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Modeling multichannel home video demand in the U.S. motion picture industry

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The U.S. motion picture industry has become increasingly reliant on posttheatrical channel profits. Two often-cited drivers of these profits are cross-channel substitution among posttheatrical channels and seasonality in consumer preferences for any movie. The authors use a differentiated products version of the multiplicative competitive interaction model to investigate these two phenomena. They estimate the model using data from 2000 and 2001 on two posttheatrical channels in the U.S. market: purchase and rental home viewing channels. Contrary to expectations based on business press commentary, after controlling for seasonality and movie attributes, the authors find low cross-channel price and availability elasticity for both channels. To measure the extent of cross-channel cannibalization, they simulate a 28-day window of sequential release with either purchase or rental channel going first. They find that windowing reduces the sum of revenues across both channels, because more consumers choose to not purchase or rent when faced with older movies in their favored channel rather than to switch to the alternative channel with newer movies.

Keywords: multiple channel demand, market share, seasonality, entertainment industry

Modeling Multichannel Home Video Demand in the U.S. Motion Picture Industry

The U.S. motion picture industry has become increasingly reliant on posttheatrical revenues for overall profitability of any movie; the high cost of movie production often exceeds the total box office revenues of the movie (Epstein 2005). However, posttheatrical movie channels pose their own set of challenges. For example, in mid-2009, several movie studios were involved in a heated dispute with Redbox, an in-store limited-selection DVD rental kiosk service. Studios claimed that these low-price and convenient rentals cannibalized purchase of DVDs (Grover and Lowry 2009). In another example, in January 2010, Warner Bros. reached a deal with Netflix, a rental-by-mail company, to postpone the availability of new Warner movies to Netflix subscribers by four weeks after they are available for DVD purchase. The ostensible reason was to reduce the cannibalization of purchase by rentals (Stone 2010).

These recent developments in home video demand illustrate two important drivers of profitability. First, the extent of substitution across home video channels (i.e., *across* rental and purchase) might be large, explaining why studios may want to postpone releasing in the rental channel, with the aim to convert renters to purchasers. Second, release timing in home video channels is crucial to profitability, given seasonally varying demand and the small window of profitability before newer releases crowd out profits. Examples include Wal-Mart's holiday season decision to reduce the shelf space for DVD purchase (Worden 2009) and Disney deciding to release *Alice in Wonderland* sooner in the home viewing channel "to take advantage of school breaks in May" (McClintock and Jaafar 2010). In addition, cross-channel substitution and seasonal effects might interact. For example, consumers might prefer purchases (e.g., for gift giving during holidays) to rentals (e.g., less time to watch movies during family holidays) in one season. Indeed, if seasonal demand variations are the dominant force in demand, cross-channel elasticity as a function of price might be small after controlling for seasonal variations.

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To address these issues of substitution and seasonality within and across the two main home channels of DVD purchase and rentals, we use a differentiated products version of a multiplicative competitive interaction (MCI) model (Cooper and Nakanishi 1988). We build a maximum likelihood estimator for our model and show through Monte Carlo simulations that this estimator is more efficient than the generalized method of moments (GMM) used in extant market share models for differentiated goods (see Web Appendix B [http://www.marketingpower.com/jmrdec11]). Next, we estimate the model on the movies with the highest DVD purchase revenue and movies with the highest rental revenue in each week, during the years 2000–2001 in the U.S. market. In the next section, we discuss why we restrict the scope of our study to the largest movies in the home video channels and sensitivity analyses for this choice set.

Methodologically, we model demand in multiple distribution channels (i.e., purchase and rental channels), while allowing consumer preferences to vary by channel and by week. Literature in marketing on the motion picture industry has primarily focused on single-channel research questions and, to a lesser extent, on modeling choice across movies within a channel (for a summary, see Eliashberg, Elberse, and Leenders 2006). In other contexts, multichannel models (e.g., those that model store and brand choice within a store, for grocery store products) have been situated in environments in which consumer preferences are time invariant. We address both issues in a single model—that is, we measure substitution between products across and within channels (substitution between movies available in rental and purchase) in a market with time-varying demand.[1]

Controlling for differences in top-selling and rental movies and for time-varying consumer preference and movie attributes, we find that in 2000–2001, substitution across channels was limited. The rental channel exerted a stronger substitution pressure on the purchase channel than vice versa. To measure cross-channel elasticity, we simulate the effect of a 1% change in the sum of the attractions of movies in a channel on the percentage change in revenue in the competing channel. We find that the average (across a year) cross-channel elasticity of DVD purchase revenue with respect to the rental channel was .0047, and the cross-channel elasticity of rentals with respect to DVD purchase was .0621.

To understand the managerial implications of our findings, we examine the impact of a 28-day delay (window) in the availability of new movies in a channel. That is, how would consumer demand for renting and buying movies change if movies were released sequentially across purchase and rental channels (with either channel going first) rather than released simultaneously, as practiced in the industry? Sequential channel release (hereinafter, we refer to this as windowing, the industry terminology for the release strategy) is a fairly common distribution strategy in media industries (e.g., audio) in which products are released in one channel before other channels. We find that in the movie industry and these two channels specifically, windowing in either rentals or purchase leads to lower revenues. Over the course of a year, windowing rentals by 28 days reduces aggregate rental revenue by US$157 million and increases DVD purchase revenue by US$17 million. Conversely, windowing DVD purchases increases rental revenue by US$2.6 million and decreases DVD purchase revenue by US$17.5 million. Note that studio profits also depend on the revenue-sharing arrangements, which in turn may vary by movie and channel. Thus, despite the decrease in net revenue, if studios receive a significantly larger fraction of profits in one channel, windowing may be a profitable strategy. Alternatively, assuming no major changes in elasticities since the time of our data, the current rhetoric of cross-channel substitution might be masking channel power dynamics (e.g., by advancing purchases over rental channels, studios obtain better terms with DVD retailers). Our results also suggest that consumer preferences in different channels (with different seasonal trends) dampen cross-channel substitution. Finally, note that we conduct counterfactuals at the industry level rather than the title level. Equivalent counterfactuals can be developed using the model to study the actions of specific studios, for specific movies, in a given week and year.

