a marginal fee. In addition, we examine how the company can improve its current PDBP design to influence the overpurchase dynamics, retention rate and overall profit. We show that overpurchase is a double-edged sword: while the company can generate higher profits from locked-in customers, it also causes customers to defect earlier. Consequently, the company can actively fine-tune its marketing mix based on observed overpurchase and usage. For instance, the company may benefit from offering targeted price discounts to consumers with excessive overpurchase.

2. Background and Data

2.1 Industry Overview

Our empirical investigation focuses on an anonymous online DVD rental company ("the focal company"). The focal company targets a niche market of family-oriented viewers by providing content-edited movies in which sexual content, violence and offensive language are removed. It employs the standard DVD rental model, which creatively integrates Internet technology and USPS service. Consumers choose among plans characterized by different price and quota combinations. They then furnish credit card information so that the company can automatically debit monthly payments from their accounts. Once the account is activated, consumers can log onto the company's website to browse movies and create personal "queues" of movie titles in the order of their viewing preference. Consumers receive the DVDs via First-Class Mail and can keep the movies as long as they like without incurring any late fees. To return the rented DVDs, they mail them back using a postage-paid envelope provided by the company. When the company receives the returned DVDs, it mails the same number of movies to the consumers. The process continues until the subscription is terminated. There is no long-term contract; however the subscription process is automatically renewed every month unless the consumers change the plan or leave the service. For the company, revenue comes solely from the monthly subscription fees. On the cost side, other than the standard overhead costs and copyright fees paid to stock the DVDs, the main variable cost for online DVD rental companies is postage; for the focal company, such cost is \$.045 for each one-way shipment.

The company provided us with a consumer panel data containing a subset of randomly selected registered consumers whose purchase and shipment histories were tracked during a 33-month observation period from August 2002 to May 2005.

2.2. Overview of the Data

The detailed shipment history for a representative consumer includes the dates when each movie was shipped out to the consumer and was received by the company. These shipping dates, along with the company-estimated one-way shipping time, enabled us to infer the dates when the consumer received the movies, based on the assumption that consumers return the DVDs immediately after watching them (Milkman, Rogers and Bazerman 2009). Similarly, the receiving dates allowed us to infer the dates of consumption.

The purchase history of a representative consumer includes the dates when the service was initiated (and, possibly, termination), dates of payment and plan choices. Two observations emerged from the payment histories. First, no customers reinstated the service after a service termination. Second, with a few exceptions, all payments were made at the beginning of the payment cycle (month), consistent with the company's policy that any plan change does not take effect until the next month. Unfortunately, consumer demographic information was very limited, except whether the consumer resided within the same state as the company.

Table 2 provides the key sample statistics based on the data. For example, the average monthly payment was \$20.68. Price discounts, averaging \$.50, were offered in approximately 2.57% of cases. The average actual movie consumption per month was 2.71, with a standard deviation of 2.37. During the observation period, consumers stayed with the company for an average of 7.68 months. Finally, 93% of the consumers lived in states different from the focal company and, thus, did not pay sales tax.

[Insert Table 2 about Here]

Table 3 summarizes the observed plan choices with the focal company. The first two columns list the monthly prices and the instantaneous quota of the six service plans offered by the company. Columns 4–8 show the purchase shares of each plan, the average numbers of movies consumed per month, total revenue, total variable cost, and total profit. Based on these statistics, we can make several observations. The dominant purchase share rests with the Standard plan, whereas the Elite plan has the lowest purchase share. When the quota increases, so does the monthly payment, but at a slower rate. The Standard plan has the highest purchase share, followed by Premium and Lite; thus, the plan popularity 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. Intuitively, given the low market shares of high-quota (and more profitable)

plans, there is potential for the company to better align popularity and profitability by either making popular plans more profitable or by making profitable plans more popular.

[Insert Table 3 about Here]

A further look into the plan switching in the data shows four patterns. First, in the majority of cases, consumers did not change plan choices. The average number of switches for a consumer during her entire tenure was 1.24. There was also significant heterogeneity in switching frequencies (including both switching among plans and dropping out) across consumers: while 81.4% of all consumers only switched once, 4.8% of them switched more than three times. Plan stickiness was highest for the Standard plan and lowest for the Elite plan. Second, most switches involved a move to adjacent plans. For the Standard plan and up, more consumers switched down to lower-level plans; however, consumers starting with the Economy and Lite plans were more likely to switch up to Standard or beyond. Third, consumers were more likely to switch down than up. Fourth, the attrition rate was higher for consumers with the Advantage and Elite plans.

2.3 Initial Insights into Consumers' Consumption

We first examine the pattern of consumption observed in the data. Consumers' realized consumption is discrete in nature, for which a Poisson model is a good choice. However, we find that there are an excessive number of zero consumption occasions that cannot be accounted for by the Poisson model. There are a large percentage (89%) of occasions where the consumer held at least 2 movies, but had zero consumption. The excessive zero consumption suggests that the zero-inflated Poisson (ZIP) model is a more appropriate modeling choice. A further check shows that consistent with the ZIP model, the variance of daily-level consumption (0.137) is significantly larger than the mean (0.084).

To check whether consumers' daily-level consumption is indeed censored by the number of movies available, we compute the average observed consumption for each possible number of available movies. Given the possible difference in the tendency to consume between weekdays and weekends, this computation is conducted separately for both cases. Confirming our expectations, we find that conditional on either a weekend or weekday, the average consumption increases with the number of movies available: the average daily consumption rate is 0.075, 0.112 and 0.157 when there are 1, 2, and 3 movies available, respectively. Furthermore, conditional on the number of available movies, the average consumption rate is larger on the weekends, compared to weekdays. For example, when the number of available movies is 2, the average consumption for weekdays (weekends) is 0.094 (0.160). To summarize, the consumption data support a zero-inflated Poisson modeling with censoring (at the available movie inventory). We develop the consumption model formally in Section 3.1.

2.4 Initial Insights into Consumers' Purchase Decisions

To understand the possible drivers of consumers' purchase decisions, we look into the systematic patterns in consumers' dynamic purchase histories, and three interesting empirical regularities in consumers' purchase decisions emerge. First, consumers' consumption needs are not always fully covered by purchased consumption capacity: consumers hit their instantaneous quota for a nontrivial percentage ($\sim 4\%$) of all consumption occasions, indicating that they face the risk of stockouts at the daily level. Second, we observe significant and persistent *overpurchase*: across all plans, the average actual consumption rates are less than half of the purchased consumption capacities. The magnitude of overpurchase implies an average price of \$6–\$8 per movie rental. Consumers thus overpay a significant amount, compared with the “ideal” situation where the plan is used more fully. Third, there is strong evidence for consumer lock-in with their current plan choices. Figure 3 plots the dynamics of average purchased consumption capacity and average movie consumption by month. Consistent with the overpurchase discussed previously, purchased consumption capacity is always higher than actual consumption. Furthermore, whereas there is a notable decline in the average consumption rate, the average amount of the purchased quota remains relatively steady. This finding implies that, on average, consumers are not fully responsive in adjusting their plan choices based on their reduced consumption. Even though some consumers adjust their purchases to avoid excessive overpurchase, many of them stay with their current plans and increasingly overpay for the service. A close look finds that 6.4% of consumers who eventually discontinued the service had *zero* consumption for at least one month before discontinuing the service. Presumably, such lock-in situations can be attributed to these consumers' switching costs, which have been found to be economically significant for subscription services (Goettler and Clay 2009).

[Insert Figure 3 about Here]

In the context of the continuous subscription industry, a forward-looking framework is suitable for studying the dynamics in purchase choices that arise because of switching costs (Goettler and Clay 2011), and the dynamics in consumption needs (Lambrecht et al. 2007). To test whether consumers' decisions are driven by future state variables, we run the following reduced-form regression:

$$\begin{aligned} OVP_{im} = & \phi_0 + \phi_1 \cdot OVP_{i,m-1} + \phi_2 \cdot Consump_{i,m+1} + \phi_3 \cdot Nswitch_i + \phi_4 \cdot Consump_{i,m+1} \cdot Nswitch_i \\ & + \phi_5 \cdot PeakConsump_{i,m+1} + \phi_6 \cdot NumPeakConsump_{i,m+1} + \varepsilon_{im} \end{aligned}$$

where the dependent variable, OVP_{im} , is the overpurchase by consumer i in month m , and $OVP_{i,m-1}$ is the amount of overpurchase in the preceding month, which we include to capture the possible inertia in the overpurchase amount. $Consump_{i,m+1}$ is the total amount of consumption in the next month, and is a reduced-form approximation of future consumption needs (assuming rational expectations on the

consumer side). The main distinction between a static and dynamic model is whether consumers' purchase decisions are influenced by future state variables. $Nswitch_i$ is the total number of switches and is a proxy for the (lack of) switching costs. $PeakConsump_{i,m+1}$ is the maximal realized consumption in the next month, and $NumPeakConsump_{i,m+1}$ is the number of days on which maximal consumption occurred.

We find that ϕ_1 is positive ($\phi_1=0.30$, $t=28.1$), indicating strong inertia toward overpurchase. ϕ_2 is positive ($\phi_2=0.004$, $t=3.31$): when future consumption needs are high, forward-looking consumers are more likely to purchase higher plans in the current period in order to avoid future stockout. ϕ_3 is negative ($\phi_3=-0.122$, $t=-29.7$), suggesting that consumers with higher switching costs are more likely to trade off the disutility from payment for reducing the switching costs. ϕ_4 is negative ($\phi_4=-0.035$, $t=-41.9$), indicating that consumers with higher switching costs are more likely to buy higher plans to cover future consumption and avoid switching costs. Both ϕ_5 and ϕ_6 are positive and significant ($\phi_5=0.0004$, $t=2.48$, $\phi_6=0.309$, $t=27.8$), again implying that consumers consider potential stockout risk factors in the future in making their purchase decisions – consistent with forward-looking consumers. To sum, we found evidence of stockout, overpurchase, (imperfect) lock-in and forward-looking. This evidence motivates us to form a purchase utility model that incorporates the instantaneous quota, usage uncertainty, switching costs and consumer forward-looking. This model, presented in Section 3.2 below, enables us to rationalize seemingly suboptimal consumer choices and explain the systematic dynamics of overpurchase.

3. The Model

In this section, we first present the zero-inflated Poisson (ZIP) model for the consumer's *daily* consumption needs, and demonstrate how a representative consumer forms her expected consumption and stockout, accounting for the role of the daily quota. We then present the model for the consumer's monthly purchase utility.

3.1. The ZIP Model for Consumption Needs

We model the consumer's realized consumption needs as a zero-inflated Poisson (ZIP) process with censoring. This choice is based on three considerations. First, a Poisson model is a natural choice for modeling realized consumption, which includes positive integers (e.g., 2 movies). Second, based on previous research in consumer-packaged goods (e.g., Erdem, Imai and Keane. 2003), it is important to account for occasions when consumers may have zero consumption needs for the service. Adding the zero-inflation part is also consistent with the fact that realized consumption is zero for many days, even

when the consumer has movies available for consumption. Finally, the censoring is consistent with the fact that the number of movies available restricts consumption.

In the absence of restrictions involving the instantaneous quota, the daily expected consumption needs, c_{it}^* , is assumed to follow a ZIP distribution with two parameters, $c_{it}^* \sim ZIPoisson(\pi_{it}, \lambda_{it})$. The first parameter, π_{it} , captures consumer i 's decision about whether to consume on day t (specifically, π_{it} is the probability that the consumer does *not* have a need for movie consumption - e.g., the consumer is too busy), such that,

$$(1) \quad \pi_{it} = \text{Logit}(\theta_{0i} + \theta_{1i} \cdot \text{Weekend}_t + \theta_{2i} \cdot \text{Ngenre}_{it})$$

In Equation (1), θ_{0i} is the baseline tendency for consumer i to have zero consumption needs at time t . The second variable, Weekend_t , is a dummy variable that is 0 if day t is Monday through Thursday, and 1 if day t is Friday through Sunday. Thus, θ_{1i} measures the difference in consumer i 's tendency to watch movies on a weekday compared with the weekend. We expect θ_{1i} to be negative for consumers who are more likely to watch movies during the weekends, and the magnitude of θ_{1i} to be smaller for consumers who have flexibility in watching movies throughout the week. The final term, Ngenre_{it} , is the cumulative number of genres consumer i has watched up to time t . We include this term to account for the possibility that more variety-seeking consumers may be more likely to experience a consumption need.

