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Optimal Inter-Release Time between Sequentially Released Products*

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Optimal Inter-Release Timing for Sequentially Released Products

Abstract

Marketers routinely use timing as a segmentation device through sequential product releases. While there has been much theoretical research on the optimal introduction strategy of sequential releases, there is little empirical research on this problem. This paper develops an econometric model to empirically solve the inter-release timing problem: it involves (1) developing and estimating a structural model of consumers' choice for sequentially released products and (2) using the estimates of the structural model to solve for the optimal inter-release time. The empirical application focuses on the movie industry, where we specifically address the issue of the inter-release time between a theatrical movie and its DVD version. We find that consumers are indeed forward looking; a shrinking movie-DVD release window does negatively impact box office revenues, but there is a tradeoff in that there is greater residual buzz from the movie marketing that supports the sales of DVD due to the shorter time window. This leads to an inverted U shaped relationship between movie-DVD release window and revenues, and the theater-DVD window that maximizes industry revenue for the average movie during the data period is 2.5 months.

Keywords: Movies, sequential releases, entertainment industry, structural model, segmentation.

Conflict of Interest Statement: On behalf of all authors, the corresponding author states that there is no conflict of interest.

1. Introduction

Marketers routinely use timing as a segmentation device through sequential product releases. Customers who want to use a product early generally tend to value them more and therefore are willing to pay more. For example, publishing companies conventionally release hardcover version of a book first at a higher price and follow it up with the lower-quality, lower-priced paperback version approximately one year later. Camera manufacturers often introduce a high-end version of cameras targeted at professional users many months before introducing a lower-end version based on the same core technology. Until recently, in the motion picture industry, a movie opens first in movie theaters and is released in the home video/streaming market later.[1]

A central question facing these managers is the following: when firms seek to implement a segmentation strategy with release timing as their main segmentation tool, what should be the optimal inter-release time? The problem has been of general interest to marketers in a wide range of industries such as publishing, electronics and entertainment (e.g., Moorthy and Png 1992; Lehmann and Weinberg 2000). Recently, the problem has gained considerable attention in the context of the movie-DVD release windows. Since the DVD technology was commercially introduced in 1997, the revenue stream from DVD sales and rentals has become pivotal for studios' financial performance in recent years. In 2004, while the US box-office gross remained stagnant at about $9 billion, DVD rental and sales rapidly expanded to over $21 billion, making the DVD market twice as large as the theatrical exhibition market. The enormous growth of the DVD market has disrupted the traditional revenue structure and channel relationships in the industry, and raises a number of questions both of practical significance and of scholarly interest; in particular, whether and how studios should modify the conventional theater-to-DVD window to adapt to the reality that there is greater revenue downstream.[2] The average movie-DVD release timing has been steadily shortening over the last eight years from about 7 months in 1998 to about 4.5 months in 2005. The increasingly shrinking window has sparked much controversy within the movie industry.[3]

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[1] The pandemic has upended this sequential model with many studios going straight to streaming or simultaneously releasing in theater and streaming services.

[2] The applicability of the model may well go beyond the theater and DVD stages and extend to other stages of a typical Hollywood movie's sequential release scheme, such as pay-per-view (PPV), video-on-demand (VOD), premium channel premiere and network TV showing. We focus on the issue of theater-DVD window to simplify the conceptual underpinnings of the econometric approach. Currently, the theatrical and DVD markets combined account for over 90% of the movie-related revenue.

[3] While many executives including the President of Universal Studios Rick Finkelstein, perceive that this trend of shortening DVD releases has "gone too far," others such as Disney have proposed shortening the movie-DVD

Despite the importance of the inter-release timing issue across a wide range of industries and the especially heated arguments in the movie industry, there is little research that allows us to address this problem in an empirically grounded fashion. Our goal in this paper is to develop a structural consumer choice model that accounts for the tradeoffs in consumers' decisions towards sequentially released products, which would then enable us to solve for the optimal inter-release time in an empirical manner. Our empirical application is in the context of movie-DVD inter-release time.

We begin by considering the tradeoffs faced by managers as they decide on the optimal inter-release time. First, managers would like to reap the gains from both markets as quickly as possible (money today is better than money tomorrow) so would like to shrink the inter-release time. However, moving up the second release would cannibalize the sales of the first (and higher-margin) product because, after the second product is released, many customers who would otherwise purchase the higher-end version would switch to the lower-margin version. This is the tradeoff that has been modeled in Lehmann and Weinberg (2000). However, there two other major factors which needs to be accounted in deciding inter-release times for sequential releases.

First, we need to model how buzz spills over from the initial release to the subsequent release and how this is affected by the inter-release time. Many products like books and movies receive considerable critical attention, advertising support, and media coverage as they are initially released in hardcover or in movie theaters. These buzz effects not only affect the initial release but also the subsequent release. Another source of buzz is the word-of-mouth that comes from people experiencing the initial release. However, the buzz effect tends to decay over time for most products. And it is widely recognized in the context of entertainment products like movies and DVDs. As one studio executive put it, "Movies are like fresh fish; they become stale if you don't sell it fast." Another studio executive compared movies to ice cubes – "The longer it sits, the smaller it becomes." Hence the loss from a delayed second release not simply comes from time discounting, but, more importantly, from the lower sales potential for the second

window to a 4 month standard. At the extreme, Mark Cuban of 29/29 Entertainment has advocated a simultaneous release of movies and DVDs. In fact Mark Cuban's studio recently released Steven Soderbergh's "Bubble" in theaters only four days before it became available on DVD, but the movie proved to be a small-scale experiment since it was boycotted by major theater chains.

release due to the buzz decay. We need to empirically measure the extent of buzz decay and the effect of inter-release window on the potential of the subsequent release in our empirical work.[4]

Second, shortening the inter-release time has a *dynamic* impact on consumer choice. Even before the second product is released, forward-looking customers are likely to delay their purchases and wait for the lower-priced version if they expect the second product to become available sooner. Now that the decision to delay is related to customer expectations of inter-release times, understanding the determinants of these expectations is important as well. There is empirical evidence that consumers are indeed forward-looking when faced with choices over time. For example, Weiss (1994) use questionnaire data from firms to support the hypothesis that the firms that expect the next generation of technology to be available sooner are more likely to defer their adoption of the currently best technology. Boone et al. (2001) demonstrate similar behavior by consumers through laboratory studies. Thus, a model needs to be able to be account for these tradeoffs in deciding on the optimal timing strategy.

