



The consumer's rent vs. buy decision in the rentailer

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ABSTRACT

In this paper, we focus on the perspective and business model of the rentailer – a retail outlet that rents and sells new and used home video titles. This requires predicting the consumer's decision to rent or buy a particular title, segmenting its customer base, and pricing new and used titles. We develop a new model based on a simple heuristic found in the behavioral marketing literature of how people predict their own usage of a service. We estimate the model using a unique panel dataset obtained from a large rentailer, and find it provides a good fit to the data. Using the model estimates we obtain a metric indicating a latent customer tendency to buy at full price (compared to buying at a lower price or renting). Other diagnostic information from the model may help convert renters into buyers. First, expected viewing may be pitched to the consumer in order to persuade consumers that the movie will be well utilized. Secondly, we use the model to generate customized new and used title prices.

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1. Introduction

There has been a growing interest in research and modeling issues related to the entertainment industry in general and the movie industry in particular (see Eliashberg, Elberse, & Leenders, 2006 for a recent review). Much less research has been conducted on home video entertainment, and in particular, the managerial decision-making in this context.

A combination of factors such as the rapid adoption of DVD players (76% penetration in the U.S. by the end of 2006 and 70% penetration in Western Europe by the end of 2007), the number of titles available to consumers (estimated to be over 75,000), and the decreasing prices of DVDs have made the home video market grow quickly over the past ten years (Entertainment Merchant Association [EMA], 2006; International Video Foundation [IVF], 2008). An increase in the number of home video retail outlets, as well as the options they offer to the consumer, is another key growth factor.

Home video outlets can be classified into two different types – sell-through retailers and rentailers. Rentailers are retail outlets whose main business comes from rentals. Retailers and rentailers share a total home video business in the U.S. estimated in 2006 as \$24.9 billion: \$16.5 B in buying and \$8.4 B in rental (EMA, 2006).² In

addition to buying new titles, increasingly consumers have the option of buying previously viewed (used) titles, which are usually marked at a substantial discount. Interestingly, the consumer spending on buying DVDs includes an estimate of spending on previously viewed titles of \$1.1 B (EMA, 2006). The types and shares of the various home video outlets for sell-through retailers include: mass merchants (50% of the business), video specialists (12%), consumer electronics stores (9%), online sellers (9%), direct mail companies such as Columbia House (7%), and supermarkets (4%). For rentailers, the types and shares include: major chains such as Blockbuster, Hollywood Entertainment, and Movie Gallery (43%), independently owned video stores (39%), pure online subscription rentailers (16%), and supermarkets (2%) (Adams Media Research, 2005).

New emerging technologies and content distribution outlets present challenges to the future growth of the traditional home video retailing market. One recent example is the Vudu box, which sits on top of a TV and can access over 10,000 titles from the internet on demand for both rental and purchase. Consequently, retailers and rentailers have been experimenting with various business models, trying to sustain their future business. For example, Walmart, the largest seller of DVDs in the U.S., discontinued its policy of renting videos online through its downloading service in what was widely perceived as a failed experiment (Richtel & Stone, 2008). Meanwhile, Apple, which has made movies available for purchase online through its iTunes store since 2006, decided to give customers the option to rent in January 2008. Thus, some of the business models focus only on consumer rentals, others focus solely on consumers buying only new DVDs or on consumers buying new DVDs and previously viewed titles (PVTs), and yet others are trying to capitalize on both the rent and buy opportunities. Some operate

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² The 2007 total home video spending in Europe is estimated at €11.5 B, with €9.6 B spent on purchasing and €1.9 B spent on renting (IVF, 2008).

only online, while others operate both online and offline. Netflix, for instance, represents a renter operating a DVD online rental service, with 6 million subscribers who create their movie wish list (from a library of 75,000 titles), receive the DVDs from the list by mail, return the viewed movies by mail, and then receive the next title on their list. Netflix has begun offering the option to purchase PVTs to its subscribers. Columbia House's DVD Club represents the sell-through only business model. It offers 5 DVDs for \$0.49 each for consumers who join the club and who then become obligated to buy 5 more DVDs within the next 2 years, at regular club prices. Blockbuster represents the "rent and buy" business model with both "brick and click" presence. On its web site, the subscriber can find a rental service very similar to that of Netflix, while at the same time, the consumer can purchase the same title as well as PVTs. See Table 1 for more examples.

There are broader implications to the study of renters in the home video market. Videos are a type of information good, such as books, music, and software (Varian, 2000).³ Since these goods can be copied, shared, resold, and rented, there exists an increasing array of options for consumers to access them. A key feature shared by these examples is that the chosen option critically depends on the customer's estimate of future utilization. There has been growing interest in economics and marketing (e.g., Nunes, 2000; Della Vigna & Malmendier, 2006) in understanding usage expectations when confronted between a flat-fee option for unlimited use and a pay-per-use option. This feature is central to many managerial and retailer related issues such as supply-side contracting (Mortimer 2008), pricing and sharing (Varian, 2000), and inventory management (Dana & Spier, 2001; Cachon & Lariviere, 2005). Our focus is on optimal pricing and customer segmentation for a renter that rents and sells both new and previously viewed titles. While our results are specific to the home video market, our methods may be applicable to renters of other information goods.

While conventional wisdom as well as some industry-based anecdotal evidence concerning consumer behavior in the home video outlet exists, to our knowledge this area has received scant attention from marketing scholars. Statements from the industry include, for example, the observation from the former president of Sony Home Entertainment that some consumers are "collectors," while others are merely "watchers" (Gertner, 2004). According to the EMA U.S. survey (2006), the average "active" DVD household purchased 18 DVDs and rented 23 DVDs in that year, and the average household owns more than 40 DVD movies. There has also been an attempt to profile buyers/renters based on technographics (Video Software Dealers Association, 2005). Wedel and Kamakura (2002) note that in industries where customer retention is a primary goal, segmentation "has become very effective so that firms can identify, profile, target and reach segments using their own customer transaction databases" (pg 181). We propose here more rigorous metrics based on transaction data that can assist in segmenting customers as collectors and watchers.

We assume that, similar to book buyers who head to bookstores with a purpose, a key characteristic of consumer behavior at the renter is that the customer walks into the renter knowing he or she will come out with a movie, either rented or purchased (Random House/Zogby International, 2008). Hence, for most, if not all of the renter's customers, the option of leaving the renter empty-handed is not viable. From a title selection standpoint, we assume that the decision as to which movie to watch can be either planned or opportunistic (Bucklin & Lattin, 1991), with the decision made either before entering or once in the store. In terms of the transaction decision (rent vs. buy), we assume that the decision is opportunistic, i.e., the consumer decides in the store whether to rent or buy it. For example, a customer may enter the store intending to rent one movie,

Table 1
Taxonomy of video retailer business models.

Retailer	Sell-through	Rental	On/off-line
Vudu	Y	Y	On
Amazon	Y	Y	On
Columbia House	Y	N	On
Movielink	Y	N	On
CinemaNow	Y	N	On
Wal-Mart	Y	N	On/off
Netflix	Y	Y	On
QwikFliks	N	Y	On
Blockbuster	Y	Y	On/off
Movie Gallery	Y	Y	On/off
The Video Station	Y	Y	On/off
Apple iTunes	Y	Y	On

and may change his or her mind if the store carries the specific title in PVT format, or if the store has available another new title at an attractive price. One main reason why it is likely to be opportunistic is that the consumer does not know with certainty when (if ever) the title will be available as a PVT and at what price. Hence, for consumers interested in a certain title, waiting for a title to be offered at a PVT price at some point in the future is not a viable option. On the other hand, if the consumer is informed while in the store that a PVT version of the title happens to be available, buying it is then a viable option.