The second parameter, λ_{it} , is the mean of the Poisson model. It captures factors affecting the consumer's decision about *how many* movies to watch:

$$(2) \quad \lambda_{it} = \alpha_{0i} + \alpha_{1i} \text{Weekend}_t + \sum_{k=1}^3 \alpha_{1+k,i} \text{PastConsump}_{it,k} + \alpha_{5i} \text{AccConsump}_{it}$$

In Equation (2), α_{0i} is the baseline rate of consumption needs. Weekend_t captures the persistent difference between the consumption needs on the weekends vs. weekdays, conditional on having a positive consumption need. In order to account for the persistent consumption pattern, we include realized consumption on the same weekday (e.g., Thursdays when t is a Thursday) in the past three weeks, denoted by $\text{PastConsump}_{it,k}$ ($k = 1, 2, 3$). The coefficient $\alpha_{1+k,i}$ captures potential habit persistence (e.g., Chaloupka 1988; Mullahy 1986) in consumption needs.² The term AccConsump_{it} measures accumulated movie

² There exists empirical evidence that consumers may have time-inconsistent preferences and exercise self-control (e.g., Wertenbroch 1998), which is certainly possible for movie consumption (Milkman and Bazerman 2009; Read et al. 1999). Including past consumption into the consumption needs equation also accounts for the possibility that consumers exhibit self-control, such that they reduce current consumption needs when past consumption has been excessive (e.g., Jain 2012). Thus, the coefficients should be interpreted as the net effect of habit formation and self-control. Broadly speaking, the degree of self-control likely depends on the type of rental products, for example, one may expect that self-control is more

consumption for consumer i up to time t . The effect of accumulated consumption can be either a positive, “reinforcing” effect (consumers becomes more addicted to movie consumption), or a negative, “fatigue” effect. The fatigue effect can occur, given the limited inventory of the company’s content-edited movies. Including accumulated consumption controls for the possibility that it becomes more difficult to find movies suitable for consumption as accumulated consumption increases. A priori, it is unclear which effect is stronger, and α_{5i} captures the net effect of accumulated consumption on consumers’ consumption needs.³

3.2 The Purchase Utility Model

Informed by the focal company’s policy that plan-switching can only occur at the beginning of each month⁴, we model consumers’ purchase decisions at the *monthly* level. We note that other PDPB services may use different plan-switching policies. For example, the most recent policy of Netflix allows its customers to upgrade on any given day, and downgrade at the beginning of the next month. Nevertheless, our modeling framework can be readily adapted to accommodate alternative types of plan-switching policies without affecting the way we model the instantaneous quota and stockout risk. Later, we investigate the implications of Netflix’s plan-switching policy with a counterfactual exercise.

The company offers J plans. Each plan, or “bucket” j is defined by a fixed and prepaid monthly fee P_j and an *instantaneous quota* IQT_j , which stipulates the number of “outstanding” movies allowed at one time. There are I consumers who make plan-choice decisions among the J plans at the beginning of each month $m = 1, \dots, M$. Consumers can also choose the outside option $j = 0$, thereby discontinuing the service.

Due to the temporal separation between payment and consumption, consumers must form expectations about their future daily consumption needs and then compare them with the quota of each

serious for businesses specializing in video game rentals (e.g., Gamefly), compared with those who rent books (e.g., BookSwim).

³ We conducted various robustness checks before settling on Equation (2). Specifically, we tested for the possible inclusion of the quadratic form of accumulated consumption, which we found to be statistically insignificant ($p > 0.40$). We tested different orders of $PastConsump_{i,k}$ and found that the model fit significantly increased, with up to a third lagged consumption; improvements from higher orders of $PastConsump_{i,k}$ were negligible. We also checked for multicollinearity between accumulated consumption and lagged weekly consumption. These correlations were all less than 0.16. Furthermore, following Menard (2002), we found that the variance inflation factors were all smaller than 2. Thus, multicollinearity was not an issue. Finally, we included days to the next payment date to test whether there was a payment effect on consumption, and found no evidence.

⁴ This policy is confirmed by observed plan decisions in the data: with only a few exceptions, all payments occurred at regular monthly intervals.

plan to determine the expected consumption realization and expected consumption stockout. We propose a simple model to approximate the expected daily consumption needs and expectations on stockout at the beginning of each payment cycle. Next, we explicitly consider how the available quota restricts consumers' consumption decisions at the daily level (compared with the monthly level), a fact that has not been addressed by the existing research (Iyengar, 2010; Schlereth and Skiera, 2012).

3.2.1 Instantaneous Quota and Available Quota. A key operational characteristic of the PDBP model is the instantaneous quota (also known as “max-outs”), which specifies the number of DVDs in the mailing process on any given day. It is important to note that due to the non-trivial mailing time, the real consumption constraint facing consumers is the number of movies immediately available (available quota). Below, we briefly discuss the relationship between the instantaneous and available quota. Let IQT_{ijt} be the instantaneous quota of the plan j chosen by consumer i , and let A_{ijt} be the movies *available* to her on day t . The instantaneous quota is the total number of movies in the mailing process, which consists of A_{ijt} and the movies in transit that are not available for immediate consumption, denoted as T_{ijt} .

$$(3) \quad \begin{aligned} IQT_{ijt} &= A_{ijt} + T_{ijt}, \\ A_{ijt}, T_{ijt} &\geq 0 \end{aligned}$$

Equation (3) implies that A_{ijt} is nonnegative and will never exceed IQT_{ijt} . Conditional on the same IQT_{ijt} , A_{ijt} is larger (smaller) if the number of movies in the mailing process (T_{ijt}) is smaller (larger). The detailed shipping dates allow us to compute A_{ijt} for each day the consumer stays with the company. Furthermore, we can impute A_{ijt} for any hypothetical plan j based on the consumption needs and the exogenous shipping policy of the firm, i.e., after receiving the returned DVDs, the firm sends the consumer the same number of DVDs⁵. Please see Figures A1 and A2 in Appendix A for an illustration of the relationship between IQT_{ijt} and A_{ijt} .

3.2.2 Expected Consumption

We model the consumption outcome at the daily level to be consistent with the design of the instantaneous quota. We define c_{ijt} , the daily consumption that can be realized when plan j is chosen.

$$(4) \quad c_{ijt} = \begin{cases} 0 & \text{if } c_i^* \leq 0 \\ c_i^* & \text{if } A_{ijt} > c_i^* > 0 \\ A_{ijt} & \text{if } c_i^* \geq A_{ijt} \end{cases}$$

⁵ We check the data and did not find evidence that the focal company delayed sending new movies.

Equation (4) reflects the fact that realized consumption is left-censored at 0 (realized consumption must be non-negative) and right-censored at A_{ijt} (realized consumption cannot exceed the expected available movies). The consumer's consumption utility comes from the realized part of expected consumption, which is determined by the chosen plan and movie availability.

Combining the definition of realized consumption, conditional on plan choice j (Equation 4) and the distributional assumption made regarding consumption decisions, we can write the expected consumption, $E[c_{ijt}]$:

$$(5) \quad E[c_{ijt}] = (1 - \pi_{it}) \cdot \left[\sum_{k=0}^{A_{ijt}-1} \frac{\lambda_{it}^k e^{-\lambda_{it}} (k - A_{ijt})}{k!} + A_{ijt} \right]$$

From Equation (5), we can show that expected consumption increases with the probability of having a positive consumption need ($1 - \pi_{it}$), the magnitude of consumption needs conditional on a consumption need arising (λ_{it}), and the number of DVDs available for consumption (A_{ijt}).

3.2.3 Expected Stockout

Note that when a consumer's consumption needs exceed the number of movies available, she experiences stockout. The stockout cost can be thought of as the consumer's disutility from her consumption "fall[ing] short of the desired amount" (Erdem et al. 2003). Conceptually, the magnitude of such costs depends on the specific service category – it is low if the service is nonessential and there are many substitutes, and high otherwise. A priori, we expect the stockout cost to be large for the focal service (content-edited movies) because watching such movies can be an inexpensive, but not easily substitutable pastime for the entire family; such costs should be especially large for consumers with a strong preference for "movie night" (watching multiple movies on one occasion) because the disutility from not being able to do so is high. Unlike 3PT, in which consumers are not concerned about being constrained in their consumption, consumers of a PDBP service must evaluate the chance of stockout situations associated with each plan j . The expected value of stockout plan j , $E[so_{ijt}]$ ⁶, is

⁶ A forward-looking consumer may account for the time-inconsistency in forming her expected stockout. Our consumption needs model includes the effect of past consumption and accounts for the possibility that the consumer adjusts her consumption needs to avoid disutilities from an excessive consumption rate (e.g., Jain 2012). If the consumer is forward-looking and has time-consistent (i.e., between the purchase and consumption occasions) expectations for stockout, then the estimated stockout coefficient is not biased. Consumer forward-looking is consistent with the results of the later model comparison (Section 4.1), which finds that a forward-looking model for purchase decisions outperforms its myopic counterpart.

$$(6) \quad E[so_{ijt}] = (1 - \pi_{it}) \cdot \left[\sum_{k=A_{ijt}+1}^{\infty} \frac{\lambda_{it}^k e^{-\lambda_{it}} (k - A_{ijt})}{k!} \right]$$

Based on the Equation (6), we can show that the expected stockout increases with the probability of having non-zero consumption and the mean consumption needs, but decreases with the number of movies available for consumption.

Since consumers make plan choices at the monthly level, we need to compute the number of expected monthly stockouts by aggregating across days. More specifically, $E[SO_{ijm}] = \sum_{t=1}^{T_m} E[so_{ijt}]$, where T_m is the number of days in a month. Similarly, the monthly expected consumption realizations are given by

$$(7) \quad E[C_{ijm}] = \sum_{t=1}^{T_m} E[c_{ijt}]$$

3.2.4 Purchase Decision and Utility

We use D_{ijm} to represent consumer i 's plan choice in month m :

$$(8) \quad D_{ijm} = \begin{cases} 1 & \text{if consumer } i \text{ chooses plan } j \text{ in month } m \\ 0 & \text{otherwise} \end{cases}$$

We assume that the consumer makes plan choices based on the benefit from consumption, C_{ijm} , the monetary costs of the subscription price of the chosen plan, P_{ijm} , and the nonmonetary stockout cost. The consumer may also incur a switching cost if she switches to a different plan. We assume that the utility function can be approximated by a multi-attribute, the additive compensatory utility model (Lancaster 1966):

$$(9.1) \quad U_{ijm} = \beta_{0i} + \beta_{1i}C_{ijm} + \beta_{2i}SO_{ijm} + \beta_{3i}P_{ijm} + \beta_{4i}SW_{ijm} + \varepsilon_{ijm}$$

We make two notes of (9.1). First, unlike consumer-packaged goods (e.g., ketchup) the PDBP service quota usually cannot be carried over to the next period. Consequently, the consumption utility is affected only by the quota (plan) chosen for the same period. We also allow for possible switching costs, despite the fact that the focal company does not impose any explicit monetary penalty on switching or early termination. There are two reasons to include switching costs. First, the automatic continuation of payments and the separation of payment and consumption occasions may lead to the ‘‘status-quo’’ bias, which is a psychological switching cost that has been found in previous papers (e.g., Goettler and Clay

2011), even where there is no explicit monetary penalty. Second, Zauberman (2003) shows that even a small switching cost can lead to persistent lock-in for the current choice. Based on these reasons, we include SW_{ijm} to allow for the potential costs required to switch to another plan: it is a dummy variable that is 0 if consumer i chooses to stay with her current plan in month m , and 1 if she chooses a different plan, or when she drops out. We leave it to the data to show whether psychological switching cost is significant.

As discussed above, given the advance purchase, we need to account for the uncertainty in consumers' consumption needs. Such uncertainty is inherent because of many factors, such as the amount of time available for consumption, all of which cannot be perfectly anticipated by the consumer. Thus, following the subscription pricing literature (e.g., Miravete 2002; Narayanan et al. 2007; Lambrecht et al. 2007) modeling usage uncertainty, we let consumers make plan-choice decisions based on their expected utility for plan j , given by

$$(9.2) \quad E[U_{ijm}] = \beta_{0i} + \beta_{1i}E[C_{ijm}] + \beta_{2i}E[SO_{ijm}] + \beta_{3i}P_{ijm} + \beta_{4i}SW_{ijm} + \varepsilon_{ijm}$$

The first term, β_{0i} , measures the baseline utility of using the subscription service (e.g., convenience of getting movies in the mail). The next two terms in (9.2) are related to usage; in particular, their expectation signs indicate uncertainty in usage. As we elaborated earlier, the variable $E[C_{ijm}]$ represents the expected consumption realization for consumer i during month m , given that plan j is chosen. Expected consumption is plan specific because the quota associated with each plan determines the consumption quantity. The expected stockout, $E[SO_{ijm}]$, is the expected amount of stockout, as defined previously. We include this variable to capture the possibility that the amount of unmet consumption needs plays a role in determining consumer plan choice. P_{ijm} is the price of the chosen plan. Although the listed price of each plan, P_j , is identical for all consumers, the actual paid prices, P_{ijm} , 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, P_{ijm} , the actual price paid by consumer i for plan j in month m is

$$(10) \quad P_{ijm} = P_j - DSCT_{ijm} + TAX_i \times 0.066 \times P_j$$

where P_j is the listed monthly price for plan j , $DSCT_{ijm}$ is the price discount received by consumer i in month m for plan j , and TAX_i , assumed to be known with certainty, is a dummy variable that equals 1 if the consumer pays sales tax, and 0 otherwise.