In addition, optimizing inter-release strategies for movies and DVDs have certain special modeling and empirical challenges, compared to product categories like books and electronics. At least two critical modeling challenges exist in this context. To begin with, if the sequentially released products are perfect substitutes, then one can model the consumer decision of when (and what) to buy as an "optimal stopping problem", because once the consumer decides to purchase the product, there is no need to revisit the decision, and the consumer's problem is simply when to stop search and make the purchase. However, sequential releases are not necessarily purely substitutable, for instance, a substantial proportion of consumers who watch a movie in the theater actually buy the DVD later. In fact, for some people, enjoying a movie in theater makes them more likely to purchase the DVD later. Thus theatrical movies and DVDs cannot be simply treated as substitutes, which implies that this problem is a more difficult consumer decision problem than the optimal stopping problem that has been extensively studies in previous dynamic choice literature (e.g., Melnikov 2000; Song and Chintagunta 2003; Gowrisankaran and Rysman 2005). Further, the degree of substitution (or even complementary, depending on the direction of the dynamic interrelationship) may vary across products and across consumers, suggesting the presence of heterogeneity in (even the sign of) cross-elasticities.

[4] Note that we do not *assume,* that buzz will decay or inter-release window negatively affects DVD sales. The sign and magnitude of these effects are empirically estimated in the model.

While recent papers such as Gentzkow (2004) and Song and Chintagunta (2005) have proposed flexible models of the substitution and complementarity between *static* offerings, the model cannot be readily adapted to a dynamic setting with sequential options and uncertainty about future offerings as well as inter-release time. Estimating such a model with heterogeneity in cross-elasticities between sequentially released products also leads to data and identification challenges that we need to address. We show how a flexible structure of substitution and complementarity can be accommodated in a dynamic optimization problem with consumer uncertainty.

In sum, a structural model of consumer choice between sequentially released products, particular in the context of movies and DVDs, should model (1) consumers' forward-looking choice behavior that takes into account consumers' adaptive expectations about the inter-release times, price and product quality; (2) the possibility of multiple purchases over time, implying that the dynamic problem is not an optimal stopping problem typically studied in product line settings; (3) observed and unobserved consumer heterogeneity in not only overall consumer preferences for movies and DVDs, but the nature of substitution (substitutability as well as complementarity) between them; and (4) the buzz spillover from movies to DVDs and its decay over time.

We calibrate the models using sales and marketing-mix data on about 600 movies released domestically in theaters and on DVDs during an approximately three-year period (Oct. 2000 - Jan. 2004). Since it is empirically impossible to recover the distribution parameters of individual-level preferences over inter-temporal movie and DVD choices using purely aggregate market-level data, we augment the market-level data with a cross-sectional consumer survey data set that reveals information about consumers' attitudes and habits regarding movie and DVD consumption. We also introduce a novel estimation approach by using a simulation-based fixed-point algorithm that nests the consumer dynamic programming problem within a GMM framework.

Our key findings are that consumers are indeed forward looking; a shrinking movie-DVD release window does negatively impact box office revenues, but there is a tradeoff in that there is greater residual buzz from the movie marketing that supports the sales of DVD. Given this there is an inverted U-shaped relationship between movie-DVD release window and revenues, and the optimal average window for the period of the data is 2.5 months.

The rest of the paper is organized as follows. In Section 2, we discuss the related literature and the contributions of the current paper. In Section 3, we describe the empirical setting and data. The econometric model is introduced in Section 4, and the estimation methodology is detailed in Section 5. Section 6 presents the estimation results and policy analysis. Section 7 concludes and suggests future research directions.

2. Related literature

We next discuss the literature on sequential product introductions, also making specific linkages to the application domain of movie releases. We then discuss the related modeling literature on dynamic structural models of choice, and in particular sequential choices.

2.1. Sequential product introductions

Despite the importance of the inter-release timing issue for firms' new product development and marketing-mix strategies, academic research in this area has been sparse. In the context of industrial markets, Weiss (1994) collected survey questionnaires from 85 firms and shows that firms that expect a faster pace of technological improvements tend to delay their adoptions of the current technology. Boone, Lemon and Staelin (2001) used a series of laboratory experiments to support their hypothesis that consumers' perceptions of the rate and pattern of a firm's introductory strategy can influence consumers' adoption decisions concerning the firm's current offering. Prasad et al. (2004) propose a theoretical model that emphasizes the role of consumers' expectations on the demand for sequential releases yet offers no empirical recipe for measuring such effects. In this paper, we propose a structural model of consumer choice that enables us to quantify the effect of inter-release time on sequential decisions, which is amenable to policy analysis such as solving for the profit-maximizing inter-release time.

There is a related literature that studies the demand for successive generations of product advances (Norton and Bass 1987; Padmanabhan and Bass 1993) or for sequential product line extensions (Wilson and Norton 1989). These models are usually based on overlapping-generation diffusion curves and do not consider how consumers' expectations about future introductions would impact the demand patterns; particularly, the entry time of future products is typically assumed to be exogenously given and not a decision variable in the model.

Specifically, in the context of our application domain of movie releases in entertainment marketing, an extensive literature in marketing has been devoted to forecasting the performance of theatrical films (e.g., Sawhney and Eliashberg 1996; Zufryden 1996; Neelamegham and Chintagunta 1999; De Vany and Lee 2001; Ainslie et al. 2004). In particular, both theoretical and empirical studies have been dedicated to the release timing of theatrical movies with emphasis on competition and seasonality (Krider and Weinberg 1998; Radas and Shugan 1998; Einav 2003; Foutz and Kadiyali 2003). In comparison, there has been scant marketing research on the home video market, though the home video market has larger share relative to the theatrical market ($25 billion vs. $10 billion in 2004). A few studies have examined certain aspects of the home video market. For instance, Knox and Eliashberg (2004) look at how consumers choose between rental and buying at a video store. Mortimer (2004) studies the inter-temporal price discrimination traditionally used by video distributors due to the U.S. intellectual property protection (i.e. First Sale Doctrine) by estimating a data set of video stores' rentals and sales information. Chellappa and Shivendu (2003) study the economic implications of region-specific technology standards for DVD piracy and conclude that maintaining separate technology standards benefits both firms and consumers. But unlike the current study, these papers focus on the demand in the video market and do not consider the interaction between the theatrical and the home video markets.

Closely related to the current paper's focus on the sequential introduction of movies and home videos are by Lehmann and Weinberg (2000) and Prasad et al. (2004). Lehmann and Weinberg (2000) formulate a mathematical model to study how the firm should tradeoff the cannibalization of the earlier (i.e., theatrical) version, which is assumed to be of higher margin, and a postponed revenue flow from the later (i.e., home-video) version, which is assumed to be of lower. However, their model ignores the effect of consumer expectation and forward-looking behavior, a critical element in quantifying the effect of inter-release timing. Prasad et al. (2004) develops a theoretical model of industry-equilibrium video release timing strategy that takes into account consumer expectations. Our current work can be viewed as complementary to their study, since we develop a structural demand model, which accommodates product characteristics, consumer heterogeneity, and expectation formation, to empirically test their hypotheses and render policy recommendations. Rao (2016) estimates a dynamic structural model considering the tradeoffs between purchase and rental markets, but focuses on the supply side question of pricing online content for purchase versus rentals.