In this paper we take the renter's perspective. To manage the video outlet effectively, management needs to understand its customer (subscriber) behavior. More specifically, segmenting the customer base, targeting individual customers, pitching expected utilization that the renter may feel is relevant to a particular consumer ("I believe that you will watch this title at least 10 times"), and pricing accordingly are decisions of highest importance in managing the renter effectively. In contrast to the research on information goods, in this paper we adopt an empirical micro-level modeling approach assisting managers in making these decisions. Using a unique panel dataset of individual-level transactions for customers at a home video outlet, we first descriptively develop a metric that can be used to rank customers depending on their inherent tendency to buy, relate movie buyability to several covariates, and estimate expected viewing for each individual-movie transaction. Secondly, we normatively illustrate how the renter manager should customize price, for both new and PVT (if available) titles, in order to maximize expected transaction profit.

We also report several empirical findings that contribute to the literature on the entertainment and home video industries. The data obtained reveal that buying is a relatively rare but profitable event for the renter. The model estimates imply that individual differences, rather than title differences, explain the majority of variation in the rent vs. buy decision. Hence, it may make more sense for the renter to emphasize customer, rather than movie, segmentation. Nevertheless, certain observable movie attributes, such as whether the movie is of the action genre or is rated R, are significant predictors of whether a title will be rented or bought. Customers in our data have the option to purchase in advance a set of rentals and are given quantity discounts on the rental price depending on how many they purchase in advance. Interestingly, we find that customers who self-select into the lowest-costing rental price plan are more intrinsic buyers rather than renters.

Our research objectives – understanding local home video subscriber behavior, segmenting customers, and pricing accordingly – are in line with previous research that has addressed the unique managerial problems of a particular theatrical location showing movies (Swami, Eliashberg, & Weinberg, 1999; Eliashberg, Swami, Weinberg, & Wierenga, 2001; Eliashberg et al., in press). Hence, the results reported in this paper are limited in their generalizability, but they are applicable to the sub-population of renters and their clientele that are similar to the focal renter we analyze in this paper.

³ Roehl and Varian (2001) present many interesting parallels in the historical development between the home video market and the growth of profit-seeking rental libraries in Britain from 1725–1850.

The paper is organized as follows. In [Section 2](#) we review the relevant literature on the home video industry and behavioral models of customer choice between flat-fee and pay-per-use options. [Section 3](#) describes the context and the model. In [Section 4](#) we describe the data employed to estimate the model. The empirical results and the managerial implications are provided in [Section 5](#). [Section 6](#) summarizes the work and provides suggestions for future research.

2. Relevant literature

There are three different sets of literature relevant to our research and to which we contribute.

2.1. Managing the video rental retailer within the supply chain

A number of theoretical models which address the home video retailer and its pricing and inventory decisions under vertical contracts have been developed. [Dana and Spier \(2001\)](#), [Cachon and Lariviere \(2005\)](#) and [Gerchak, Cho, and Ray \(2006\)](#) all focus on the effect of different contracts with the distributor (e.g., revenue sharing) on the store's shelf-space management and the overall supply chain performance. For example, [Cachon and Lariviere \(2005\)](#) consider a rental-only video retailer, and find that revenue-sharing contracts, where the retailer agrees to pay the supplier a portion of the rental revenue, coordinates the supply chain so that double marginalization is avoided (i.e., the retailer chooses the optimal price and quantity levels for both retailer and distributor). This finding mirrors the experience of Blockbuster, the largest video retailer in the U.S., which was able to increase availability of titles by striking revenue-sharing contracts with suppliers beginning in 1998. We revisit this issue in the context of the customized pricing illustration.

2.2. Models of consumer demand to address home video distributor strategies

There are a few papers that investigate empirically the effects of home video distributor strategies on retailer performance. [Mortimer \(2008\)](#) empirically evaluates the effects of revenue sharing on retailer profits and inventories, while taking into account the selection effect of the contract choice. She finds that both distributor and retailer profits increase by about 10% from revenue sharing. [Mortimer \(2007\)](#) investigates optimal indirect price discrimination for the distributor and welfare effects given U.S. copyright law, which forbids direct price discrimination. She considers buying and renting to be vertically differentiated products, and shows that distributors, in choosing whether to adopt "rental" or sell-through pricing, are in effect choosing whether to use inter-temporal price discrimination to segment high and low value customers.

A key strategic decision on the part of distributors is whether to release a title simultaneously to both rental and sales markets, or to release it sequentially. Before the advent of DVDs, 90% of VHS videos were released sequentially – first to the home video rental market, then to the retail market. In contrast, DVDs are mostly released simultaneously to both rentalers and retailers. Studying these strategic decisions, [Hu, Eliashberg and Raju \(2004\)](#) develop a model of the consumer that incorporates heterogeneity and forward-looking behavior in terms of the number of expected viewings. They find that the optimal release strategy is influenced by both movie characteristics and heterogeneity in consumers' expected number of viewings. The consumer model draws on [Varian \(2000\)](#), who examines whether a firm without the ability to inter-temporally price discriminate should price to sell or rent an information good. Both of these models assume that the consumer is concerned merely with the number of times the good will be used. Another relevant study is [Hui, Eliashberg, and George \(2008\)](#). They focus, however, only on the sell-through market (i.e., the consumer purchasing decision). When a DVD title is

announced prior to actual distribution, consumers often pre-order the title and receive it as soon as it is released. Alternatively, once a title becomes available (i.e., formally released), consumers can purchase it with minimal delay. They develop an individual-level behavioral model that captures the aggregate pre-order/post-release sales of DVDs.

2.3. Consumer choice between a flat-rate and pay-per-use

In general, the decision of whether to buy or rent an asset shares characteristics with a more general set of decisions often encountered in daily life: the decision of whether to pay a flat fee for unlimited consumption or to pay at each time of consumption. Some common examples of firms that offer both flat-rate and pay-per-use options found in the literature include health club membership, online grocery shopping, and telephone calling plans. The goal of this recent literature in economics and marketing is to draw conclusions about the decision process from initial contract choice and subsequent usage. Here, the literature has found a consumer bias for the flat fee in most cases and a bias for the pay-per-use in a few cases ([Lambrecht & Skiera, 2006](#)). [Nunes \(2000\)](#) presents a behavioral study of consumers who use simplified heuristics to estimate usage in the context of online grocery shopping, gym membership, and swimming pool fees. In his model, a consumer estimates a threshold and matches the probability that usage exceeds the threshold with the probability of choosing the flat-fee option. This helps explain why consumers habitually overestimate their usage and choose the flat-fee option. [Della Vigna and Malmendier \(2006\)](#) show that gym members who choose the flat monthly fee end up paying more per visit than the offered per-visit price. They model the consumer as forward-looking, but with time-inconsistent preferences, and examine consumers' sequence of price and usage choices. [Miravete \(2002\)](#) finds a bias toward the pay-per-use option, based on transactional data from a tariff experiment. Another explanation for the flat-fee bias found in the literature is that unlimited consumption includes an option value if consumers are uncertain of their preferences ([Kridel, Lehman, & Weisman, 1993](#)).

Our approach differs substantially from the home video papers cited above in that we directly develop our model at the individual-level and test it with individual-level data. While [Mortimer \(2007\)](#) and [Hu et al. \(2004\)](#) develop individual-level consumer demand models of renting and buying, they do not test them directly. Instead, they derive the implications of such consumer demand models on distributor strategy and use differences in distributor strategy and realized aggregate sales data across movies as evidence for the model. Unlike [Varian \(2000\)](#), but similar to [Hu et al.](#) and [Nunes \(2000\)](#), we consider the expected number of viewings as a key driver of the consumer rent or buy decision.

Second, we differ from the extant literature by focusing on the video retailer and its customers, not on the distributor. This requires that we use a model that can render individual-level buy and rent probabilities. These predictions can help the retailer better understand its customer base as well as its portfolio of movies, and consequently design customized pricing, a scenario we analyze in [Section 5](#).

3. Model development

We first develop the model of renting vs. buying at the individual-level and pay particular attention to the features of this model that make it amenable for addressing our managerial problems. We next discuss the rental price plan model, which allows us to control for selectivity bias in the parameter estimates.

