Who Wants What’s Hot?

Popularity Profiles and Customer Value

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Online content aggregators such as DVD-rental companies offer their customers a wide selection of products, ranging from the most popular to the most obscure. Although there has been a sharp debate about the demand for niche products in the “long tail” of an aggregator’s library, leading to questions around optimal strategies, research has not linked the consumption of popular and obscure offerings to customers’ value to the firm. We propose that firms can use information on “who wants what’s hot” (and what’s not) to assess which customers are the most valuable and which are at the greatest risk for defecting. Using data from an online DVD-rental company, we present a joint model of the time until customers begin service, their consumption of titles of varying degrees of popularity, and the duration for which they maintain service. We find that customers’ “popularity profiles,” which characterize how choices are distributed across popular and unpopular offerings, are associated with customers’ service usage frequencies and discounted expected tenures, both of which reflect customers’ value to the service provider. We demonstrate how firms can employ information on the set of titles consumed to update expectations of customers’ remaining values and likelihoods of canceling service.

*Keywords: long tail, customer relationship management, customer retention, entertainment*
INTRODUCTION

Online aggregators, particularly those in markets for entertainment or information goods, typically offer their customers a wide selection of products, ranging from the most popular to the most obscure items. In recent years, there has been a sharp debate about the demand for niche products in the “long tail” of content aggregators’ libraries.\(^1\) While some have claimed that the larger collections offered online will better match consumers’ tastes and lead to significant demand shifts from “hits” to “niches” (e.g., Anderson 2006; Brynjolfsson, Hu and Smith 2006), others have countered that the availability of obscure products will do little to change the dominance of hit products (e.g., Elberse 2008; Tan and Netessine 2009). Because the costs of acquiring, offering and managing a vast assortment can be substantial (even for information products that can be fully digitized), the debate raises important questions about optimal marketing and customer management strategies.

In this study, we focus on contractual service providers that allow customers to use or borrow products from their assortment in exchange for a subscription fee, such as digital music service providers like Rhapsody and DVD-rental companies like Netflix. We propose that such firms can benefit from understanding how the value of customers relates to their choices from the available assortment of popular and unpopular products. That is, building on the idea that firms should manage their customers on the basis of their value to the company (e.g., Blattberg and Deighton 1996; Gupta, Lehmann and Stuart 2004), we posit that knowing “who wants what’s hot” (or what’s not so hot) can help a firm allocate its resources effectively across its customer base. Using rich, longitudinal customer-transactions data from an online DVD rental company, we estimate a joint model of the time until a customer signs up for the service (acquisition), the length of time for which the customer maintains service (retention), and the

\(^1\) We use terms such as “unpopular,” “obscure” and “niche” interchangeably, as well as “popular” and “hit.”
customer’s consumption of products of varying degrees of popularity (usage).

Specifically, we describe a bivariate timing model for customers’ service acquisition and retention, and incorporate a Poisson-multinomial model that expresses how customers choose titles from the available assortment. In modeling a customer’s usage of the assortment, we estimate his “popularity profile,” which captures how his choices are distributed among popular and unpopular offerings. The popularity profile considers both the general tendency to choose (un)popular products, and the variation in the popularity of the chosen titles. For example, do a customer’s choices mainly reside in the tail of the distribution of titles ranked by their rentals, does he occasionally dabble in obscure products but primarily choose hits, or does the customer exclusively wants what’s “hot”? To the best of our knowledge, we are among the first to jointly model the duration of customers’ subscription service (accounting for both acquisition and retention) and their choices from the available assortment.

Our study makes a number of substantive contributions, three of which are particularly noteworthy. First, we find that the popularity profiles of customers vary substantially and – what we view as our primary contribution – relate to the length of their relationships with the service provider. We describe four latent classes of customers: two classes that primarily choose the most popular products, and two classes that primarily focus on obscure products. We find that, interestingly, customers who tend to consume a greater share of products from the “long tail” tend to consume with a higher frequency and are more likely to retain service over time. Although a large body of research has examined the drivers of customer retention in contractual service settings (e.g., Bolton 1998), and researchers have examined the link between assortment size and consumption in transactional settings (e.g., Borle et al 2005), the relationship between how customers use a service provider’s assortment and their tenure with a contractual service
provider has not been explored. Such research is much needed, as we show that even for
customers with similar levels of usage, differences in popularity profiles alone can be associated
with significant variations in retention probabilities.

Second, using our modeling framework, we demonstrate how an aggregator can draw on
the observed choices of popular and unpopular products (which reveal customers’ popularity
profiles) to update its belief that customers will cancel service in the next month and their
discounted expected remaining lifetimes (Fader and Hardie 2009b). In our empirical analysis, we
see that some customers are prone to canceling their subscriptions early on, but that this tendency
gradually diminishes as time goes on. Because retention probabilities vary dramatically across
customer classes, our findings underscore the likely benefits that service providers can generate
from continuously tracking popularity profiles (information that is internally available to the
firm) and allocate resources among their current and prospective customers accordingly.

Third, our findings take the long-tail debate into the realm of customer management, and
provide a more nuanced perspective on the debate’s main issues than previously documented.
Although research is starting to uncover the potential appeal (or lack thereof) of offering a vast
assortment to customers (Elberse 2008), extant studies have largely examined demand for long-
tail products at the aggregate level and have not linked the consumption of these products to
customer value. By providing empirical evidence of the relationship between customers’
consumption of less popular products and their likelihood of retaining service, we highlight the
potential long-run merits of investing in large assortments as a means of managing customers. At
the same time, our results call into question the existence of “long-tail-only customers” who
exclusively prefer unpopular offerings and are keen to escape the “tyranny of the hit” (Anderson
2006) – a common belief among proponents of the long-tail theory. Rather, our results reveal
that customers who prefer less popular offerings also regularly choose popular products—a finding that is in line with sociological theories of how people choose among competing alternatives (e.g., McPhee 1963).

In the following sections, we start by discussing the relevant literature and describing the data we use in our empirical analysis. We then present the development of our modeling framework and discuss the results of our analysis. We conclude by summarizing the study’s main findings, outlining managerial implications, and listing potential future research avenues.

**PREVIOUS LITERATURE**

Given our core objective of linking customers’ choices from large assortments to their value to online content aggregators, our research cuts across a number of topics. First, it addresses a current issue for content aggregators—the potential pay-offs of catering to customers attracted to a long-tail assortment—that is just beginning to be examined by scholars in marketing, operations, and other fields. Our research is also relevant to two areas in the mainstream marketing literature: the large body of work on customer management and valuation, and extant research on the relationship between assortment size and consumer choice. We discuss how our study relates to each literature stream below.

