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Forecasting in Rapidly Changing Environments: An Application to the US Motion Picture Industry

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Abstract

Markets with rapidly changing environments provide forecasting challenges because of fewer similarities between past and future outcomes. In this paper, we provide a methodology that enables forecasting with relatively short histories. The application is to the U.S. motion picture industry where we forecast revenues in theatrical, sales (DVD and VHS), and rental channels. Using short market histories of similar products, we account for (1) observed and unobserved movie-specific characteristics, (2) seasonality of demand, (3) competition within and across multiple distribution channels (4) market expansion, substitution and complementarity between movies inside and across distribution channels. We extend the multiplicative competitive interaction model (Cooper and Nakanishi (1988)) to multiple distribution channels and build a novel two-step estimation method that allows for endogenous release schedules. We find our model outperforms existing models in most cases.

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1. Introduction

Industry watchers and researchers have discussed how a growing number of industries are facing rapidly changing environments. Example drivers of change are technology, globalization, capital market pressures, and new ownership structures via mergers and spin-offs. In changing environments, long histories for a product are unavailable or not reliable in changing environments, managers in such industries face difficulty in forecasting what lies ahead. Our goal in this paper is to provide a tool for sales forecast in rapidly changing environments using relatively short histories.

The application is to the U.S. motion picture industry.[1] The high costs of movie production and frequent failures at the box office raise the stake in forecasting movie revenues. Several factors make forecasting movie sales inherently difficult: the difficulty in quantifying what makes a movie successful (the role of unobservables in the data), short lifecycles of the product, and facing different competitive sets each week. Changing consumption patterns, driven by improvements in technology, reduce the usefulness of historical data in forecasting.

We build a model that forecasts revenue for movies before they are launched and in four separate channels: theatrical release, DVD sales, VHS sales and rentals, by title, by week. Our model extends the Multiplicative Competitive Interaction model of Cooper and Nakanishi (1988) to account for unique features of this market. Specifically, we account for (1) observed and unobserved movie characteristics, (2) seasonality of demand, (3) competition within and across multiple distribution channels, (4) market expansion, substitution and/or complementarity between movies inside and across distribution channels. This involves significant data efforts. This also involves overcoming an important methodological issue. We allow for general correlation in error structures to do (4). Therefore, we cannot use movie characteristics in one channel as instrumental variables for movie performance in another channel because characteristics of a movie in one channel are likely to be systematically correlated with error terms in the other channel. Therefore,

[1] While our application here is to movies, our model is equally applicable to other products with similar characteristics. Examples include television shows (on television, off-network syndicates, and home videos), music (audio and video singles in hard copy, on-line, as part of an album and then in broader compilations), and even books (hard bound and then in paperback and e-books.). The fashion industry also has similar characteristics of short lifecycles, seasonality, and cross-channel competition.

we modify existing methodology (Chiou, 2007) to estimate our model. We find that our model improves forecasts in the sequential distribution channels, with lower mean squared error in out of sample validation than extant models.

The rest of the paper proceeds as follows. In the next section we discuss issues in forecasting revenue in the movie industry. Next, we provide a literature overview. In section 4 we discuss our model in greater detail. In section 5, we provide details on the empirical application. The last section concludes.

2. Issues in Forecasting Movie Revenue

As mentioned in the introduction, movies are highly differentiated products, and it is nearly impossible to gather enough data to explain all the determinants of revenue success. For example, genre is likely to be a useful (observed) characteristic of a movie in any forecasting exercise. However, a movie's plot likely also matters for revenue forecasts. However, data on plots is not easy to quantify as an explanatory variable. We want to model competition among movies within and across channels. This raises additional issues related to unobservables. Some movies may be complementary; the release of a popular movie on DVD may increase visits by to retailers, and hence increase sales of other titles. Promotions for titles with similar plots might have positive (or negative) spillover effects across titles. In our model, we control for unobservables and in modeling competition across channels, allow for market expansion (or contraction), complementarity and substitution within and across channels.

Consider next the issue of short-life cycle of a movie in theatrical release, and the large number of alternatives available in theatrical and across other channels. This leads to intense market share competition (Epstein, 2005). Consumers who do not watch a title in a channel, may either substitute the title entirely and never watch the title, or watch the title in a different channel, substituting across channels. The short life-cycle in the primary channels increases the need for accurate forecasts of revenue for the first weeks post release. Should forecasts of demand be inaccurate, there is not much time to improve non optimal promotion and distribution strategies.

Further, the large proportion of sales in the first weeks post-release (Ainslie, Dreze and Zufryden, 2007), causes data constraints in forecasting. In more prevalent approaches in marketing focused on established brands and products, long data histories are used to estimate brand-specific parameters when forecasting future demand. A managerially relevant forecasting model for the movie industry must only use the set of observables known to a manager at the time of forecasting and cannot use prior weeks' revenues to forecast later week revenues. Thus, our goal is to forecast sales by title using data available prior to release of the title in the channel.

Another issue in movie forecasting is the seasonality of demand for movies in both primary and secondary channels (see figure 1). Studios account for this seasonality in their theatrical and secondary channel distribution (see Einav 2003), with the most highly awaited movies released in weeks of peak demand. For accurate forecasts, it is important to account separately for changing seasonal demand and market expansion due to new releases. That is, are more movies released in a high-demand season because of the high demand, and/or do they cause demand to increase given the greater variety (and possibly quality) of movies available to viewers in these weeks? Our model separately controls for both effects in each distribution channel.

---[Insert Figure 1]---

Over the last 2 decades, the movie industry has faced a rapidly changing environment. The advent of the video cassette (particularly VHS) in 1984 and then the Digital Versatile Disc (DVD) in 1997, made home-viewing possible. These technologies led to new channel partners (and new complementors via merchandizing deals), altering competitive landscapes. Secondary channels and merchandizing deals grew in importance to the industry.[2] Expectedly, the entry of new players in the industry landscape, led to changes in pricing and distribution policies in channels. For example, in the period of 1996-1999, the introduction of a new rental revenue sharing mechanism reduced inventory risk allowing rental chains to keep more copies of a title in stock (see Mortimer, 2004). Other changes include the growth of the online rental and sales channels, and peer to peer movie piracy (Smith and Telang, 2006).