3.1. A model of renting vs. buying based on breakeven watching

We model the rent or buy decision as an in-store, opportunistic decision (see [Bucklin & Lattin, 1991](#)). Our modeling objective is to

provide a predictive yet representational model of the consumer's decision of whether to rent or buy a chosen title. Evidence regarding the amount of pre-orders of DVD titles (Hui et al., 2008) suggests that buyers are not sensitive to future price changes when they make their purchasing decisions. While there may exist a segment of consumers which first rents the DVD and then buys it, our focus here is on modeling the segment (captured in our data) that either rents or buys the title.⁴

Nunes (2000) provides experimental evidence that consumers often form breakeven thresholds of expected usage to simplify the decision of whether to play a flat fee for unlimited consumption or pay-per-usage occasion (e.g., gym memberships). In the proposed model, the consumer is concerned with whether the *anticipated number of times* he or she is likely to watch the movie (N) is above a certain threshold. This threshold is the ratio of the price of buying (defined as K , typically \$20) to the price renting (k , typically \$3.50). If the consumer's anticipated number of viewings is greater than or equal to the threshold, the consumer decision is to buy the title. Otherwise, the decision is to rent it. More formally,

$$\begin{aligned} \text{Buy} & \quad \text{if } N \geq \frac{K}{k} \\ \text{Rent} & \quad \text{if } N < \frac{K}{k} \end{aligned} \quad (1)$$

From the modeler's standpoint, the buy/rent choice is treated probabilistically and N , the number of times up until the final watching of the movie, is a random variable. We therefore estimate the probability that this random variable is greater than the threshold by assigning N a (discrete) probability distribution over the range $(1, 2, \dots)$. We choose the shifted-geometric distribution as a reasonable modeling approximation for parsimony and interpretability. It has only one parameter, p , interpreted as the probability that the next watching is the final one.

The breakeven number is the threshold ratio of purchase price to rental price, which we denote $\tau = \text{floor}[K/k]$. In the empirical application we make p a function of both individual i and movie j characteristics. Using some simple tools from a geometric series we can write (see Appendix A):

$$P_{ij}(\text{Buy} | p_{ij}) = \sum_{x \geq \tau} p_{ij} (1 - p_{ij})^{x-1} = (1 - p_{ij})^{\tau-1}. \quad (2)$$

A high value of p_{ij} implies that the consumer will soon stop watching the video. This naturally makes the probability of buying lower. We use the above model to address managerial issues of critical interest to the renter: segmentation, usage pitching, and pricing. We discuss each issue in turn.

First, we can use the model outlined above to examine whether differences in individuals or differences in titles can explain the majority of variation in the rent vs. buy decision. The answer to this question has implications for whether the renter should emphasize segmenting customers or titles. We allow for the key viewing parameter p_{ij} to be a flexible function of both individual and title characteristics by letting:

$$\text{logit}(p_{ij}) = \beta_j Z_j + e_j, \quad e_j \sim N(0, \sigma_e^2) \quad (3)$$

where Z_j is a column vector ($m \times 1$) including an intercept and a set of observable movie characteristics such as box office gross, critical review score, MPAA rating, genre and distributor information (more information is provided in the data section), β_j is a row vector ($1 \times m$) of customer preferences for these characteristics, and e_j is a zero mean random error, with variance σ_e^2 , that captures the effect of unobserved movie characteristics on anticipated viewing. In particular $\beta_{i,1}$ (i.e., the

intercept) can be interpreted as customer i 's unobserved propensity to rent after controlling for his or her preferences for the various movie characteristics. Once estimated, we use estimates of $\beta_{i,1}$ to segment customers into collectors (intrinsic buyers) with a high reservation price, opportunistic buyers who only buy when the price is low enough, and watchers (intrinsic renters) who expect to watch any movie just a few times.

Second, the expected number of anticipated viewings for a given customer i of a given title j is $\frac{1}{p_{ij}}$. We argue subsequently that this metric can be pitched to the customer in some cases in order to convert a rental into a purchase transaction at the point of sale. Last, we use estimates of p_{ij} to customize prices of both new and PVT titles that maximize profitability in the long-run, taking into consideration that a customer may re-rent a particular movie.

3.2. A model for rental price plan choice

In addition to renting and buying, the renter whose data we have access to offers its customers the option of paying in bulk for a quantity of rentals, with mild quantity discounts given to customers who pay up front for more rentals. Hence, the customer's decision of whether to buy or rent a given title may be dependent on his or her choice of rental price plan. This represents a form of selectivity bias, and we address this issue by simultaneously estimating the rent/buy model outlined in Eqs. (2) and (3) with a model of selecting rental price plans developed below. Following Maddala (1983), we allow the individual-level error terms of these models to be correlated.

There are four rental price plans observed in the data. Let $T_i = \{1, 2, 3, 4\}$ denote the rental plan chosen by customer i .⁵ The four options available to the consumer are: (1) no prepayment, full price, $k = \$3.50$; (2) prepay for 10 rentals, rental price is $k = \$3.00$; (3) prepay for 25 rentals, rental price is $k = \$2.75$; and (4) prepay for 50 rentals, rental price is $k = \$2.50$. The majority of customers (87%) do not choose to buy in bulk, and so pay \$3.50 ($T = 1$).

A natural choice for a statistical model of T_i is an ordinal model, since the prices are not continuous but have a definite ordering from lowest to highest. We follow Congdon's (2003) development of the ordinal logit model in modeling the customer's choice of rental price plan:

$$P(T_i \leq \ell | \theta_\ell, \beta_{i,m+1}) = \frac{e^{\theta_\ell - \beta_{i,m+1}}}{1 + e^{\theta_\ell - \beta_{i,m+1}}} \quad \text{for } \ell = 1, 2, 3. \quad (4)$$

Here θ_λ represents the cut point corresponding to the λ th price plan, $\beta_{i,m+1}$ and represents the unobserved propensity of the consumer to rent in bulk. We need three cut points to identify four possible price plan choices. All other things remaining equal if $\beta_{i,m+1}$ is larger, there is a greater likelihood that the customer will opt for the 50 rental price plan at $k = 2.50$. We take differences of the cumulative distribution function to calculate the probability that a customer will choose one of the four available price plans:

$$\begin{aligned} P(T_i = 1) &= P(T_i \leq 1) \\ P(T_i = k) &= P(T_i \leq k) - P(T_i \leq k - 1) \quad \text{for } k = 2, 3 \\ P(T_i = 4) &= 1 - P(T_i \leq 3) \end{aligned} \quad (5)$$

Following Congdon (2003), to identify the model we fix the first threshold to zero. The other two thresholds are sampled from

$$\begin{aligned} \theta_2 &\sim N(0, \sigma_\theta^2) I(0, \theta_3) \\ \theta_3 &\sim N(0, \sigma_\theta^2) I(\theta_2, \infty) \end{aligned} \quad (6)$$

where $I(x, y)$ indicates that the two estimated threshold are drawn from truncated normal distributions to ensure that $\theta_2 < \theta_3$.

⁴ Our data, described in the next section, cover only a 6 month period, with many movies introduced after the start of the data. Hence we are unlikely to observe multiple transactions with the same title.

⁵ There is no time subscript because there are no rental price plan changes observed in our data.

We allow the customer preferences ($\beta_{i,1:m}$) and propensity to prepay for rentals in bulk ($\beta_{i,1+m}$) to be correlated by using a multivariate normal prior:

$$\beta'_i \sim MVN(\bar{\beta}, \Sigma) \quad (7)$$

where $\bar{\beta}$ is a column vector ($m+1 \times 1$) of mean customer preference coefficients, and Σ is a variance covariance matrix ($m+1 \times m+1$). Of particular interest is the correlation between estimates of the propensity to rent and propensity to prepay for rentals in bulk. On the one hand, customers may substitute away from buying to renting to reflect the relatively lower cost of renting. On the other hand, if the income effect dominates, instead of renting more, the customer may transfer the savings gained from renting at a lower price to buying more.

4. Data and estimation

In this section, we briefly discuss the nature of the data and the hierarchical Bayes procedure used to estimate the parameters.