To summarize, β_{1i} measures the unit benefit of movie consumption. β_{2i} represents consumer sensitivity to stockouts. β_{3i} measures price sensitivity. β_{4i} represents switching cost, which is incurred if the consumer switches to a different plan or leaves the company. Finally, ε_{ijm} represents the random errors related to choosing plan j , observable by the consumer, but not by the researcher.

The utility of the outside option ($j = 0$) is specified as:

$$(11) \quad U_{i0m} = \kappa_{1i} \cdot NFLXP_m + \kappa_{2i} \cdot BBL_m + \varepsilon_{i0m}$$

where $NFLXP_m$ is the price of the most popular Netflix plan at month m , and BBL_m is a dummy variable that is 1 if Blockbuster Online is operating at month m , and 0 otherwise.⁷ Thus, κ_{1i} and κ_{2i} measure the extent to which the outside option becomes more or less attractive because of the two major competitors. Furthermore, consumers are assumed to have no uncertainty regarding the utility of the outside option at month m ; thus, $E[U_{i0m}] = \kappa_{1i} \cdot NFLXP_m + \kappa_{2i} \cdot BBL_m + \varepsilon_{i0m}$.

Given a consumer's rational expectations on her future consumption needs, each plan implies a stream of positive consumption utilities and a stream of negative stockout and payment utilities. In addition, the consumer accounts for the (psychological) switching cost, which can be economically significant for continuous subscription services (Goettler and Clay (2011) and the possibility of lock-in (Zauberman 2003). When evaluating plan choices and deciding on whether to switch plans, the consumer trades off the benefit of higher consumption and lower stockout with the higher costs of the subscription payment and switching. The dynamic programming problem of the consumer is as follows. At the beginning of time t , consumer i observes the state variables ($S_{im} = [Ngenre_{im}, PastConsump_{im}, AccConsump_{im}, D_{i,m-1}]$), where the first three terms can be summarized by the probability of non-zero consumption π , and the amount of consumption λ . The consumer then forms expectations on her future consumption needs. When evaluating each plan, she takes into account the instantaneous quota that limits her daily consumption and estimates the amount of consumption that can be realized, and hence, the associated stockout risks. She then makes a plan choice decision that maximizes the discounted value of a stream of utilities defined by consumption, stockout, payment, and switching cost. In this model setup, the consumer is allowed to intertemporally trade off among the consumption benefit, stockout cost, price and switching cost so as to maximize long-term utility. For

⁷ These variables reflect our efforts to obtain the best measures to control for competition. Arguably, Netflix and Blockbuster Online are the two major competitors of the focal company. Ideally, we would use the sales figures for Blockbuster Online, which were launched in August 2004. However, for our observation period, only the total Blockbuster revenue from both online and offline channels was available at the quarterly level. While Bloomberg now records Blockbuster Online revenue, they started doing so only after the second quarter of 2006.

example, when deciding on whether to upgrade, the consumer can enjoy a higher number of movies consumed and avoid stockout situations. However, the extra utility comes at a cost: she needs to incur an additional switching cost (mental costs from remembering to do so, time spent signing in and making the plan change) and higher financial payment. She will not upgrade if the downside dominates the upside. For example, to avoid the future disutility associated with stockout and to avoid switching costs, the consumer may be willing to purchase a higher plan at the cost of a higher financial payment.

Formally, we model the consumer as a forward-looking decision-maker who makes advance plan choices to maximize her total discounted future expected utility over an infinite horizon:

$$(12) \quad \max_{D_{ijm}} \left\{ E \left[\sum_{\tau=m}^{\infty} \delta^{\tau-m} U_{ij\tau} \right] \right\},$$

where $U_{ij\tau}$ is the single-period utility function, and δ is the discounting factor that measures the trade-off between current and future expected utilities. Since we do not have the exclusion restriction as in Chung, Steenburgh, and Shdhir (2010) and Ching et al. (2012), we follow the convention (e.g., Erdem and Keane 1996; Sun 2005) and fix the monthly discount factor at 0.98.

The Bellman equation is given by

$$(13) \quad V_{im}(S_{im}) = \max_{D_{ijm}} \{V_{ijm}(S_{im})\} = \max_{D_{ijm}} \left\{ E[U_{ijm} | S_{im}] + \delta E[V_{i,m+1}(S_{i,m+1})] \right\}$$

where S_{im} denotes the set of state variables, including the probability of zero consumption needs (π), the mean consumption needs (λ), and the consumer's previous plan choice, $D_{i,j,m-1}$ ($j=1, \dots, J$). The state-transition for π and λ are estimated based on the data. The optimal plan choice is given by

$$(14) \quad D_{ijm}^* = \arg \max_{D_{ijm}} \left\{ \sum_{j=0}^J D_{ijm} V_{ijm}(S_{im}) \right\}.$$

When comparing the attractiveness of each service plan, consumers calculate the expected consumption realization and the probability of a stockout situation on the basis of the mean of future consumption needs, λ_t , and the stockout probability, based on the quota associated with each plan. Consumers then form expectations about the expected utility, $E[U_{ijm}]$, and choose the service plan that maximizes the sum of their discounted future utilities, generating a sequence of optimal plan choices.

Each month, when evaluating plan choices and deciding on whether to switch to another plan, customers balance off the benefit of higher consumption and lower stockout with the higher costs of the

subscription payment and switching. Specifically, they will recognize that the high switching cost also implies that a purchase decision now may become a commitment to the same service plan in the future. It is interesting to examine whether the data support the notion that consumers take such a commitment into consideration when making current plan decisions.

3.3 Heterogeneity and Estimation

We employ Kamakura and Russell's (1989) latent-class approach to control for unobserved heterogeneity. Suppose there are N distinct latent segments, and each consumer has a probability $q(n)$ of belonging to segment n . Then, the vector $\Theta = [\theta_0(n), \theta_1(n), \theta_2(n), \alpha_0(n), \dots, \alpha_5(n), \beta_0(n), \dots, \beta_4(n), \kappa_1(n), \kappa_2(n), q(n)]$ represents all parameters to be estimated and the segment size $\pi(s)$ for all s .

Define $V_{ijm}^* = V_{ijm} - \varepsilon_{ijm}$ as the deterministic part of the value function. The error term ε_{ijm} captures the unobservables affecting plan utilities and is assumed to be independently and identically extreme-value distributed. We obtain the probability of consumer i choosing plan j in month m in the familiar multinomial logit formula:

$$(15) \quad \text{Pr ob}(D_{ijm} = 1 \mid \Theta) = \sum_{n=1}^N \pi(n) \frac{e^{V_{ijm}^*(n)}}{\sum_{j=0}^J e^{V_{ijm}^*(n)}}$$

Our calibration sample consists of 800 randomly selected consumers, and the holdout sample contains an additional 800 randomly selected consumers. We use simulated maximum likelihood (Keane 1993; McFadden 1989) for the estimation. Because some of the state variables in Equation (13) are continuous, we encounter the problem of a large state space. We first discretize the continuous spaces and then adopt Keane and Wolpin's (1994) interpolation method to 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. Observed consumption is estimated simultaneously with the plan choices. Readers can refer to Appendix B for more details on the estimation procedure.

3.4 Identification

Identification for the Zero-Inflated Poisson Model. The ZIP model has two parts, summarized by Equations (1), (2) and (4). Equation (1) implies that on any given day, there is a positive probability for the consumer to have no need to watch movies. Equation (2) implies that conditional on having a positive consumption need,

the number of movies that the consumer would like to watch can be characterized by a Poisson distribution. Equation (4) suggests that the actual consumption needs may be capped by the number of movies available. We discuss intuitions on how parameters in these three equations are identified separately. Specifically, the identification of parameters in Equation (2) uses observations with a positive number of available movies. The identification is achieved from the variation in the explanatory variables included (e.g., recent consumption rate and accumulated consumption). The parameters in Equation (1) (e.g., θ_1 and θ_2) are identified by occasions where movies are available, but the consumer chooses not to watch any. For example, consider a consumer with the same number of DVDs available, but at different days of the week. The different frequencies of *excessive* zero consumption (i.e., relative to what can be explained by a standard Poisson model) on weekdays vs. weekends help to identify θ_1 , and so on.

Identification for the Plan Utility Model. The identification of β_1 and β_2 are achieved by the variation in expected consumption and stockout, both of which arise from the interaction between the quota and time-varying consumption needs. Identification of the price coefficient, β_3 , is based on the variation in the effective prices, which varies both across consumers in the same segment (differences in the tax amount between in-state and out-of-state consumers) and within consumers (discounts). The identification of the switching cost, β_4 , is based on the observed switching patterns in plan choices. In particular, the identification is facilitated by the consumer's likelihood of staying with the service in months when the realized consumption is low (i.e., when both consumption needs and stockout costs are close to zero).

4. Results

4.1. Model Comparison

To see whether incorporating consumption uncertainty, switching costs, stockout risk, and forward-looking better explains consumer advance-purchase behavior, we estimate five models. In the first benchmark model, we assume that there is no uncertainty on the expected usage or stockout, and consumers' plan-specific utility includes the instantaneous quota and price. This 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) introduces uncertainty by incorporating expected consumption without the expected stockout cost. By introducing uncertainty, this model recognizes that consumers make their advance-purchase decisions with imperfect information. This model is similar to Lambrecht et al. (2007); however, this model does not account for the stockout risk, which is unique to PDBP. The third benchmark model (Model 3) recognizes both expected consumption and stockout, but does not include the switching cost. The fourth benchmark model (Model 4) extends Model 3 by including

switching costs. In Models 1-4, consumers are assumed to be myopic rather than forward-looking, such that they maximize their current utility without accounting for future switching costs. The fifth model (Model 5) is our proposed model with usage uncertainty, stockout, switching costs and forward-looking consumers.

As we use the latent-class approach to account for consumer heterogeneity, we must determine how many segments best fit the data for each of the five models. We estimate each of the competing models with various segments ($N = 1, 2, \text{ and } 3$). The results suggest that Models 1 and 2 with three segments and Models 3–5 with two segments are the best fits. For example, the log-likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) of our proposed model are $-44,754.5$, $89,543.1$ and $89,710.2$, respectively, for one segment, $-44,541.8$, $89,149.6$ and $89,474.0$ for two segments, and $-44,467.2$, $89,182.6$ and $89,614.0$ for three segments.

In Table 4, we report the log-likelihood, AIC, BIC and hit rates of the five competing models with the optimal numbers of segments. Model 1 has the worst fit among all five models (LL= -48241.5 , AIC= 96541.0 , BIC= 96826.0), which is not surprising, given that the instantaneous quota (IQT_j) as an explanatory variable is the same across all consumers and across time. This static variable fails to capture the individual-level heterogeneity and dynamics in consumption needs. Replacing the instantaneous quota with the individual-specific and time-varying $E[C_{ijm}]$ results in a significant increase in model fit of the second baseline model (LL= -47111.9 , AIC= 94281.8 , BIC= 94566.9). Model 3 further improves the model fit by including the expected stockout $E[SO_{ijm}]$, which captures consumers' high disutility for stockout situations. Model 4 incorporates switching costs, which helps explain the quite persistent pattern of choices observed in the data. The model fit increases significantly, suggesting the importance of switching costs in our context. For Model 4, we use a discount factor of 0 – that is, consumers are assumed to be myopic and oblivious to future lock-in. Model 5 is our proposed model, extending Model 4 by allowing the consumer to be forward-looking. The improvement of model fit from Models 4 to 5 suggests that a forward-looking model better explains consumer plan choices. Model fit indices for both the calibration and holdout samples show that our proposed model significantly outperforms all four benchmark models, with the highest hit rate among all five models (91.6% for the calibration sample and 90.3% for the holdout sample). In addition, we test alternative discount factors for the dynamic model.⁸ The results confirm the robustness of the main model.

To sum, the model comparisons show that it is important to allow for uncertainty in consumption needs, stockout and switching costs, and forward-looking consumers in modeling consumer purchase

⁸ We tested two models with discount factors 0.99 and 0.95. Both model fit less well compared with the model with the assumed discount factor of 0.98: ($LL_{\delta=0.99} = -44566.2$, $BIC_{\delta=0.99} = 89522.8$; $LL_{\delta=0.95} = -44654.3$, $BIC_{\delta=0.95} = 89699.0$).

decisions under PDBP. The comparison also suggests that adding switching costs contributes the most to improving the data fit, followed by incorporating future consumption needs, expected stockout and forward-looking consumers. Because Model 5 is the best-fitting model, our subsequent discussions focus on it.