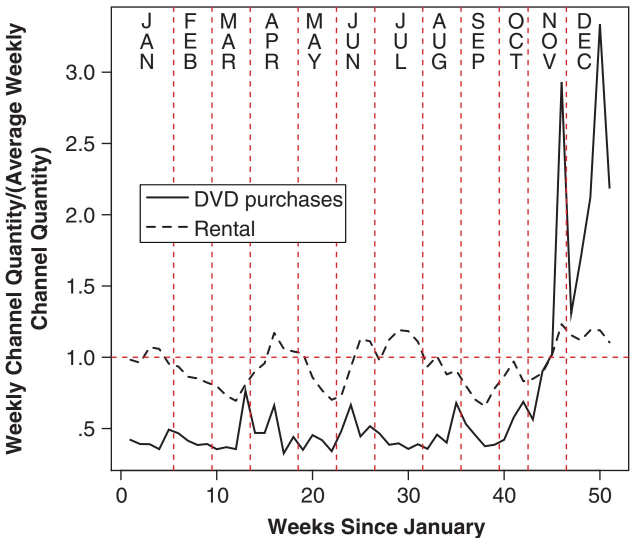
Although our analysis pertains to the U.S. motion picture industry's posttheatrical revenues, our research question has application in other industries with multiple channels and/or products with short life cycles. Examples include television shows (television, off-network syndicates, and home videos), music (audio and video singles in hard copy, online, as part of an album, and in broader compilations), and the fashion industry (with seasonally varying cycles and diffusion from haute couture to mass-market). Whether these cross-channel substitutions are more sensitive to price and choice set rather than innate seasonal preferences or product attributes in these other industries is unknown but explorable through our model.

DATA

We use data of the top revenue movies in two home video channels—rentals and DVD purchases—from January 2000 to December 2001. We use Nielsen VideoScan data (including weekly units purchased and price) for the top 35 selling movies. Prior research has also used this data set to study movie DVD purchase (Elberse and Oberholzer-Gee 2007). The data do not include Wal-Mart. In our period of interest, Wal-Mart was a major retailer of DVDs that carried a smaller inventory of movies than comparable national retailers. Thus, our sample may understate the importance of larger movies and overstate the importance of smaller movies. We use the weekly national revenue by movie for the top 35 renting movies in a week, according to *Video Store Magazine*'s Rental Charts. To better understand seasonality, Figure 1 plots what the fraction of any channel's annual revenue that comes from any particular week. That is, the revenue from all movies present in each channel in each week, divided by the average cumulative weekly revenue, for the channels across the year.

[1]A more complete model of movie choice should include other distribution channels, including movies running concurrently in the theatrical channel. Our model is scalable to more channels of movies distribution. To simplify the model, estimation, and our inference, we focus on two channels most likely to show intense competition and estimate the model on data from a period when online purchase and rentals, as well as illegal digital downloads, were likely not important cross-channel demand drivers.

Figure 1
SEASONALITY OF SALES



We restrict the scope of our study to the top revenue movies in both channels for three reasons. First, the primary purpose of our model is to investigate substitution, within and across channels, and thus it is reasonable to estimate the model on the largest revenue movies most likely to have the largest substitution impact on other movies. Sampling by rank enables us to retain the largest revenue movies and drop movies that are less likely to exert substitution pressures. Second, although our model is a reasonable description (required to develop a market share model admitting heterogeneity) of consumers choosing between the largest revenue movies in a week, choice sets that include smaller movies would likely require additional considerations. For example, theatrical revenue is likely to be a poorer predictor of home video revenue for smaller movies targeted at niche audiences. Third, nonlinear market share models are computationally expensive. Similar to extant literature, we face a trade-off between the generalizability of the model using a larger data sample and simulation or computational error, which limits us in the size of the choice set that we can use in estimation (for a discussion of the implementation of the estimation algorithm, see Appendix A [http://www.marketingpower.com/jmrdec11]).

To test the robustness of our model and findings to this assumption, we reestimated our model with the top 25 movies in each channel, rather than the choice set of 35 movies per channel. We also reestimated it using a larger set of movies in the purchase channel (top 100 movies) than in the rental channel (top 25 movies) to ensure that our findings are not being driven by the sampling methodology. The market share for a movie in the rental channel becomes quite small as we go down the list of rental ranking and diminishes faster than shares in the purchase channel for equivalent rankings. The top-renting movie had greater than 20% within-channel market share (share of revenue of the channel), while the top-selling movie had 14% within-channel market share (on average across all weeks in our data). The 25th largest movie by rental revenue had a mean within-channel market share of .5%, versus 1.1% for the 25th largest movie by purchases. By adding more movies to the purchase channel, we offset the effect of the long tail. Our substantive findings remained the same in both cases.

We assume that the total market for posttheatrical purchases and rentals is 208 million consumers, corresponding to the population of the United States between 15 and 75 years of age in 2000. To accommodate the possibility of both buying and renting DVDs in any single week, we allow for two decision occasions for each consumer on average, leading to 416 million total decision occasions. In each decision occasion, a consumer can purchase or rent a movie or choose the outside alternative.

Pricing policies differ across the purchase and rental channels. In the rental channel, prices are almost always uniform (Orbach and Einav 2007) and revenue shared between the rental store and the studio. We assume a mean rental price of $2.50 per movie for the duration of the study (Hettrick 2000) and find that our results are robust to a range of price means. In DVD purchases, we use the weekly price of each movie averaged across all discount mass stores, drugstores, and grocery stores in the United States (which account for approximately 43% of all units sold in the data set). As Table 1 shows, substantial variation exists in DVD purchase prices across movies (across both weeks and movies in any week).

To enrich the forecasting model, we gather data on additional variables. Box Office is the box office revenue of a movie before its released in the home video channel. Budget is the cost of making the film. We obtain data on print and advertising expenditure (P&A) for each movie at the box office stage from Paul Kagan Associates. We use the percentage of positive critics' reviews for a movie, the Tomatometer, available at Rotten Tomatoes (http://www.rottentomatoes.com), as a summary measure of critics' ratings. We also have data on when a movie was released in theaters and in home video channels.