4.1. Data

The data we use to calibrate the model were provided by a home video renter that operates online as well as offline (six stores in Philadelphia and New York City), rents and sells new and PVT titles, VHS and DVDs, including both theatrical and direct to video titles. In 2002, it was ranked 15th in revenue across the U.S. for specialty stores (exclusively DVD/VHS) according to Video Store Magazine.

Within each store, the renter maintains two separate areas, one for renting, the other for buying. We focus on DVD transactions for two reasons. First, DVDs are priced to sell in the \$10–\$25 region compared to VHS tapes, which can be priced as high as \$100. Because studios are more inclined to adopt sell-through pricing for DVDs than VHS (see Mortimer 2008; Hu et al., 2004), the DVD price makes the option of purchasing more reasonable to the consumer. Secondly, given the scenario we model, both options – renting and buying – have to be available at the same time for the choice to be legitimate. As mentioned earlier, DVDs are most commonly released for rental and purchase markets simultaneously, whereas VHS tapes are more often released sequentially.

The data in our sample come from the renter's largest store, and cover a six-month time period: the last two quarters of 2003. Overall there were over 20,000 titles that were either rented or bought during this time horizon, and over 10,000 customers who either bought or rented these titles. In order to estimate the model, we first reduce the dataset by focusing on a subset of movies and customers.

Two criteria were used in filtering down the list of titles in our dataset. First, we selected the top 100 grossing home video titles that were released over the observation period.⁶ The second criterion was that the movie be available simultaneously for renting and buying at the renter whose data we use. We were able to verify this for 76 of the 100 movies in the sample. Hence, the useable dataset consists of 76 movies that were released over the 6 month time horizon of our data. A list of the movies used in the analysis is provided in Appendix B. The total number of transactions from these 76 movies is over 17,000, which presents some difficulty for model estimation. To reduce the dataset to a more manageable size, we randomly sample half of the transactions. Since we have randomly sampled transactions within the set of 76 movies, one can use estimates from the sample to make inferences about the population of customers who transact at least once with these movies. For example, to make inferences about the distribution of intrinsic renters and buyers in this population, one can draw from the posterior distribution of the population level coefficients (using Eq. (7)). To make inferences about all the customers in the database, including those that

do not transact with the top 76 movies, however, one would need to assume that the distribution of customer preferences is the same for customers who transact with the 76 movies and those who do not. This assumption should be empirically tested before attempting to make such an inference.

The final dataset thus leaves us with a total of 8801 buy or rent transactions of 2018 customers with 76 movies. We present histograms of the number of purchases and rentals across consumers in Fig. 1 ($n=2018$).

The data reveal that a small fraction of customers buy (7%), and the overall proportion of buy transactions in the data is low (3%). A store statistic sometimes cited in the trade literature is the ratio of rented to purchased units. For this renter, the ratio is 34.3. Using some back-of-the-envelope calculations to convert sales figures into units, we estimate the market ratio in 2003 to be approximately 4.5, which suggests that the renter in question had fewer purchases relative to the overall market.⁷ The abundance of rentals to purchased units implies that there exists a sizeable opportunity for the renter of interest to convert many of these rental transactions to purchases.

We supplement our data with a set of nine (i.e., $m=9$) movie covariates (Z_j) collected from IMDB.com and metacritic.com. IMDB.com provides raw data such as box office gross, MPAA rating, genre and distributor information. Metacritic.com aggregates reviews to come up with a 0–100 point scale, the Metascore, which is a weighted average of individual critic scores.

4.2. Model estimation

The limited observations for some individuals and movies in the dataset present an empirical challenge that can be overcome by using a hierarchical Bayes estimation procedure. Two features of our dataset make it amenable to using a hierarchical Bayes estimation procedure. First, our dataset is somewhat sparse. We observe many individuals who never buy and some movies that are never bought. Maximum likelihood estimates of the parameters of interest would likely be driven to the boundary of acceptable parameter values. The hierarchical Bayes estimation allows information to be shared when observations are sparse. The number of observations per individual and movie varies greatly. For individuals, the range is 1–36 observations, with an average of 4.4. For movies, the range is 43–328, with an average of 116. Secondly, a Bayesian approach allows for parameter uncertainty, which may have an important effect on the expected profit from the customized pricing example (Rossi, McCulloch, & Allenby, 1996).

We put slightly informative but vague priors on the parameters of interest in order to ensure proper posteriors, but primarily to let the data govern inferences (similar to Park & Bradlow, 2005). We describe the estimation details and prior values chosen in Appendix C. We employ Monte Carlo sampling from a Markov Chain to obtain marginal parameter inferences (Gelfand & Smith, 1990). Inferences were obtained using the Bayesian inference software, WinBUGS.⁸ Inferences reported for all parameters are based on the draws of two independent chains run for 120,000 iterations each, discarding the first 100,000 iterations as burn-in, from over-dispersed starting values. Convergence of the Markov chains (burn-in) was assessed by making use of the F-test statistic of Gelman and Rubin (1992).

5. Empirical results

We now turn to discussing the empirical findings. We first examine the ability of the model to fit the data. Next, we use insights obtained from the model to discuss differences in buying and renting choices

⁶ The practice of restricting analysis to the top N brands is common in scanner panel data. Zanutto and Bradlow (2000) discuss the effects of such sampling procedures.

⁷ Adams Media Research (2005) reports that \$9.8 B USD was spent on rentals and \$14.4 B USD was spent on purchases. These figures are converted to units by using prices \$3 and \$20 for rental and purchase respectively.

⁸ Available at <http://www.mrc-bsu.cam.ac.uk/bugs>.

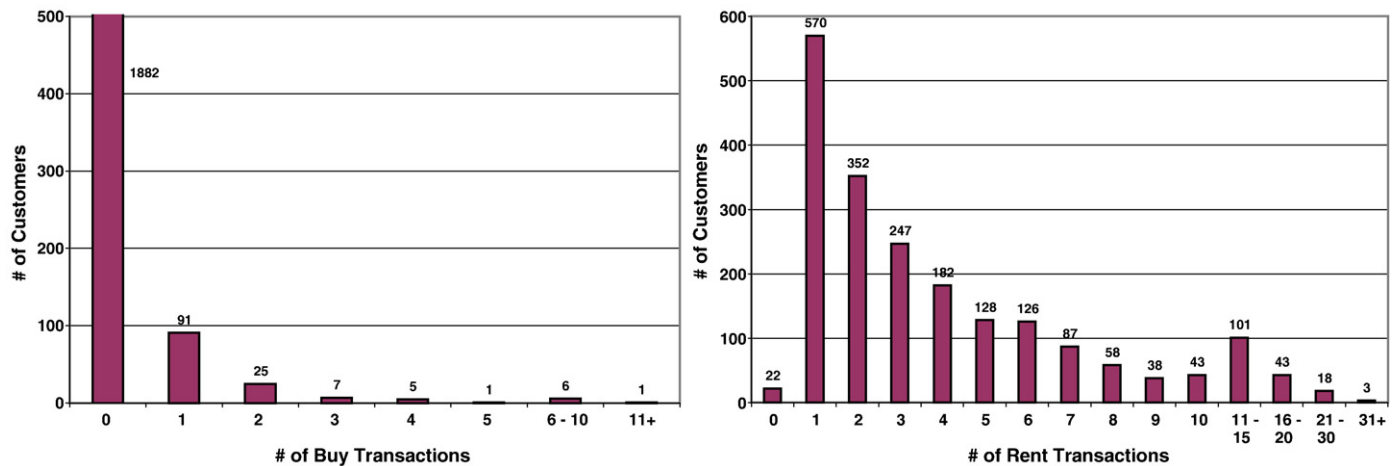


Fig. 1. Histograms of buying and renting in the population (out of 2018 consumers).

across customers and movies. We then examine the managerial applications using the model.

5.1. Model fit and findings

We estimate the model on the full set of 8801 transactions. The log-marginal likelihood, using the importance sampling technique proposed by Newton and Raftery (1994), is -496.8 . The hit rate is 0.36. While this may seem low, recall that buying is a rarely occurring event in the dataset with a base rate of 0.03. The mean absolute error is 2.8%. In summary, the model appears to fit the data well.⁹ We next turn to investigating the model estimates.