**The Long Tail.** Because transaction costs are much lower for online retailers than for their brick-and-mortar counterparts, online channels facilitate the distribution of a vast assortment of products. For example, while online rental business Netflix offers up to 100,000 unique DVD titles, brick-and-mortar DVD rental stores usually stock up to 1,500 DVDs (Brynjolfsson, Hu and Smith 2006) and video-rental-kiosk operator Redbox, arguably Netflix’s closest offline competitor, only averages 200 unique titles per location (The New York Times 2009). Some observers believe that the increasing product variety offered through online
aggregators, combined with consumers’ enhanced ability to find products that match their tastes (e.g., using search and collaborative filtering tools) will fuel a shift in demand away from a relatively small number of hit products in the head of the distribution toward a much larger number of niche products in the tail, a phenomenon described as the “long tail” theory by Chris Anderson (2006) in his bestselling book. He argues that we are leaving the “watercooler era” in which people choose from the same, relatively small pool of hit products and are entering the “micro-culture era” when people are all interested in different products (Anderson 2006, p. 185). While this perspective has gained much attention in recent years (e.g., The Economist 2005) and has led to calls for profound changes in strategies for online businesses (Brynjolfsson, Hu and Smith 2006), the view stands in sharp contrast with the more established economic theory of “superstars” (Rosen 1981), which predicts that lower transaction costs will homogenize, not fragment, patterns of consumption, leading to winner-take-all trends (Frank and Cook 1995).

Early empirical studies on the nature of online markets indeed provide evidence of an increased concentration of demand in entertainment product categories such as DVD rentals (Tan and Netessine 2009), home video sales (Elberse and Oberholzer 2008) and music (Elberse 2008). Doubts can also be cast on the notion of “long-tail customers” who exclusively prefer unpopular offerings. In his “theory of exposure,” the sociologist McPhee (1963) describes a general phenomenon, which he called “natural monopoly,” that consumers with light exposure to products in a certain category constitute a larger proportion of the audiences of the hit titles than of the obscure titles (“the most popular product gets not only more raw numbers of people of otherwise marginal participation in the field, but a disproportionate share of its audience… consists of just such marginal people,” p. 127). In our context, this implies that hit products “monopolize” the rental activity of light DVD consumers, while heavy consumers choose a mix
of hit and obscure products – a pattern that is directly at odds with the intuitively appealing notion that audiences for niche titles tend to be composed of loyal, die-hard fans (also see Webster 2005). McPhee (1963) further argued that obscure titles are generally appreciated less than the more popular products (“the larger the proportion of the people that is not familiar with a given alternative, then the less likely are those who are familiar with it to like it especially,” p. 133), a phenomenon he introduced as “double jeopardy”\(^2\) (also see Elberse 2008).

These realizations put pressure on online content aggregators who have invested – and continue to invest – in expansive assortments. While offering larger assortments is thought to benefit consumers (Brynjolfsson, Hu and Smith 2003), it remains unclear whether it makes for a sound strategy for aggregators. The value of the customers that these businesses attract should emerge as the critical success factor. For instance, are customers who choose the most obscure products more valuable to the firm, or are aggregators better off focusing on serving customers who only prefer the hits? What usage patterns are most commonly associated with long and lucrative customer-firm relationships?

**Customer Value, Service Retention, and Acquisition.** The notion that firms should manage customers rather than products, and seek to attract and retain the highest-value customers, has gained momentum in the marketing literature. It has led many to explore how firms can best analyze and value their customer base (e.g., Blattberg and Deighton 1996; Gupta and Lehmann 2003; Gupta, Lehmann, and Stuart 2004; Fader and Hardie 2007, 2009a, 2009b). One way in which content aggregators can value their customers is by measuring the frequency with which they consume products, sometimes referred to as the depth of the customer-firm relationship (e.g., Bolton and Lemon 1999). In contractual service settings, the duration of the

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\(^2\) This theory lies at the root of the marketing literature on the relationship between brand shares and loyalty, where double jeopardy is described as the dual problem of small and disloyal consumers.
customer’s tenure with the firm (i.e., the length the customer-firm relationship) is another relevant metric of customer value. As revenues are generated from each period until a customer cancels service in a contractual setting, the expected duration of a customer’s relationship is linked to his value to the firm (e.g., Schweidel, Fader and Bradlow 2008b).

A large body of research has examined customer retention and its relationship to customer value. Many studies focus on the antecedents of customer retention, such as customer satisfaction (e.g., Rust and Zahorik 1993; Bolton 1998; Bolton and Lemon 1999). In their review of this area of research, Bolton, Lemon and Verhoef (2004) argue that there is much work to be done to understand how various components of customer value – including the duration of the relationship and the depth of usage – are related to each other, and what their drivers are. One possible factor associated with customer retention is the time of service acquisition. Whereas some studies consider the acquisition and retention processes as independent (e.g., Gupta et al 2004; Blattberg and Deighton 1996), Schweidel, Fader and Bradlow (2008a) specifically examine how the two constructs may be related and discuss the implications of this relationship on the value of prospective customers. We extend this idea by linking retention and acquisition to service usage, and consider both total usage and how this usage is distributed among popular and unpopular titles.

**Customer Value and the Role of Assortments.** A growing body of work examines the link between the available assortment and the value that can be captured from customers. Much of this research examines behavior in transactional settings (such as grocery stores) in which the frequency of store visits or the quantities purchased are the metrics of interest. Much attention focuses on the relationship between the assortment size and sales, with some studies supporting a positive relationship (e.g., Kahn and Lehmann 1991; Kahn 1995; Dukes, Geylani and Srinivasan
2009) but others casting doubt on the idea that more variety is necessarily better (e.g., Huffman and Kahn 1998; Iyengar and Lepper 2000; Boatwright and Nunes 2001; Gourville and Soman 2005). One topic in this research is how much popular versus unpopular products contribute to sales and, for instance, whether firms can safely remove unpopular items from their assortment without adversely affecting overall sales (e.g., Broniarczyk, Hoyer and McAlister 1998; Borle et al 2005; Kalyanam, Borle and Boatwright 2007).