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[2] In 1980, the industry made approximately 30% of its revenues from the domestic box office, and 7% of its revenues from home video (including rentals and sales); in 2000 the industry made approximately 15% of its revenue from box office and 38% of its revenue from home video (Vogel, 2004).

We build a model taking in to account the issues mentioned above. Empirically, the time period for which we forecast the secondary channel revenues are the last 4 months of 2001. Rapid change in an industry environment implies that the window of past data useful in forecasting is likely to be small. Cognizant of the data limitations imposed by the changing environment in the movie industry, we estimate and benchmark models using the data from January 2000 to the last week of June 2001.

3. Literature Review

The movie industry has invited considerable attention from several marketing scholars (see Eliashberg, Elberse and Leenders, 2006, for a summary). We organize our review below as models of single movie performance, models with competition within a channel, and models with competition across channels. Our model is in the final category.

Consider papers that examine single movie performance with no competition within and across channels. Sawhney and Eliashberg (1996) propose a model (BOXMOD) for box office performance. Eliashberg, Jonker, Sawhney, and Wierenga (2000) propose a model (MOVIEMOD) for predicting pre release awareness, adoption intent and cumulative penetration in consumers. Neelamegham and Chintagunta(1999) and Elberse and Eliashberg (2003) focus on international box office receipts.[3] These papers model sales as a function of observable characteristics (such as budget) and past performance of a movie. Our formulation for market attractiveness is informed by these papers, and we compare our model performance to BOXMOD, modified for the sequential channels.

Other single-movie papers have modeled other important industry features. Shugan (1998) looks at the impact of the production team on box office success. Krider and Weinberg (1998) discuss competition when faced with seasonal demand variations. Radas and Shugan (1998) outline an approach for including seasonal trends in estimating demand curves by taking a transformation of time. Important insights from this literature for our model are the decline of

[3] Lee, Boatwright and Kamakura (2003) draw upon single movie prediction models and specify a hierarchical Bayesian model, to forecast sales of music albums, prior to their launch. Whilst the industry of their study is different, the research question and modeling challenges faced are similar.

receipts over weeks post release, and the impact of print and advertising expenditure on box office performance.

Consider next papers that model model within-channel competition. Three approaches have been used here. Swami, Eliashberg, and Weinberg (1999) study multiplex screen allocation decisions and formulate a model to optimize exhibitor scheduling. Ainslie, Dreze and Zufryden (2007), hereafter ADZ, build on the BOXMOD model and study the lifecycle of a movie at the box office, measuring the substitution effects of competition within a channel. Einav (2007) presents an empirical analysis of release timings in the U.S. movie industry, studying both seasonality and competition. In a companion paper, these estimates are used to study the timing game, and optimal timings calculated for the industry (Einav, 2003).

Our model is similar to ADZ and Einav (2007) in allowing for flexible competitive structures and seasonality. Expanding on these models, we include market expansion and allow for more flexible revenue patterns beyond the two-way classification of steady decay blockbuster movies and sleeper movies. It is not clear ex-ante if only two types of patterns are present in secondary channels, and how the primary channel revenue patterns might change when we consider the substitution/complementarity of secondary channels and the longer availability of a title in a channel. Therefore, our model can be seen as a general case of their model. Also, unlike these papers, we cannot use long datasets to estimate relatively stable traits like seasonality, and our model of competition within and across channels poses additional data gathering and methodological tasks.

A third relevant stream of literature examines competition across channels. Here, researchers have examined competition for any given movie across channels, without modeling competition amongst movies within a channel. An example is Lehmann and Weinberg (2000), who develop a model of the optimal time to enter a second channel for any movie. They calculate optimal release timings in rentals accounting for the cannibalization of sales from theatrical release. They do not study cannibalization across the secondary channels. Prasad, Bronnenberg, and Mahajan (2004) use an analytical model to study the effect of consumer expectations on optimality of the timing decision. The duration between releases is treated as an unwritten covenant of the industry, shaping customer expectations. In contrast, the optimal timing policy for a distributor depends on current expectations, leading to an impetus to cheat and release early. Luan and Sudhir (2007) model the impact of cannibalization of sales and rentals of movies, on box office revenues, accounting for forward looking behavior of the consumer at the theatre.

Two papers study movies in a multiple channel setting. First, Hennig-Thurau et al, 2007, use individual level discrete choice data to study the effect on studio profitability of different configurations of sequential distributional channels, optimizing release timings across these channels. As their goal is to study hypothetical configurations vastly different from current market conditions, they use conjoint data to model channel substitution, without accounting separately for either complementarities or market expansion. Second, Chiou (2007) models seasonal demand variation in secondary channels, controlling for competitive interactions within the rental revenue channel and in DVD and VHS sales. While Chiou's model is the closest to ours, we cannot use her estimation methods in a multi-channel setting where unobservables across channels might be correlated. Therefore, we develop methodology more appropriate to our setting. More on that in section 4 below.

4. Revenue Prediction Model

We first outline the market attraction function. Second, we describe our model of market share across channels. We conclude by describing the estimation methodology needed to forecast revenues.

4.1: Market Attraction

In the MCI model, the market share of a product is a function of the ratio of the market attraction of the product to the sum of the market attractions of all products. We define our market attraction a for movie m, in channel k, in week w, year y as below:

$$\ln(a_{mkwy}) = \ln(\delta_{mkwy}) - \tau_{kw} + \xi_{mkwy} \qquad \text{(Eqn 1)}$$

The components of the attraction are as follows. The deterministic component (δ_{mkwy}) is a function of observed variables. The specification of this function and a description of its components in our empirical application, are provided in section 5.2. τ_{kw} is a weekly unobservable shock common to all products in a given channel and week. It is likely that the opportunity cost of watching a movie in the theatre, and/or on video rental, varies by week. For example, opportunity cost is low during holidays and higher during working days. In the summer, the costs of driving to a store can be considerably different from that in the winter. Unobserved product attributes are modeled as product specific shocks, ξ_{mkwy}. These include movie plot, and the psychological and informational setting of a consumer (Eliashberg and Sawhney, 1994, and Neelamegham and Jain,1999).