MODELING ISSUES AND APPROACH

Models of Multichannel Consumer Demand

We begin by providing an overview of multichannel models of movie demand in empirical literature, focusing on possible differences in our study. Luan and Sudhir (2007) model the impact of cannibalization of purchase and rentals of movies on box office revenues for any single movie, accounting for consumers' forward-looking behavior at the theater. We take theatrical performance as a given and instead focus on possible competition between rentals and DVD purchases. Our motivation and substantive findings therefore are complementary to Luan and Sudhir.

Hennig-Thurau et al. (2007) use conjoint methods to examine how consumers may substitute between channel assortments, considered by the industry but not yet found in the market (e.g., the simultaneous release of a movie in theatrical and home video channels). Knox and Eliashberg (2009) model the rent or buy decision at a "rentailer" (a rental store that also sells movies). They focus on identifying different consumer segments, based on the propensity to buy and rent movies, and develop pricing strategies for the rentailer tailored for each segment. Our model complements both studies by examining rental and purchase decisions across all retail and rental stores in the United States

Table 1
SUMMARY STATISTICS

	Price	Box Office (in Millions of Dollars)	P&A (in Millions of Dollars)	Budget (in Millions of Dollars)	Critics' Rating	Weeks Since Theatrical Release	Weeks Since Home Video Release
DVD Purchase							
Minimum	5.02	1.00	.20	275	3.00	14.57	1.00
Median	19.97	66.00	30.00	42.00	63.00	68.57	28.00
Mean	20.26	89.06	28.81	49.35	59.99	136.82	49.78
Maximum	35.00	601.00	66.00	218.25	100.00	589.00	242.00
SD	3.36	76.16	13.32	34.64	26.13	37.52	100.2
Rental							
Minimum	N.A.	1.00	600	750	3.00	14.29	1.00
Median	N.A.	34.00	25,000	33,600	47.00	28.29	5.00
Mean	N.A.	54.52	25,618	41,465	47.82	28.93	4.97
Maximum	N.A.	431.00	63,600	182,500	100.00	63.57	13.00
SD	N.A.	55.27	14.11	32.11	27.03	5.88	3.49

Note: N.A. = not applicable.

and investigating strategic decisions of a studio optimizing across channels at the national level.

Finally, Chiou (2008) measures two drivers of market expansion (and contraction) in the home video market: intertemporal differences in consumer preferences and intertemporal differences in the quality of new releases. Similar to single-channel models, as in Einav (2007), Chiou uses a homogeneous market share model to allow the transformation of the shares to a quasilinear function of the movie observables. Our model extends this model by including full heterogeneity across coefficients, which reduces restrictions on the substitution patterns across products and channels and enables us to investigate time-varying and cross-channel substitution effects.

Market Attraction

We begin with a description of the MCI model (Cooper and Nakanishi 1988). In MCI, the market share of a product is a function of the ratio of the mean market attraction of the product to the sum of the mean market attractions of all products. For our application, let a_{mcwy} be the attraction of movie m in channel c, week w, and year y, and let C_{cwy} be the choice set of movies in channel c, week w, and year y (we include the last to account for market growth in the two-year period of the our data). The market share of movie m (denoted ms_{mcwy}) is as follows:

$$ms_{mcwy} = \frac{\exp[\log(a_{mcwy})]}{\sum_{k \in C_{cwy}} \exp[\log(a_{kcwy})]}.$$

Our model adds three components to MCI. First, the model allows for different substitution structures within and across different channels. For example, a movie may have greater share in rentals than purchase, implying a different within-channel cross-elasticity (substitution pressure on other movies) in rentals than in purchase. Second, the model allows the attraction to change with seasonality (specifically by week). Third, we include heterogeneity in the attraction function. We discuss each of these subsequently, followed by a discussion of the operationalization of the attraction function.

Multiple Channels

Taking the MCI model and drawing from the nested logit model, we write a consumer i's in-channel probability of choosing movie m in channel c, week w, and year y (denoted $ms_{imcwy|icwy}$) as follows:

$$ms_{imcwy|icwy} = \frac{\exp[\log(a_{imcwy})/\rho_c]}{\sum_{k \in C_{cwy}} \exp[\log(a_{ikcwy})]/\rho_c} = \frac{\exp[\log(a_{imcwy})/\rho_c]}{D_{icwy}}.$$

Similar to nested logit models, we constrain ρ_c (hereinafter called "channel nesting parameters") to be strictly between 0 and 1. The channel nesting parameters control market expansion and cross-channel substitution. The release of a new movie in channel c increases D_{icwy}, with ρ_c determining the new total channel revenue after market expansion. A larger channel parameter implies that the cumulative channel market share is more sensitive to the cumulative market attraction of the channel: A new movie leads share to be stolen from other channels (cross-channel substitution) and from the outside good (market expansion). Cross-channel substitution occurs because the same movie is often present in both channels (though a top-renting movie might not be in the top-selling movie list, and vice versa), and a focal movie in a channel may substitute across channels to other movies and/or cannibalize its own revenues in other channels. To set scale, we set the mean attraction of the outside good and, thus, D_{i0wy} to 1. The outside good refers to any customer neither buying nor renting in a week (recall our previous discussion of market size). We model the probability of purchasing or renting a movie in channel c (ms_{cwy}) as follows:

$$ms_{icwy} = (D_{icwy})^{\rho_c} \Bigg/ \left[1 + \sum_{k \in \text{channels}} (D_{ikwy})^{\rho_k}\right].$$

A limitation of our model is that because of the significant challenge of gathering representative disaggregate data, we assume that consumers choose to purchase and/or rent a movie (or choose the outside option) in every decision occasion in a week and that choices across decision occasions are made independently. Estimating a model that separates state dependence (modeling the statistical relationship between the multiple decision occasions in each week across multiple purchases/rentals by each consumer) from unobserved heterogeneity (unobserved differences in preferences across consumers) would require individual-level (disaggregate) data representative of the national U.S. market (for a recent application, see Dubé, Hitsch, and Rossi 2010). To the best of our knowledge, such data are not available commercially for the home video market. Therefore, our study complements research conducted on the movie industry (e.g., Knox and Eliashberg 2009) that uses disaggregate data to identify drivers of individual behavior, but the findings are necessarily limited to consumers of a store or group of stores and to a specific geographical area. In contrast, our data represent aggregate trends across the national market, allowing for substantive findings that measure the effectiveness of national marketing strategy decisions of the studios.