To the best of our knowledge, previous research has not probed the relationship between how customers utilize an assortment (i.e., what mix of popular or unpopular products they choose) and the duration of their tenure with a contractual service provider. Yet, there are good reasons to expect that customers with different popularity profiles may be of varying values to the service provider. Simonson (1990), for instance, finds that those customers who buy larger quantities at one purchase occasion tend to select a greater variety of items. In our context, this may suggest that heavy users more frequently select niche offerings than light users do. Whether this tendency to “venture into the tail” is related to retention probabilities and hence customer value, however, has yet to be examined.

**DATA AND EMPIRICAL CONTEXT**

We obtained data from Quickflix, a leading online DVD-rental and movie-subscription service in Australia. For a monthly fee, subscribers can access a large assortment of movie and television titles. Customers can compile a list of DVDs they would like to receive via regular mail, keep the DVDs that have been delivered as long as they want, and receive a new title when they return one (where more expensive plans allow customers to rent more DVDs each month). During the first month of service, customers receive a “free-trial” introductory promotion. As of early 2009, Quickflix carried over 35,000 titles in its library, making it Australia’s largest
collection of movie and television titles. From its five distribution centers, the company delivers over 130,000 DVDs each month to households across Australia.

We received transaction data for a random sample of 4,968 customers who began service between March 2006 and January 2009. We randomly divided these customers into a calibration sample and a holdout sample, each consisting of 2,484 customers. The data include the month in which a customer began service, what titles were shipped to the customer each month during the 35-month observation period and, if the customer terminated service in this period, when service stopped. Our sample of customers requested 154,479 rentals, involving a total of 32,732 unique titles. We provide descriptive statistics of our data in Table 1.

--- Insert Table 1 ---

Monthly rental activity in our data conforms to a “long-tail” distribution in which most rentals are concentrated in a small group of hits while the lion’s share of titles each account for an exceedingly small share of rentals. We illustrate the distribution of rentals across titles for an arbitrarily chosen month, December 2007, in Figure 1.

--- Insert Figure 1 ---

Although the company had approximately 29,646 titles in its library in this month, “only” 18,403 titles were rented at least once. Rental activity is heavily concentrated: the 23 most popular titles – less than 0.1% of all available titles – account for 10% of the rentals in this month; the 68 most popular titles account for 20% of all rental activity; and the 168 most popular titles make up 30% of rentals. Nearly a quarter of all titles, namely the 8,368 least popular titles, account for just 10% of rental activity. To put these numbers in perspective: Hollywood studios release just over 600 movies yearly (MPAA 2008), while a typical DVD retailer carries around 1,500 DVDs (Brynjolfsson, Hu and Smith 2006).
Popularity Bins. For each month of the study period, we segment the DVD titles into “bins” of descending popularity based on the titles’ total rentals across the company’s full customer base in the previous month. The first bin contains the most popular titles in the previous month that accounted for 10% of the company’s total rentals that month, whereas the tenth bin contains those titles with the fewest (or no rentals) in the previous month that comprise 10% of the company’s total rentals that month. Given the distribution of rental activity, the ten bins do not contain an equal number of titles: bins with more popular titles contain fewer titles, whereas bins with less popular titles contain more titles. We have opted for this bin structure because of the highly concentrated long-tail distribution of rentals across titles.\(^3\) Titles that are new to the company’s library in a given month are assigned to an eleventh bin.

The popularity of titles may change from month to month. Although demand for entertainment products is often thought to drop off quickly after their release, an examination reveals that in our setting, titles exhibited only a limited range of movement through the popularity bins from the moment they are added to the library. Titles move an average of 2.37 consecutive bins (with an SD of 1.77) during the observation period; 57% of titles move within a range of less than three popularity bins and 87% of titles move less than five popularity bins, while less than 2% of titles have a range of more than six popularity bins. The relative stability in the popularity of titles during our observation period is noteworthy – it means that content aggregators will likely be able to predict a title’s popularity using historical data (such the title’s performance in a previous theatrical window), which in turn contributes to the managerial relevance of customer-value metrics based on popularity profiles.

\(^3\) An alternative method would be to create bins of an equal number of titles by splitting the assortment into deciles. However, given the concentration of rental activity (see Figure 1), the lion’s share of rental activity would then occur in the top decile (and the lower-decile bins would each represent marginal rental activity), and each decile would contain many more titles than are available through brick-and-mortar rental locations.
Managing Assortments: The Link Between Popularity and Customer Value. The main challenge that DVD-rental-service providers such as Quickflix face when it comes to managing their assortment is two-fold: first, how far to expand “into the tail” (i.e., how many titles to acquire that may generate only very limited demand), and second, how many copies to acquire of each title. The cost per copy primarily varies depending on the popularity and the age of the title, with new and popular titles being the most expensive. As a result, in an effort to maximize the profit per transaction, DVD-rental-service providers will often seek to steer demand from popular titles to more niche offerings, and smooth demand for new releases out over a longer period so as to minimize the number of copies needed to at the peak of the demand for a title. However, adding many more niche offerings also incurs a cost: for instance, it may complicate inventory management (particularly when there are multiple distribution centers) and it may increase the search costs for customers (who may find it cumbersome to wade through thousands of unfamiliar offerings), and therefore increases the demands on recommendation technology. The core premise underlying our research is that content aggregators can only truly assess which approach to managing their assortment is preferred if they understand how their customers utilize that assortment and how valuable those customers are to the firm over their lifetime. We next present our modeling approach to this problem.

MODEL DEVELOPMENT

We build a joint customer-level model that considers (1) the time at which a customer signed up for the focal content aggregator’s service (acquisition), (2) the duration for which customers maintain their service (retention), and (3) the number of products consumed each

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4 For Quickflix, certain niche titles can cost as little as AUS$5, while popular titles can run up to AUS$35. New releases are typically priced anywhere between AUS$25 and AUS$35, catalogue titles (which are older than two months) below AUS$15, and back catalogue titles (which are older than six months) below AUS$10. In the last month of the study period, 1 Australian dollar averaged 0.67 U.S. dollar.
month and the relative popularity of those products (usage). We first describe a bivariate timing model for customers’ service acquisition and retention, then present a model for the number of rentals a customer makes each month from the popularity bins, and finally discuss incorporating unobserved heterogeneity and permitting correlation in these three processes across customers using a latent class model.⁵

**Modeling Time until Acquisition and Service Duration.** We first assume that the time at which customers begin service is governed by a parametric distribution with a cumulative distribution \( F_A(t| \Theta) \), with subscript \( A \) referring to the acquisition process. The probability that a customer signs up for service in the \( t \)th month of observation is then given by:

\[
f_A(t | \Theta) = F_A(t | \Theta) - F_A(t - 1 | \Theta)
\]