[Insert Table 4 about Here]

4.2 Parameter Estimates

The latent-class estimates indicate that 86.4% of consumers belong to the first segment, and the other 13.6% belong to the second segment.⁹ We start with the parameter estimates and *t*-statistics for the expected consumption needs process in the upper part of Table 5. Results from the zero-inflation model show that both segments are much less likely to have zero consumption needs on the weekends. Notably, the weekend effect is much higher for the first segment ($\theta_1 = -0.39$ vs. -0.22). As expected, consumers who watch more movie genres are less likely to have zero consumption needs ($\theta_2 = -0.017$ and -0.031). Turning next to the Poisson model, the weekend effects in this model are positive for both segments ($\alpha_1 = 0.45$ and 0.25). Combined with previous estimates of the same variable in the zero-inflation equation, we conclude that consumers in the first segment are more likely to cluster their consumption at convenient times—i.e., weekends—while consumers in the second segment are more flexible in planning their consumption over the entire week. Based on this finding and for the ease of exposition, we label the first segment as *convenience* and the second segment as *value-seeking*. The coefficients of average realized consumption in the three preceding weeks are positive and significant for the second segment, indicating the importance of controlling for inertia in consumption needs. The effect of accumulated consumption is different for the two segments. For the convenience segment, accumulated consumption has a small, yet significantly negative, “fatigue” effect on consumption needs ($\alpha_5 = -0.002$): cumulative consumption may exhaust the consumer choice set and the needs for future movies. In contrast, we find a significant positive, “reinforcing” effect of accumulated consumption for the value-seeking segment ($\alpha_5 = 0.001$). A likely explanation is that value-seeking customers are more variety seeking in their viewing preferences for different movie genres. Consistent with this explanation, the value-seeking segment watched an average of 6.0 genres throughout their tenure, significantly more than the 4.1 viewed by the convenience segment.

⁹ We follow Kamakura and Russell (1989) and assign consumers into each of the two segments, using 0.5 as the cutoff probability (e.g., Bucklin and Gupta 1992, p. 211).

We next turn to the point estimates and t -statistics for parameters in the expected plan-utility equation, shown in the lower part of Table 5. First, the Blockbuster dummy (BBL_m) does not have a significant effect on outside utility; however, the price of Netflix has a small and marginally significant effect for the convenience segment ($\kappa_1 = -0.02$, $t = -3.28$). A possible explanation is that by operating in the niche market of content-edited movies, the focal company was able to avoid direct competition with Blockbuster, but less so with Netflix. As we expected, the consumption-benefit coefficients are positive and significant for both segments (0.461 and 0.672). Stockout coefficients are significant and negative for both segments, which means that consumers are sensitive to the negative utility caused by quota capping their consumption¹⁰. Switching costs are negative and statistically significant for both segments ($\beta_4 = -7.36$, $t = -9.80$; $\beta_4 = -3.25$, $t = -5.97$). These switching costs are also economically significant: the monetized switching cost is about \$25 for the first segment and \$10 for the second. The magnitude of the switching cost is interesting, considering that the focal company does not charge any fee for plan changes or service termination. However, as we conjectured earlier, the auto-payment mechanism of the company may have induced substantial psychological and transactional costs favoring the company. The relatively higher switching cost for the convenience segment is likely due to their higher opportunity cost of time, which is consistent with the fact that their movie consumption is more likely to occur on weekends rather than weekdays.

A comparison of the two segments' coefficients reveals additional interesting differences. Compared with the value-seeking segment, consumers in the convenience segment have a higher intrinsic preference for the online DVD rental service (2.23 vs. 1.53), a higher stockout cost (-2.42 vs. -1.81), less price sensitivity (-0.29 vs. -0.35) and a higher switching cost (-7.36 vs. -3.25).

[Insert Table 5 about Here]

4.3 Drivers and Consequences of Overpurchase

In this section, we focus on the drivers of overpurchases, a unique phenomenon under PDBP. We first show how overpurchase is related to stockout and switching costs (Section 4.3.1 and 4.3.2). We then present evidence on an inverse relationship between overpurchase and customer retention (Section 4.3.3). This last finding indicates that a large overpurchase is not always to the company's advantage and

¹⁰ Caution should be exercised in interpreting the stockout coefficient because of possible dynamic inconsistency in the consumption needs, a phenomenon long recognized by the literature (e.g., Laibson 1997; Thaler 1981) and empirically found in the context of movie consumption (Milkman and Bazerman 2009; Read, Loewenstein & Kalyanaraman 1999). For example, an alternative and behavioral explanation of observed (suboptimal) overpurchase is that at the time of purchase, the consumer simply fails to account for the decrease in consumption needs. This will then lead to an overestimate of the size of the expected overpurchase (compared with the observed overpurchase). Consequently, the stockout coefficient will be biased downwards.

motivates counterfactual analyses of alternative pricing decisions that trade off between overpurchase and retention. We also investigate how the company can fine-tune its pricing strategy to achieve better profitability - the reader is referred to Appendix C for the procedure and results of this exercise.

4.3.1 Overpurchase, Stockout Cost and Switching Cost

Stockout arises as a unique feature of PDBP because of the constraint of the instantaneous quota. The significance of the stockout-cost estimates suggests that it is a major driver for consumers' overpurchase as a way of avoiding the disutility of stockout. This is intuitive because unlike consumer-packaged goods (e.g., Ailawadi and Neslin 1998; Erdem et al. 2003), the consumer cannot stockpile. Consequently, the consumer must purchase higher plans in order to decrease stockout risk. Switching costs, on the other hand, may also increase the overpurchase, as they prevent the consumer's timely plan-choice adjustments in the presence of dynamic consumption needs. In this simulation, we compute the overpurchase rate as the percentage of the unused purchased quota, averaged across consumers and months, where the overpurchase for a representative consumer-month is $\sum_{i=1}^{T_m} (A_{ijt} - C_{ijt}) / \sum_{i=1}^{T_m} A_{ijt}$.

Figure 4 plots the average overpurchase rate against the different magnitudes of the stockout and switching costs. On the horizontal axis, each cost is varied from 50% to 150% of its respective parameter estimates. We find that, consistent with the intuition described above, the overpurchase increases with both stockout and switching costs. For example, increasing the stockout cost by 25% leads to a 6% increase in the overpurchase, and a 25% increase in the switching cost increases the overpurchase by 4%. Furthermore, we find that at the current parameter estimates, the change in the overpurchase is more sensitive to the change in the stockout costs. This indicates that the main reason behind the consumers' sacrifice in paying for a high-quota plan is to ensure an adequate stream of consumption utilities.

[Insert Figure 4 about Here]

4.3.2 Overpurchase Dynamics

To gain deeper insights into overpurchasing, we next relate overpurchase dynamics to switching costs. Intuitively, consumers with high switching costs are likely to experience persistent overpurchases, even after the consumers' consumption needs have declined. This intuition is confirmed in Figures 5A and 5B, which show the distributions of overpurchase for the convenience and value-seeking segments. While the overpurchases of frequent and infrequent switchers do not differ much in the initial month, the overpurchase is significantly higher after the 20th month, indicating that consumers with high switching costs are more susceptible to lock-in situations. Overall, the convenience segment incurred a larger

overpurchase during its entire lifetime than the value-seeking segment (74.1% vs. 65.9%), suggesting that the convenience segment is more susceptible to lock-in.

[Insert Figures 5A and 5B about Here]

Figure 6A presents a more complete picture of the overpurchase dynamics for both segments. The significant downward trend of overpurchase for the value-seeking segment can be attributed to the interplay between the “reinforcing” effect of accumulated consumption on consumption needs ($\alpha_3 = 0.001$), and the relatively lower switching cost ($\beta_4 = -3.25$), which allows consumers in the value-seeking segment to adjust their plan choices and align their purchased consumption capacity with their evolving consumption needs. In contrast, the overpurchase of the convenience segment exhibits a significant and increasing trend over time. That is, consumers in the convenience segment do not adjust plan purchases frequently enough. This is consistent with both the “fatigue” effect of accumulated consumption on consumption needs ($\alpha_3 = -0.002$) and the relatively higher switching costs ($\beta_4 = -7.36$).

Interestingly, during the early stage of their tenure, the convenience segment overpurchases *less* than the value-seeking segment (67.1% vs. 71.2%). Such patterns seem puzzling at first, but fit nicely with predictions for forward-looking consumers. On one hand, lock-in arises because of the consumers’ significant switching costs and their tendency to delay the switching (switching costs incurred in the distant future are discounted more than switching costs in the immediate future). On the other hand, by anticipating a higher probability of lock-in for the future, it is optimal for consumers with higher switching costs to choose a conservative (or lower) plan at the beginning of their tenure in order to avoid too much overpurchase from future lock-in. In contrast, consumers with lower switching costs are less susceptible to future lock-in; as a result, they are likely to start with a higher plan and are able to avoid excess overpurchase by adjusting their plan choices later.

[Insert Figure 6A about Here]

4.3.3 Overpurchase and Attrition

Focusing now on consumers’ dropout decisions, we found that convenience segment switchers are more likely to leave the company early. As Figure 6B shows, the retention probability of the convenience segment is significantly lower than that of the value-seeking segment over time. Combined with the estimation results, an intuitive explanation is that the convenience segment values consumption less, and their consumption is more easily satiated. Given the increasing mismatch of the value and cost of payment, as well as their unwillingness to incur additional switching costs to go with lower-level plans, consumers in the convenience segment are more likely to end the lock-in situation by directly dropping out. In contrast,

the higher retention rate of the value-seeking segment can be attributed to both higher consumption inertia and their abilities to switch down.

[Insert Figure 6B about Here]

In summary, the above analyses show that consumers with high switching costs are much less likely to adjust plan decisions over time to reduce overpayment. Furthermore, consumers with higher switching costs are also less likely to start with high-quota plans and are more likely to drop out sooner.

4.4 Understanding the Roles of Instantaneous Quota and Stockout

The two unique features of PDBP are the instantaneous quota and the stockout risk it induces. As the simple examples in Figures A1 and A2 of Appendix A illustrate, the instantaneous quota “penalizes” peak consumption needs, so that for the same monthly consumption needs, consumers with high peak consumption needs are more likely to incur stockout. Furthermore, there is no stockout risk in 3PT. These observations naturally lead to two interesting questions. First, should the company use an instantaneous or monthly quota? Second, if the company allows the consumer to pay a marginal fee to cover the stockout risk, would the extra gain marginal fees be sufficiently large to compensate the (expected) loss in fixed fees? To explore these two questions, we use Monte Carlo simulations to compare the expected profits in three cases. Case 1 is the “standard” PDBP with the instantaneous quota. Case 2 is PDBP with the monthly quota, the standard practice of other non-linear price formats, such as 3PT. Case 3 approximates 3PT in two ways: a monthly quota and the option for the consumer to pay a marginal fee for consumption in excess of the monthly quota.¹¹ Case 3 is different from the first two cases, in that the stockout risk of the consumer is eliminated. The simulations are based on the 800 consumers in the estimation sample. Next, we discuss the operationalization of the simulation exercises and the results.

Case 1: Standard PDBP. For each of these consumers, we iteratively simulate purchase decisions made at the beginning of every month. More specifically, at the beginning of each month, we compute the daily-level expected consumption and stockout for the consumer and then aggregate to the monthly level. Using these quantities, as well as the parameter estimates, we compute the expected utilities for each of the

¹¹ We emphasize that Case 3 is an approximation of 3PT, with the assumption that the consumer is only concerned about maximizing consumption utility, subject to the budget constraint (Lambrecht, Seim and Skiera 2007). Ascarza, Lambrecht, and Vilcassim (2012) found evidence that the consumers also value the “free” units of 3PT, above and beyond its effect on the budget constraint. To ensure comparability of the three scenarios, we make the following assumptions: first, the consumer’s latent consumption needs are the same in all scenarios. Second, we assume that the structural parameters in the utility function, such as the utility from consumption (β_{1i}), the price sensitivity (β_{2i}) and the switching cost (β_{3i}) are identical for both price formats. Third, all three scenarios have the same operational characteristics. Specifically, the consumer must wait for the same mailing time in order to receive the new rental products. Consequently, the marginal price for the approximate 3PT is charged for movies that arrive in the mail, not for immediate viewing.

available plans. We then apply the multi-logit formula to compute the probability of choosing each of the available plans, as well as the outside option. These choice probabilities allow us to simulate the plan choice (or leaving the service). After a plan choice is drawn, we simulate the daily-level consumption, subject to the quota constraints of the simulated plan choice, until we come to the next payment period. We continue this procedure until the outside option (i.e., dropped out) is drawn, at which point the consumer's tenure, total revenue, cost and profit are recorded; then, we move on to the next consumer.

Case 2: PDBP with Monthly Quota. We now explore whether the company would benefit from replacing the instantaneous quota with an equivalent monthly quota. Intuitively, a monthly quota would increase the consumer's flexibility in fulfilling her consumption needs because she can pick and choose when to consume in order to maximize her consumption needs and to reduce the stockout risk. Thus, based on the estimated consumption needs, we let the consumer solve a new constrained optimization problem, with the equivalent monthly quota as the new binding constraint. Assuming that consumers take one day to watch a movie, the equivalent monthly quota of plan j , MQ_j , is approximated as follows: $MQ_j = IQT_j \times (\text{Number of business days in a month} / (1 + T))$, where T is the number of days required for two-way shipping, as explained in Appendices A and B.