We do not specify the distribution of unobserved characteristics, ξ_{mkwy}. Instead we only restrict its first moments in a quasi likelihood specification for identification, setting $E\left[\xi_l \in \Xi_{wy} \mid x_{mkwy}, \tau_{kw}\right] = 0, \forall \xi_l \in \Xi_{wy}$, with Ξ_{wy} a vector of all product shocks is in week w, year y. Our specification is flexible enough to accommodate three important sources of covariance in the movie industry. First, we expect contemporaneous correlation between movie specific shocks in a given channel, in each week. For instance, movies released in summer might share similar characteristics. Second, shocks of movies of movies released in different weeks may show different contemporaneous correlation. For instance, while the older summer blockbuster titles in September would continue to exhibit summer-movie correlation, newer movies released in September might have fall-movie characteristics. Hence the unobservables of new releases will have a different correlation from older releases. Third, noting the rapid decrease in market attractiveness post release, and the simultaneous release of a title in DVD sales, VHS sales, and rentals, shocks from a title will exhibit serial correlations across different weeks of demand, and across different channels.

Our quasi likelihood specification allows for these possibilities. Compare it to a (hierarchical) Bayesian specification, similar to Lee, Boatwright and Kamakura (2003). The latter requires explicitly modeling the covariance matrix of the unobservables. The likelihood of the observed data, a key component of such a model, cannot be formed unless one specifies the relationship between observations in different channels and across different weeks. Without significantly restricting degrees of freedom for the covariance matrix, the limited number of observations on each movie makes for imprecise estimates of this matrix. Instead, we choose to use a more flexible specification that provides less efficient but consistent estimators.

4.2: Market Share Model

Let $_{kwy}$ be the choice set of movies in channel k, week w, and year y. In MCI, the market share of movie m (denoted ms_{mkwy}) is written as

$$ms_{mkwy} = \frac{\exp\left(\ln(a_{mkwy})\right)}{\sum_{i \in \ {}_{wy}} \exp\left(\ln(a_{ikwy})\right)} \qquad \text{(Eqn 2)}$$

Our model applies to any nesting structure with as many channels; in our empirical application we model four channels for which we have data. For each additional channel, the number of coefficients grows linearly. We write the in-channel market share, percentage of cumulative sales of all movies in the channel of movie m in channel k, week w, year y (denoted $ms_{mwy|kwy}$) as

$$ms_{mwy|kwy} = \frac{\exp\left(\frac{\ln(a_{mkwy})}{(1-\rho_k)}\right)}{D_{kwy}} \qquad \text{(Eqn 3)}$$

$$\text{where } D_{kwy} = \sum_{i \in \ {}_{kwy}} \exp\left(\frac{\ln(a_{ikwy})}{(1-\rho_k)}\right).$$

We allow the attraction functions of new title releases to be correlated. Thus we account for complementarities between titles, for instance if such titles were sequels, and crowding out/ negative externalities exerted by simultaneous releases.

We constrain ρ_k to be strictly between 0 and 2 to maintain consistency with the literature in discrete choice models. The cumulative market share of all titles in a channel k (ms_{kwy}) is:

$$ms_{kwy} = \frac{D_{kwy}^{1-\rho_k}}{1 + \sum_{j \in \{Channels\}} D_{jwy}^{1-\rho_j}} = \frac{D_{kwy}^{1-\rho_k}}{D_{wy}} \qquad \text{(Eqn 4)}$$

ρ_k is a channel nesting parameter that controls market expansion, cannibalization and substitution. The release of a new title in channel k increases D_{kwy}, with (Eqn 4) determining the new total channel revenue after market expansion. The market attraction function is scaled by the channel nesting parameter in the market share model, thereby controlling substitution of movies within a channel. Between the values of 0 and 1, the derivative of the market share function with respect to the nesting parameter is positive, suggesting an increased sensitivity to differences in the attraction functions. Between the values of 1 and 2, the derivative of the market share function is negative; suggesting that the market share function reverses direction. Cannibalization is controlled by the nesting parameters of the channels that the title has been released in. Release of a new title into channel k increases D_{kwy} with (Eqn 4) determining the new total channel revenue for channels in which the title was currently available, after cannibalization.

4.3: Deriving the Revenue Forecasting Equation

To forecast revenue we have to account for both τ_{kw} and ξ_{mkwy}. We develop a novel forecasting model in two steps. First we integrate product shocks, ξ_{mkwy}. Second, we substitute for channel specific, unobserved time shocks, τ_{kw}.

Define Eq_{wy} as the expected aggregate volume of titles bought or rented (across all channels) in week w, year y; Eq_{kwy} as the expected aggregate volume of titles bought or rented (channel specific) in channel k, week w, year y; Eq_{mkwy} as the expected volume of movie m, bought or rented in channel k, week w, year y.

We predict revenue by setting $Eq_{mkwy} = Ems_{mkwy}M$. While M is set to a large number and never observed, ms_{mkwy} is a function of stochastic variables $\left\{\xi_{mkwy}\right\}$. Note that $ms_{mkwy}\left(\xi_{mkwy}\right)$ is strictly monotonically increasing in ξ_{mkwy}, continuous and differentiable everywhere. The first order Taylor expansion around $E\left[\xi_l \in \Xi_{wy}\right] = 0, \forall \xi_l \in \Xi_{wy}$ leads to $E\left[ms_{mkwy}(\xi_i \in \Xi_{wy})\right] \approx ms_{mkwy}(E\left[\xi_i\right] \in \Xi_{wy})$.

Hence, we substitute the expected unobserved product shock for the unobserved product shock in the first step. In the second step we substitute for the unobserved time shock. Index channels as B for box office, D for DVD sales, V for VHS sales, and R for rentals. Define:

$$D_{kwy} \quad \sum_{i \in C_{kwy}} \exp\left(\frac{\ln(\delta_{ikwy}) - \ln(\tau_{kw})}{1-\rho_k} \right) \qquad \text{(Eqn 5)}$$

$$\kappa_{kwy} \quad \sum_{i \in C_{kwy}} \exp\left(\frac{\ln(\delta_{ikwy})}{1-\rho_k} \right) \qquad \text{(Eqn 6)}$$

$$\gamma_{wy} \quad \frac{(\kappa_{Bwy})^{1-\rho_B}\,\tau_{Bwy} + (\kappa_{Dwy})^{1-\rho_D}\,\tau_{Dwy} + (\kappa_{Vwy})^{1-\rho_V}\,\tau_{Vwy}}{\tau_{Rwy}} + (\kappa_{Rwy})^{1-\rho_R} \qquad \text{(Eqn 7)}$$

From(Eqn 4), we write $$Eq_{wy} = \frac{\gamma_{wy}}{\tau_{Rwy} + \gamma_{wy}} M \qquad \text{(Eqn 8)}$$

The goal of this paper is to derive a model for predicting the sales of a title, in a given week, in a given channel, before release of that title in that channel. The above expressions derive total sales in a week, summed over all channels, as a function of the total market size, M, and unobserved parameter τ_{Rwy}.