The current paper contributes to this literature by proposing a modeling framework that explicitly captures consumers' forward-looking behavior and allows for rich patterns of interactions between sequential products (movies and DVDs) so that marketers and researchers can infer the effect of inter-release time on the demand for sequentially introduced products.

2.2. Dynamic structural models of choice

Our approach to modeling consumers' choice behavior is related to an increasing body of empirical literature in marketing and economics that examines consumers' forward-looking choice behavior. In such models, the consumer's current choice is allowed to depend on not only the characteristics of the choice set immediately available to them but also on the expected characteristics of future choice set(s). Most of the existing studies are focused on price: consumers can adjust their purchase timing or quantity in anticipation of future price series (Melnikov 2000; Hartmann 2004; Gowrisankaran and Rysman 2005; Israel 2005). These studies have shown that ignoring inter-temporal substitution would lead to biased estimates of price elasticities and misleading economic and marketing implications (Hendel and Nevo 2002).

Some of these studies investigate consumers' purchase decisions about consumer durable products (especially consumer electronics), which are often characterized by declining price (typically accompanied by improving quality) over time; a forward-looking consumer, expecting such trend, may postpone purchase in the hope of buying a cheaper and/or better product in the future (Melnikov 2000; Song and Chintagunta 2003; Gowrisankaran and Rysman 2005). An assumption made in these models is that *adoption is a one-time event*: once the consumer purchases one unit of the product (e.g., digital camera), he or she drops out of the market permanently, an assumption that enables researchers to solve the consumer's dynamic optimization program as an *optimal stopping problem*. This assumption is innocuous if the consumer faces the same choice set or very similar choice sets over time, e.g., the consumer who has bought a video game will never buy the same game again. Nevertheless, it typically does not capture the consumer behavior towards sequential releases: for instance, a consumer who has viewed a movie in theater may still want to buy the DVD released later; owners of a commercial software package may still expect to purchase an upgraded version when it becomes available.

To model consumers' behavior in these markets, we need to allow consumers to make multiple purchases over time rather than restrict the choice process *a priori* to an optimal stopping problem. In these settings (sequential releases such as theatrical movies and DVDs), we cannot make the simplifying assumption that sequential products are pure substitutes. The standard optimal-stopping dynamic choice models of product adoption, therefore, are inappropriate for such problems. To achieve such flexibility, our model provides a framework that allows consumers to make multiple purchases sequentially and thus captures a richer pattern of substitutability and complementarity between dynamically related choice options.

In a static context, Gentzkow (2004) develops a model that allows for multiple choices and captures a rich patterns of substitution and complementarity, which is impossible in a conventional discrete choice model. He applies the model to assessing the relationship between a print newspaper and its online edition. In his models, the utility from a bundle is specified to include a discrete-form second-order Taylor approximation; for instance, the utility from a bundle of two related products includes an interaction (or "synergistic") effect, which would be positive if they are complements and negative if substitutes. Song and Chintagunta (2005) extend this model to include multiple brands nested in multiple categories.

Our model further extends the issue of multiple choices to a dynamic choice setting. Similar to Gentzkow (2004), the current model accommodates a rich structure of substitution and complementarity between choice options rather than assume them to be pure substitutes. In addition, our model allows consumers to be uncertain about the availability of future releases and incorporates consumer expectations into the choice model.

3. The Empirical Setting and Data

3.1. The DVD market

The DVD (digital versatile or video disc) technology, commercially introduced in 1997, created a very profitable hardware and software market in just a few years. DVD players became the fastest-growing consumer electronic product in history (The Digital Entertainment Group 2005), outpacing even CD players and PCs);[5] by 2005, DVD players were adopted by 75 million U.S. households (68% penetration rate) and pre-recorded DVD software had mushroomed from 5,000 to over 40,000 titles. Over 3.9 billion pre-recorded DVDs had been shipped to retailers between 1997 and 2004; a household that owns a DVD player bought 16 discs per year; the purchase rate was as high as 24 discs per year for households owning multiple players. By 2004, while U.S. box-office gross remained stagnant at about $9 billion,

[5] It took only five years for 30 million DVD players to be sold, compared to about eight years for CD players, and 10 years for PCs to reach the same volume mark.

DVD sales had increased to $15.5 billion.[6] The industry began to view films being "released theatrically as a giant marketing exercise for DVD sales."

Although over 90% of an average movie's box-office revenue is obtained during the first two months of theatrical opening, the theatrical-to-video window in 2004 was typically four to six months (See Figure 2 for a histogram of the theatrical-to-video windows in our sample of DVDs released from 2000 to 2004). But despite the predominant industry-level regularity in the window schedule, there is still considerable variation across movies. For instance, the window for "50 First Dates" was 123 days, and for "Mystic River" 244 days, with the latter window almost double the former. Deciding the theater-to-DVD window is among the most important strategic decisions for studio distributors. (McBride 2004)

The movie industry, as a whole, has been gradually shortening the theater-to-video window (Gilbert-Rolfe et al. 2003). The industry-average window length in 2004 was approximately four and half months, compared to a seven-month window in 1998. Furthermore, some studios had begun to experiment with what were then revolutionary release strategies; for instance, in Nov. 2004, a holiday movie called "Noel", starring Penelope Cruz and Susan Sarandon, were released into theater and disposable DVDs (priced at $4.99; exclusive on Amazon.com) at the same time, and, a couple of weeks later, aired on the TNT cable channel. Industry observers viewed the "multi-pronged release strategy" for "Noel" as a "small-scale test that most of the Hollywood studios are mulling… to release movies to theaters and homes simultaneously" (*Video Business* 2005). Another new movie, "National Lampoon's Blackball," was released on DVD only four days after its theatrical debut.

Such a trend towards shorter theater-DVD release window angered theater owners and worsened the channel relationship, since theater owners believe that studios are aggressively cashing in the more lucrative DVD market at the expense of box-office sales. John Fithian, president of the National Association of Theater Owners, said that "a shortened video and DVD market impacts theater admissions… I get lots of calls from concerned members." Even some studio executives have expressed doubts about an ever faster DVD release. Frank Finkelstein, President of Universal Studios, said to reporters, "As an industry, we may simply

[6] DVD rentals totaled $5.7 billion, up from $4.5 billion in 2003. Couple that with DVD sales of $15.5 billion, the DVD market over twice as large as the theatrical exhibition market. With DVD penetration spiraling, VHS market has been dwindling: VHS sales dropped 42 percent to 240.4 million from 2002, while VHS rentals fell 23 percent to 53.2 million (MPAA 2004). Therefore, the empirical study does not consider the VHS market.

have gone too far with moving up DVD releases." (*Video Business* 2005) How studios should design their theater-to-DVD windows became one of the most critical channel relations issues in the movie industry. In this empirical study, using data from this high-growth period of DVDs, we examine the effects of inter-release time on various channel members via "what-if" policy analysis, and provide a framework to addressing these heated and debated questions that continue to have new relevance today with streaming platforms.