With the monthly quota, the utility function is specified as:

$$(16) \quad E[U_{ijm}] = \beta_{0i} + \beta_{1i} E[C_{ijm} | MQ] + \beta_{2i} E[SO_{ijm} | MQ] + \beta_{3i} P_{BP,j} + \beta_{4i} SW_{ijm} + \varepsilon_{ijm}$$

The utility specification (16) differs from Equation (9.2) in that we assume the company replaces a daily-level quota with a monthly quota (MQ). This change gives the consumer higher flexibility in consumption, manifested in plan-specific realized consumption ($E[C_{ijm} | MQ]$) and consumption over the quota ($E[SO_{ijm} | MQ]$), accounting for the change to the monthly quota. Figure A3 of Appendix A provides a simple illustration. Note that (16) is still PDBP and does not allow the consumer to cover the stockout with a fee.

Revenue, Cost and Profit for PDBP. These marketing outcomes for Cases 1 and 2 are computed in the same way: for each consumer, tenure is counted as the total number of months she chooses to stay with the company. The total revenue is determined by the consumer's simulated sequence of plans and payments. The total cost is computed using the simulated and realized consumption, conditional on consumers' consumption needs and the chosen plan's quota. Total profit is simply the difference between the total revenue and total cost. These quantities are summarized below.

$$\text{Rev}_{BP} = \sum_{i=1}^I \sum_{m=1}^{M_i} \delta^m \sum_{j=1}^J D_{ijm} P_j, \quad \text{Cost}_{BP} = \sum_{i=1}^I \sum_{m=1}^{M_i} \delta^m \sum_{j=1}^J D_{ijm} E[C_{ijm}] \cdot mc, \quad \text{Profit}_{BP} = \text{Rev}_{BP} - \text{Cost}_{BP}$$

where mc is the marginal cost for each DVD consumed, approximated by the two-way postage fee of \$0.90 and an estimated handling fee of \$1.10 per DVD. δ is the discount factor that the company uses to discount profits accruing from future sales, and is set to be the same as in the consumer model. Note that the profit function above reflects an important way in which PDBP differs from other pricing formats: total revenue is completely driven by the demand quota, and not directly by actual consumption.

Case 3: Approximation of the Three-part Tariff. In this case, a representative service plan j consists of a fixed fee (P_j), a marginal fee (r_{3PT}) and a plan-specific quota ($QT_{3PT,j}$). Consumer i 's expected monthly utility for plan j is:

$$(17) \quad E[U_{ijm}] = \beta_{0i} + \beta_{1i} E[C_{ijm} | MQ] + \beta_{2i} P_{3PT,j} + \beta_{3i} \cdot r_{3PT} \cdot E[SO_{ijm} | MQ] + \beta_{4i} SW_{ijm} + \varepsilon_{ijm}$$

To reiterate, the key difference between (16) and (17) is that the disutility of stockout ($\beta_{2i} E[SO_{ijm} | MQ]$) is replaced by the marginal fee ($\beta_{3i} \cdot r_{3PT} \cdot E[SO_{ijm} | MQ]$).

The simulation procedures of Cases 2 and 3 are very similar to those of Case 1 (standard PDBP). Note that for 3PT, the company's total revenue, costs and profit are computed differently. In particular, the total revenue for 3PT consists of both the fixed fee and the marginal revenue collected from the avoided stockout, or the difference between the realized consumption and the quota of the chosen plan. The marginal fee is set at \$2.99, the same as the rental price Blockbuster charged for first-release movies. The additional consumption is also added to the company's operating cost. These quantities are summarized below.

$$Rev_{TP} = \sum_{i=1}^I \sum_{m=1}^{M_i} \delta^m \sum_{j=1}^J D_{ijm} [P_j + E[SO_{ijm}] \cdot p_r], \quad Cost_{TP} = \sum_{i=1}^I \sum_{m=1}^{M_i} \delta^m \sum_{j=1}^J D_{ijm} [E[C_{ijm}] + E[SO_{ijm}]] \cdot mc, \quad Profit_{TP} = Rev_{TP} - Cost_{TP}$$

We compare the overall performance of the three cases based on three dimensions: tenure (total number of months the consumers stay with the company), total costs and total revenue. Table 6a shows the comparison between the instantaneous and monthly quotas. First, when the company switches to the monthly quota, the tenure increases by 9.0%: consumers are also likely to stay with the company for a longer time due to increased flexibility. Second, the monthly quota allows consumers to significantly increase their consumption rates, which significantly increases the company's operating costs by 11.2%. This is expected because consumers' consumption is less constrained by the monthly quota. Third, the revenue also decreases by 1.3%. This is because with the monthly quota, consumers with large peak consumption are less likely to be constrained by the instantaneous quota; thus, they have less incentive to purchase higher plans. Overall, a switch to the monthly quota would reduce the total net profit by 3.2%. The last result suggests that the company does *not* gain by switching from an instantaneous to a monthly quota.

Table 6b compares the standard PDBP and (approximate) 3PT. With 3PT, the simulated average tenure increases modestly by 5.0%, and the average costs increase by 9.0%. The additional revenue collected from the marginal fee of the alternative 3PT (\$25.4 per consumer) is equivalent to 5.3% of the total revenue (fixed fees) from PDBP. Third, the fixed fees that the company can collect from the fixed subscription fee is 9.1% lower, compared with PDBP. Overall, the net profit decreases by 5.7% if the company uses the approximate 3PT. The intuition is that by allowing consumers to go over the quota at the cost of a marginal fee, 3PT also significantly decreases consumers' stockout risk. Consequently, consumers have less incentive to purchase high-level plans; in addition, the company's ability to extract revenue from the consumer diminishes significantly. Indeed, given the high disutility from stockout (\sim \$8), PDBP induces customers to pay higher fixed subscription fees and incur a high overpurchase¹².

[Insert Tables 6a and 6b about Here]

4.5. Alternative Ways to Improve the Current Design of PDBP

Having identified the conditions under which the company may prefer PDBP to 3PT, we now investigate ways by which the company can fine-tune its current PDBP design. The first three counterfactuals are informed by industry practices. First, the company may allow the consumer to switch more often than its current policy (once per month). Netflix, for example, allows its subscribers to call in at any time to upgrade plans. The second counterfactual we consider is motivated by Netflix's now well-known throttling practice of intentionally delaying the turnaround time for heavy (and less profitable) users. Since this tactic specifically targets heavy users, we assume this would be applied to the company's 10% heaviest users (based on the average monthly consumption rates). The third counterfactual is motivated by the fact that all PDBP services we know of are continuous subscription service: the customer lifetime value depends not only on per-period profit, but also on retention. Intuitively, overpurchase can be a double-edged sword. A high overpurchase increases the company's short-term profit (consumers overpay for the service and the cost of serving them is low); however, persistent overpurchases can reduce the consumer's retention rate. Thus, it is important for the focal company to understand how to optimally balance overpurchase, costs and retention in order to optimize long-term profitability. Since overpurchase is readily observable, the company could actively monitor and manage it. A direct way to mitigate the downside of overpurchase (the fourth counterfactual) is to give *targeted* price discounts to consumers who are observed as having excessive levels of overpurchase. The idea is based on the rationale that consumers who

¹² Note that the preceding counterfactual analyses are based on the focal firm's (once-every-month) switching policy, and the results should be interpreted with this assumption in mind. To extend our modeling framework to another firm, the consumer's purchase decisions must be modeled at a different timeframe consistent with the firm's switching policy.

overpurchase more (because of the increasing gap between their reduced consumption needs and the quota) have higher risks of defection.¹³

Note that all of these counterfactuals can be readily implemented by the company. For each counterfactual, we compare the simulated overpurchase, average tenure and profit, summarizing the results in Table 7. We also refrain from conducting segment-specific counterfactuals because it may be impractical for the company to implement segment-specific marketing actions. Combining the simulated purchase and consumption and summing them over all of the months, the simulated customer i 's lifetime overpurchases can be written as

$$(18) \quad \sum_{m=1}^{M_i} D_{ijm} \sum_{t=1}^{T_m} (A_{ijt} - E[c_{ijt}]) / \sum_{m=1}^{M_i} D_{ijm} \sum_{t=1}^{T_m} A_{ijt}$$

Alternative Plan-Switching Policy. One of the insights from our model is that persistent overpurchase can be explained by substantial switching costs identified from the data. While such switching costs emerge from consumers' psychological inertia, and not from an explicit penalty imposed by the company, it is interesting to investigate a hypothetical scenario where the company allows its subscribers to switch more frequently. We conducted a counterfactual exercise where the company adopts the switching policy of Netflix, the largest online movie rental company. Netflix allows consumers to upgrade their plan choice on any day, but only allows them to downgrade at the beginning of the next billing cycle.¹⁴ Row (A) of Table 7 shows the results of this simulation. We find that the Netflix switching policy decreases the average overpurchase by 7.4%. Such a reduction is expected because consumers now have more flexibility in adjusting their plan choices, and consequently reduce overpurchase. The overall profit is 2.9% less than with the current switching policy.

Figures 7A and 7B further compare the simulated dynamics of overpurchase with the current and Netflix switching policies. The dynamic paths of overpurchase for both consumer segments remain qualitatively the same. The hypothetical switching policy results in a substantial decrease in overpurchase, especially for the value-seeking segment. Nevertheless, Netflix's switching policy does not completely eliminate overpurchase, which remains positive and significant. Intuitively, the restriction on the downgrade and the high switching costs continue to prevent consumers from adjusting their purchases quickly enough so that the need for overpurchase remains for consumers. Together, these results suggest that Netflix's somewhat restrictive plan-switching policy and high switching costs contribute to the observed overpurchase.

¹³ Another way (the fourth counterfactual) is to fine-tune the price levels (e.g., reducing the prices for high-quota plans to increase purchase shares for these plans) – we find in Appendix C that the company can improve profits by 8.4%.

¹⁴ Information obtained through a phone interview with the customer service of the Netflix DVD rental department on Jan 3rd, 2015.

[Insert Figures 7A and 7B about Here]

Throttling. It is well known that some companies (e.g., Netflix) deliberately increase the turnaround time for the heaviest users in order to reduce the operational costs of serving them. It is interesting to understand to what extent such a practice will indeed improve the company's profits. In this counterfactual, we first identify the heaviest 10% of users, based on the average monthly consumption rates. We then approximate the practice of throttling by reducing the available movies, by either 10% or 20%. The other 90% of consumers are not affected. Rows B1-B2 of Table 7 show the results. The per-customer total costs for the company dropped 5.0% and 12.2%, respectively, following a reduction of available movies by 10% and 20% for the heaviest 10% of users. The cost savings turn out to be greater than the reduced revenues and eventually result in a per (affected) customer profit increase of 8.9% and 12.4% for the two levels of reduction. These results suggest that the practice of throttling may effectively increase the net profit for the heaviest users. However, an important caveat is that such a practice has generated very negative publicity (as in the Netflix case, Netflix had to settle a class-action lawsuit). Thus, we hesitate to recommend such a practice.

Targeted Price Discount. Row (C) of Table 7 shows the simulation of giving price discounts to consumers with excessive and persistent overpurchases. More specifically, a 50% price discount is given to consumers whose overpurchase has exceeded 80% for at least two periods. The rationale is that while these consumers generate high profits in periods when they choose to stay with the company; their stays are mainly due to high switching costs and not the value derived from the service. Thus, these customers are at a high risk of leaving the company permanently (recall that in the data, we do not observe any consumer reinitiating the service). The company would rather keep these customers at a lower profit margin than lose them forever. We assume that the price discount will not affect their consumption decisions. Results show that the price discount is very effective, increasing tenure by 7.9%. As a result, the overpurchase is increased by 5.3%, and the total profit increases 3.3% for an average targeted consumer.

[Insert Table 7 about Here]

To summarize, the additional counterfactual exercises demonstrate various ways of improving the design of PDBP. The consistent theme across these exercises is that the company benefits by achieving a better tradeoff between overpurchase and quota.

5. Conclusions, Managerial Implications and Future Research

Despite the economic significance of PDBP and its unique design, no existing research has systematically studied consumers' decision calculus within this price format. We contribute to the marketing literature by building the first empirical model of dynamic purchase decisions under PDBP. Our model encapsulates several joint drivers of consumers' dynamic purchase decisions for continuous subscription services: uncertainty in consumption needs, switching costs and consumer forward-looking. Furthermore, our model incorporates the instantaneous quota, an essential and unique feature of PDBP. We show how stockout risk induced by the instantaneous quota rationalizes persistent overpurchase, a seemingly irrational behavior observed under PDBP.

Broadly, our research contributes to the non-linear pricing literature, especially research in 3PT (e.g., Lambrecht et al. 2007). Whereas 3PT allows consumers to balance between upfront fixed subscription fees and marginal fees, PDBP introduces a new tradeoff for consumers, i.e., between stockout costs and fixed fee payments by eliminating marginal fees. We show that the company also faces a new tradeoff: between overpurchase (which drives short-term profitability) and customer retention (which drives long-term profitability). We conduct counterfactual analyses to generate some initial insights into how the firm may benefit from the instantaneous quota and the ensuing stockout risk.