First, noting that this parameter, τ_{Rwy}, is the same over a particular week in the two year sample, we substitute for the unobserved terms in the equation for the second year, to get:

$$Eq_{w2} = \frac{\gamma_{w2}}{\left(\frac{M\gamma_{w1}}{Eq_{w1}} - \gamma_1 \right) + \gamma_2} M \qquad \text{(Eqn 9)}$$

Next, we re-arrange and derive an equation for the total sales in a week, in a given channel. From (Eqn 9) and(Eqn 4), we write:

$$\begin{aligned} Eq_{Rw2} &= \frac{(D_{Rw2})^{1-\rho_R}\, Eq_{w2}}{(D_{Bw2})^{1-\rho_B} + (D_{Dw2})^{1-\rho_D} + (D_{Vw2})^{1-\rho_V} + (D_{Rw2})^{1-\rho_R}} \\ &= \frac{(\kappa_{Rw2})^{1-\rho_R}}{\gamma_{w2}} Eq_{w2} \end{aligned} \qquad \text{(Eqn 10)}$$

Next, we derive the final equation for sales of a title, in a given week, in a given channel. Without loss of generality, consider forecasts for movie m, in rentals channel subscripted by R, in week w, year 2. Using (Eqn 10), (Eqn 3) and (Eqn 4), we get:

$$Eq_{mRw2} = \exp\left(\frac{\ln(\delta_{mRw2})}{(1-\rho_R)}\right)\frac{M(\kappa_{Rw2})^{-\rho_R} Eq_{w1}}{\left(M\gamma_{w1} - \gamma_1 Eq_{w1}\right) + Eq_{w1}\gamma_2} \qquad \text{(Eqn 11)}$$

To predict revenue we replace expected sales in year 1 with observed sales in year 1.

$$q_{mRw2} \approx \exp\left(\frac{\ln(\delta_{mRw2})}{(1-\rho_R)}\right)\frac{M(\kappa_{Rw2})^{-\rho_R} q_{w1}}{\left(M\gamma_{w1} - \gamma_1 q_{w1}\right) + q_{w1}\gamma_2} \qquad \text{(Eqn 12)}$$

Our final forecasting equation (Eqn 12) can be used for long term forecasts, predicting revenue on a set of movie characteristics and observables available months earlier, prior to the release of the movie in that particular channel. Note that when using a longer dataset,(Eqn 12) can be used for each preceding year and an estimate formed from the (weighted) average.

4.4: Two-Step Estimation for Endogenous Choice Sets

Our nested MCI model is similar to a formulation by Chiou (2007) where (Eqn 2) leads to:

$$\ln(ms_{mkwy} / ms_{0wy}) = \ln(a_{mkwy}) - \rho_k \ln(ms_{mwy|kwy}) \qquad \text{(Eqn 13)}$$

The last term, in-channel market share, $\ln(ms_{mwy|kwy})$, is endogenous and correlated with the product shock in the attraction function. Commonly, attributes of other titles in the channel that affect the in-channel share and are not correlated with the market attraction, are used as instruments. For instance, Chiou (2007) uses the sum of the characteristics of other products, as instruments.

This estimation strategy requires the attributes of other titles in the channel to not be correlated with the product attraction shock. As discussed earlier, studios time the release of the best movies to be in periods of highest demand. The number of movies released in a given week as well as the cumulative budgets of all movies in the channel in a given week, show strong seasonal patterns. Hence, attributes of films released in the same week are strongly correlated. For instance, blockbusters in theatrical, sales and rentals, are all simultaneously released in the same weeks in December. Therefore, characteristics of movies in one channel cannot be used as instruments for a market-share model for another channel, as the unobservables might be correlated across channels (e.g. summer-themed movies are released in theatrical and sales channel in summer and winter-holiday themed movies are released in theatrical and sales channels around the winter holidays).

Thus, the release timing game implies that the assumption of exogenously determined choice sets is likely to be inaccurate, biasing the described instrumental variable estimator. For instance, movies released in a peak summer week have systematically larger budgets, and systematically larger average product attractions as they were picked by studios to be summer releases. Conversely, movies with smaller product attraction shocks, should on average, be released in weeks with less competition. Instrumental variable estimates of the nesting coefficient are biased in both cases.

In addition, channel coefficients are identified through the variance across the characteristics over the years, for the same week. Due to the release timing game and the underlying stability of seasonal patterns, such variance remains limited when compared to variance across weeks in a year. For instance, holiday weeks across years have similar cumulative budgets over all releases in a week, as all big budget movies of the year are released in this period. These concerns are amplified when using a shorter dataset, as in our problem, where there are far fewer overlapping weeks over which one can identify the channel coefficients.

To summarize, in entertainment markets, unlike markets with long stable product histories, the econometrician cannot instrument for in-channel market share in the nested MCI model. As the product attraction shock of the movie in a week is likely to be correlated with channel attributes, such as number of releases in the week, instruments that utilize characteristics of competing products, lead to biased estimates of channel coefficients. The definition of the market attraction function does not allow for an instrument that utilizes observables of the same title.

Given the issue with instrumental variable, we use a two-step estimation process. In the first stage, we identify the market attractiveness function to scale by regressing a function of market shares on characteristics. In the second stage, we estimate channel nesting parameters by minimizing an objective function formed through prediction errors of the forecasting equation.