We briefly review the implications of the coefficient's sign. For the rent/buy model, a negative coefficient decreases the geometric probability parameter p that the next viewing is the last. Hence, negative coefficients for the covariates imply greater expected viewings. Consequently, a *negative* coefficient for a movie covariate implies that the consumer is *more* likely to buy rather than rent.

Table 2 presents the posterior mean and 95% Bayesian confidence interval of the model parameters. The first set of results display the mean population movie attribute sensitivity coefficients ($\bar{\beta}_1, \dots, \bar{\beta}_9$) and the propensity to rent in bulk ($\bar{\beta}_{10}$). The large value of $\bar{\beta}_1$ indicates that, on average, the shifted-geometric parameter p is large, the anticipated number of viewings (N) is low, and hence, on average customers are more likely to rent rather than buy. The average predicted probability of a purchase transaction is 0.024. This is consistent with the data: the average predicted probability of a purchase transaction in the data is only 0.028. While the preferences for movie attributes are individual-specific, in aggregate movies which are rated R or are a romance have on average less anticipated viewing and hence are more likely to be rented. Action movies have on average more anticipated viewing, and hence are more likely to be bought. Lastly, the negative value of the price plan intercept in the propensity to rent in bulk ($\bar{\beta}_{10}$), together with the positive estimates of the two threshold parameters (θ_2 and θ_3) indicate (as mentioned before) that most customers do not prepay for rentals in bulk.

The next set of results, presented in Table 3, indicates the amount of variation in these preferences for renting vs. buying, prepaying for rental in bulk, and the amount of variation in unexplained movie characteristics. In particular these results relate to the ability of the renter to

⁹ We compare predictive fit to two benchmark models that we do not include due to space limitations. These models assume that utility is stochastically related and decreasing on average over viewings. In the first model, the customer is forward-looking and determines the threshold number of watchings endogenously as the solution to an optimal stopping problem. In the second, the customer is assumed to be myopic. It outperforms these two other benchmark models in out-of-sample validation tests.

segment its customer base. The diagonal elements in the variance covariance matrix ($\Sigma_{k,k}$) are given first. (The posterior mean estimates of the full 10×10 variance covariance matrix are given in Appendix D.) The large variation in individual propensities to rent ($\Sigma_{1,1}$) relative to the variation in movie characteristics (σ_e^2) suggests that unobserved individual differences, rather than movie differences, may explain the majority of variation in the rent vs. buy decision. Hence it may make more sense for the renter to emphasize segmenting customers rather than movies.

Table 3 also shows that there is substantial customer heterogeneity in the propensity to pay for rentals in bulk ($\Sigma_{10,10}$). We note that all the individual-level coefficients are allowed to covary with each other across the population of customers. One correlation of particular interest is that between the individual propensity to rent ($\beta_{i,1}$) and the propensity to prepay ($\beta_{i,10}$). The posterior correlation between these two parameters is -0.41 .¹⁰ This indicates that customers who have a higher propensity to prepay in bulk for rentals are *less* intrinsic renters and more intrinsic buyers. This would lend support to the argument that customers who prepay in bulk for rentals are more serious “collectors,” rather than “watchers,” of movies. This could also be due to a simple income effect, where customers who prepay in bulk hold their amount of renting constant and transfer their savings from renting at a lower price to purchasing more titles. Empirically distinguishing between these two stories would require at least some changes in price plan choices over time.

In the next section, we examine differences across movies in our sample in terms of expected viewings, average buy price, and the number of purchases and rentals. We show that ranking movies based on expected viewings rather than observed statistics yields more insights about the buyability of various titles. Then, we turn to comparing customers. An advantage of the panel data is that we can learn about individual customer sensitivities for different types of movies, as well as propensities to buy or rent after controlling for these observed movie characteristics. This unobserved individual propensity for buying (vs. renting) has implications for whether the customer (in the words of the former president of Sony Home Entertainment) is truly a “collector” (i.e., an intrinsic buyer), merely an opportunistic buyer who purchases only when the price is low, or a “watcher” (intrinsic renter). We explore this issue further below. Secondly, this individual propensity to buy allows the renter to know for a given buy and rent price the likelihood that a particular individual will buy a particular movie (given that the movie has already been selected by the customer). Thus, the renter can customize prices to optimize transaction profit.

¹⁰ The correlation is calculated as $\rho_{1,10} = \frac{\Sigma_{1,10}}{\sqrt{\Sigma_{1,1}}\sqrt{\Sigma_{10,10}}}$.

Table 2

Posterior mean estimates and 95% confidence intervals of population preference coefficients (β_1, \dots, β_9), propensity to prepay for rentals in bulk (β_{10}), and estimated thresholds ($\theta_1, \theta_2, \theta_3$).

Parameter	Posterior mean	95% Posterior interval	
		Lower	Upper
Intercept (β_1)	1.214*	0.748	1.629
Box office gross (β_2)	0.027	-0.242	0.257
MetaCritic (β_3)	-0.255	-0.572	0.004
Rated R (β_4)	0.397*	0.010	0.765
Drama (β_5)	0.232	-0.131	0.744
Action (β_6)	-0.341*	-0.556	-0.033
Thriller (β_7)	0.134	-0.346	0.583
Romance (β_8)	0.480*	0.142	1.261
Major distributor (β_9)	-0.019	-0.207	0.197
Intercept price plan (β_{10})	-2.190*	-2.375	-2.037
Threshold 1 (θ_1) (fixed)	0		
Threshold 2 (θ_2)	0.471*	0.371	0.578
Threshold 3 (θ_3)	1.623*	1.383	1.886

Negative sign for β_1, \dots, β_9 imply more likely to buy (vs. rent); for β_{10} negative sign means less likely to prepay for rentals in bulk. 95% posterior interval excludes zero.

5.2. Classifying movies based on anticipated viewing

We compare movies by ranking them based on the posterior mean anticipated viewings, $E[N_j]$, averaged across all rent and buy transactions with that movie. In Table 4, we present the top and bottom five movies. Since the average masks some of the variability in anticipated viewings, we present the upper 97.5 percentile across the transactions (the lower 2.5 percentile is the lower bound of the distribution for $N, 1$). Additionally, we display the number of rentals, purchases, and the average purchase price in our sample of 76 titles. *Quiet American* has the greatest average anticipated viewings of the movies considered in the dataset at 3.36. The distribution of anticipated viewings for this movie has a longer tail. The customers who value this movie most anticipate watching it more than 10 times.

As one moves further down the table, average anticipated viewing rapidly decreases to slightly above one. Movies at the top of the list, such as *Lord of the Rings* and *Catch Me If You Can*, are expected to be watched more by customers who either rent or bought either movie, and hence they are more likely to be bought. Movies at the bottom of the list, such as *Life of David Gale* and *How to Lose a Guy in 10 Days*, are expected to be watched almost once, the lower bound of the distribution on N . Hence, these movies are more likely to be rented.

Note that this rank based on latent expected viewings produces different results than ranking movies based on the actual number of purchases. For example, *Chicago* was bought more often (13) than *Talk to Her* (6) and *Catch Me If You Can* (11), yet it has a lower

Table 3

Diagonal elements of the variance covariance matrix ($\Sigma_{k,k}$) and unobserved movie heterogeneity (σ_e^2) posterior mean estimates and 95% confidence intervals.

Parameter	Posterior mean	95% Posterior interval	
		Lower	Upper
Unobs. individual heterogeneity ($\Sigma_{1,1}$)	0.384	0.176	0.666
Box office gross ($\Sigma_{2,2}$)	0.120	0.061	0.219
MetaCritic ($\Sigma_{3,3}$)	0.121	0.062	0.205
Rated R ($\Sigma_{4,4}$)	0.364	0.136	0.706
Drama ($\Sigma_{5,5}$)	0.183	0.073	0.467
Action ($\Sigma_{6,6}$)	0.176	0.067	0.387
Thriller ($\Sigma_{7,7}$)	0.174	0.076	0.358
Romance ($\Sigma_{8,8}$)	0.412	0.127	0.934
Major distributor ($\Sigma_{9,9}$)	0.157	0.078	0.295
Unobs. price plan heterogeneity ($\Sigma_{10,10}$)	0.358	0.116	0.918
Unobs. movie heterogeneity (σ_e^2)	0.081	0.029	0.172

Table 4

Top and bottom 5 titles based on the posterior mean of $E[N_j]$ averaged across transactions, along with the upper 97.5 percentile of expected anticipated viewings, the number of rentals, purchases, and the average purchase price observed in the data.