If the total size of the market was known, it would be straightforward to construct the likelihood function, which would be comprised of the likelihood of those individuals who began service in a given month of the observation period \( (f_A(t| \Theta)) \) and a component for those who did not sign up for service by the end of the observation period in month \( T \) (given by the survival probability \( 1 - F_A(T| \Theta) \)). The data we employ in our empirical analysis include only those customers who began service by the end of the observation period, and hence the data are right truncated. We explicitly account for this by modeling the acquisition time conditional on customers beginning service by month \( T \) (e.g., Moe and Fader 2002). For customers who signed up for service during the observation period, the probability of having done so in month \( t \) is then given by:

\[
f_A(t | \Theta) = \frac{F_A(t | \Theta) - F_A(t - 1 | \Theta)}{F_A(T | \Theta)} \quad \text{for } t=1,2,\ldots,T
\]

We assume that the time until customers commence service is governed by a Weibull distribution with parameters \( \lambda \) and \( c \), which has a hazard function and cumulative distribution

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⁵ For ease of exposition, we suppress the subscript of the latent class in expressing the customer-level model.
function (c.d.f.) given by:

\[
\begin{align*}
    h(t \mid \lambda, c) &= \lambda c t^{c-1}, \\
    F(t \mid \lambda, c) &= 1 - e^{-\lambda c t^c}
\end{align*}
\]  

(3)

Importantly, the Weibull distribution allows us to capture a range of patterns. If \(c=1\), the Weibull distribution is equivalent to the exponential distribution, meaning customers’ likelihood of starting service given that they have not yet done so remains constant over time. Values of \(c>1\) indicate positive duration dependence, with customers becoming more likely to sign up for service as time passes. If \(c<1\), there is negative duration dependence and customers become less likely to acquire service over time if they have not yet done so.

After starting service at time \(t_A\), we assume that the duration for which customers retain service follows a different Weibull distribution with parameters \(\gamma\) and \(d\). Using a proportional hazards model (e.g., Seetharaman and Chintagunta 2003) to incorporate the effect of the introductory month (and covariates, in general), the probability of maintaining service until month \(t_R\) is given by the survival function:

\[
S_R(t_R \mid t_A, \gamma, d, \beta, Promo) = e^{-\gamma \sum_{i=1}^{t_R-t_A} (t_{i+1}-t_i)^\gamma} \exp(\beta \cdot Promo(v))
\]  

(4)

with subscript \(R\) referring to the retention process, \(Promo\) is an indicator variable equal to 1 in month \(t_A\) (a customer’s first month, in which he is granted a free trial) and 0 otherwise, and \(\beta\) captures the effect of the introductory month on the decision to retain service. The resulting probability that a customer terminates service after month \(t_R\) is:

\[
f_R(t_R \mid t_A, \gamma, d, \beta, Promo) = S_R(t_R \mid t_A, \gamma, d, \beta, Promo) - S_R(t_R + 1 \mid t_A, \gamma, d, \beta, Promo)
\]  

(5)

The joint likelihood of customer \(h\) signing up for service at time \(t_Ah\) and maintaining service through month \(t_{Rh}\) is then given by:
where $Censor_h$ is an indicator variable equal to 1 if the subscriber maintains service throughout the observation period (i.e., is censored) and 0 otherwise.

**Incorporating Customers’ Popularity Profiles.** The model detailed thus far accounts for the time at which a customer begins service and the duration for which service is maintained, information typically available to contractual service providers. In many subscription contexts, usage is also observed. We consider both customers’ overall service usage levels (i.e., the number of titles rented each month) and how their rental activities are distributed across the firm’s assortment. To capture the distribution of a customer’s rental activity, we describe his “popularity profile,” on two dimensions. The first is his general tendency for renting popular or unpopular titles. The second aspect is the variation in popularity: does a customer exclusively prefer more (or less) popular titles, or some mix of these offerings?

To model a customer’s monthly rental activity and popularity profile, we first assume that the total number of rentals a customer makes each month follows a Poisson distribution with a mean of $\kappa$. Conditional on making $N_{hm}$ rentals in month $m$, we let $q_{hmP}$ denote the number of rentals customer $h$ makes in month $m$ from bin $p$ such that $\sum_q q_{hmP} = N_{hm}$. The distribution of rentals across the bins thus follows a multinomial distribution, with a vector of probabilities denoted $C$.

We let $\upsilon$ be the probability of renting a title that was added in the current month (and hence does not belong to any of the previous months’ popularity bins), meaning $1 - \upsilon$ is the probability of renting a title that was previously in the library.

As a parsimonious alternative to estimating ten probabilities (per latent class) to characterize the distribution of a customer’s rental activity across the popularity bins, we parameterize the probability of choosing a title from bin $p$ conditional on renting a title that was
already in the company’s library (given by $C_p/(1-\nu)$ for $p=1,2,\ldots,10$) using the c.d.f. of a beta distribution with parameters $a$ and $b$. The c.d.f. is given by:

$$F_{\nu}(x | a, b) = \frac{1}{B(a, b)} \int_0^x t^{a-1} (1-t)^{b-1} dt, x \in [0,1]$$

(7)

where $B(a, b)$ denotes the beta function and the subscript $U$ indicates usage. We model the probability of renting a title from the $p^{th}$ bin as:

$$C_p = \begin{cases} 
(1-\nu)F_{\nu}(p/10 | a, b) - F_{\nu}((p-1)/10 | a, b) & p = 1,2,\ldots,10 \\
\nu, p = 11 
\end{cases}$$

(8)

Like the beta distribution, our parameterization allows us to capture a range of popularity profiles – an interior mode, J-shaped, reverse J-shaped, and U-shaped pattern. While we consider ten popularity bins and an eleventh “new products” bin, our approach is generalizable to problems in which there are coarser or more granular measures of ordinal assortment.