Let s_{jkt} be the market share of movie j in channel k, in week w, year y, in quantities. Define the geometric mean of in group market shares as $\ln(s^g_{kwy}) = \frac{1}{N_{kwy}} \sum_{i \in C_{kwy}} \ln(s_{ikwy})$. Then from (Eqn 2) :

$$\ln(s_{jkwy}) - \ln(s^g_{kwy}) = \ln(\delta_{jkwy}) - \frac{1}{N_{kwy}} \sum_{i \in C_{kwy}} \ln(\delta_{ikwy}) + \xi_{jwy} - \frac{1}{N_{kwy}} \sum_{i \in C_{kwy}} \xi_{ikwy} \quad \text{(Eqn 14)}$$

In the first stage, coefficients from (Eqn 14) are estimated using Ordinary Least Squares[4] and used in the second stage to find the channel nesting parameters. Conditional on a guess of channel coefficients, we calculate differences in the response to mean price and the seasonal change in demand. Using (Eqn 12), we can predict the total revenue of a channel in the future weeks.

Having estimated the first stage on the first 84 weeks, we use the next 4 weeks to find channel nesting parameters that minimize the sum of squared errors in the prediction sample.[5] As our objective function does not have analytical derivatives, we utilize a Nelder Mead simplex search followed by the Broyden-Fletcher-Goldfarb-Shannon method (with numerical derivatives), to find the minimum. While we do not prove the existence of a unique global minimum, varying starting values we find the algorithm converges to a unique parameter vector. Robustness tests indicate that our prediction results are not affected by the size of the market, as long as we choose M larger than the maximum total quantity of entertainment products sold.

Thus, we develop a new estimation algorithm to account for systematic correlation between weeks of peak demand and the release schedule of better performing movies, and face the burden of estimating without movie-specific parameters. Note that our model of competition is reduced-form. A full structural model of competition that accounts for substitution, complementarity and market expansion is beyond the scope of our research question. Instead, we

[4] Clustering errors by week and using White's correction for heteroskedasticity does not improve fits and/or predictions.
[5] The sum of squared errors and the sum of absolute errors led to similar estimates and predictions.

build a model that has a flexible competitive structure and market attraction formulation, without attempting inference on competitive structures.

5. Empirical Application: Forecasting Weekly Movie Revenues

We describe the data used in our empirical application, forecasting movie revenues in the U.S. motion picture, the operationalization of the forecasting model, and present our results.

5.1: Data

We use data from three distribution channels – the primary channel i.e. theatrical release, and two secondary channels, rentals and sales. As mentioned previously, the data are for January 2000 through December 2001.

We obtained data from Nielsen EDI for nationally aggregate theatrical revenues (and distributional reach) in the first ten weeks of theatrical release for all movies released on box office. In the dataset there are about 40 movies being exhibited across theaters nationwide in any given week.

Nielsen Videoscan collects DVD and VHS sales data from retailers at the point of sale. We use data (including weekly sales and price) for the top 500 selling movie titles in each channel, which covers all movies that sell over 300 copies in a format, in a particular week nationally. Other researchers have used this dataset to study movie VHS and DVD sales (Elberse and Oberholzer-Gee, 2006). There are significant differences in lifecycle, pricing and other competitive issues. Therefore, we model the two formats separately. The data does not include Walmart. In our period of interest, Walmart was a major retailer of DVD and VHS that carried a smaller inventory of possible titles than comparable national retailers. Hence, our sample may understate the importance of larger titles and overstate the importance of smaller titles.

Rental data comes from Video Store Magazine's Rental Charts. This source tracks weekly national revenue by title for the top 50 selling titles that week. Video Store Magazine constructs estimates from a panel of suppliers and retailers. Therefore, compared to the sales data from VideoScan, these data might be more inaccurate but relatively unbiased if the panel of suppliers and retailers is representative. Also, unlike the sales data, rental data is not divided by DVD/VHS format.

Pricing policies differ across channels. In movie theatres and home video rentals, prices are almost always uniform (Einav and Orbach, 2007), and revenue shared between the exhibitor/rentailer and distributor We assume a mean box office ticket price of $6.00 per title, and a mean rental price of $2.50 per title for the duration of the study (Hettrick 2000, Vogel 2004) and find our results robust to a range of price means.[6] In DVD and VHS sales, we observe the weighted average price for a title (reported by week, by title) sold in all Discount Mass, Drug & Grocery stores, which account for about 43% of all units sold in the dataset, and assume it to be equal to mean price of the movie across all reporting retailers.[7]

To enrich the forecasting model, we gather data on additional variables by title. We obtain data on print and ad spending (P & A) for each movie at the box office stage from Paul Kagan and Associates. We also use user ratings from Internet Movie Database (http://www.imdb.com) to proxy for user reported quality. We complement user ratings with a summary measure of critics' ratings. Available at Rotten Tomatoes (http://www.rottentomatoes.com), the Tomatometer, captures the percentage of positive critics' reviews for a title. Additionally, sales of a movie may be influenced by the "star" power of the actors and directors involved in the movie (see Elberse, 2006 for a summary of studies on star power). Ulmer (2000) published a list of the top 200 actors and top 10 directors in Hollywood, measured on their "bankability" at the box office, through an industry wide survey of Hollywood professionals. We gather data on all actors and directors featured in a movie, and check if those actors were included in the top 200 and top 10 lists respectively. Finally, we include studio fixed effects.

--- [Insert Table 1 here] ---

[6] Two major retail pricing schemes existed in DVD and VHS. First, in "sell-through" pricing, retail prices were set with the expectations of direct purchase by consumers and rental stores, and the title distributed widely to media retailers. Second, in "rental-window" pricing, a movie was priced above the average retail price of other VHS or DVD available at retailers, and distribution curtailed to rental stores. While DVDs were introduced in 1997 with "sell-through" pricing, "rental-window" pricing was the norm for VHS cassettes through the late nineties. Further information on theatrical contracts can be found in Einav (2007), and on rental contracts can be found in Mortimer (2004) and Chiou (2007).

[7] A number of retailers, including Target and Kmart but excluding Walmart, are included in the category.

Table 1 presents key summary statistics. All variables reported are means across title, in the channel, in a week. For instance, the first row, channel gross, is the total sales of a title in the channel in the week. The average title running in theatres grosses approximately 3.5 million dollars each week of its run, while the average DVD in our dataset, has total sales of approximately 100,000 dollars each week.