Modeling Seasonality

Consider a movie released in home video at the beginning of November. In the third week of November, during the peak holiday shopping season, the movie will be well positioned to take advantage of consumers buying gifts for their family and friends. That is, with its release in the midst of the holiday shopping season, purchases of the movie will be higher than in a lean season. However, in the same season, the movie may not do well in rentals, because viewers are busy with other pursuits (shopping or spending time with family).

As this example suggests, our model must capture changes in purchases/rentals due to seasonal changes in consumer preferences (e.g., an increase in preference for purchases in the holiday season). In addition, accounting for the seasonal consumer preferences, studios will likely release their best movies in November (though modeling studios' decisions is outside the scope of this article, and we take their decisions as exogenous in the model). Therefore, the model must also capture market expansion due to changes in the number and quality of choice sets over seasons (e.g., more and higher-quality DVDs released in the holiday season, increasing the overall demand for DVD purchases for gifting).

We add channel-specific week fixed effects to the market attractions of movies to capture seasonally changing consumer preferences (for a homogeneous version of this model, see Einav 2007). The seasonal fixed effect accounts for changes in the attraction of purchase and rental options across seasons compared with the outside good: how much more or less the purchase or rental of any movie is attractive to a consumer in each week. Note that we allow seasonal changes in preferences across the two channels to be systematically correlated with each other (e.g., we allow the demand for rentals to decrease and demand for purchases to increase in a week because consumers are busy shopping for gifts and therefore have less time to watch rental DVDs). These fixed effects can be inconsequentially small or even zero. That is, we allow, but do not require, consumer preferences to be seasonal. A positive weekly coefficient for a channel increases the total number of purchases for the channel in a week because it increases the mean attractiveness of movies in the channel, winning customers from other channels (interchannel substitution) and the outside option (market expansion). A negative coefficient has the opposite effect. We capture market expansion due to changing choice sets by D_{icwy} increasing with better and more movies released in a week. Formally, we define the mean market attraction a_{mcwy} to a consumer i for movie m in channel c, week w, and year y as follows:

$$\log(a_{imcy}) = \log(\delta_{imcwy}) - \tau_{cw} - \tau_{cy} + \xi_{mcwy}. \quad (1)$$

In Equation 1, the components of attraction are as follows: The deterministic component δ_{imcwy} is a function of observed variables, such as movie genre, theatrical advertising, and so on. Subsequently, we discuss our specification of this function and provide a description of its components. The term τ_{cw} is a channel-specific weekly unobservable shock, estimated as a channel–week fixed effect, common to all choices in a given channel and week, and is allowed to be different across rentals and purchase and to vary freely across the year. To model overall changes in consumer preferences, we also include a channel-specific time trend τ_{cy} in each channel. We model unobserved product attributes as product-specific shocks. These include movie plot and the psychological and informational setting of a consumer (Neelamegham and Jain 1999; Sawhney and Eliashberg 1996).

In the single-channel model, the channel coefficient is (implicitly) set at 1, yielding the multinomial logit specification on choice probabilities. Prior research that has built a likelihood estimator for single-channel models (e.g., Jiang, Manchanda, and Rossi 2009; Park and Gupta 2009) has assumed a parametric distribution on ξ_{mcwy}. Unlike the logit model, in the nested logit model, the scaled shock ξ_{mcwy}/ρ_c shifts within-channel probabilities. The model allows the cross-channel coefficient to have values between 0 and 1 and is underidentified if we specify only a distribution on ξ_{mcwy}. We build on the single-channel models and use the natural corollary of their parameterization: We parameterize the distribution of ξ_{mcwy}/ρ_c to be a draw from a multivariate normal distribution and recover ρ_c nonparametrically.[2] Conditional on the channel coefficient, the within-channel probability model is equivalent to the single-channel models discussed previously. In our model, a change in within-channel probabilities (equivalent to the single-channel model) identifies all coefficients, except the channel coefficient. Identification of the channel coefficient comes from the change in the probability of purchasing versus renting versus the outside good (i.e., the choice of channel identifies the channel coefficient).

Modeling Heterogeneity

Movies are highly differentiated products, and it is nearly impossible to gather enough data (e.g., on movie plots) to explain all the determinants of revenue success. Therefore, we use a random coefficient nested logit share model that allows for movie-specific unobservables. In line with Nevo's (2000) terminology, the model has the following

[2]Park and Gupta (2009) find that a model defined using the multivariate normal specification is reasonably robust to different data-generating processes.

sets of coefficients: Linear coefficients refer to components of the mean attraction of a movie. Channel coefficients are the channel nesting parameters discussed previously. Nonlinear coefficients are the components of the individual-specific (heterogeneous) attraction of a movie discussed subsequently.

To model consumer heterogeneity, similar to Lee, Boatwright, and Kamakura's (2003) specification, we model the covariance matrix of the unobservables ($v_i \in \Xi$) as a multivariate normal distribution. This formulation allows for covariance in the taste for different product attributes. Therefore, market shares are as follows (for further discussion of our maximum likelihood estimator of this market share model, see the "Model Estimation" section):

$$ms_{mcwy} = \int_{v_i \in \Xi} ms_{imcwy\,|\,icwy} ms_{icwy}\, dv_i = \int_{v_i \in \Xi} ms_{imcwy}\, dv_i.$$

Operationalizing the Attraction Function

In our attraction function, we use many of the commonly used product descriptors for movies (e.g., genre, production budget) in a straightforward manner, and so we do not discuss them further. In addition, we control for "perishability," or the age of movies in the home video channel, by making the attraction function a function of time since theatrical release and the time in the home video channel. In the theatrical channel, Sawhney and Eliashberg (1996) propose a three-parameter gamma model (BOXMOD) for predicting box office revenue. After a meta-analysis of earlier movies, they predict first week, peak, and decay of theatrical revenue over weeks. Einav's (2007) model assumes a steady exponential decay in attractions in the weeks following release. Ainslie, Drèze, and Zufryden (2005) distinguish between a blockbuster decline (early peak) and a sleeper decline (later peak).