Rank	Title	Average $E[N_j]$	97.5 percentile	Rent	Buy	Average price (\$)
1	Quiet American	3.36	14.04	125	7	18.17
2	Talk to Her	2.63	8.06	79	6	16.98
3	Catch Me If You Can	2.62	8.04	112	11	22.52
4	Chicago	2.35	7.85	201	13	21.94
5	Lord Of The Rings: Two Towers	2.30	6.74	262	19	21.91
72	How to Lose a Guy in 10 Days	1.23	2.23	173	0	17.99
73	House of 1,000 Corpses	1.22	1.99	78	0	20.99
74	Boat Trip	1.21	2.28	76	0	23.99
75	Guru	1.21	2.17	47	0	22.99
76	Life of David Gale	1.19	2.05	179	0	25.19

expected viewings than these two titles. This could be due to a few reasons. First, *Chicago* is transacted more often, yet bought less often. Hence, more “trials” but only slightly more “successes” implies lower expected viewings for *Chicago*. Secondly, *Chicago* is priced (on average) lower than *Catch Me If You Can*, but more than *Talk to Her*. Hence, the threshold for buying *Chicago* is lower than *Catch Me If You Can*. In other words, *Chicago* purchases may imply, on average, lower values of expected viewing relative to *Catch Me If You Can*. We revisit the expected anticipated viewings and movie differences taken together with customer differences in the customized pricing section.

How would such viewing information be useful to managers? As discussed earlier, many consumers are unable to predict their future usage accurately for a variety of product and service categories (e.g., Nunes, 2000; Miravete, 2002). Having usage-related information may affect their choices, and hence, become an effective marketing tool for converting renters into buyers (Nunes, 2000).

5.3. Segmenting customers: collectors, opportunistic buyers, and watchers

An advantage of the model is that it produces posterior distributions of individual-level preference parameters. We focus on one in particular, $\beta_{i,1}$, which captures the extent to which any particular customer is more of a “collector” (intrinsic buyer), an opportunistic buyer, or a “watcher” (intrinsic renter). The empirical results presented in the last section, which suggest that customer differences rather than movie differences explain the majority of variation in the rent vs. buy decision, underscore the importance to the renter of understanding its customers.

We seek a metric capable of quantifying the extent to which a particular customer is an intrinsic buyer relative to the population of customers at the renter. To make it more comparable to the “average” customer, we transform $\beta_{i,1}$ by subtracting off the mean value, $\bar{\beta}_1$ and taking expectations. We denote this new customer-level metric $E[v_i | \text{data}]$ and it is defined as:

$$E[v_i | \text{data}] = E[\beta_{i,1} | \text{data}] - E[\bar{\beta}_1 | \text{data}]. \tag{8}$$

A low value of this metric indicates that the customer is more of an intrinsic buyer relative to the population of customers. We argue and demonstrate below that this metric, derived from the model, provides a superior customer segmentation than simple statistics based on only observable data such as buy/rent ratios or the number of movies bought.

First, the metric $E[v_i | \text{data}]$ is able to capture differences between customers with the same buy/rent ratio but with a different number of transactions. Comparing customers in our dataset who buy all the time, (i.e., the proportion of transactions which are purchases is one) a customer with 10 purchases should be more of a collector than a customer with eight. We illustrate this in Table 5. The metric $E[v_i | \text{data}]$

Table 5
Comparing customers who always buy.

Customer	Transactions	# Buys	Buy proportion	$E[v_i data]$
1	15	15	1.00	-2.16
2	10	10	1.00	-1.12
5	8	8	1.00	-0.93
27	2	2	1.00	-0.84
30	1	1	1.00	-0.35

naturally accounts for differences in the number of observations across consumers. For example in Table 5, customer 1 who buys 15 titles in 15 transactions has a lower value of $E[v_i|data]$ than customer 2 who buys 10 titles in 10 transactions.

Secondly, the metric $E[v_i|data]$ naturally takes into account differences between “opportunistic” buyers who buy only when the price is low enough, and “collectors,” or buyers who buy at any price while holding the number of purchases constant. This is illustrated in Table 6 for a few customers who made one or two purchases out of nine total transactions at the renter. Customer 23 purchases one movie at \$9.99 while customer 28 purchases one movie at \$ 29.99. Thus, it seems likely that customer 23 is more of an opportunistic buyer than customer 28. This is reflected in the difference of $E[v_i|data]$ for the two customers. This pattern is also illustrated for two customers who make two purchases out of nine transactions as well. Customer 17, who pays the least on average, has a higher posterior mean $E[v_i|data]$ than customer 21, who pays more on average to purchase.

Finally, and somewhat more subtly, the $E[v_i|data]$ metric weighs purchases of rentable titles more than buyable titles. Holding rentals, purchases, and prices constant, a customer who buys a less buyable title signals that he or she is more of an intrinsic buyer than a customer who buys a more popular often-bought title. In other words, the model infers that the reason for buying is due more to the customer rather than the movie. This is illustrated in Table 7. Customers 88 and 84 have the same “summary” statistic profile – one purchase at \$9.99 and three rentals. Customer 84 purchased a very buyable movie, *Quiet American*, which had the greatest average anticipated viewings according to Table 4. Customer 88 purchased a less buyable (but rented often) title, *Die Another Day* (from the James Bond franchise). We see that as a result, customer 88 has a lower (more negative) $E[v_i|data]$ value, indicating that that customer is more of an intrinsic buyer, than customer 84. We can also compare customers 120 and 142, who buy *Lord of the Rings: Two Towers*, the most frequently bought title in our database, with customers 70 and 64, who buy *Bowling for Columbine*. While we cannot exactly hold constant the other factors discussed – price paid, and ratio of purchases to rentals – these customers are very close in terms of these other statistics and differences in $E[v_i|data]$ are likely due to differences in the purchased title. As expected, we find that customers 70 and 64 have lower values of the metric than customers 120 and 142. Hence, they are more intrinsic buyers (i.e., collectors).

In summary, we have argued that the metric $E[v_i|data]$ combines information from three different sources – the buy/rent transaction ratio, price paid, and popularity of movie purchased. It is well-suited for segmenting customers along the continuum of being either “collectors,” “opportunistic buyers,” or “watchers” and is useful for the retailer in order to gain better insight into its customer base. A natural question is: given these intrinsic customer propensities, how

Table 6
Comparing customers with different prices paid.

Customer	Transactions	# Buys	Buy proportion	$E[v_i data]$	Average price paid (\$)
23	9	1	0.11	-0.12	9.99
28	9	1	0.11	-0.73	29.99
17	9	2	0.22	-0.34	8.99
21	9	2	0.22	-1.09	19.99

Table 7
Comparing customers with different titles purchased, holding price, rentals and purchases constant.

Customer	# Buys/# rents	$E[v_i data]$	Price paid	Title purchased
84	1/3	-0.178	9.99	Quiet American
88	1/3	-0.299	9.99	Die Another Day
120	1/13	-0.371	21.99	Lord of the Rings: Two Towers
142	1/12	-0.361	21.99	Lord of the Rings: Two Towers
70	1/11	-0.715	20.99	Bowling for Columbine
64	1/12	-0.832	24.29	Bowling for Columbine

can the retailer increase the profitability from such customers? We explore this issue further in the next section.