3.3. Data

Our sample includes newly released movie DVDs that were introduced between January 2000 and October 2003.[7] The movies in our sample opened in theaters between 1999 and 2003.[8] For each of the 526 DVD titles in our sample, we collect data on box-office variables (e.g., box-office opening date, number of exhibitors' screens, box office revenues, advertising expenditure for the theatrical release, competitive set, and seasonality), DVD variables (e.g., DVD release date, retail price, sales, TV advertising GRPs,[9] DVD content enhancements, and distributor label) as well as movie attributes (such as its production budget, genres, awards and nominations, star power ratings, MPAA ratings, and critical reviews). Data on marketing-mix variables and DVD sales are from a proprietary data set collected by one of the major studios. We also collect the average user ratings for each of the movie from www.imdb.com (Internet Movie Database). Among the 526 titles in the sample, weekly rental data is available for 256 titles released for the latter half of the sample period. Table 1 reports the key descriptive statistics of the sample, while Table 2 summarizes the relevant categorical variables used in the empirical implementation. The DVD market is an oligopolistic market, with seven major

[7] The study does not consider previously viewed DVDs for the following two reasons: first, the sales of previously owned DVDs was approximately $2 billion in 2004; only 7-8% of the $26 billion DVD market. Second, previously viewed DVDs usually contribute revenues to video retailers (or "rentailers") but not to the studios, so they would have a negligible impact on the studios' marketing-mix decisions. Nevertheless, some consumers may strategically wait to purchase previously viewed DVDs, and, as a result, the pricing and timing decisions of the new DVD release might have an effect on the incentive to do so. However, modeling such effect requires a different approach that resembles previous models on secondhand markets such as used automobile or textbook markets. And we do not consider catalog DVDs (i.e., DVD release for movies more than two years old) for three reasons. First, new-release DVDs account for a large majority of revenues while catalog DVDs represent a small proportion of total pre-recorded DVD sales. Second, since catalog DVDs are released long after their theatrical release dates, the timing decisions are affected by different factors than what is considered in our model; for instance, the DVD of "Assault on Precinct 13" (1976) was released when the remake of the movie was about to open in theaters.

[8] We focus on movies whose box office gross was above five million dollars because extremely small-budget movies are usually marketed differently (for instance, such movies are targeted at a small niche market and are usually supported by no advertising; they may simply go directly to videos, bypassing the theater channel altogether).

9 TV is the major channel for DVD advertising, representing 60-70% of the industry spending because of TV's ability to show DVD trailers.

studios taking up more than 90% of the total market. Table 3 presents the market share of each of the major studio (label) in 2003.

The total market size for DVDs is taken as the total number of U.S. households with DVD players installed. We collect monthly data on DVD player penetration rate in the U.S. to control for the effect of a growing hardware installation base on the software sales. The annual theatrical admission prices are collected from the MPAA annual reports and deflated with CPIs. The nominal prices for 2000, 2001, 2002, and 2003 are 5.39, 5.65, 5.8, 6.03, respectively. Consistent with previous studies, we incorporate distribution intensity in the theatrical demand model using numbers of screens exhibiting the film each week. Movie demand is higher in the summer than in other seasons, primarily due to the long school recess of teens and teenagers, many of whom are frequent movie-goers. Certain holiday weekends, such as Easter, Memorial Day, July 4th, Thanksgiving, Christmas and New Year also attract a larger movie audience. We include dummies for summer and major holidays to control for the seasonality effects.

We supplement this aggregate-level data set with a consumer survey sample of over 5,000 U.S. consumers collected by *UniversalMcCann*, a media and advertising agency, in 2003, and so contemporaneous with the movie period data. In the survey, consumers were asked to rate the importance of each of a list of variables (such as star power, word-of-mouth and advertising) in their decisions regarding movie-going and video-watching. They were also asked how likely they are to view the home video of a movie that they have already seen in theater. The answers to these survey questions fall into ordinal categories. Table 4 presents a summary of the marginal distributions of these attitudinal variables.

4. The econometric model

In this section, we describe the econometric model. We introduce the model in the specific context of theatrical movies and DVDs to facilitate exposition; however, the modeling framework is generalizable to a broader range of marketing settings where consumers make decisions about related products that are sequentially released.

4.1. Utility from viewing theatrical movies

The general environment facing a consumer is as follows: movie m opens theatrically at time zero and runs for T_m weeks in movie theaters. At the beginning of week W_m, the movie is released in the DVD market for rental and for retail.

Our model is set up in a consumer-level random-utility framework, from which aggregate-level market demand is then derived. Consumer *i*'s indirect utility from viewing movie *m* in theaters (superscript *T*) during week *t* is given by

$$U_{imt}^{T} = x_{mt}^{T}{}' \beta_{i}^{T} + \xi_{mt}^{T} - \gamma_{i} t - \alpha_{P} \ln(p_{m}^{T}) + \varepsilon_{imt}^{T}, \; t = 1, 2, ..., T_{m} \quad (1)$$

where x_{mt}^{T} is a vector of theatrical movie *m*'s observable characteristics that may affect the consumer *i*'s utility from watching it in week *t*, such as distributional scale (i.e., number of screens exhibiting the movie), production budget, advertising expenditure, critical reviews, stars' power rating, MPAA rating, genre, and whether it is a sequel. We use a discrete-time specification for decision-making periods because data on box-office sales, screens and advertising are customarily tabulated on a weekly basis. The parameters associated with these movie-specific characteristics, β_{i}^{T}, are allowed to vary across consumers. For instance, while some consumers pay more attention to the presence of movie stars, others are more susceptible to word-of-mouth recommendations from friends. ξ_{mt}^{T} is the econometrically unobservable characteristic that affects movie *m*'s attraction at week *t*.[10] $-\gamma_{i} t$ captures the fact that the appeal of pop-culture entertainment products such as movies may diminish over time and it is consistent with the exponentially decaying box-office demand pattern characterizing majority of feature movies (Krider and Weinberg 1998; Einav 2004). The individual-specific coefficient, γ_{i}, allows consumers to have different decay rates over time. (Note that, while we expect $\gamma_{i} \geq 0$ for most consumers, we do not make restrictions on it *a priori*.) p_{m}^{T} is the real price of movie-theater admissions. Notice that movie theaters conventionally adopt a uniform pricing scheme for all movies, which means that there is practically no price variation across movies and very little variation from year to year after inflation adjustment[11]; therefore, the price coefficient, α_{p}, is not identifiable from the theater-window demand alone. We leave the identification of the price coefficient to the DVD-period demand. ε_{imt}^{T} is an idiosyncratic error in the utility function and we assume it to be distributed type-I extreme value i.i.d. across consumers, movies, and time with its scale parameter normalized to one.