To capture similar patterns, we follow Sawhney and Eliashberg's (1996) suggestion and use a bivariate generalized gamma formulation (this formulation is known as the generalized Leontief function in production economics literature) on two dimensions: time since theatrical release and time since home video release. The bivariate generalized gamma distribution allows the interaction of the dimensions (random variables) in the shape parameter to capture the aforementioned interaction effect. Suppressing subscripts denoting movie m, channel c, week w, and year y, we write the deterministic component as follows:

$$\begin{aligned}\log(\delta_i) &= \beta_{ip}\log(p) + \beta_{iBO}\log(BO) + \beta_{iP\&A}\log(P\&A) + \beta_x \log(x)\\ &\quad + \beta_1(WB) + \beta_2(WHV) + \beta_3(WB)(WHV) + \beta_4\log(WB)\\ &\quad + \beta_5\log(WHV),\end{aligned}$$

where p is the price, BO is box office revenue, P&A is print and advertising expenditure in the primary channel, WT is weeks since theatrical release, and WHV is weeks since release on home video. The term $WB = WT - WHV$ is the time between theatrical and home channels, or the number of weeks between the two releases. Furthermore, x includes all movie-specific observables (e.g., genre) to capture the mean attraction of the movie. Box office revenue captures the impact of unobservables and is a proxy for movie quality (Krider and Weinberg 1998; Lehmann and Weinberg 2000). As explained previously, we assume that the price of a rental remains constant over the length of the data set, and we use the observed mean transaction price in DVD purchases.

We abstract from questions related to the retailer and rental store marketing-mix variables (including stock and breath of products carried) and assume that movies on home video have uniform distribution intensity. As we are studying the highest-selling and highest-renting movies, including sales from online distribution channels, product unavailability is of lesser concern in our application. Furthermore, unlike theatrical releases, home video releases are always simultaneous across all regions of the United States; there is no equivalent on home video, in wide release or limited release (differences in distribution intensity by geography), of a movie.

MODEL ESTIMATION

Maximum Likelihood Estimation

We first provide a brief overview of the estimation algorithm and then discuss the statistical properties of our estimator and alternative estimators. The estimator is as follows:

$$\begin{aligned}\underset{\theta}{\operatorname{argmax}} \Pr(P\,|\,\aleph;\theta) &= \underset{\theta}{\operatorname{argmax}} \prod_{\{w,y\}} \left(\int_{s(M)} \mu_\xi\{\xi[\hat{s}_{wy}(M)]\}\, ds(M) \right)_{wy}\\ &= \underset{\theta}{\operatorname{argmax}} \prod_{\{w,y\}} \mu_\xi\{\hat{\xi}[\hat{s}_{wy}(M)]\} + O_p(\sqrt{M}),\end{aligned}$$

where P is the purchase vector, $\aleph$ is the set of independent variables (e.g., box office gross), $\xi \triangleq \{\xi_{mcwy}/\rho_c\}$ is the vector of mean attraction shocks, $\hat{\xi}$ is the vector of recovered shocks, μ_ξ is the conditional distribution on the mean attraction shocks, and $\hat{s}_{wy}$ is the share vector in week w and year y. For a set of nonlinear parameters, we construct the likelihood in three steps:

Step 1: Recover fixed points: We use the contraction mapping that Berry and Jia (2010) suggest to solve the model for $\bar{a}_{mcwy}/\rho_c$, the recovered mean attractions of each movie. Berry, Levinsohn, and Pakes's (1995) Theorem 1, restated in our context, shows that a set of shares in an infinitely large market (infinite consumers) corresponds to a unique vector of mean attractions per movie in a channel, a week, and a year. The contraction map solves for the unique vector of attractions corresponding to the vector of nonlinear coefficients.

$$(\bar{a}_{mcwy}/\rho_c)_{j+1} = (\bar{a}_{mcwy}/\rho_c)_j \times \frac{\hat{s}_{mcwy}}{s_{mcwy}(\bar{a}, \rho)}.$$

Step 2: Recover mean attraction shocks: We project $\log(\bar{a}_{mcwy}/\rho_c)$, recovered in Step 1, on the design matrix (observables) corresponding to the linear model for mean attraction to recover $\hat{\xi}$.[3]

[3]To correct for endogenous variables, we can replace the design matrix with an instrumented design matrix (e.g., a design matrix formed by projecting endogenous variables on the instruments). Alternatively, we can add a function of the residuals from the linear projection of the endogenous variables on instruments to the projection equation (see Petrin and Train 2010). Substituting the recovered coefficients in the original normal equation leads to consistent estimates of the mean attraction shocks.

Step 3: Construct likelihood: We construct the log-likelihood from the recovered mean attraction shocks.

$$\log[\Pr(P \mid \aleph; \theta)] = \sum_{\{w,y\}} \log\left(\mu_\xi\{\hat{\xi}[\hat{s}_{wy}(M)]\}\right).$$

Web Appendix A (see http://www.marketingpower.com/jmrdec11] provides details on the estimation and computation of the likelihood. Web Appendix B provides simulations that describe the properties of our estimator.

Efficiency and Consistency of Estimators

We use the conditional probability of the mean error (ξ_{mcwy}/ρ_c) to build a maximum likelihood estimator for our model. Our approach has two advantages over building the likelihood as in the work of Park and Gupta (2009) and Jiang, Manchanda, and Rossi (2009). First, the likelihood of purchases defined in their models tends toward zero at an exponential rate with a large number of brands and/or purchases. We estimate our model on 70 products in each period, which is considerably larger than the number of purchase choices considered in either of the other likelihood-based approaches. For a small number of brands, we can randomly sample the purchase vector to estimate the model. However, the random sample needs to be large when some brands have low market share. In contrast, the mapping, given previously, is stable when recovering mean attractions of small market share brands. Second, we assume sampling without replacement, which is the likely sampling mechanism in a market in which all the potential consumers are represented in the aggregated data. The generalization is important when recovering heterogeneity parameters.