5.4. Converting potential rent transactions: customized purchase price

The renter's profit margin is larger when a customer purchases rather than rents. Under a typical revenue-sharing agreement, the renter pays a one-time fee of \$2–\$4 per title and 40% of the rental revenue to the distributor (Said, 1999; Roehl & Varian, 2001). Ignoring the fixed cost, this implies that the marginal revenue to the renter is approximately \$2.10 ($= 3.50 \times 0.60$) per rental transaction. The wholesale cost to the renter of procuring a new title for sale is \$14 (Gertner, 2004). The typical retail selling price is \$20, which means the profit to the renter of selling a new title is \$6, three times the profit from a rental transaction. The margin is likely to be even higher for previously viewed titles (PVT). Hence, converting potential rent transactions into purchase is of interest to the renter. This can be achieved through pitching expected utilization to a particular customer (“I believe that you will watch *Lord of the Rings* four times”) as the customer approaches the checkout counter with a movie that he or she intends to rent. This may be done separately from or in conjunction with customizing a purchase price that maximizes expected long-run transaction profit of the renter. In customizing prices, we choose to focus on the profitability of the renter, taking into account competitive prices. That is, we focus on converting potential rent transactions, a major opportunity for a renter where there are on average 34 rentals for every purchase.

Customized pricing applications are becoming available in various retail outlets due to cheaper and more comprehensive technology. For example, IBM's Shopping Buddy can store grocery lists, loyalty program benefits, in addition to giving personalized discounts on preferred brands (Shermach, 2004). In the home video retail market, Blockbuster has begun to use customized e-coupons to induce customers who rent online to purchase PVTs from local offline stores. In the general context of targeted promotions, Rossi et al. (1996) show how a retailer can use posterior distributions of a choice model to customize coupon values based on consumer transaction history. We follow a similar strategy in customizing purchase prices for a sample of transactions from our data. In the current rent vs. buy problem there is an important difference with price customization in the previous literature. In the current setting, the firm is guaranteed renting the movie as the price of buying increases. Thus there is a lower bound on the firm's profitability from price customization that is absent from the typical price customization scenarios considered (e.g., buy Brand A vs. buy Brand B).

It is important to note that our customizing price illustrations are conditional on the movie title already being selected by the customer at the renter. What is envisioned here is the following scenario: (1) the customer roams the store (or an online renter's outlet) with a title he or she intends to rent; (2) the customer then proceeds to the checkout point; and (3) based on the output of the model, the renter offers the customer a “one-time only” chance to buy the movie at the customized price. This scenario may be more feasible in an online environment.

We consider two scenarios, one in which only a new title is available, and one in which a PVT is also available in addition to the

new title.¹¹ We take into consideration that a customer who does not purchase and expects to watch a title only two times (for example) will return and re-rent the movie. We assume that the period between renting is fixed, and allow for a discount rate δ over this period.¹² Thus, the renter receives a series of discounted profits from the customer if he or she chooses to rent or re-rent, or an up-front amount if he or she chooses to buy. The renter is maximizing the expected long term profit for both new and PVT titles.

The renter's expected total profit from consumer i and title j is:

$$\text{Scenario 1 : } E[\tilde{\pi}_N] = \sum_{t=1}^{\tau(K_N, k)} P(N_{ij} = t | \tilde{\theta}) \sum_{s=1}^t \delta^{s-1} m_r k + P_{ij}(\text{Buy} | \tilde{\theta}, K_N, k) (K_N - c_N)$$

If only a new title is available

$$\text{Scenario 2 : } E[\tilde{\pi}_{PVT}] = \sum_{t=1}^{\tau(K_{PVT}, k)} P(N_{ij} = t | \tilde{\theta}) \sum_{s=1}^t \delta^{s-1} m_r k + P_{ij}(\text{Buy} | \tilde{\theta}, K_{PVT}, k) (K_{PVT} - c_{PVT}) \tag{9}$$

If a PVT is also available

where $\tilde{\theta}$ is a vector that denotes the model parameters, c_N is the wholesale cost of a new DVD to the renter, c_{PVT} is the cost of the PVT, and m_r is the renter margin from renting, and $\tau = \text{floor}[K/k]$ is the ratio of the buy to rent price. We set the wholesale cost $c_N = \$14.00$, in line with most sell-through title pricing, the cost of a PVT, $c_{PVT} = \$3.00$, and the margin from renting $m_r = 0.6$ (Said, 1999; Gertner, 2004). Under scenario 1, searching over a range, $c_N \leq K_N \leq \bar{K}_N$, where \bar{K}_N is the average competitive price for a new title, at each value of K_N we simulate the posterior distribution of expected total profit by drawing from the posterior distribution of θ . Under scenario 2, we search over a range $c_{PVT} \leq K_{PVT} \leq \bar{K}_{PVT}$ where \bar{K}_{PVT} is the average competitive price for a PVT. The posterior distribution of θ allows us to incorporate uncertainty about the individual's willingness to purchase and the movie's purchaseability and measure their effects on the posterior distribution of expected transaction profits to the retailer. In the case of the new title, we vary K_N in increments of \$0.25 from \$14.00 to \$24.00, which represents the competitive price for a new title. In the case of the PVT, we vary K_{PVT} from \$3.00 to \$15.00, which represents the upper bound to competitive prices for PVTs available on eBay, for example. We then calculate averaged posterior expected profits from a sample of 2000 draws in order to find the profit-maximizing K for the new and PVT title for Eq. (9).

In Table 8 we illustrate some examples with specific profit-maximizing new and PVT prices alongside the new purchase price and the expected anticipated number of viewings ($E[N_{ij}]$). In keeping with our proposed scenario of converting rental to purchase transactions, all of the transactions in Table 8 (e.g., customer 26, Gangs of New York) are titles that the customer chose to rent in our data.¹³ Customer 26 bought two titles at full price (\$22.99 and \$17.99) and rented seven titles in our sample over the six-month period. We calculate the expected profit-maximizing purchase price for several of the titles this customer rented. For example, the movie *Gangs of New York* has a prevailing shelf price of \$22.99. The expected profit-maximizing price (\$24.00) is at the upper bound of our customized price region. Since the expected anticipated

Table 8

Illustration of customized new and PVT prices, prevailing new title prices, and expected anticipated viewings for customers 26, 24 and 21.

Cust	Title	Prevailing buy price	Scenario 1 (new) buy price	Scenario 2 (PVT) buy price	Anticipated viewings $E[N_{ij}]$
26	Gangs of New York	22.99	24.00	15.00	7.00
26	How to Lose a Guy in 10 Days	17.99	23.75	14.75	3.06
26	Raising Victor Vargas	21.99	23.75	14.75	3.48
24	How to Lose a Guy in 10 Days	17.99	17.25	6.75	1.42
24	About Schmidt	18.95	20.75	10.25	2.01
21	How to Lose a Guy in 10 Days	17.99	19.00	8.00	2.16

number of viewings for this customer-movie combination is already high (7.00) and this customer has demonstrated that he or she may be an intrinsic buyer by paying full price for two titles, the renter should not have to lower prices in order to induce a purchase. If a PVT copy is available, the expected profit-maximizing PVT price is \$15.00 (also at the upper bound).

We can also see how the new and PVT expected profit-maximizing prices of another title, *How to Lose a Guy in 10 Days*, vary across three different customers. Customer 24 who buys two movies at discount and rents 11, is less of an intrinsic buyer than customers 26 and 21. The expected profit-maximizing price for a new video for customer 24 is \$17.25, \$6.50 less than that of customer 26 and \$1.75 less than customer 21.

We can focus attention on the profit-maximizing prices of the same movie (*How to Lose a Guy in 10 Days*) for customers 26 and 21, both of whom have similar summary statistics (i.e., two purchases, seven rentals). Customer 21 appears to command a lower profit-maximizing price than customer 26. This is due to the difference in expected viewing: customer 21 is expected to watch the movie less than 26, and thus needs further price discounting in order to be persuaded to buy. Of course the discounting comes at the expense of renter profits, and the procedure trades off the increase in probability of buying by lowering the price with the reduced profit conditional on purchase. Note that a feature of the current problem that is different than typical customized pricing examples is that the expected profit asymptotes to a strictly positive value even as the buy price becomes large. This is due to the fact that the renter is “guaranteed” renting the movie for k , because if the buy price K is extremely high the consumer will always rent with probability 1. Thus the margin from renting is a lower bound on the expected profitability for the renter.