The utility from not viewing the theatrical movie *m* in week *t* is given by

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[10] Such characteristics of movies may include news coverage of the movie and/or tabloid fame of its stars.

[11] Orbach and Einav (2002) examine the uniform pricing scheme in the theatrical movie market and argue that this regime is inferior to alternative pricing strategies.

$$U_{i0t}^{T} = -\psi^{T\prime} SEASON_{mt} + \alpha_{C}^{T} COMP_{mt} + \varepsilon_{i0t}^{T} \quad (2)$$

where $SEASON_{mt}$ is a set of seasonality dummies and ψ^{T} is a vector of the corresponding coefficients that capture the highly fluctuating overall box-office demand (the negative sign facilitates the interpretation of results, i.e., a positive estimate would mean that the total box-office demand is high). $COMP_{mt}$ is the strength of competition that movie *m* faces in week *t*. In our empirical implementation, we use two proxies to measure competition: (1) the total production budgets of all movies of the *same* genre released in the previous two weeks and (2) the total production budgets of all movies of *different* genres released in the previous two weeks. ε_{i0t}^{T} is also assumed to be i.i.d. type-I extreme value error.

Since the choice outcome in a logit model only depends on the differences in utility levels, we take the difference of (1.1) and (1.2) to obtain

$$u_{imt}^{T} = x_{mt}^{T\prime} \beta_{i}^{T} + \xi_{mt}^{T} - \gamma_{i} t - \alpha_{P} \ln(p_{m}^{T}) + \psi^{T\prime} SEASON_{mt} - \alpha_{C} COMP_{mt} + \varepsilon_{imt}^{T} \quad (3)$$

In each week during the theatrical run, consumers decide whether to view the movie in theaters ($y_{imt}^{T} = 1, t = 1, ..., T_{m}$) or not ($y_{imt}^{T} = 0$). We assume that once a consumer has viewed the movie in theater, he or she drops out of the theatrical market (while still remaining in the market for the DVD). [12]

Suppose that the consumer is *myopic*; that is, they make their movie-going decisions purely based on theatrical viewing utilities, without considering the future opportunity of renting or buying the DVD, then the consumer's decision problem reduces to a static discrete choice problem and the discrete-time hazard rate of viewing movie *m* in theater in week *t* is given by the familiar logit formula

$$\Pr(y_{imt}^{T} = 1) = \frac{\exp(\tilde{U}_{imt}^{T})}{1 + \exp(\tilde{U}_{imt}^{T})} \quad (4)$$

where $\tilde{U}_{imt}^{T} = x_{mt}^{T\prime} \beta_{i}^{T} + \xi_{mt}^{T} - \gamma_{i} t - \alpha_{P} \ln(p_{m}^{T}) + \psi^{T\prime} SEASON_{mt} - \alpha_{C} COMP_{mt}$.

Let $y_{im}^{T} \equiv \max(y_{imt}^{T}), t = 1, ..., T_{m}$, so that if consumer *i* has viewed the theatrical movie *m* by the time it exits the theater then $y_{im}^{T} = 1$ and otherwise $y_{im}^{T} = 0$; the probability that consumer *i* would see movie *i* in theater during its entire theatrical run is given by

12 We believe it to be an innocuous assumption; we also estimated a specification without this single-viewing constraint, and the estimation and policy analysis results remain virtually unchanged.

$$\Pr(y_{im}^T = 1) = 1 - \prod_{t=1}^{T_m}(1 - \frac{\exp(\tilde{U}_{imt}^T)}{1+\exp(\tilde{U}_{imt}^T)}) \quad (5).$$

4.2. Utility from DVDs

The DVD of movie *m* is released at time W_m. There are two special modeling issues to consider in specifying the consumption utility for DVDs. First, when the DVD is released, consumers can either buy or rent it. Because of the institutional characteristic of the U.S. home video market,[13] the rental DVD and retail DVD are available to the consumers at the same time. We model the consumer's DVD consumption as a discrete choice problem. The consumer's choice set includes DVD rental (**R**ent), DVD purchase (**B**uy), and an outside option.[14] Second, the utility that a consumer obtains from the DVD may be affected by the consumer's previous experience with the movie. After having viewed a particular movie in theater, the consumer's utility from the DVD might be reduced to a certain extent due to satiation; however, the exact amount in utility reduction can vary substantially among consumers and across movies. On the other hand, she would even obtain greater utility from DVD compared to the scenario where she had not viewed the movie previously (which might be due to consumption complementarity, learning, or uncertainty reduction). Therefore, we need to model this form of state dependence in the consumer's DVD utility function in a flexible manner.

Consumer *i*'s valuation of the DVD is assumed to be

$$VD_{im}(y_{im}^T) = \exp(\tilde{u}_{im}^{DVD}(y_{im}^T)) \cdot (\tilde{\delta}_i(y_{im}^T))^{W_m}, \ \tilde{\delta} \in (0,1), \ W_m \geq 0 \qquad (6)$$

where $\exp(\tilde{u}_{im}^{DVD}(y_{im}^T))$ represents the "attraction" of DVD *m* to consumer *i* if it is released at the same time as the theatrical movie (the exponential specification ensures that the attraction value is positive), and $\delta_i(y_{im}^T)$ indicates the decay rate of the DVD's attraction when its release is temporally delayed from the theatrical release. Consumers' awareness of the movie and their purchase intention tend to be highest at the movie's box-office opening and gradually

13 The U.S. Copyright Act of 1976 stipulates that the owner of a legally owned copy of a copyrighted product is entitled to "first use" (commonly known as the *First Sale Doctrine*), which invokes copyright jurisdiction only upon the first sale of videos so that subsequent usage (such as rental) no longer generates revenue to the copyright holder. This effectively prevents movie studios to discriminate between institutional buyers (i.e., video rental stores) and individual buyers. See Mortimer 2004 for a detailed discussion of its implication on studios' pricing strategies and the difference between the U.S. market and the E.U. market.