To ease interpretation, we reparameterize the beta distribution in terms in terms of its mean ($\mu=a/(a+b)$) and polarization ($\phi=1/(1+a+b)$), both of which lie in the interval $(0,1)$, and which reflect the tendency to rent unpopular titles and the variation in a customer’s popularity profile, respectively. Customers with low values of $\mu$ will primarily rent more popular titles, whereas those with high values of $\mu$ will be more inclined to choose less popular titles. For a given level of $\mu$, customers may differ in the variety they display in choosing popular and unpopular titles, governed by the polarization parameter $\phi$. A value of $\phi$ near zero indicates little polarization, resulting in most rentals coming from a single bin or bins in close ordinal proximity. In contrast, values of $\phi$ close to 1 can result in a bimodal distribution, with the weight of the mass in the first and tenth bins depending on the value of $\mu$.\(^6\) Thus, our parameterization can yield a range of popularity profiles, such as customers who prefer “only hits, all the time”

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\(^6\) See Fader and Hardie (2009b) for a discussion of the shapes that can be captured by the beta distribution.
(low \(\mu\) and low \(\phi\)), those who “live in the long tail” (high \(\mu\) and low \(\phi\)), customers who only “dabble in the obscure” (low \(\mu\) and high \(\phi\)), and those who occasionally “dabble in what’s hot” (high \(\mu\) and high \(\phi\)).

In the first month of the observation period, we do not have data on the popularity of titles from the previous month. For this month, we model the total number of a customer’s rentals according to a Poisson distribution with rate \(\kappa\). In subsequent months, the number of rentals from bin \(p\) follow a Poisson distribution with rate \(\kappa \cdot C_p\). Thus, the likelihood of observing customer \(h\)’s rental activity from the time he began service \((m=t_{Ah})\) until he canceled service or the observation period ended \((m=t_{Ah}+t_{Rh})\) is given by:

\[
L2(\kappa, \mu, \phi, u | t_{Ah}, t_{Rh}, q_p) = \left( e^{-\kappa \left( \sum_{h \in \Pi} q_{ht_{Ah}} \right)} \right)^{1(t_{t_{Ah}}=1)} \left( \prod_{p=1}^{11} e^{-\kappa \cdot C_p \left( \frac{\kappa \cdot C_p}{q_{ht_{Ah}p}} \right)^{w_{ht_{Ah}p}}} \right)^{1(t_{t_{Ah}}=1)} \left( \prod_{m=t_{Ah}+1}^{t_{t_{Ah}}} \prod_{p=1}^{11} e^{-\kappa \cdot C_p \left( \frac{\kappa \cdot C_p}{q_{ht_{Ah}p}} \right)^{w_{mp}}} \right)^{1(t_{t_{Ah}}<t_{t_{Ah}})}
\]

(9)

where \(1(x)\) is an indicator function equal to 1 if \(x\) is true and 0 otherwise. The first two terms account for rental activity in the customer’s first month of service (depending on if they started in the first month of the observation period or later) and the final term accounts for rental activity in subsequent months of service. The joint customer-level likelihood is then given by the product of equations (6) and (9).

**Incorporating Correlation and Unobserved Heterogeneity via Latent Classes.** The model presented in equations (1) through (9) assumes that the acquisition, retention, and rental processes are the same across customers. To account for unobserved heterogeneity, and consequently correlate the processes across customers, we employ a latent class model with \(S\) unobserved classes (e.g., Kamakura and Russell 1989). This allows us to identify patterns that exist among the different model components, in particular the retention process and the popularity profile. Letting \(\pi_s\) denote the probability that customer \(h\) is in class \(s\), the resulting
unconditional likelihood is given by:

\[ L(\lambda, c, \gamma, d, \beta, \kappa, \mu, \phi, v \mid t_{th}, t_{Rh}, q_{h}, \text{Promo}, \text{Censor}_h) = \sum_{s=1}^{S} \pi_s L(\lambda_s, c_s, \gamma_s, d_s, \beta_s \mid t_{th}, t_{Rh}, \text{Promo}, \text{Censor}_h) L(\kappa_s, \mu_s, q_s, v_s \mid t_{th}, t_{Rh}, q_{h'}) \] (10)

**EMPIRICAL ANALYSIS**

We estimate the model described in equations (1) through (10) via maximum likelihood in MATLAB. To compare the performance of the models, we examined the log-likelihood and the mean absolute error (MAE) in the rental activity for both the calibration and holdout samples. These measures are presented in Table 2 for the series of models that were estimated.

--- Insert Table 2 ---

While the overall model performance as measured by the log-likelihood continues to improve in both the calibration and holdout samples as we add latent classes, we see that the model with four latent classes does best in predicting rental activity. Rental activity across the different bins is a key metric for our focal content aggregator because it (as we discussed) is directly related to the service provider’s profitability. We therefore present detailed results and demonstrate the applicability of the proposed modeling framework using the four-class model.

In Figure 2, we illustrate the performance of the four-class model along a number of dimensions. Figure 2a displays the estimated acquisition and retention behavior as well as the observed behavior in the calibration and holdout samples. Figure 2b reflects the actual and estimated amount of rental activity, in the aggregate and for three selected bins.

--- Insert Figure 2 ---

As we see, the model captures the general trend in the acquisition and retention processes, as well as the rental activity. We next discuss how these behaviors differ across the latent classes.

**Model Results.** Table 3 reports the parameter estimates for each of the classes, which
are ordered in terms of an increasing expected number of rentals each month. While the first three classes comprise a substantial fraction of the customers – 30%, 42%, and 22%, respectively – the fourth class accounts for just 6% of the customers. The classes vary in their choices of titles across the popularity bins, as well as in their acquisition and retention activity.

--- Insert Table 3 ---

**Assortment Usage.** The estimates of $\kappa$ show that customers differ in the number of titles they are expected to rent each month. Customers in Class 1 are expected to rent an average of 1.5 titles per month (“low frequency”), customers in Class 2 and Class 3 are expected to rent 5.2 titles per month (“moderate frequency”), and customers in Class 4 rent 14.4 titles per month (“high frequency”).

We also observe differences in how customers’ rentals are distributed across the popularity bins. Using the parameter estimates for $\mu$, $\phi$, and $\nu$, which reflect the mean of the popularity profile, polarization of the popularity profile, and probability of renting a new title, respectively, we illustrate each class’ distribution of rental activity across the bins in Figure 3.

--- Insert Figure 3 ---

The estimates for $\mu$ reflect that customers in Class 1 and Class 2 exhibit a higher tendency to rent popular titles (i.e., those in the lower bins in Figure 3) than customers in Class 3 or Class 4, who appear to lean toward unpopular titles. Put differently, customers in Class 1 and Class 2 exhibit a stronger preference for “what’s hot” than those in Class 3 and 4. Based on the estimates for $\nu$, it appears that Class 2 customers have the highest probability of renting new titles, while Class 3 customers have the lowest. The estimates for $\phi$ reveal that each class has a considerable degree of variation in its popularity profiles (as is also clear from Figure 3): a fraction of Class 1 and Class 2’s rental activity takes place in the less popular bins “in the tail,” while a fraction of Class
3 and 4’s rentals come from the bins with the popular titles. Specifically, 24% of rentals made by customers in Class 1 and 13% of rentals by customers in Class 2 are expected to be from the three least popular deciles, while 15% of rentals made customers in Class 3 and 12% of rentals by customers in Class 4 are expected to be from the three most popular deciles.