6. Discussion

In this paper, we model the consumer's decision to rent or buy a particular movie at a video outlet and test it using unique panel data from a renter. To our knowledge, this is the first study that has attempted to model this particular decision with individual-level data. We model the consumer, in line with previous research, as calculating a breakeven threshold, based on the costs and benefits of renting and buying. Applying that model to our data, where buying is a relatively rare (but profitable) event (3% of transactions, 7% of customers) for the renter, we find substantively that (1) individual differences rather than title differences explain the majority of variation in the buying vs. rent decision, (2) customers who have a greater propensity to pay a lower price for rentals (through buying in bulk) have a greater propensity to buy rather than rent, and (3) action titles are more likely to be bought, whereas romances and titles with an R-rating are more likely to be rented. Using posterior model estimates we show that a particular metric that summarizes information on customer history, prices paid, and popularity of titles

¹¹ We assume that if both a PVT and a new title are available, the customer will opt for the lower PVT price.

¹² We set $\delta = 0.95$ in the customized pricing example. If $\delta = 1$, then there is no discounting.

¹³ That is, in line with our proposed mechanism, we are taking movies already selected for rental by the customer and proposing “one-time only” customized purchase prices.

bought can be used to segment customers according to a latent tendency to buy at full price, buy at a lower price, or rent. Finally, we demonstrate that the model can be used to help convert more renters into buyers. Expected viewings for a particular customer–title pair, as estimated by the model, can be pitched to the customer in order to persuade customers that a purchased movie will be well utilized. The model can also be used to generate customized expected profit-maximizing prices for new and PVT titles that may be available in the rentailer.

We offer two possibilities for further research. First, in this paper we chose to model only the rent/buy decision conditional on movie choice. This is in line with research in the video game market, where the purchase decision is modeled separately for each game (Nair, 2007). Future research, if the right data exist, could integrate such a model with other customer decisions such as whether to view the movie in the theater, or wait until released to home video or cable TV. For example, Cleeren, Dekimpe and Verboven (2006) use aggregate data on the number of video rental stores per geographic area and find that rentailers face more competition from “upstream” sources such as movie theaters rather than premium TV channels. Second, in this paper we demonstrated room for improved profitability via the customization of prices. Such dynamic pricing, admittedly, is not easy to implement in practice, particularly in an offline environment. It would also be costly (computer system, training, incentives for clerks, slowing down checkout times, etc.). It may be more cost efficient in an online environment. Clearly, this issue deserves future consideration.

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Appendix A. Proof of Eq. (2)

Since the survivor function of the shifted-geometric distribution is $(1 - p)^t$ (ignoring subscripts), it follows that

$$P(\text{Buy} | p) = P(N \geq \tau) = S(\tau - 1) = (1 - p)^{\tau - 1} \tag{10}$$

where $S(\cdot)$ is the survivor function.

Appendix B. List of movies used in analysis

List of movies used in the analysis.

Movie titles	
2 Fast 2 Furious	House of 1,000 Corpses
25th Hour	How to Lose a Guy in 10 Days
About Schmidt	Hunted
Adaptation	Identity
Analyze That	Irreversible
Anger Management	Jerry Seinfeld Comedian
Animatrix	Just Married
Antwone Fisher	Kid Stays in the Picture
Basic	Laurel Canyon
Bend it Like Beckham	Life of David Gale
Boat Trip	Lord of the Rings: Two Towers
Bowling for Columbine	Lost in La Mancha
Bringing Down the House	Love Liza
Bulletproof Monk	Malibu's Most Wanted
Catch Me If You Can	Man Apart, A
Chicago	Mighty Wind

Appendix B (continued).

Movie titles	
Confessions of a Dangerous Mind	Narc
Confidence	Old School
Core	Phonebooth
Daddy Day Care	Pianist
Dancer Upstairs	Punch-Drunk Love
Daredevil	Quiet American
Dark Blue	Rabbit-Proof Fence
Deliver Us From Eva	Raising Victor Vargas
Die Another Day	Real Women Have Curves
Dreamcatcher	Recruit
Dysfunkcional Family	Russian Ark
Final Destination 2	Secretary
Frida	Shanghai Knights
Gangs of New York	Shape of Things
Gods and Generals	Solaris
Good Thief	Spider
Guru	Spirited Away
He Loves Me/He Loves Me Not	Spun
Head of State	Talk to Her
Heaven	Tears of the Sun
Holes	Two Weeks Notice
Hours	View From the Top

Appendix C. Estimation details

We assume standard prior distributional forms for the hierarchical parameters and place large variances on the prior distributions so that the data, rather than the prior, govern parameter inferences (Congdon, 2003). The mean vector and variance covariance matrix of customer preferences are given normal and inverse-Wishart distributions:

$$\bar{\beta}_j \sim N(0, 100) \quad \Sigma \sim \text{Inv-Wishart}(R, df) \tag{11}$$

where $R = I_{10}$ and $df = 10$. The variance parameter of movie unobserved characteristics in Eq. (3) is given a diffuse inverse gamma prior.

$$\sigma_e^2 \sim \text{Inv-Gamma}(0.01, 0.01). \tag{12}$$

Lastly, for the rental price plan model, we set the prior variance of the estimated thresholds $\sigma_{\theta}^2 = 100$.

We observe individuals $i = 1, \dots, I$ who choose to either rent or buy $j = 1, \dots, J_i$ movies. Define c_{ij} as the binary indicator that equals 1 if i buys j otherwise zero, and $t_i = \{1, 2, 3, 4\}$ as the indicator of which rental price plan was chosen by customer i . Define the observation matrix $C = (c_{ij})$, the probability matrix for the model $Pb = P(\text{Buy}_{ij})$, $T = (t_i)$ as the vector of rental price plan choices for each customer and $Pt = P(T_i = k)$ as the probability for the price plans. The likelihood for the model is a product of Bernoulli probabilities (for the rent/buy choice) and ordinal probabilities for the (for the rental price plan model).

$$L(C, T | Pb, Pt) = \prod_i \prod_{k=1}^4 (P(T_i = k))^{t_i = k} \prod_j P(\text{Buy}_{ij})^{c_{ij}} (1 - P(\text{Buy}_{ij}))^{1 - c_{ij}} \tag{13}$$

Denote θ as the complete set of parameters with priors over them. The marginal posterior for a particular parameter θ_q amounts to integrating the product of the likelihood and prior over all other parameters, θ_{-q} .

$$L(\theta_q | C, T) = \int \prod_i \prod_{k=1}^4 (P(T_i = k))^{t_i = k} \prod_j P(\text{Buy}_{ij})^{c_{ij}} (1 - P(\text{Buy}_{ij}))^{1 - c_{ij}} \pi(\theta) d\theta_{-q} \tag{14}$$

Since the above integrals cannot be computed in closed-form, we use standard Monte Carlo simulation routines to make inferences in the parameters.

Appendix D. Estimated variance covariance matrix (Σ)

Mean posterior estimates of variance covariance matrix (Σ).

		1	2	3	4	5	6	7	8	9	10
1	Unobs. ind. hetero.	0.384									
2	Box office gross	0.038	0.120								
3	MetaCritic	0.037	0.020	0.121							
4	Rated R	0.193	0.070	0.034	0.364						
5	Drama	-0.009	0.018	-0.026	0.006	0.183					
6	Action	0.058	-0.010	0.020	0.034	-0.018	0.176				
7	Thriller	-0.007	-0.005	0.004	-0.022	0.001	-0.007	0.174			
8	Romance	0.165	0.048	0.023	0.159	0.049	0.056	-0.001	0.412		
9	Major distributor	-0.008	-0.005	0.005	-0.023	-0.037	0.002	-0.002	-0.016	0.157	
10	Unobs. ind. price	-0.167	-0.025	-0.021	-0.139	0.000	-0.033	-0.002	-0.083	-0.003	0.358

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