Another alternative to our estimator is the GMM estimator proposed by Berry, Levinsohn, and Pakes (1995). We show through Monte Carlo simulations (see Web Appendix B [http://www.marketingpower.com/jmrdec11]) that the estimator in our model is significantly more efficient than the GMM estimator. In addition, in our research setting, good candidates for the instruments required by the GMM estimator are not available (for a discussion on commonly chosen instruments, see Nevo 2000). For example, unlike in Berry, Levinsohn, and Pakes's original application to the automobile market, in the home entertainment industry, the marginal costs of manufacturing DVDs are not significant cost shifters, and thus they cannot be used as cost-side instruments. Our described likelihood estimator does not require similar instruments to build an objective function, making it a natural fit for our research question.

A limitation of our estimation strategy is that we ignore sampling error and thus require a large "aggregation population": the number of potential customers who made a purchase (or no purchase) decision in each week. In our application, similar to extant applications of the framework to nationally aggregated market share data, we estimate the model on data aggregated over purchases and rentals across the United States. Park and Gupta's (2009) approach allows for sampling error because it was developed for the converse situation—in which aggregate shares are observed in a grocery store. Our approach is appropriate only when considering large market sizes and, thus, in situations in which the sampling error is minimal enough to be assumed away in the optimization. We suggest that researchers interested in using either likelihood method for estimating market share models should choose the appropriate estimation strategy based on the size of the underlying "aggregation population" and the number of brands/products considered in the problem.

RESULTS

Drivers of Movie Market Share

As in Lehmann and Weinberg (2000), we find that larger box office revenue predicts larger home video channel attractiveness. Similar to prior findings, we find that a greater number of weeks since theatrical release decrease the attractiveness of the movie for purchase. However, posttheatrical perishability does not affect the attractiveness of rentals. Both channels show nonlinear patterns in attractiveness with time since release on home video and time since release in the theatrical channel. The interaction between weeks between theater and home video and weeks since release on home video is not significant in both purchase and rentals. Table 2 reports the estimates of the linear coefficients.

We find that theatrical P&A has a negative coefficient for the mean attractiveness in purchase, suggesting negative spillovers across channels. A possible reason for this is as follows: A movie with high levels of advertising might generate high theatrical revenues, but if it fails to live up to its hype, there might be negative word of mouth from theatrical viewers that drives down the subsequent demand in DVD purchase. To quantify the negative impact of excess theatrical P&A, consider the movie *The Thomas Crown Affair*, with descriptive characteristics very similar to the

Table 2

ESTIMATED COEFFICIENTS OF MEAN ATTRACTION IN HOME VIDEO CHANNELS

	Purchase		*Rentals*	
	Coefficient	*SE*	*Coefficient*	*SE*
(Intercept)	−6.927***	.249	−8.132***	.436
Log(theatrical revenues)	6.251***	.173	4.360***	.104
Log(P&A)	−3.660***	.251	−.040	.160
Log(production budget)	−.039**	.018	.079***	.012
Log(critics' ratings)	.189***	.018	−.0002	.011
Weeks in home video channel (WHV)	.012***	.0006	−.319***	.010
Weeks between theater and home channel (WB)	−.0008**	.0004	−.023***	.007
WHV × WB	.00001	.00002	.0007*	.0003
Log(WHV)	−.906***	.013	.416***	.029
Log(WB)	.028	.036	.317*	.178
PG-rating dummy	−.472***	.054	−.147**	.038
PG13-rating dummy	−.504***	.048	.006	.036
R-rating dummy	−.018***	.048	.065*	.035
Comedy dummy	−.199***	.029	.035	.024
Family dummy	−.556***	.054	−.593***	.043
Foreign movies dummy	−.272***	.103	−.232**	.080
Horror dummy	−.033***	.047	.063*	.037
Mystery suspense dummy	−.237***	.039	.040	.030
Science fiction dummy	.244***	.037	−.011	.045
Western dummy	−.468	.303	−.680***	.021

*$p < .1$.
**$p < .05$.
***$p < .01$.
Notes: N.A. = not applicable.

mean/median descriptive characteristic of all movies in our data set, as Table 1 describes. The movie made a cumulative $69 million in its theatrical release. It cost $50 million to make, with a further $28 million spent on theatrical P&A. It had a Rotten Tomatoes (critics') rating of 69 out of 100 and was released in the first week of January 2000, 21 weeks after its theatrical release date. Our estimates imply that, all else being equal, a further $25 million spent promoting the movie in the theatrical channels, without a change in box office revenue, would reduce DVD purchase revenue by 6%.

We estimate coefficients of the variance matrix by bootstrapping from the upper Cholesky matrix. Table 3 reports the mean and the lower and upper bound at the 95% confidence interval for all coefficients. The significance codes correspond to a null hypothesis of the covariance matrix coefficient being equal to 0. We find that consumers who are more sensitive to theatrical revenues and/or more sensitive to theatrical promotions and advertising expenditure have a lower price response coefficient for DVD purchase (covariance coefficients for price and theatrical revenue and for price and theatrical P&A are both negative). The implication is that consumers who are more receptive to higher theatrical revenue and theatrical P&A are less price sensitive than the average consumer.

Substitution Between DVD Purchase and Rentals

As we noted previously, studios claim that the major driver for changing release timings across channels is that cheap rentals are cannibalizing the more profitable DVD purchases. Similar to a measure of elasticity with respect to price, we require a measure of cross-channel elasticity with respect to the mean quality of movies released in a channel. The measure corresponds to this thought experiment: If we lower/raise the mean quality of movies in a channel, how many consumers would substitute across channels? Higher cross-channel elasticity indicates stronger consumer substitution, while lower cross-channel elasticity indicates lower consumer substitution.