We do not find evidence for the existence of a class of customers who exclusively prefer offerings from the most popular bins, which is intuitive given the low number of titles in these bins and the profile of our focal firm. While those consumers who are solely attracted to hit titles may choose to never become customers, our findings also do not point to there being a class of customers who only prefer obscure offerings. Rather, as the popularity profiles reflect, all customers exhibit some degree of variation in the popularity of the offerings they choose—customers do not appear keen to break free from what Anderson (2006) erroneously terms the “tyranny of the hit.” In fact, our findings are extremely consistent with the “natural monopoly” phenomenon (McPhee 1963) in which light consumers (“low frequency” customers in Class 1) primarily choose popular products in the head of the distribution and heavy consumers (“high frequency” customers in Class 4) choose a larger proportion of products from the tail. That is, the quantity customers rent each month is positively related to their tendency to choose unpopular products.

**Acquisition Process.** The estimated values of \( \log(\lambda) \) and \( \log(c) \) capture the scale and shape of the acquisition processes. The results indicate that all four classes demonstrate positive duration dependence (\( \log(c)>0 \)), meaning that the probability of customers starting the service goes up over the study period. We illustrate the probability of acquiring service over the course of the observation period, given that a customer has done so by the end of the observation period and given the class to which he belongs, in Figure 4a.
The estimated values for log($\lambda$) and log($c$) differ sharply across the four latent classes, which indicates there is considerable variation in the time at which customers from different latent classes will begin service. We see that the customers in Class 1 are most prone to acquiring service early in the observation period, whereas customers in Class 2 and, particularly, Class 3 appear more likely to begin service later in the observation period. The heavy renters in Class 4, in contrast, are most likely to begin service in the middle of the observation period.

**Retention Process.** To see how customers in the latent classes differ in their value to the service provider, we next turn to the retention process – the duration for which customers maintain their subscriptions. The estimates of log($\gamma$) and log($d$) capture the scale and shape of the process. While the acquisition process was marked by positive duration dependence, the class-specific retention processes reveal negative duration dependence (log($d$)<0) and hence customers become less likely to end their subscription the longer they have maintained service. In contrast to previous research that has found decreasing churn rates at the aggregate level to be explained by a “sorting effect” in which customers with high churn rates drop service faster and only customers with low churn rates remain (e.g., Fader and Hardie 2007, 2009a), we see that customers in each latent class become more likely to retain service as their tenure increases. As we would expect, the introductory promotional activity in which the company engages reduces the likelihood that customers will cancel service ($\beta$<0).

We present the probabilities that customers in each of the four classes will maintain service in Figure 4b.

We see that the survival curves for the four latent classes become flatter as more time passes,
indicative of the finding of negative duration dependence in the retention process. Customers in Class 4, who have a higher usage frequency and preference for unpopular offerings, are more likely to maintain service than customers in the remaining three latent classes. Interestingly, customers in Class 2 and, to a lesser extent, Class 1, who both rent fewer titles per month and focus on more popular offerings, are most likely to end their relationship with the service provider. Customers in Class 3 appear prone to dropping service early on, but they become much less likely to end service the longer that they have maintained service.

From the survival probabilities, we can estimate the discounted expected tenure of customers from the time at which they begin service (also see Fader and Hardie, 2009b). The class-specific discounted expected tenure is given by:

\[
DET_s = \sum_{t=0}^{\infty} \delta^t S_p(t | \tilde{a}, d, \beta, Promo)
\]

where \(\delta\) is a discount rate that we assume is equal to 15% annually. The discounted expected tenures of customers in the four classes are as follows:

- Class 1 (low usage frequency, focus on popular titles): 11.6 months
- Class 2 (moderate usage frequency, focus on popular titles): 7.4 months
- Class 3 (moderate usage frequency, focus on unpopular titles): 13.7 months
- Class 4 (high usage frequency, focus on unpopular titles): 23.5 months

Two main dimensions appear to underlie the results: first, the higher the usage frequency, and, second, the stronger the focus on unpopular titles, the longer is generally the expected tenure. Customers’ tendency to venture into the long tail of offerings matters greatly: across the four classes, the DET is greatest among customers who concentrate their rental activity on unpopular products.

The sizable difference in discounted expected tenures for Classes 2 and 3 is particularly
noteworthy, as both classes tend to acquire service later in the observation period and are expected to rent the same number of titles each month – but primarily differ in their popularity profiles. An increased focus on less popular offerings appears linked to a higher discounted expected tenure. The direction of the result may come as a surprise – the “double jeopardy” empirical generalization would predict that obscure offerings are generally appreciated less. We think the findings point to this (smaller) group of customers better fitting the model of the online aggregator with a vast assortment. For consumers primarily interested in hit products there are ample opportunities to satisfy their needs online and offline, whereas leading online aggregators such as Quickflix are often the only option for consumers with an interest in obscure products, leading these customers to remain subscribers longer. Put differently, service providers seeking to differentiate themselves through a large assortment will ultimately find this strategy works best with those customers who regularly venture into the tail.7

Cancellation Risk and Discounted Expected Remaining Lifetime. While it is interesting to learn that customers’ discounted expected tenures differ across the latent classes, in practice, the firm will not be able to conclusively say to which class a customer belongs. What, then, is a service provider seeking to make appropriate investments in its customer base to do? Using Bayes’ rule, the firm can update its belief as to which class a customer belongs based on the information available to date. At the time of service acquisition, the only information available to the service provider is the month in which service was acquired. In subsequent months, rental activity (both the total number of rentals each month and how these rentals are

---

7 The idea is analogous to Hoch, Bradlow and Wansink’s (1999) view of the variety of an assortment as a means of cultivating store choice. Another explanation for the finding that customers who focus on popular products tend to have shorter discounted expected tenures could be that they simply run out of options, i.e., that there are only so many hit products to satisfy them and once those are consumed, they cancel service. However, the sheer size of Quickflix’s library, and the fact that in our definition popular products are not a select group of new releases but encompass hundreds of titles, makes it unlikely that our results can be fully explained by the notion of customers “exhausting” viable options.
distributed across the popularity bins) as well as the duration for which service has been maintained can be used to update the firm’s belief as to which class a customer belongs – and thereby to calculate managerially relevant metrics such as how likely it is that the customer will cancel service by the next month and how long the customer is expected to retain service.