The second and third rows are only for secondary channels. Box Office is the cumulative box office (primary channel) gross of a title, now released in the secondary channel. Screen-Weeks is the sum of screens on which the movie showed, over the first 10 weeks of its theatrical run. Budget is the cost of making the film. Print & advertising spending measures expenditure on both advertising as well as the cost of creating prints for distribution. User Rating and Critic's Ratings were described earlier. Weeks in Channel measures how long the movie has been in that channel post release, and Inter Release Time measures the time between primary and secondary channel release.

5.2: Operationalizing the Deterministic Component of Attraction Function

We discuss the mathematical form and variables used in modeling the deterministic component (δ_{mkwy}), first in the primary channel, and then in the sequential channels.

In the theatrical channel, Sawhney and Eliashberg (1996) proposed 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. ADZ make the distinction between blockbuster decline (early peak), or a sleeper decline (later peak).

In the box office, we extend these two extant models to incorporate more explanatory variables, particularly P & A, user ratings and critics' ratings, improving fit significantly. Suppressing subscripts denoting movie m, in channel k in week w, year y, we write the deterministic component in box office as[8]

$$\delta = p^{\alpha_k}\left[BB:\log(PA)\right]^{\beta_{1k}} x^{\beta_{2k}} w_R^{\left(\beta_{3k}+\beta_{4k}\lg(PA)\right)} e^{\left(\beta_{5k}+\beta_{6k}\lg(PA)\right)w_R} \qquad \text{(Eqn 15)}$$

[8] Comparing fits, we find little difference in using the logarithm of the price and characteristics, and the untransformed variables. Varying the form of (Eqn 15) increases the variance of estimates, but does not substantively change predicted values.

where p is the price, BB is a set of dummy variables coded using 4 levels of print and advertising expenditure (henceforth P&A) to capture blockbuster status, PA stands for P&A, x is a characteristics vector and w_R is weeks spent in the channel post release.

We assume that the price of a box office ticket remains constant over the length of the dataset. We interact of blockbuster status with P&A to allow for a non linear relationship between gross and P&A. While we observe the P&A for the theatrical channel, we do not observe the marketing mix used by the firm.

For all channels, the characteristics vector x we include the following measures of differentiation among movies: studio dummies, dummies for genre, dummies for animation movies, MPAA ratings, and dummies for the presence of star actors and director. We also use user ratings to measure consumer reported quality and a summary measure of critics' ratings.

In the sequential channels, we interact movie characteristics time spent in channel and inter release time. Suppressing subscripts denoting movie m, in channel k in week w, year y, we write the deterministic component in sequential channels as

$$\delta = \left\{ [BB:p]^{\alpha_{1k}} \; p^{\alpha_{2k} \log(w_R + w_C)} \right\} \left\{ [BB:\log(BO)]^{\beta_{1k}} \; {x_m}^{\beta_{2k}} \right\}$$
$$\left\{ {w_R}^{(\beta_{3k} + \beta_{4k} \lg(BO))} {w_C}^{\beta_{5k}} \right\} \left\{ e^{(\beta_{6k} + \beta_{7k} \lg(BO)) w_R + \beta_{8k} w_C + \beta_{9k} w_R w_C} \right\} \qquad \text{(Eqn 16)}$$

where BB is a set of dummy variables coded using 4 levels of box office gross to capture blockbuster status, BO stands for box office gross, PA stands for P&A in the primary channel, w_C is weeks spent (inter release time) between the theatrical and sequential channels and other variables are as described for equation (15) above.

As explained earlier, we assume that the price of a video rental remains constant over the length of the dataset, and use the mean price in sales. As the price elasticity of a movie in DVD or VHS sales may depend on its box office gross and the time since the movie was released in theaters, we interact blockbuster status with price and time since theatrical release when identifying the price response coefficient. The interaction of blockbuster status with box office gross allows for a non linear relationship between gross and box office. We observe the P&A for the theatrical channel, but not the marketing mix used by the firm. Lacking similar data at the sequential channels, we use P&A estimates from the box office stage to proxy for spend in promotions at the sequential channel.

For sequential channels, there are other variables included in the x vector. Box office revenue captures the impact of unobservables and is a proxy for market size in secondary channels (Krider and Weinberg,1998, and Lehman and Weinberg,2000). We use the number of screens a movie was show in during the first week, and sum over the number of screens a movie was shown in during the first 10 weeks of its run (henceforth Screen-Weeks) to capture distribution effects.[9] Last, we use the ratio of budget to box office gross (henceforth Profitability Index), to differentiate between smaller budget and larger budget films with the same box office gross.

Extant forecasting models have not considered multiple channels, and hence do not suggest a relationship between the inter release time (number of weeks between release in the theatrical and sequential channels), w_C, and the decay in revenue over the weeks post release. The complexity of the underlying cannibilization and dynamic decision making process, and the network effects in evaluating entertainment products would suggest non-linearaties in this relationship. For instance, a longer inter release time may lead to a saturation of the word of mouth, attracting more consumers in earlier weeks, and then showing faster decay post release? Alternatively movie with shorter inter release times may attract more customers in earlier weeks because of the heavy advertising in the box office channel, and then show faster decay post release? Further, the effect of the inter release time may differ for blockbusters, than for smaller budget movies. (Eqn 16) accounts for these possibilities.

5.3: Results and Model Comparisons

In this subsection, we first we discuss the coefficients estimated. Second, we present our predictions and compare them with other models.

[9] Major studio typically release movies first in the theatres, and then for sale in VHS/DVD format and in rental stores. While the primary to secondary distribution channel gap has shrunk in recent times (Luan and Sudhir, 2007), the mean duration in our dataset is 24 weeks. Thus, it is safe to assume that few movies remained in theatres for 6 months. Hence, cannibalization of sales across sequential distribution channels will primarily occur through forward looking conjectures of theatrical consumers, and not due to direct substitution of a movie at the theatre with the same movie at a rental store.

Table 2 reports coefficients estimated for the attraction function in each channel. Table 3 reports elasticities estimated at mean levels of variables.