Our research also generates several important managerial implications. First, we help managers gain deep insights into consumers' dynamic choices among competing PDBP plans. We propose two key measures for PDBP— overpurchase and retention— both of which can be readily observed by the company. The company should be aware that both are driven by consumption uncertainty, stockout costs and switching costs, and should recognize overpurchase as a double-edged sword. Second, we show various ways in which the company can leverage insights from consumers' decision-making to improve PDBP design. In addition to the counterfactual analyses in the paper, there are more fundamental ways by which the company can influence consumers' purchase decisions. For example, the company can either strategically increase consumers' switching costs (e.g., by charging explicit fees for plan switching), or decrease such costs (e.g., by sending reminder emails to consumers, or by making the switching process more friendly) when it is more profitable to do so. Apparently, the substantial heterogeneity among consumers forms a meaningful basis for targeted marketing actions. The common rationale behind the many possibilities available to the company (e.g., instantaneous vs. monthly quotas, alternative prices) is that the company should balance overpurchase and retention (and manage the less-obvious downside of overpurchase) so as to increase overall profitability. Third, our research also sheds new insights into the

differences between PDBP and 3PT, which is useful for companies that have already adopted either one of these two popular price formats, but may consider the other alternative.

Our research is subject to several limitations, which provide promising avenues for further research. First, some of our findings (e.g., comparison between PDBP and 3PT) are based on parameter estimates (e.g., stockout costs and price coefficients) from a specific data. These results must be interpreted with caution. It is worthwhile for future research to extend our framework to other service categories with different magnitudes of stockout and switching costs to examine the generalizability of these results. Second, we did not fully capture competitive effects, and our measures of competitive effects (Netflix price and Blockbuster presence) are arguably imperfect. While we believe these are unlikely to be of serious concern for our focal company (which focuses on the niche market of family-oriented movies and is not in direct competition with Netflix or Blockbuster), future research can more fully model competition facing the company. Third, we focus on modeling consumers' dynamic purchase decisions in a time-consistent framework. However, a limitation of our model is treating consumption needs as exogenous. For example, an alternative behavioral explanation of overpurchase is that at the time of purchase, the consumer simply does not account for the future fall in consumption needs.¹⁵ Thus, caution is advised in interpreting the stockout coefficient. We provide four suggestions to future attempts to apply our modeling framework to other PDBP services: (1) researchers should be sensitive to the possible presence of dynamic inconsistency, and should be aware that time-inconsistency may be stronger for certain "vice" products (e.g., video games) than for other products (e.g., books); (2) researchers should try to collect additional data (e.g., survey data used in DellaVigna and Malmendier 2006) to measure the extent to which the consumer's expectation of usage is consistent with her actual behavior, or should try to collect measures that meaningfully correlate with the degree of dynamic inconsistency (e.g., preference for "high-brow" vs. "low-brow" movies, examined in Milkman and Bazerman 2009 and Read, Loewenstein & Kalyanaraman 1999); (3) researchers should check other possible behavioral explanations of overpurchase, such as social comparison and bunching of consumption below the quota; and (4) as the theoretical literature (e.g., DellaVigna and Malmendier 2004; Ellison 2006; Jain 2012) suggests, the firm can leverage time-inconsistency in designing its pricing strategies. For example, if consumers consistently overestimate their consumption needs, the

¹⁵ The findings from the behavioral literature on movie consumption (e.g., Milkman and Bazerman 2009; Read et al. 1999) suggest the possibility of dynamic-inconsistency in consumption preference. If consumers are forward-looking in the sense of correctly forming their expectation for future consumption needs, and they make purchase decisions accordingly, the parameter estimates in the purchase utility model will not be biased. However, if consumers are myopic in the sense of failing to anticipate the change in consumption preference between the purchase and consumption occasions, then dynamic inconsistency in conjunction with myopic consumers can potentially bias the magnitude of overpurchase and the estimated stockout coefficient along the same direction. Based on the findings of Milkman and Bazerman (2009), we conduct a simple test (details available upon request) for dynamic inconsistency, and do not find strong evidence that consumers' overpurchase is systematically related to their movie preference.

firm may have an incentive to raise the price of plans with a larger quota. Fourth, to facilitate model identification, we follow the previous literature and fix the discount factor, which is likely to be a strong assumption (e.g., Frederick, Loewenstein, and O'Donoghue 2002). Given the recent advances in estimating the discount factors (e.g., Dubé, Hitsch, and Jindal 2010), future research can use additional information (e.g., consumer surveys) for more accurate estimates of the discount factor. Fifth, due to the lack of demographic information, we used a latent-class approach to capture consumer heterogeneity. Future research with access to more information can apply the Bayesian estimation methods proposed by Imai, Jain and Ching (2009). Finally, due to data restrictions, our counterfactuals focus on existing customers and do not consider the potential effects of various marketing strategies on customer acquisition. Future research can examine both retention and acquisition for PDBP services.

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TABLE 1
Examples of PDBP

Industry	Representative service ^a	Monthly price	Number of rentals allowed at one time
Online movie rental	Netflix.com	\$7.99	1
	Blockbuster Online	\$11.99	2
		\$15.99	3
Online game rental	Gamefly.com	\$15.95	1
	Gamerang.com	\$22.95	2
	Gottaplay.com	\$29.95	3
	Rentzero.com	\$36.95	4
	GameMine.com	\$36.95	4
Book rental	Bookswim.com	\$23.95	3
	Booksfree.com	\$29.95	5
	Paperspine.com	\$35.95	7
	Skoobit.com	\$59.95	11
Online CD and audio book rental	Audiotogo.com	\$16.99	1
	Jiggerbug.com	\$24.99	2
	Audiobooksonline.com	\$34.99	3
	Kitabe.com	\$41.99	4
		\$51.99	5

Note: ^a Columns 3 and 4 describe the service structure of the business listed first for the category, e.g., Netflix.com in the online movie rental category. All plan information was retrieved on 11/15/2013.

TABLE 2
Summary Statistics

Variables	Explanation	Mean	Standard deviation
Purchase share D_{ijt}	Purchase probabilities of each service plan		NA
	Economy	.0282	
	Lite	.0425	
	Standard	.8348	
	Premium	.056	
	Advantage	.0311	
	Elite	.0075	
P_{ijt}	Monthly payment including tax	20.68	3.89
$DSCT_{ijt}$	Amount of discount off monthly payment	.50	2.72
C_{it}	Actual monthly consumption	2.71	2.37
$TENURE$	Number of months with the company	17.68	6.25
MON	Monday dummy	0.143	0.350
TUE	Tuesday dummy	0.142	0.349
WED	Wednesday dummy	0.142	0.349
THU	Thursday dummy	0.143	0.350
FRI	Friday dummy	0.143	0.350
SAT	Saturday dummy	0.143	0.350
SUN	Sunday dummy	0.142	0.349
D_{TAX_i}	Dummy variable equal to 1 if the consumer resides outside the state and 0 otherwise	0.07	0.25

TABLE 3
Prices and Quotas of Alternative Plans and Profit Contribution

Plans	Price	DVD quota	Purchase share	Average actual consumption ²	Total revenue	Total variable costs ³	Total profits
Economy ¹	\$9.95	1	.0282	1.26	\$33,352	\$8,446	\$24,906
Lite	\$12.95	1	.0425	1.53	\$65,475	\$15,471	\$50,004
Standard	\$19.95	2	.8348	2.82	\$1,980,935	\$560,024	\$1,420,911
Premium	\$27.95	3	.056	4.31	\$186,147	\$57,408	\$128,739
Advantage	\$37.95	5	.0311	6.29	\$140,339	\$46,520	\$93,819
Elite	\$57.95	7	.0075	8.02	\$51,402	\$14,226	\$37,176

Note: 1. The total monthly consumption on the Economy plan is limited to two.

2. 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 and the DVDs that the customer held over from the previous month.
3. Variable cost is approximated as the sum of postage cost, or \$0.45 for one-way delivery and an estimated \$1.10 for overhead costs.

TABLE 4
Model Comparisons

	Model 1	Model 2	Model 3	Model 4	Model 5
<i>Calibration sample</i>					
Log-likelihood	-48241.5	-47111.9	-46516.0	-44995.8	-44541.8
AIC	96541.0	94281.8	93094.1	90057.7	89149.6
BIC	96826.0	94566.9	93398.8	90382.1	89474.0
Hit rates	84.12%	85.61%	86.60%	90.44%	91.60%
<i>Holdout sample</i>					
Log-likelihood	-49254.1	-48073.4	-47597.2	-45909.4	-45069.2
AIC	98566.1	96204.9	95256.4	91884.8	90204.4
BIC	98850.9	96489.7	95560.9	92208.9	90528.5
Hit rates	83.60%	85.12%	85.72%	89.43%	90.52%

TABLE 5
Estimation Results of the Proposed Model

Parameters	Estimates and <i>t</i> -values					
	Convenience segment			Value-seeking segment		
	<i>Coefficient</i>	<i>t</i> -value		<i>Coefficient</i>	<i>t</i> -value	
Consumption needs – zero-inflation model						
Constant	θ_{0i}	-0.496**	-9.88		-0.876**	-9.74
Weekend	θ_{1i}	-0.394**	17.07		-0.218**	-9.40
Number of genres	θ_{2i}	-0.017**	-4.00		-0.031**	-2.46
Consumption needs – Poisson model						
Constant	α_{0i}	-1.096**	-50.78		-1.128**	32.45
Weekend	α_{1i}	0.453**	21.27		0.246**	15.44
Lag consumption week 1	α_{2i}	-0.335**	-29.89		0.095**	6.12
Lag consumption week 2	α_{3i}	0.152**	15.91		0.208**	15.29
Lag consumption week 3	α_{4i}	0.188**	19.27		0.179**	12.82
Accumulated consumption	α_{5i}	-0.0016**	-33.66		0.001**	5.50
Plan-utility equation						
Constant	β_{0i}	2.225*	2.84		1.53**	3.25
Expected consumption	β_{1i}	0.461**	4.35		0.672**	5.14
Stockout amount	β_{2i}	-2.421**	-37.10		-1.813**	-15.93
Price	β_{3i}	-0.293**	-34.08		-0.354**	-51.16
Switching cost	β_{4i}	-7.360**	-9.80		-3.248**	-5.97
Netflix price	κ_{1i}	-0.02**	-3.28		0.03	1.06
Blockbuster dummy	κ_{2i}	0.14	0.77		0.10	0.62
Estimated segment size		86.4%			13.6%	

* $p < 0.05$, ** $p < 0.01$

TABLE 6a
Overall Comparison of PDBP with IQ and MQ

	PDBP with IQ	PDBP with MQ	Percentage difference
Tenure (months)	7.9	8.6	9.0%
Cost(\$)	65.7	73.1	11.2%
Revenue (\$)	475.6	469.8	-1.3%
Total Profit(\$)	409.8	396.7	-3.2%

TABLE 6b
Comparison between PDBP and Approximate 3PT

	PDBP with IQ	Approximate 3PT	Percentage difference
Tenure (months)	7.9	8.3	5.0%
Cost(\$)	65.7	71.6	9.0%
Revenue from fixed part(\$)	475.6	432.4	-9.1%
Revenue from marginal part(\$)	NA	25.4	NA
Total Profit(\$)	409.8	386.3	-5.7%

Note: PDBP =Price-Discrimination bucket pricing; 3PT = three-part tariff. IQ = instantaneous quota; MQ = monthly quota

TABLE 7
Overpurchase Tenure and Profit under Alternative Marketing Strategies

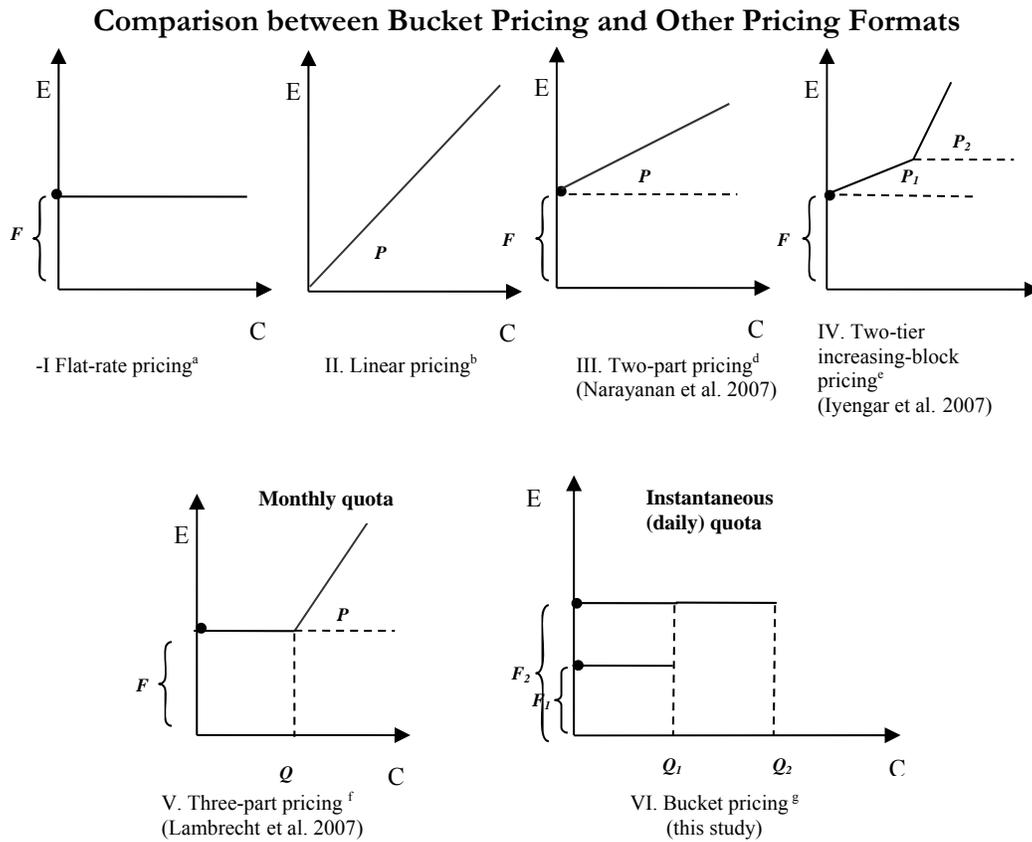
	All consumers		
	Percent change in overpurchase	Percent change in tenure	Percent change in profit per customer
A: Uses Netflix's most recent switching policy	-7.4%	4.1%	-2.9%
B1: Throttling (reducing available DVDs by 10%) for the heaviest 10% of users	6.7%	-5.0%	8.9%
B2: Throttling (reducing available DVDs by 20%) for the heaviest 10% of users	14.3%	-12.2%	12.4%
C: Giving price discounts to consumers who exhibit excessive overpurchase	5.3%	7.9%	3.3%

FIGURE 1

“Movie-in-mail” Model of Netflix

Source: Netflix

FIGURE 2



Note: ^a In I–VI, the horizontal axis, C , is the usage amount of the service, and the vertical axis, E , denotes the expenditure.