We find that in 2000–2001, controlling for differences in movies available for rental or purchase, consumers were less likely to substitute from the rental channel to the purchase channel than from the purchase channel to the rental channel. We find that the average (across a year) cross-channel elasticity of DVD purchase revenue is .0047 while the cross-channel elasticity of rentals is .0621. It is important to note here that this result of small cross-channel elasticity is significantly based on controlling for seasonal preferences and movie characteristics. That is, these controls influence consumer choice of whether to rent or purchase (or do neither) more than the simple cross-channel substitution based on movie quality in the other channel.

To understand the managerial implications of our findings, we simulate a 28-day delay (window) in the availability of new movies in a channel relative to release in the competing channel. Our simulation corresponds to our previous example of movie studios imposing a 28-day window for new releases, in which movies are not available for rentals on Netflix but are available for purchase on DVD.[4] Thus, in the simulation, we preserve the selection (number and identity) of movies available in the first channel and delay the launch in the second channel, altering the choice set of movies available to consumers. We find that windowing reduces overall revenues. Postponing rentals (channel exclusivity for DVD purchases) increases revenue from purchases by US$17 million over a year and decreases rental revenue by US$157 million in the same year (see Figure 2, Panel A). Postponing DVD purchases (channel exclusivity for rentals) decreases revenue from purchases by US$17.5 million over a year and increases rental revenue by US$2.6 million in the same year (see Figure 2, Panel B). In other words, when faced with older movies in their preferred channel versus newer movies in their nonpreferred channel, consumers opt to not purchase rather than to switch to the nonpreferred channel.

As mentioned previously, studios make more profits in the purchase channel than in the rental channel. If the studio margin from DVD purchase is significantly larger than the margin from rental, studios may be able to increase their profits by postponing release in the rental channel despite a decline in overall revenue. This is especially likely if studios can get better terms from DVD retailers when they offer purchase exclusivity by postponing rentals (i.e., if their channel power increases with the change in distribution policy). For example, as mentioned previously, studios moved to postpone rentals on Netflix. The entry of Redbox led to significantly lower rental margins, making a case

Table 3

ESTIMATED NONLINEAR (HETEROGENEITY) AND CHANNEL COEFFICIENTS

Channel	*Variable*	*Coefficient*[a]	*SE*
Purchase	Variance (price)	.206*	.00198
	Variance (log[theatrical revenue])	.149*	.00693
	Variance (log[P&A])	3.13*	.0238
	Covariance (price, log[theatrical revenue])	−.0130*	.00365
	Covariance (log[theatrical revenue], log[P&A])	.0645*	.00333
	Covariance (price, log[P&A])	−.624*	.0166
Rentals	Variance (log[theatrical revenue])	1.50*	.0351
	Variance (log[P&A])	.934*	.0258
	Covariance (log[theatrical revenue], log[P&A])	−1.16*	.0288
Purchase	Channel nesting coefficient	.999	.0183
Rentals	Channel nesting coefficient	.880	.294

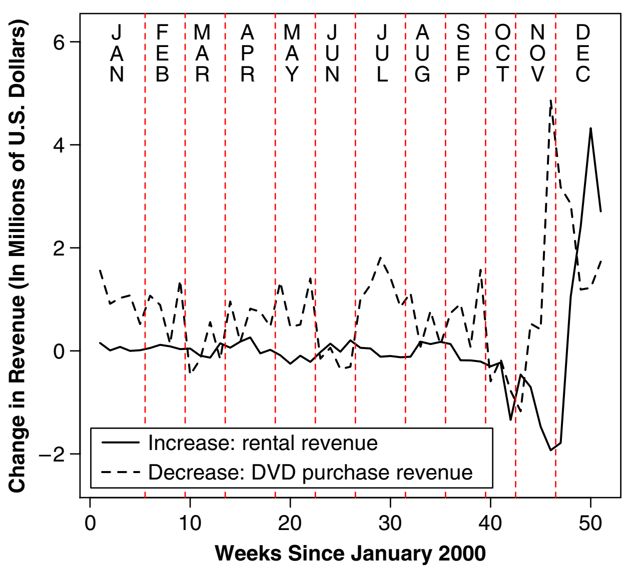
*$p < .01$.

[a]Significance codes are for t-tests that compare coefficient estimated with a null hypothesis of the coefficient being 0. There is no null hypothesis for the channel coefficient. The distribution of the bootstrapped channel coefficients is truncated at 0 and 1.

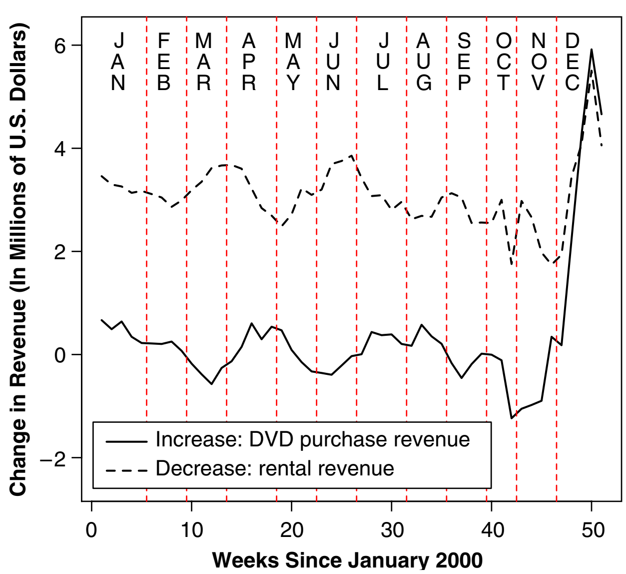
[4]We are assuming that all studios pick this window for all movies. A complete model of competitive studio behavior should include endogenously determined optimal windowing (which might vary by studio, movie, and channel) and its impact on changed DVD titles available for purchase and rental. Such a model is outside the scope of this article.

Figure 2
28-DAY CHANNEL EXCLUSIVITY

A: For Rentals



B: For Purchases



for advancing the more profitable DVD purchase channel release date despite potentially lower overall revenues.