---[Insert Table 2 and Table 3 here]---

We find that market attraction is well predicted by the print and ad spending of a movie, the user ratings and critics' ratings of a movie, all of which are positively correlated with larger box office revenues. Larger number of weeks since theatrical release significantly decreases the attractiveness of the movie.[10] As in Lehmann and Weinberg (2000), we find that performance measure from the primary channels help improve fit and prediction in the secondary channels. Larger box office gross and greater screen-weeks exposure leads to larger secondary channel attractiveness. Similar to Luan and Sudhir (2007), we find that longer inter release times between channels, decreases market attractiveness.

We compare three models that have the same deterministic specification for market attraction. Similar to ADZ, first write the generalized gamma formulation of BOXMOD as:

$$S_{mkwy} = \eta_i t^{\gamma_i / \beta_i} e^{1-t / \beta_i} \qquad \text{(Eqn 17)}$$

One can rewrite BOXMOD as:

$$S_{mkwy} = \beta_{1i} t^{\beta_{2i}} e^{\beta_{3i} t} \qquad \text{(Eqn 18)}$$

As the original model does not restrict the three parameters of the gamma function ($\eta_i, \gamma_i, \beta_i$), (Eqn 18) is a re-parameterization of the original formulation(Eqn 17). Comparing (Eqn 18) with (Eqn 16), our model has to additionally account for the inter release time and its interaction with the time spent in the channel. Hence, when modeling secondary channels, we modify BOXMOD to include time spent in channel and inter release time (t_C, t_{IR}respectively):

$$S_{mkwy} = \beta_{1i} t_C^{\beta_{2i}} t_{IR}^{\beta_{3i}} e^{\beta_{4i} t_C + \beta_{5i} t_{IR} + \beta_{6i} t_C t_{IR}} \qquad \text{(Eqn 19)}$$

[10] We try different time specifications and do not see a difference in fit across different specifications, including higher order polynomials of time spent in channel.

To reduce computational complexity, BOXMOD can be estimated using a hierarchical two step approach: the three parameters for the gamma function are fitted separately for each movie and then the estimated parameters projected onto the observables of the movie. Substituting the linear model for each parameter into(Eqn 18), and then taking logs on both side, yields the efficient estimator. Noting that (Eqn 15) is the best fit[11] for this class of models and substituting in (Eqn 18) and (Eqn 19), we get:

$$\ln(S_{mkwy}^{M1}) = 1 + \ln(\delta_{mkwy}) + \xi_{mkwy} \quad \text{(Eqn 20)}$$

In the second model, we include a weekly seasonality dummy to allow for seasonal trends, and a yearly dummy to control for technology trends:

$$\ln(S_{mkwy}^{M2}) = t_{ky} + t_{kw} + \ln(\delta_{mkwy}) + \xi_{mkwy} \quad \text{(Eqn 21)}$$

(Eqn 20) and (Eqn 21) are estimated by OLS. The third model is the efficient estimator model. This utilizes the methodology described above to predict both market shares and the aggregate rental revenue. While the first and second model outperform our model in the box office validation sample, our model has the lowest rMSE in all secondary channel validation samples. In DVD sales, VHS sales and Rentals, our estimator shows 2%, 4% and 6% lower rMSE respectively.

There are two important reasons why this might be so. First, primary channels are less likely to be prone to cannibalization or complementarity from other channels when compared to secondary channels. Our model places heavier demand on data to estimate this flexible competition model (within and) across channels, and therefore appears to not do as well in primary channels where this is less of a concern. Second, unobservables play a larger role in the box office channel model than they do in the secondary channel model. Recall that in the secondary channels, the presence of box office gross controls for many of these. Hence, all three forecasting models perform very poorly in the primary channel.

--- [Insert Table 4 here] ---

[11] White's correction, clustering errors by time spent in channel, inter release time, and/or week of observation, do not improve fit.

6. Conclusion

We describe, estimate and then benchmark a model to predict weekly rental revenue by title. Our model incorporates both seasonal demand variation and the market effects of better movies being released in periods of peak sales. To ensure managerial relevance, the model only utilizes data from available months prior to the week of interest.

We find that prior channel performance helps predict future performance. However, we cannot and do not differentiate between causality and correlation. A larger box office gross might potentially lead to more word of mouth and hence more future revenues, or might simply indicate movies of higher quality. Greater distribution (screen-weeks) might indicate a longer runs (better quality) or might capture increased cannibalization across channels. Allowing for a general model of competition within and across channel keeps the model flexible without separating these forces.

Additionally, we find that movies show decay in market share with inter-release and time spent in the channel, and that this effect is highly nonlinear. We find the interaction of these variables remains critical to good forecasts. The non-linearity of time trends in the market attractiveness function process hints both at the complexity of the underlying cannibilization and dynamic decision making process, and the network effects in evaluating entertainment products. This is an interesting avenue for future research.

Our model has some drawbacks. First, we assume inviolate channel boundaries. As different channels begin to overlap both in product and the timing of release, the model will be affected by endogeneity concerns and network effects. Second, our model does not include other sources of entertainment that compete with movies. Not including competitive sources of entertainment, such as television shows when modeling rentals, increases forecast error. While we control for seasonal trends, including major entertainment events such as the Super Bowl, might improve predictive capabilities. Finally, in markets where long stable sales histories are available to marketing managers, our method will have limited usability. Using brand specific parameters and past sales should provide superior forecasts, but are unavailable or inappropriate in rapidly changing industries.

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Table 1: Summary statistics by channel*

	Box Office	***DVD Sales***	***VHS Sales***	***Rentals***
Channel Gross (in $)	3,278,381 (8,270,558)	97,127 (23,577)	82,045 (47,888)	2,030,033 (2,495,021)
Box Office (in $) (for sequential channels)	n/a	80,941,000 (74,159,950)	91,119,160 (75,999,900)	46,447,260 (54,094,390)
Screen-Weeks (for sequential channels)	n/a	14,490 (6,725)	15,666 (6,548)	10,503 (7,260)
Budget (in $)	26,554,000 (30,896,000)	47,234,000 (35,774,350)	47,113,940 (34,818,370)	36,299,480 (31,767,270)
Print & Ad (P&A) (in $)	15,715,000 (14,620,000)	27,978,000 (13,039,970)	29,342,490 (13,128,040)	22,828,910 (14,316,330)
User Rating (out of 10)	6.13 (1.17)	6.51 (1.11)	6.45 (1.12)	5.97 (1.18)
Critics' Ratings (out of 100)	54.71 (26.85)	59.06 (25.83)	59.13 (25.49)	49.40 (27.19)
Weeks in channel (in weeks)	5.31 (2.85)	62.85 (57.22)	90.93 (94.33)	6.85 (3.97)
Inter release time	n/a	87.43 (106.23)	95.20 (108.26)	24.42 (6.06)
Price	n/a	20.08 (4.15)	10.76 (3.43)	n/a

*Mean followed by standard deviation in parenthesis.