^b In I: F is the fixed fee.

^c In II: P is the marginal price.

^d In III: F is the fixed fee, and P is the marginal price.

^e In IV: F is the fixed fee, and P_1 (P_2) is the first (second) marginal price.

^f In V: F is the fixed fee, Q is the “free” allowance, and P is the marginal price.

^g In VI: Only two plans are shown here: F_1 (F_2) is the price for the first (second) plan, and Q_1 (Q_2) is the quota of the first (second) plan.

FIGURE 3

Evolution of Purchased and Realized Consumption over Tenure

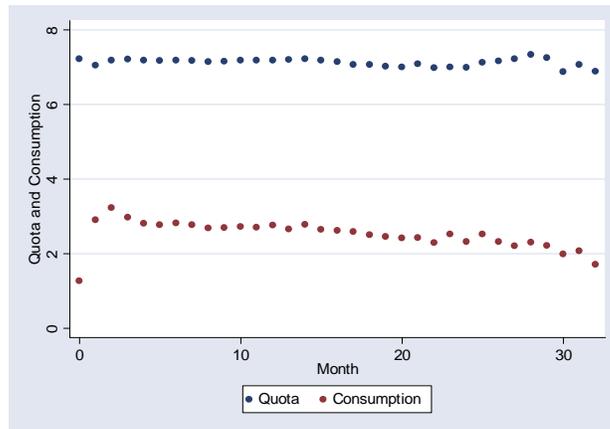


FIGURE 4

Overpurchase, Stockout and Switching Costs

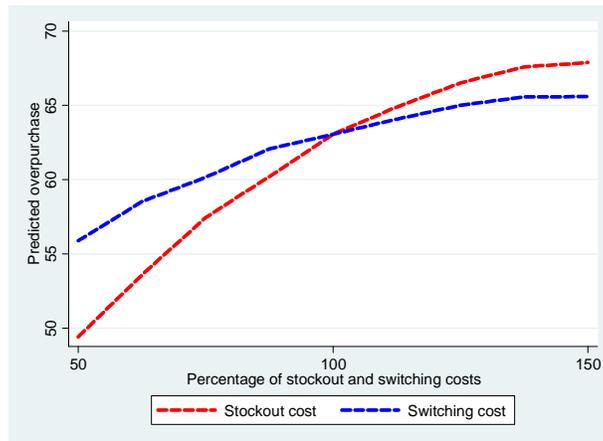


FIGURE 5A
Overpurchase in the First Month, by Segment

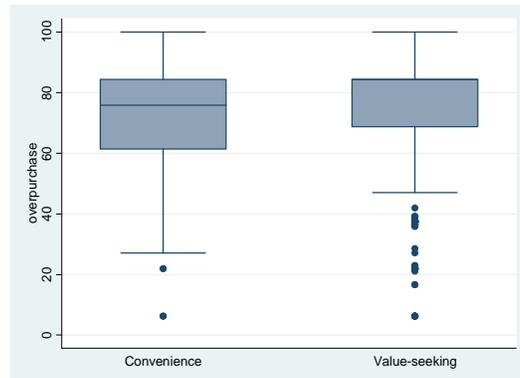


FIGURE 5B
Overpurchase after the 20th Month, by Segment

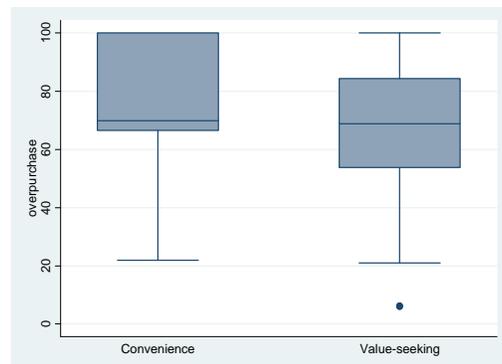


FIGURE 6A
Dynamics in Overpurchase, by Segment

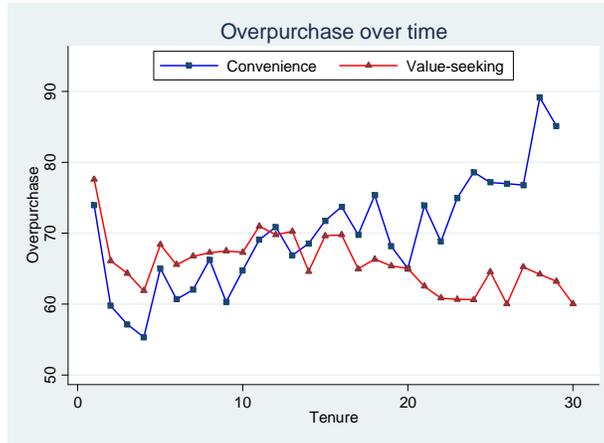


FIGURE 6B
Dynamics in Retention Rate, by Segment

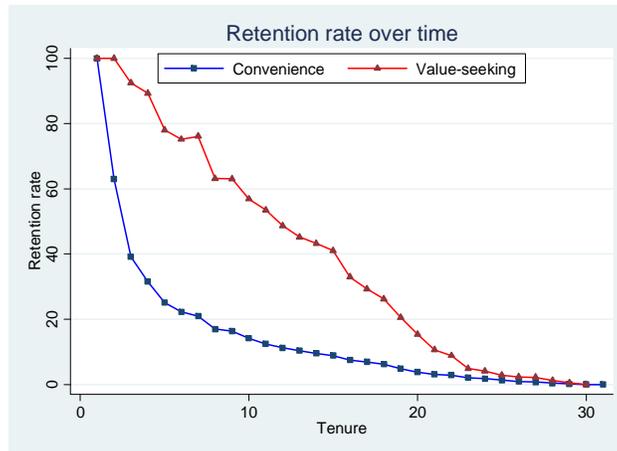


FIGURE 7A
Overpurchase Dynamics, Convenience Segment

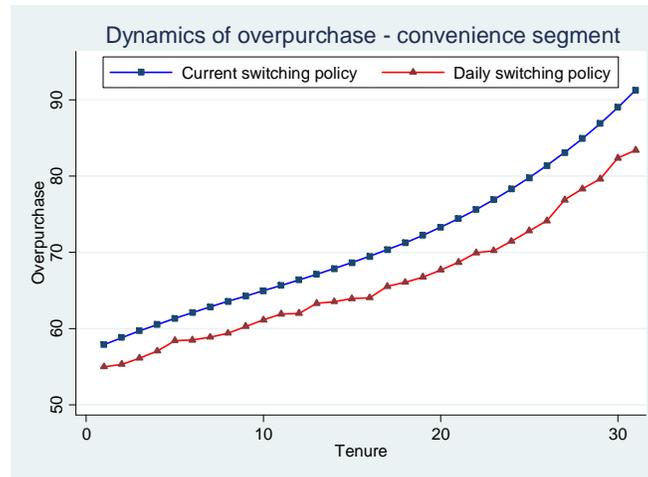
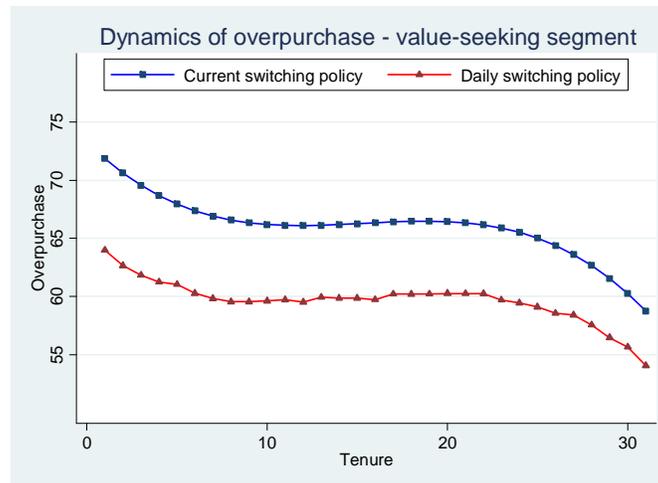


FIGURE 7B
Overpurchase Dynamics, Value-Seeking Segment



APPENDIX A

Relationship between the Instantaneous Quota (IQT) and Available Inventory (A)

Recall from text Equation (1) that the instantaneous quota (IQT) is the sum of A_{ijt} – the number of DVDs at the hands of the consumer immediately available for consumption – and T_{ijt} is the number of DVDs in the mailing process not immediately available for consumption.

$$(1) \quad \begin{aligned} IQT_j &= A_{ijt} + T_{ijt}, \\ A_{ijt}, T_{ijt} &\geq 0 \end{aligned}$$

To completely characterize the mailing process of consumer i at time t , we use vector M_{ijt}

$$M_{ijt} = [A_{ijt}, s_{ijt,1}, s_{ijt,2}, \dots, s_{ijt,T}]$$

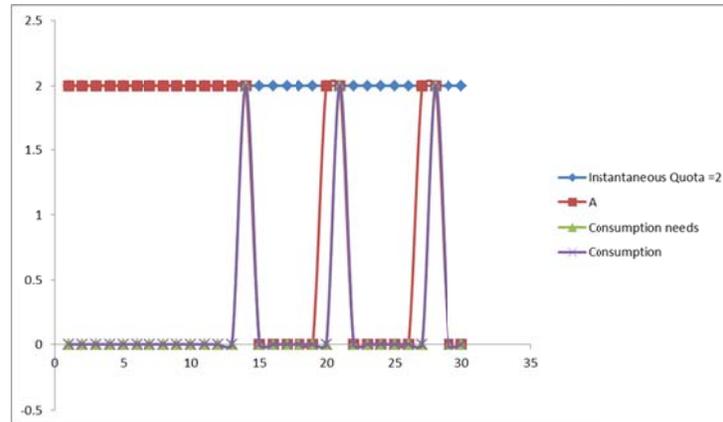
M_{ijt} has length $T+1$, where T is the total (two-way) mailing time, i.e., the number of days between the time that the consumer sends back the already-watched DVDs and the time she receives new ones in the mail. The first element of M_{ijt} is A_{ijt} , and the remaining T elements are $s_{ijt,k}$ ($k=1, \dots, T$), which includes the number of DVD(s) in transit that will be delivered to the consumer after k day(s). Given our assumption that consumers will mail back the DVDs immediately after their consumption, this is equal to the number of movies consumed on day $t - (T - k)$. Thus, we can rewrite text Equation (1) into:

$$(A1) \quad \begin{aligned} IQT_j &= A_{ijt} + \sum_{k=1}^T s_{ijt,k}, \\ A_{ijt}, s_{ijt,1}, \dots, s_{ijt,T} &\geq 0 \end{aligned}$$

Equation (A1) implies that (1) the available DVDs, A_{ijt} , is always no greater than IQT_j , and A_{ijt} is larger (smaller) if the number of movies in the mailing process ($\sum_{k=1}^T s_{ijt,k}$) is smaller (larger), and (2) A_{ijt} is generally higher for a plan with a higher IQT_j .