14 We do not model the case in which the household first rents the video and then buys, or the reverse. We do not think such a simplification severely compromises the validity of the model implications.

evaporate over time; in other words, the faster the DVD release, the more it would appeal to an average consumer. Note that both the attraction value, $\tilde{u}_{im}^{DVD}(y_{im}^{T})$, and the decay rate, $\delta_i(y_{im}^{T})$, depend on whether the consumer has viewed the movie in theater previously. The "attraction" of the DVD is specified as

$$\tilde{u}_{im}^{DVD}(y_{im}^{T}) = \begin{cases} \tilde{u}_{im}^{R} = x_m^{DVD\prime}\beta_i^R + \xi_m^R - \alpha_P \ln(p_m^R) - ST_{im} \cdot y_{im}^{T} + \varepsilon_{im}^{R}, \ \text{if } y_{im}^{R} = 1; \\ \tilde{u}_{im}^{B} = x_m^{DVD\prime}\beta_i^B + \xi_m^B - \alpha_P \ln(p_m^B) - ST_{im} \cdot y_{im}^{T} + \varepsilon_{im}^{B}, \ \text{if } y_{im}^{B} = 1; \end{cases} \quad (7)$$

where $y_{im}^{R} = 1$ indicates that consumer *i* rents DVD *m*, and $y_{im}^{B} = 1$ indicates that consumer *i* buys DVD *m*. In the above equation, x_m^{DVD} is a vector of DVD *m*'s observed characteristics. Aside from the movie-specific variables considered in the theater-period demand, it also includes DVD content enhancements such as filmmaker commentary, deleted scenes, music videos, DVD-ROM features and children's games. Moreover, the model also allows the movie's performance in the theatrical window to affect its performance in the DVD window; to this end, x_m^{DVD} includes the logarithm of the opening box-office gross for movie *m*. ξ_m^R and ξ_m^B are the econometrically unobserved components in the renting and buying utilities, respectively, of DVD *m*. p_m^R is the DVD rental price[15] and p_m^B is the DVD retail price. The idiosyncratic errors ε_{im}^{R} and ε_{im}^{B} are assumed to follow i.i.d. extreme value distribution over alternatives, movies, and consumers, with variance $\kappa^2 \cdot (\pi^2/6)$. ST_{im} indicates how the consumer's utility from the DVD is affected by the consumption of the theatrical movie. A consumer may become *less* inclined to watch the DVD after having viewed it in theater due to consumption satiation or substitution; in this case, $ST_{im} > 0$. If ST_{im} is sufficiently large, then the consumer would not consider renting or buying the DVD at all after having seen it in theater. However, in some cases, a consumer may become *more* inclined to watch the DVD after having seen the movie in theater, due to consumption complementarity or learning, implying that $ST_{im} < 0$. $ST_{im} = 0$ implies the lack of state dependence, i.e., whether consumer *i* has viewed the theatrical movie has no impact on her decisions about the DVD whatsoever. Note that this mathematical formulation is similar to the way that some previous studies have modeled the state dependence in consumer choice of frequently purchased consumer-goods

[15] Video rental stores typically set a uniform price for all new releases. Therefore, we let $p_m^R = p^R$.

(Keane 1997; Seetharaman 2003). We let ST_{im} be a function of movie-specific characteristics and an individual-specific intercept

$$ST_{im} = g_i + z_m{}'g + \Delta g_{im}, \quad \Delta g_{im} \sim N(0, \sigma_g^2) \quad (8)$$

where z_m is a vector of movie attributes (such as genres and word-of-mouth reviews) and g_i is an individual-specific parameter.

Note that we allow different sets of parameters to be associated with the rental option and the buying option to reflect the fact that these characteristics may have differential effects on *renting* utility and *collecting* utility obtained from the DVD. (For instance, the filmmaker commentary tends to be valued if the DVD is collected for long-run enjoyment, but it may not significantly enhance the renting utility since renters rarely view the DVD a second time with the commentary turned on.) By allowing different parameter values for these two different options, we allow for a quite flexible structure on the renting vs. buying decisions.[16]

Suppose the utility function takes the form

$$U_{im}^{DVD} = \ln[VD_{im}(y_{im}^T) \Big/ \left(P_m^{DVD}\right)^{\alpha_P}] \quad (9)$$

where the log functional form and the power coefficient of price, α_P, are intended to model concavity in utilities desirable to capture the wide price (and value) gap between the renting and buying utilities. Given (6), (7) and (9), consumer *i*'s utility from the DVD, depending on whether if she has viewed the theatrical movie, can be rewritten as

$$U_{im}^{DVD}(y_{im}^T = 0) = \begin{cases} (\equiv \tilde{u}_{im}^R) = x_m^{DVD\prime}\beta_i^R + \xi_m^R - \alpha_P \ln(p_m^R) - \delta_i^{R,0} W_m + \varepsilon_{im}^R, & \text{if } y_{im}^R = 1; \\ (\equiv \tilde{u}_{im}^B) = x_m^{DVD\prime}\beta_i^B + \xi_m^B - \alpha_P \ln(p_m^B) - \delta_i^{B,0} W_m + \varepsilon_{im}^B, & \text{if } y_{im}^B = 1; \end{cases} \quad (10)$$

and

$$U_{im}^{DVD}(y_{im}^T = 1) = \begin{cases} (\equiv \tilde{u}_{im}^R) = x_m^{DVD\prime}\beta_i^R + \xi_m^R - \alpha_P \ln(p_m^R) - \delta_i^{R,1} W_m - ST_{im} + \varepsilon_{im}^R, & \text{if } y_{im}^R = 1; \\ (\equiv \tilde{u}_{im}^B) = x_m^{DVD\prime}\beta_i^B + \xi_m^B - \alpha_P \ln(p_m^B) - \delta_i^{B,1} W_m - ST_{im} + \varepsilon_{im}^B, & \text{if } y_{im}^B = 1; \end{cases} \quad (11)$$

where $\delta_m^{R,0} \equiv -\ln(\tilde{\delta}_m^R(y_{im}^T = 0))$, $\delta_m^{B,0} \equiv -\ln(\tilde{\delta}_m^B(y_{im}^T = 0))$, $\delta_m^{R,1} \equiv -\ln(\tilde{\delta}_m^R(y_{im}^T = 1))$, and $\delta_m^{B,1} \equiv -\ln(\tilde{\delta}_m^B(y_{im}^T = 1))$ We also assume that the outside option provides utility

$$U_{i0}^{DVD} = \varepsilon_{i0}^{DVD} \quad (12)$$

16 Another way to model such difference is to view the buying utility as a discounted sum of per-period utilities and explicitly specify the discounting patterns (Knox and Eliashberg 2004).

where ε_{i0}^{DVD} is also distributed extreme value with scale parameter κ.

Therefore, the probabilities of renting and buying, respectively, DVD *m* for consumer *i* if she has not viewed the theatrical movie previously are given by

$$s_{im}^{R,0} = \Pr(y_{im}^{R} \mid y_{im}^{T} = 0) = \frac{\exp[(\tilde{U}_{im}^{R} - \delta_i^{R,0} W_m)/\kappa]}{1 + \exp[(\tilde{U}_{im}^{B} - \delta_i^{B,0} W_m)/\kappa] + \exp[(\tilde{U}_{im}^{R} - \delta_i^{R,0} W_m)/\kappa]} \quad (13)$$

$$s_{im}^{B,0} = \Pr(y_{im}^{B} \mid y_{im}^{T} = 0) = \frac{\exp[(\tilde{U}_{im}^{B} - \delta_i^{B,0} W_m)/\kappa]}{1 + \exp[(\tilde{U}_{im}^{B} - \delta_i^{B,0} W_m)/\kappa] + \exp[(\tilde{U}_{im}^{R} - \delta_i^{R,0} W_m)/\kappa]} \quad (14)$$

where

$$\tilde{U}_{im}^{R} = x_{mt}^{DVD\prime} \beta_i^{R} + \xi_m^{R} - \alpha_P \ln(p_m^{R}) \quad (15)$$

and

$$\tilde{U}_{im}^{B} = x_{mt}^{DVD\prime} \beta_i^{B} + \xi_m^{B} - \alpha_P \ln(p_m^{B}) \quad (16)$$