Table 2: Coefficients of Market Attraction

	Box Office	*DVD*	*VHS*	*Rentals*
log(Budget)	0.208 ** (0.031)	-0.037 ** (0.011)	-0.006 (0.012)	0.097 ** (0.014)
log(Screens in Week 1)	n/a	0.115 ** (0.007)	0.073 ** (0.007)	-0.026 ** (0.007)
log(Screen Weeks)	n/a	0.011 (0.017)	0.058 ** (0.019)	0.116 ** (0.013)
log(Print and Advertising) (P&A)	n/a	-0.155 ** (0.014)	-0.227 ** (0.015)	0.016 (0.015)
Profitability Index	n/a	-0.00002* (0.00000)	- 0.00005** (0.00002)	0.000002 (0.000004)
log(User Rating)	1.110 ** (0.149)	2.06 ** (0.053)	0.633 ** (0.048)	0.565 ** (0.063)
log(Critics' Ratings)	0.377 ** (0.044)	-0.180 ** (0.015)	-0.004 (0.014)	-0.116 ** (0.017)
Weeks since release (WR)	0.388 ** (0.122)	0.019 ** (0.001)	0.006 ** (0.001)	-0.215 ** (0.015)
Inter Release Time (WB)	n/a	0.002 ** (0.000)	0.005 ** (0.000)	-0.034 ** (0.006)
WR*WB	n/a	- 0.000003* (0.000001)	-0.00002** (0.00000)	0.001 ** (0.000)
log(WR)	1.610 ** (0.502)	-0.725 ** (0.034)	0.282 ** (0.033)	0.352 ** (0.063)
log(WB)	n/a	-0.024 (0.023)	-0.195 ** (0.022)	0.462 ** (0.165)
Star Actor	-0.115 * (0.052)	-0.009 (0.017)	-0.002 (0.017)	0.025 (0.018)
Star Director	0.107 (0.100)	0.020 (0.019)	-0.162 ** (0.020)	-0.061 * (0.029)
BB1* Price	n/a	-0.047 ** (0.004)	0.051 ** (0.005)	n/a
BB2* Price	n/a	-0.017 ** (0.005)	0.047 ** (0.005)	n/a
BB3* Price	n/a	0.091 ** (0.015)	0.035 ** (0.012)	n/a
BB4*Price	n/a	-0.124 $^{+}$ (0.064)	0.003 (0.055)	n/a

(WR+ WB)* log(Price)	n/a	-0.116 ** (0.012)	-0.215 ** (0.010)	n/a
BB1*log(P&A) for primary BB1*log(Box office) for secondary channels	1.250 ** (0.044)	0.786 ** (0.026)	0.961 ** (0.028)	0.582 ** (0.019)
BB2*log(P&A) for primary BB2*log(Box office) for secondary channels	1.300 ** (0.041)	0.694 ** (0.031)	1.020 ** (0.030)	0.526 ** (0.018)
BB3*log(P&A) for primary BB3*log(Box office) for secondary channels	1.340 ** (0.041)	0.126 + (0.067)	1.020 ** (0.038)	0.550 ** (0.022)
BB4*log(P&A) for primary BB4*log(Box office) for secondary channels	1.350 ** (0.042)	1.090 ** (0.236)	1.100 ** (0.177)	0.464 ** (0.028)
WR*log(P&A) for primary WR*log(Box Office) for secondary	-0.073 ** (0.014)	-0.002 ** (0.000)	0.001 ** (0.000)	-0.031 ** (0.004)
Log WR*log(P&A) for primary Log WR*log(Box Office) for secondary	-0.208 ** (0.056)	-0.082 ** (0.008)	-0.210 ** (0.008)	-0.012 (0.018)

We do not report coefficients on animation, genre and rating.
B1, BB2, BB3 and BB4 are the blockbuster status, in ascending order of P&A for primary channels and Box Office Gross for secondary channels.
Significance codes: 0.001 '**' 0.01 '*' 0.05 '+'

Table 3: Elasticity of Market Attraction*

	Box Office	*DVD Sales*	*VHS Sales*	*Rentals*
Price	n/a	0.607	-1.09	n/a
Box Office Gross	n/a	0.436	-0.006	0.530
Screen Weeks	n/a	0.011	0.058	0.116
Screens 1st Week	n/a	0.120	0.073	-0.026
Budget	0.208	-0.040	-0.006	0.097
Print & Advertising	0.576	-0.160	-0.227	0.016
Profitability Index	n/a	-0.00002	-0.00005	0.000002
Time Since Release	-6.21	-3.03	-1.63	-4.92
Inter Release Time	n/a	1.62	0.117	-0.164
User Ratings	1.11	2.06	0.633	0.565
Critics' Ratings	0.377	-0.180	-0.004	-0.116

* Elasticity computed using dataset means, and accounts for all significant parameters associated with the variable.

Table 4: rMSE of models

	BOXMOD equivalent	*Seasonal BOXMOD equivalent*	*Our model*
Box Office (training)	1.46E+06	1.56E+06	5.90E+05
Box Office (validation)	3.99E+05	4.59E+05	8.43E+05
DVD Sales (training)	1.21E+04	1.24E+04	1.27E+04
DVD Sales (validation)	4.27E+04	3.27E+04	3.21E+04
VHS Sales (training)	7.76E+03	7.91E+03	7.64E+03
VHS Sales (validation)	5.74E+04	5.62E+04	5.38E+04
Rentals (training)	6.28E+05	4.66E+05	4.38E+05
Rentals (validation)	5.10E+05	4.58E+05	4.29E+05

Fig 1: Aggregate Weekly Revenue