We also measure substitution patterns as a function of DVD purchase prices (approximating the cross-channel price elasticity). Consider again the movie *The Thomas Crown Affair* described previously, which is similar to the mean/median title in our data set. We simulate the effect of increasing the DVD purchase price by $1 (corresponding to a 5% price increase; the original price of the DVD was $20). We find a large within-channel substitution effect, with 80% of consumers substituting the purchase of that DVD for the next best-selling DVD. Less than 1% of those substituting the DVD chose a rental movie, echoing previous findings of low cross-channel elasticities across both channels.

Seasonality of Demand

There are three time-varying demand drivers in our model: seasonal change in consumer preferences, possible market expansion due to the release of more and better movies in a period, and the substitution effects of movies within and across channels. Although our model is general enough to conduct simulations to analyze the managerial implications of changes in any of these factors, in this section we discuss the recovered seasonality of demand and conduct a counterfactual that measures aggregate demand if consumer preferences are not seasonal.

Figure 3, Panel A, plots the recovered seasonality in consumer preferences. The results indicate that DVD purchase is more seasonal than renting. To understand the role of seasonality in shaping observed demand, in Figure 3, Panel B, we analyze the effect of seasonal changes on the revenue of movies in a channel. We simulate channel revenue in a nonseasonal market (assuming the average seasonal effect across all weeks) without changing the substitution set in any week. If the observed increases in total channel revenue (DVD purchase or rentals) were solely due to market expansion, the simulated revenue (without seasonal changes in consumer preferences) should be equal to the observed revenue. The simulation (Figure 3, Panel B) shows that seasonal changes in preferences are a strong driver of DVD purchase but do not affect DVD rentals as significantly. In particular, cumulative DVD purchases drop to approximately 25% of the observed (seasonal) sales in the peak weeks of demand (around Thanksgiving) in our simulation, if preferences were deseasonalized as described previously.

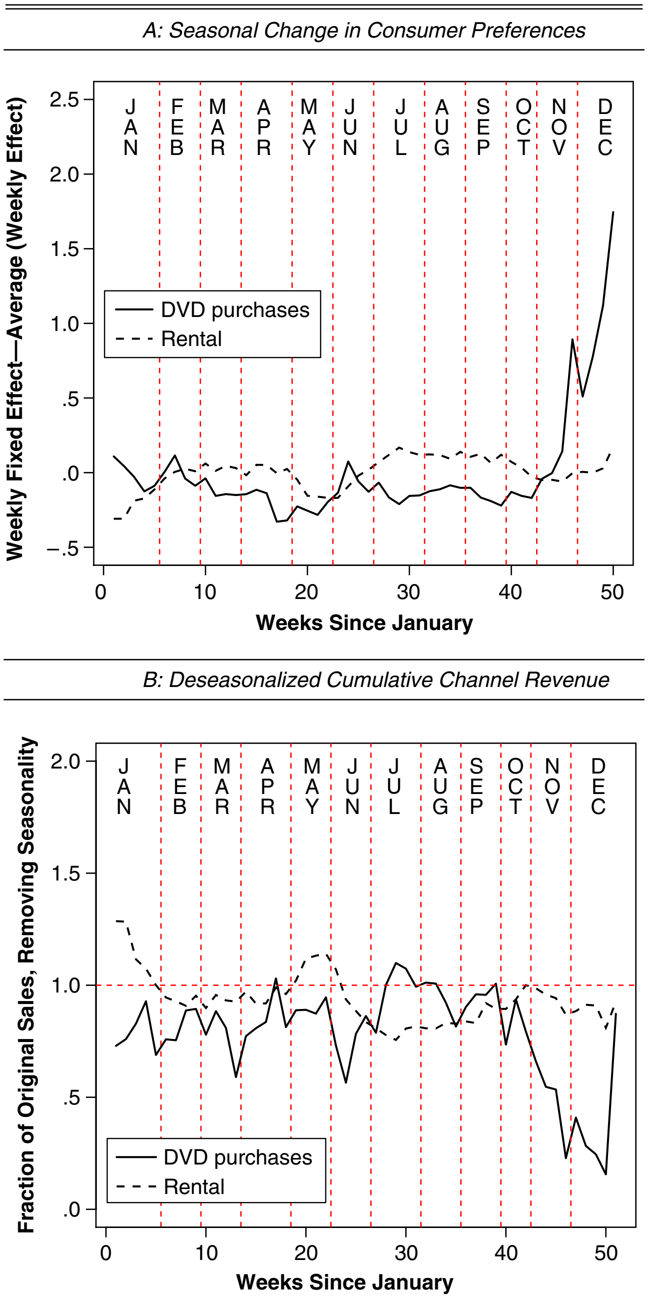
Our estimates of the random coefficients nested channel–movie selection model enable us to conduct simulations to answer managerial questions pertaining to the impact of DVD purchases on rentals (and vice versa), the impact of pricing on channel revenues, and the influence of seasonal effects on demand. Additional counterfactuals that can be conducted using our model include measuring demand by movie, channel, and week with either a change in consumer preferences or a change in release date and/or price of the movie.

CONCLUSION

We describe and estimate a model of weekly DVD purchase and rental revenue by movie. Our model incorporates both seasonal demand variation and the market effects of better movies being released in periods of peak sales. Among our main findings are the following: First, there is limited cross-channel substitution pressure, with an asymmetry in substitution between DVD purchase and rentals. Consumers were less likely to substitute from the rental channel to the purchase channel than from the purchase channel to the rental channel. Second, consumers who are more receptive to higher theatrical revenue and theatrical P&A are less price sensitive than the average consumer.

Our model has several drawbacks. First, we do not include other sources of entertainment, such as television, that might have systematic time variance and compete with movies on home video. Not including competitive sources of entertainment may misstate the estimated substitution effects. Second, we estimate our model on data from the

Figure 3
IMPACT OF THE SEASONALITY OF CONSUMER PREFERENCES ON CUMULATIVE CHANNEL REVENUE



two primary channels of home video demand in our period of interest. A study of home video channels using more recent data would not change the modeling problem but would require data on additional channels than rentals and purchases. Thus, our estimates of cross-channel substitution should be interpreted with caution in the current home video landscape.

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