The probabilities of renting and buying, respectively, DVD *m* for consumer *i* if she has viewed the theatrical movie previously are given by

$$s_{im}^{R,1} = \Pr(y_{im}^{R} \mid y_{im}^{T} = 1) = \frac{\exp[(\tilde{U}_{im}^{R} - \delta_i^{R,1} W_m - ST_{im})/\kappa]}{1 + \exp[(\tilde{U}_{im}^{B} - \delta_i^{B,1} W_m - ST_{im})/\kappa] + \exp[(\tilde{U}_{im}^{R} - \delta_i^{R,1} W_m - ST_{im})/\kappa]} \quad (17)$$

$$s_{im}^{B,1} = \Pr(y_{im}^{B} \mid y_{im}^{T} = 1) = \frac{\exp[(\tilde{U}_{im}^{B} - \delta_i^{B,1} W_m - ST_{im})/\kappa]}{1 + \exp[(\tilde{U}_{im}^{B} - \delta_i^{B,1} W_m - ST_{im})/\kappa] + \exp[(\tilde{U}_{im}^{R} - \delta_i^{R,1} W_m - ST_{im})/\kappa]} \quad (18)$$

where $\tilde{U}_{im}^{R}$ and $\tilde{U}_{im}^{B}$ are defined in (15) and (16).

Given the conditional probabilities given in (13), (14), (15) and (16), we can compute the *unconditional* probability for consumer *i* to rent and buy DVD *m*:

$$\begin{aligned} s_{im}^{R} &= s_{im}^{R,0} \cdot (1 - s_{im}^{T}) + s_{im}^{R,1} \cdot s_{im}^{T} \\ s_{im}^{B} &= s_{im}^{B,0} \cdot (1 - s_{im}^{T}) + s_{im}^{B,1} \cdot s_{im}^{T} \end{aligned} \quad (19)$$

The total number of DVD rentals and that of DVD purchases are then obtained by integrating over consumer heterogeneity

$$\begin{aligned} Q_m^{R} &= M_m^{DVD} \int_{v_i} s_{im}^{R}(v_i) dP(v_i) \\ Q_m^{B} &= M_m^{DVD} \int_{v_i} s_{im}^{B}(v_i) dP(v_i) \end{aligned} \quad (20)$$

where v_i represents individual heterogeneity and $P(v_i)$ is its distribution function. M_m^{DVD} is the potential market size, which is taken as the number of households that have adopted DVD players by the time DVD *m* is released.

4.3. Dynamic choice behavior of forward-looking consumers

Since a consumer utility from the DVD depends on whether she has viewed the movie or not, a forward-looking consumer would seek to optimize her utilities inter-temporally; in deciding about movie-going, consumer *i* who has not viewed movie *m* up to the *t*-th week of its theatrical run would solve the problem

$$\max_{y_{imt}^{T}\in\{0,1\}}\{u_{imt}^{T}+\lambda E[\max U_{im}^{DVD}\mid y_{im}^{T}=1],\lambda E[\max U_{im}^{DVD}\mid y_{im}^{T}=0]\} \quad (21)$$

where λ reflects the relative weights of the two periods in the consumer's decision process.

Given the distributional assumption on idiosyncratic errors, ε_{imt}^{T}, the discrete hazard rate for consumer *i* to watch movie *m* in week *t* during the theater window is given by

$$\Pr(y_{imt}^{T}=1)=\frac{\exp(\tilde{U}_{imt}^{T}+E[\max U_{im}^{DVD}\mid y_{im}^{T}=1])}{\exp(\tilde{U}_{imt}^{T}+\lambda E[\max U_{im}^{DVD}\mid y_{im}^{T}=1])+\exp(\lambda E[\max U_{im}^{DVD}\mid y_{im}^{T}=0])} \quad (22)$$

Define $\vartriangle WAIT_{im}(I_{mt})$ as the expected utility gain in the DVD period if consumer *i* bypasses the theatrical version intentionally, given the information set (I_{mt}) available to her at time *t*, we have (Rust 1987)

$$\begin{aligned}\vartriangle WAIT_{im}(I_{mt}) &\equiv E[\max U_{im}^{DVD}\big|y_{im}^{T}=0]-E[\max U_{im}^{DVD}\big|y_{im}^{T}=1]\\ &=E[l+\kappa\ln\{1+\exp[(\tilde{U}_{im}^{B}-\delta_{i}^{B,0}W_{m})/\kappa]+\exp[(\tilde{U}_{im}^{R}-\delta_{i}^{R,0}W_{m})/\kappa]\}]\\ &\quad -E[l+\kappa\ln\{1+\exp[(\tilde{U}_{im}^{B}-\delta_{i}^{B,1}W_{m}-ST_{im})/\kappa]+\exp[(\tilde{U}_{im}^{R}-\delta_{i}^{R,1}W_{m}-ST_{im})/\kappa]\}]\\ &=\kappa\int\ln\left(\frac{1+\exp[(\tilde{U}_{im}^{B}-\delta_{i}^{B,0}W_{m})/\kappa]+\exp[(\tilde{U}_{im}^{R}-\delta_{i}^{R,0}W_{m})/\kappa]}{1+\exp[(\tilde{U}_{im}^{B}-\delta_{i}^{B,1}W_{m}-ST_{im})/\kappa]+\exp[(\tilde{U}_{im}^{R}-\delta_{i}^{R,1}W_{m}-ST_{im})/\kappa]}\right)dP\left(\Psi_{m}^{DVD}\mid I_{mt}\right)\end{aligned} \quad (23)$$

where l is Euler's constant, Ψ_{m}^{DVD} is the set of state variables that affect the consumer's utility from the DVD, and $P\left(\Psi_{m}^{DVD}\mid I_{mt}\right)$ represents the distribution of Ψ_{m}^{DVD} given the information available to consumers at time *t* (i.e., I_{mt}). Therefore, $\vartriangle WAIT_{im}(I_{mt})$ represents the net ("waiting") value of foregoing the theater-viewing experience, the consideration of which distinguishes the choice behavior of a forward-looking consumer from that of a myopic consumer. Then (3.2) can be rewritten as

$$s_{imt}^{T}(I_{mt})\equiv\Pr(y_{imt}^{T}=1\mid I_{mt})=\frac{\exp(\tilde{U}_{imt}^{T})}{\exp(\tilde{U}_{imt}^{T})+\exp(\lambda\vartriangle WAIT_{im}(I_{mt}))} \quad (24)$$

If $\lambda = 0$, then (24) is reduced to (4), the myopic choice rule. Note that κ, the scale parameter of the error distribution in the DVD utility function, cannot be identified separately from λ or from the DVD preference parameters, so we normalized κ to one in the empirical implementation.