The posterior probability of customer $h$ being in class $s$ at time $t$ is denoted by:

$$
\pi^*_s(t) = \frac{\pi_s L_1 (\lambda_s, c_s, y_s, d_s, \beta_s | t_{Ah}, t, Promo, Censor_h) L_2 (\kappa_s, \mu_s, q_s, v_s | t_{Ah}, t, q_h)}{\sum_{s'=1}^S \pi_{s'} L_1 (\lambda_{s'}, c_{s'}, y_{s'}, d_{s'}, \beta_{s'} | t_{Ah}, t, Promo, Censor_h) L_2 (\kappa_{s'}, \mu_{s'}, q_{s'}, v_{s'} | t_{Ah}, t, q_h)}
$$

(12)

where $L_1$ and $L_2$ are given in equations (6) and (9), respectively. Using the posterior probability, it is straightforward to derive the probability that customer $h$ will cancel service next month given that he has not yet done so as:

$$
Pr(\text{cancel service after month } t) = \sum_{s=1}^S \pi^*_s(t) \left(1 - \frac{S_R(t+1 | t_{Ah}, \bar{a}, d_s, \beta_s, \text{Promo})}{S_R(t | t_{Ah}, \bar{a}, d_s, \beta_s, \text{Promo})}\right)
$$

(13)

A customer’s class-specific discounted expected remaining lifetime (DERL) can be derived in a similar fashion to the class-specific discounted expected tenure in equation (11) by summing the product of the survival function conditional on having maintained service until the current month and a discount factor, over time. Incorporating the posterior probability of class membership, at time $t$, a customer’s DERL can be expressed as:

$$
\text{DERL}(t) = \sum_{s=1}^S \pi^*_s(t) \sum_{i=t}^{\infty} \delta^{i-t} \frac{S_R(i | t_{Ah}, \bar{a}, d_s, \beta_s, \text{Promo})}{S_R(t | t_{Ah}, \bar{a}, d_s, \beta_s, \text{Promo})}
$$

(14)

where the inner summation calculates the class-specific DERL conditional on the customer having retained service through month $t$.

To illustrate the managerial usefulness of our framework and these metrics, we considered a set of hypothetical customers who all began service one year into our observation
period (t=13) and who rent five DVDs per month. We considered six different rental behaviors by varying the number of titles from the most popular bin and the least popular bin. That is, we considered a hypothetical customer who rented all five titles from the most popular bin, another who rented four titles from the most popular bin and one from the least popular bin, one who rented three titles from the most popular bin and two from the least popular bin, and so forth, with the final hypothetical customer renting all five titles from the least popular bin.

We illustrate the cancellation risk and DERL from the time at which the hypothetical customers begin service, assuming that service is maintained until that point in time, in Figure 5, which presents the predictions for the customer who chooses only popular titles (labeled “All Popular”), the customer who chooses two popular titles and three unpopular titles (“Mixed”), and the customer who chooses only unpopular titles (“All Unpopular”).

--- Insert Figure 5 ---

First examining customers’ cancellation risks, we see that all three hypothetical customers have the same cancellation risk when they first begin service, as they start service at the same time. We see an initial increase in the likelihood of canceling service after the first month, attributable to the end of the introductory promotional activity. The observed increase is smallest for the customer who chooses all unpopular titles and largest for the customer who has rented only popular titles. After the first month, there is a difference in the cancellation risk of nearly 40% – remarkable, given that the customers solely differ in the popularity of their choices. The cancellation probability subsequently declines the longer that service is maintained, with the customer choosing all unpopular titles continuing to have the lowest cancellation risk.

A similar pattern emerges for the customers’ DERLs. The three depicted customers all have the same DERL when they begin service. However, the difference in the popularity of the
titles they choose to rent quickly sets the customers apart. The customers who primarily or exclusively rent popular titles initially exhibit a decreasing DERL, because the end of the introductory period leads to a sudden increase in the likelihood that a customer cancels service. As these customers continue to maintain service, their DERLs increase. The customer renting only unpopular titles also exhibits an increasing DERL, but does not display the initial decrease.

As these scenarios reveal, customers who rent varying sets of popular and unpopular titles (which reveal their popularity profiles and class membership) have different remaining values to the service provider and are at different risks for canceling service – critical information for service providers seeking to optimize marketing investments.

**CONCLUSION**

By means of a summary, Figure 6 visually depicts our main substantive findings. It is organized along three key dimensions – the customer’s usage frequency, the primary focus in the customer’s popularity profile (popular vs. unpopular products), and the customer’s discounted expected tenure (long versus short) – on which the four latent classes differ.

--- Insert Figure 6 ---

Two findings on the way in which customers use large assortments stand out. First, the largest class of customers primarily prefers popular releases, while the smallest but, as measured by the frequency of usage, also the heaviest class of customers is more inclined to consume unpopular products. Second, contrary to the “micro-culture era” that long-tail-theory proponents envision (Anderson 2006), customers who exclusively prefer unpopular offerings are notably absent from our findings. We find no support for the existence of long-tail-only customers who choose to forego offerings from the relatively small pool of hit products. Rather, each class of customers consumes hit products; some simply do so with a higher frequency than others.
When it comes to the relationship between customers’ usage of assortments and their discounted expected tenure, two key findings emerge. First, the frequency with which customers use the assortment is positively related to the duration of their relationship with the service provider: the higher the frequency of consumption, the longer the customer’s expected tenure. Second, critically, the tendency to choose obscure products is positively associated with the duration of the service relationship, above and beyond usage frequency. This is most evident in our results for the two latent classes with moderate usage which together comprise approximately two-thirds of customers: the class that has a stronger focus on unpopular titles registers a markedly higher discounted expected tenure. It also emerges as a key finding in the hypothetical scenarios we consider in which customers only differ in the mix of popular and unpopular titles they choose: different mixes yield varying estimates of retention probabilities and remaining value. Consequently, even early information about a customer’s preference for popular and unpopular titles may offer a firm useful guidance as to how much to invest in a customer relationship.