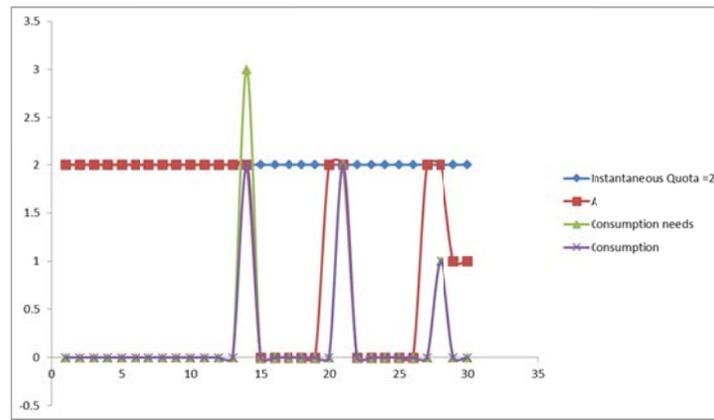
Figure A1 below uses a simple example to illustrate the relationship between the instantaneous quota (IQT) and the available quota (A) for a hypothetical consumer “Jenny” over a month for a PDBP plan with $IQT = 2$. The turnaround time T for Jenny is 6 days. In this example, Jenny has consumption needs of 2 DVDs on day 14, 2 DVDs on day 21, and 2 DVDs on day 28, and her consumption needs for all other days are zero. First, the instantaneous quota, represented by the blue series, stays constant throughout the month, whereas A , represented by the red series, varies across the month. Observe that on any given day, A is either equal to or smaller than IQT . Second, after Jenny’s consumption needs are realized, the available inventory for her is zero for the next 6 days (the time required for shipping the old movies, and for shipping the new movies), and then is fully restored to 2 on day 7 (i.e., the new movies come back in the mail). Given her consumption needs, Jenny is able to avoid stockout completely by choosing the plan with $IQT = 2$.

FIGURE A1
Dynamics of Consumption, Available Quota for a Hypothetical Consumer “Jenny”



To illustrate how PDBP penalizes consumers based on peak consumption, consider a second hypothetical consumer, “Tom,” who has consumption needs of 3 DVDs on day 14, 2 DVDs on day 21, and 1 DVD on day 28, and zero consumption needs for all other days. Thus, the total monthly consumption need for Tom is 6 movies, or the same as Jenny’s. However, Tom’s peak consumption needs (3 movies) are higher than those of Jenny’s. Suppose Tom selects the plan with $IQT = 2$: the total realized consumption is 5 movies, with a stockout of 1 movie, which occurred at Tom’s peak consumption need (3 movies). Notice that with PDBP, Tom will need to increase his purchase capacity by 50% (i.e., switch from $IQT = 2$ to $IQT = 3$) in order to fully eliminate stockout. In this case, his realized consumption only increases by 16% (from 5 to 6 movies).

FIGURE A2
Dynamics of Consumption, Available Quota for a Hypothetical Consumer “Tom”

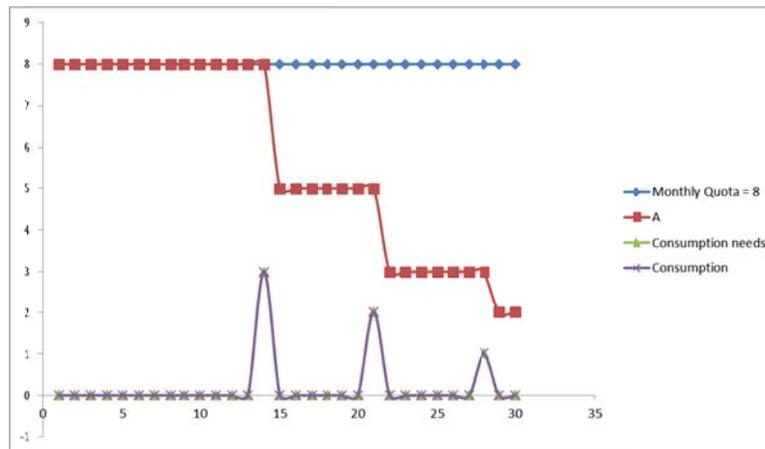


Instantaneous Quota (PDBP) and Monthly Quota (3PT)

Figure A3 illustrates why a monthly quota typically used in 3PT is less likely to induce stockout, compared with an instantaneous quota.

Following the example discussed in Figure A2 above, consider an alternative 3PT plan with a monthly quota of 8 movies. The “8 movie” quota is chosen to be the maximum consumption capacity that corresponds to a PDBP plan with a monthly quota of $IQT = 2$. In this case, Tom incurs zero stockout, which is less than the stockout for the PDBP counterpart (1 movie).

FIGURE A3
A Simple Illustration of the Monthly Quota and the Available Quota for “Tom”



APPENDIX B

Solution Approach for the Consumer’s Dynamic Problem

We embed a dynamic-programming backward-induction method with a finite horizon, $T = 36$ periods,¹⁶ within a maximum likelihood estimation procedure. The state space is the Cartesian product $P \times L \times J$, where $P = \{0, 1/200, \dots, 199/200, 1\}$ is the (discretized) space of the probability of zero consumption needs. $L = \{L_L, L_L + l, \dots, L_H - l, L_H\}$ is the (discretized) space of the mean consumption needs, where, L_L and L_H are the minimum and maximum values of L , and l is the smallest increment of L ; $l = (L_H - L_L)/200$. $J = \{0, 1, 2, \dots, 6\}$ denotes the consumer’s plan choice.

We estimate the state transition of π and λ separately from the data in the first stage. We first discretize the range of into $N = N_p \times N_L$ bins, where N_p and N_L are the cardinalities of P and L , respectively. We then estimate the $(P \times L) \times (P \times L)$ transition matrix, imposing the following restrictions: we allow the transitions only to the next ten higher or lower states for simplicity, consistent with the transitions of π and λ in the observed data. We estimate the parameters non-parametrically using a bin estimator.

¹⁶ We use a sufficiently long horizon (36 months) to approximate this problem. Sensitivity analysis shows that the computed value function is not sensitive to further extensions of T .

Procedure for Maximum Likelihood Estimation

Begin iteration for an arbitrary set of parameter values

For customer $i = 1$ to 800

For period $t = 1$ to $T = 36$

Determine the levels of state variables for each customer

For each of the seven possible plan choices

Compute customer's expected consumption daily needs in the next payment cycle

Compute customer's expected current period utility, Equation (8.2)

Recall future value function determined as a function of customer i 's state variables

Compute probability of choice using multinomial-logit formula

Increment to next plan choice

Identify the log-likelihood of the observed choice

Increment to next period

Increment to next customer

Sum the log likelihoods over all customers and periods

Use Newton–Raphson method to find the next set of parameter values

Continue iteration until parameters that maximize the overall log-likelihood are found

Procedure for Computing Value Function

For Customer $i = 1$ to 800

For $t = T = 36$ to 1 (where t is a time index for the t th future period from now)

For a randomly selected state vector (P, L, J)

Compute the probability of zero consumption needs and mean consumption needs (Equations (1) and (2))

For each of the seven possible plan choices

Determine the plan-specific expected consumption rates by averaging over draws from the individual-specific consumption-needs equation, subject to the quota of each plan

Compute the option-specific current-period expected utility, Equation (8.2)

Compute the option-specific value function, Equation (13), as a function of state variables

Increment to next option

Determine the optimal option with the maximal value function by averaging across draws to arrive at the expected value function

Store the expected optimal value as functions of the current set of state variables

Increment to next state vector in the selected set

Having obtained the value for each state vector in the selected set, we use simple linear interpolation to compute the value function for *each possible* value of the state vector (P, L, J)

Decrement to next t

Increment to next customer

Interpolation Technique (Based on Keane and Wolpin 1994)

The dynamic programming problem in Equation (12), i.e., the Bellman Equation for customer i at time t , has three state variables: the probability of zero consumption needs (continuous), mean consumption needs (continuous), and past plan choice (discrete). In computing the value function, we start by identifying the ranges for these state variables in data and construct the state space so that it covers all possibilities. We then discretize the probability of zero consumption needs into 200 points uniformly distributed in the interval $[0, 1]$ and the mean consumption needs into 200 distinct points in the interval $[0, 4]$. The overall state space is very large, and thus suffers from the curse of dimensionality. In order to alleviate the severe computational burden, we use Keane and Wolpin's (1994) linear interpolation technique. We follow backward induction: starting from the last period, we follow three steps for each

period: (1) simulate the value functions at a subset of points in the state space for that period; (2) use the value functions at these state points to fit a regression line with the value function simulated in step (1) as the dependent variable and the linear and quadratic terms of the state variables as the independent variables; and (3) based on the regression results, impute the value functions for all remaining state points in that period. For each period, the computation of the value function in step (1) is based on 50 draws, and the interpolation in step (3) is based on about 3% (randomly chosen) of all possible points in the state space in each period. We found evidence that the interpolated value function approximates the full solution (for the discretized state space described above; $R^2 = 0.59$).

APPENDIX C

Alternative Design of Price-Discrimination Bucket Pricing

We check whether the current PDBP designs can be changed to increase the company's profit. To identify the optimal PDBP, we need to solve for the monthly price and quota that jointly maximize the total, long-term profit. The specific problem we solve for the company is:

$$\max_{(P_j, QT_j), j=1, \dots, J} \sum_{i=1}^I \sum_{m=1}^M \sum_{j=1}^J \delta^m \text{Prob}(D_{ijm} = 1 | \Theta) \sum_{m=1}^{T_m} (P_j - E[C_{ijm}] \cdot mc)$$

This optimization problem takes into account consumers' reactions to the price-quota structure, through $\text{Prob}(D_{ijm} = 1 | \Theta)$ and $E[C_{ijm}]$. We use a grid search to find the best prices (P_j^*) and quotas (QT_j^*) for $j=1, \dots, 6$. Note that we leave the total number of plans unchanged. Thus, our optimization can be thought of as "local" rather than global optimization. Potentially, our focal company could also change the number of plans, as shown in Schlereth and Skiera (2012). As we believe that this possibility does not significantly add insights, we omit it from the current research.

In Table D1, we present the optimal set of prices and quotas and compare them with the existing design. We also simulate the resulting average purchase shares, consumption shares and overall profit. It is shown that, to improve profit, the company should decrease both the prices and quotas of the higher plans (Advantage and Elite) and should increase the prices of the lower plans (Economy, Lite, and Standard). The intuition of making the higher plans more attractive (in terms of reduced price per quota) is that since convenience customers are more wary of the lock-in situation, the company must significantly "sweeten" the high-quota plans in order for those plans to gain market share in the convenience segment. On the other hand, increasing the prices for the lower plans helps to increase profit accruing from the value-seeking segment, who are much more likely to purchase these plans than the convenience segment. With these adjustments, the six plans are less spread out in terms of per-quota prices. Comparing consumer purchase probabilities from the first alternative design with the optimal design, we find that more consumers are induced to choose both high- and low-quota plans than in the current design. In particular, the purchase share of the two lowest plans increased about 40% (from 2.4% to 3.4% and from 3.7% to 5.2%). On the other hand, the purchase shares of the three highest plans also significantly increased by 150%, 215% and 455%, respectively. These increases in purchase shares come at the cost of the share for the Standard plan, which drops significantly by 20.6%. Given this strategy, the simulated revenue increased by 7.9%, coupled with a 6.3% increase in the cost. The net increase in the overall profit is 8.4%.¹⁷

¹⁷ The results must be interpreted with caution for three reasons. First, the simulation analysis on the optimal price structure of the focal firm is a static, "one-shot" optimization exercise and does not consider the firm's dynamic pricing or

TABLE C1
Alternative Product Design

	No pur	Econ	Lite	Std	Pre	Adv	Elite	Total revenue	Total cost	Total profit
CURRENT DESIGN										
Quota	0	1	1	2	3	5	7	\$144,683	\$35,223	\$109,461
Current price	\$0.00	\$9.95	\$12.95	\$19.95	\$27.95	\$37.95	\$57.95			
Purchase share	16.37%	2.41%	3.67%	68.86%	4.79%	2.57%	0.65%			
Consumption	0.00%	1.13%	2.38%	79.98%	7.64%	6.65%	2.21%			
OPTIMAL DESIGN										
Quota	0	1	1	2	3	4	5	\$156,112	\$37,463	\$118,649
Best price	\$0.00	\$11.95	\$14.95	\$22.95	\$26.95	\$35.95	\$42.95			
Purchase share	12.90%	3.40%	5.10%	54.80%	12.10%	8.10%	3.60%			
Consumption	0.00%	1.53%	3.57%	52.57%	18.22%	15.47%	8.64%			

product design decisions. Our focal firm did not implement any major change in its marketing mix during the observation period. This allows us to reasonably assume exogenous firm strategy and to focus on consumer decision dynamics, assuming exogenous firm decisions. An interesting future research direction is dynamic inconsistency of the firm. In the marketing context, dynamic inconsistency may arise if the firm has an incentive (e.g., when the firm collects better information on the demand) to modify its existing marketing mixes, such as price and product design. Second, the firm should also be aware of the inherent risk associated with a sudden change in its marketing mix, suggested by anecdotal evidence. For example, Netflix experienced substantial consumer reactance following its decision to increase the price and split its DVD rental and streaming services (NY Times 2011). Third, this exercise does not account for all possible objectives of the firm, such as customer acquisition.