Managerial Implications. Our research has important implications for online content aggregators seeking to invest in broadening or deepening their assortment. First, because customers who are disproportionately active “in the tail” tend to consume with the highest frequency and are least likely to cancel service, they are the most valuable to the service provider. Aggregators seeking to cater to these customers can likely benefit from broadening their assortment. While many bricks-and-mortar retailers nowadays appear to be adopting a “less is more” approach (e.g., The Wall Street Journal 2009), offering a broad assortment can be a strong advantage for online aggregators, as long as they closely monitor the costs of offering products that are rarely consumed, and as long as the pursuit of niche products does not come at
the expense of acquiring the hit titles.

This last point is crucial, as hit products are desired by all segments of the customer base. Because the majority of customers is primarily attracted to popular products (and all other consumers regularly consume such products), second, aggregators should not undercut the prominence of their most popular products. As obscure products tend to have higher margins, it is tempting for content aggregators to lead consumers “into the long tail,” for instance by using recommendation engines, but doing so comes at a risk of alienating the largest group of customers that has a greater affinity for more popular offerings. Finding a good balance in providing and promoting unpopular versus popular products therefore is key for content aggregators. The value of popular products as loss leaders designed to attract patronage in traditional channels likely carries over into digital channels (also see Elberse 2008).

It is well known that the early stage of the customer-firm relationship is often critical in service settings (e.g., Bolton 1998), and our study confirms that customers become considerably less prone to dropping service over time. Our research demonstrates how information on customers’ usage of the available assortment can be employed to update beliefs of those customers’ remaining value to the company and their likelihood of ending service. Thus, as a third implication, we suggest content aggregators track and utilize each of their customers’ selection of popular and unpopular titles to reveal their popularity profiles and aid in the service provider’s decision-making. Unlike satisfaction and other perceptual measures obtained from surveys, such measures are available from internal data and is relatively easy to compile from usage patterns that most online businesses already monitor on an ongoing basis. By assessing how their customers choose from the available assortment and updating their expectations of customer value and defection risk, service providers can match their investments (e.g., when it
comes to extending promotional offers or handling complaints) to projected future revenue streams.

**Future Research.** We hope our manuscript stimulates further research on the relationship between how customers use assortments and their ultimate value to the firm. We think three areas will be especially fruitful. First, future research could specifically investigate the impact of acquiring unique titles and additional copies of those titles on the value of the current and future customer base, using the customer-level metrics we introduced in this study. Possible extensions of such a study are to investigate how popularity profiles vary by geographic area (so as to determine how titles are to be allocated across distribution centers) and by the way in which customers were acquired (so marketing activity can be further customized). Another extension would be to consider the usefulness of early indicators of such profiles, for example the “queues” of desired titles that customers of DVD-rental businesses compile when they first sign up for service. Second, future research could incorporate the precise costs associated with serving customers, and for instance take into account that exceedingly high usage levels within a given subscription plan may undercut a customer’s value to the firm. Third, building on the idea that online businesses’ vast assortments may better meet the needs of customers who prefer unpopular products, future research could compare popularity profiles of customers of online and offline businesses (e.g., Netflix vs. Blockbuster or Redbox), so as to better understand how each can use its library to differentiate itself. Fourth and finally, as with any study on one firm and one industry, it seems worthwhile to explore the external validity of our results by examining other settings beyond DVD rentals or entertainment goods.
### Table 1. Descriptive Statistics

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<tr>
<th>Statistic</th>
<th>Mean</th>
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<tr>
<td>Total rentals</td>
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<tr>
<td>Rentals per month of service</td>
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</table>

Note: The table reports descriptive statistics for the data used in the study.

### Table 2. Model Summary

<table>
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<th>Number of Latent Classes</th>
<th>Calibration Log-Likelihood</th>
<th>Holdout Log-Likelihood</th>
<th>Rental Activity MAE (Calibration)</th>
<th>Rental Activity MAE (Holdout)</th>
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Note: The table presents the performance of the model captured in equations (1) through (10), as measured by the log-likelihood and mean absolute error in rental activity. Model performance in terms of the log-likelihood continues to improve as additional latent classes are incorporated, but predictions of rental activity suffer as the fifth latent class is added. We therefore opt to report model estimates for four latent classes.
Table 3. Parameter Estimates

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<th>Class 2</th>
<th>Class 3</th>
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<td><strong>Class Size</strong></td>
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<td>Size of class</td>
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</table>

Note: The table reports estimates and corresponding standard errors for the parameters in the model described by equations (1)-(10). The small standard errors result in part from the magnitude of the log-likelihood, as small perturbations in estimates result in large changes to the log-likelihood.
Figure 1. Distribution of Rentals across Titles

Note: The figure displays the distribution of rental activity across Quickflix’s assortment of titles for one arbitrary month in the study period, December 2007: 23% of titles account for 10% of all rentals in this month, 68 titles account for 20% of all rentals in this month, and so on.
Figure 2a. Model Performance: Acquisition and Retention Processes

Note: The figure displays estimated and actual proportion of customers acquiring the service (left) and the proportion of remaining customers dropping service (right).

Figure 2b. Model Performance: Rental Activity

Note: The figure displays the estimated and actual number of rentals from all bins (top left), the most popular bin (top right), the least popular bin (bottom left), and the bin of new titles (bottom right).
Figure 3. “Popularity Profiles” by Class

Note: The figure presents “popularity profiles” for each of the four classes. Each popularity profile describes how customers’ rentals are distributed across the eleven bins, consisting of ten bins for each of the activity-based deciles and one bin for titles without a rental history. For instance, the figure shows that the highest proportion of titles rented by customers in Class 1 and Class 2 are the most popular titles, while customers in Class 3 and Class 4 rent a larger fraction of unpopular titles.
Figure 4a. Service Acquisition Probability, by Class

Note: The figure displays the estimated probability that customers in each of the four classes acquire service in a given month in the observation period, given that they have done so by the end of the period.

Figure 4b. Service Retention Probability, By Class

Note: The figure displays the estimated probability that customers in each of the four classes retain service in a given month in the observation period.
Figure 5a. Updated Beliefs: Cancellation Risk

Note: The figure depicts the probability that the hypothetical customers will cancel service in the upcoming month. The three depicted customers begin service one year into our observation period and rent five DVDs per month, but differ in the popularity of the titles they choose.

Figure 5b. Updated Beliefs: Discounted Expected Remaining Lifetime

Note: The figure shows the three hypothetical customers’ discounted expected remaining lifetimes, given that they have maintained service to date.
Figure 6. Schematic Overview of Main Findings

Note: The figure summarizes the main substantive findings regarding the four latent classes in our data along three dimensions: usage frequency, main tendency in the popularity profile, and discounted expected tenure.
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