The theatrical market demand for movie *m* at week *t* can then be obtained by integrating over the individual consumers' choice probabilities

$$S_{mt}^{T} = \int_{v_i} s_{imt}^{T}(v_i; I_{mt}) dP(v_i) \qquad (25)$$

4.4. Consumer expectations

In solving the dynamic optimization problem, consumers' decisions would depend on the expectations of the values of the future state variables, including the inter-release time.

Let $\Psi_m^{DVD} \equiv (\Psi_{m,1}^{DVD}, \Psi_{m,2}^{DVD})$ where $\Psi_{m,1}^{DVD}$ includes the characteristics of DVD *m* that are known to consumers upon its theatrical opening (such as star presence and genres), and $\Psi_{m,2}^{DVD}$ include the characteristics of DVD *m* that consumers are uncertain about prior to its DVD release (such as DVD retail price and inter-release time). We assume that consumers have no prior information about the idiosyncratic errors (ε_{im}^{DVD}'s) except for their distribution and that the errors are conditional independent, i.e., $f(\varepsilon_{im}^{DVD} \mid \varepsilon_{im}^{T}, \Psi_m^{DVD}) = f\left(\varepsilon_{im}^{DVD}\right)$.

Consistent with the majority of dynamic choice models in the literature, we assume that consumers are rational in the sense that they are aware of the distribution of state variables in the future. Therefore, we infer the realized stochastic distribution of $\Psi_{m,2}^{DVD}$ and then, under the assumption that consumers know this distribution, utilize it to solve the dynamic programming problem of the consumers.[17] The stochastic process that generates the DVD inter-release time is specified as follows.

$$W_m = x_m^{T\prime} \rho_W + Trend_m + \upsilon_{W,m}, \quad \upsilon_{W,m} \sim N(0, \sigma_W^2) \qquad (26)$$

where x_m^W is a vector of movie *m*'s characteristics that affect the realized (and presumably expected) window length of movie *m*. Such variables may include movie *m*'s box-office

[17] Assuming rational expectations (i.e. the agent's expectations are objectively correct) is a prevailing practice in dynamic choice economic models. However, such maintained assumptions may be questionable, given that the multiple forms of expectations can all lead to the observed choice behavior (e.g., Erdem et al. 2004). It would be ideal if we had data on stated expectations (e.g., how soon consumers expect a particular DVD to be released); however, such questions are not asked in our consumer survey data.

opening strength ("marketability"), which is mostly driven by the pre-release marketing campaign, and its momentum after the initial opening ("playability," "longevity," or "leg"), which is primarily maintained by consumer word-of-mouth recommendations (Krider and Weinberg 1998; Eliashberg et al. 2005). While the opening strength is easily measured by a movie's opening-weekend box-office revenue, the longevity of a movie is not straightforward to quantify. We need to construct a measure of the movie's "leg," i.e. its box-office staying power after the opening weekend. To this end, we fit a two-parameter Weibull distribution for each movie. The Weibull p.d.f. is given by

$$f(t \mid a_m, b_m) = \frac{b_m}{t}\left(\frac{t}{a_m}\right)^{b_m} e^{-\left(\frac{t}{a_m}\right)^{b_m}}, \; t \ge 0, a_m, b_m > 0 \qquad (27)$$

The Weibull distribution is a flexible function form capable of capturing a wide variety of box-office sales patterns, as illustrated in Figure 3 with four examples. The scale parameter, a_m, is also called the *characteristic life*, since $F(a_m \mid a_m, b_m) = 1 - e^{-1} \doteq 0.632$, i.e., a_m is the time by which 63.2% of the potential box-office sales would be realized. Therefore, it serves as a reasonable measure to distinguish movies with strong momentum (a_m will be large) from those that quickly run out of steam (a_m will be small). Table 6 shows the estimated legs and window lengths for a sample of movies.

During the movie's theatrical run, however, consumers are unaware of the entire box-office trajectory, so we allow consumers to update a_m each week as new information is observed.

Suppose that in the first two weeks the consumers will use the population distribution of a_m as prior

$$a_m \sim N(a_0, \tau_0^2) \qquad (28)$$

From Week 3, consumers would take the box-office pattern in the previous weeks (I_{mt}) to estimate a_m based on (27):

$$\hat{a}_m(I_{mt}) \sim N(a_m, s_{mt}^2) \qquad (29)$$

Therefore, the posterior distribution of a_m is given by (Gelman et al. 2003)

$$a_m \mid \hat{a}_m \sim N\left(\frac{a_0/\tau_0^2 + \hat{a}_m/s_{mt}^2}{1/\tau_0^2 + 1/s_{mt}^2}, \frac{1}{1/\tau_0^2 + 1/s_{mt}^2}\right) \qquad (30)$$

Since s_{mt}^2 is typically large in the initial few weeks and becomes smaller later into the theatrical run, the updating rule in (30) implies that consumers' expectations will rely more on the prior initially and gradually become more movie-specific.

Besides the inter-release time, the DVD retail price and the exact box-office gross (from which consumers tend to infer the quality of the movie) are also unknown to consumers during the theatrical period. Therefore, we assume price to follow a lognormal distribution and the box-office gross to follow a normal distribution and integrate over these distributions to obtain expected utilities.

4.5. Consumer heterogeneity

We incorporate consumer heterogeneity through a random-coefficient specification of individual-specific preference parameters. Let $\theta_i \equiv (\beta_i^T, \beta_i^R, \beta_i^B, \gamma_i, \delta_i^{R,0}, \delta_i^{B,0}, \delta_i^{R,1}, \delta_i^{B,1}, g_i)'$ be the set of individual-specific parameters. Suppose

$$\theta_i = \theta_1 + v_i,\ v_i = \Sigma \eta_i \qquad (31)$$

where η_i is a normed (or unit) vector and $\eta_i \sim MVN(0, \Lambda)$; by definition, $diag(\Lambda) = 1$. Σ is a diagonal matrix that transforms that correlation matrix Λ, to a full variance-covariance matrix. We describe how to estimate Λ outside the dynamic programming problem by using consumer-level attitudinal data in the data section.

4.6. Other specification issues

Note that γ_i, the consumer-specific decay factor for the theatrical movie, tends to be correlated with $\delta_i^{j,0}$ and $\delta_i^{j,1}$ ($j = R, B$). Therefore, we let

$$\delta_i^{j,0} = c_0 \gamma_i + c_{1,i}, \quad c_{1,i} \sim N(0, \sigma_c^2), \quad j = R, B \qquad (32)$$

$$\bar{\delta}_i^{\,j} = \delta_i^{j,1} - \delta_i^{j,0} = d_0 + d_1 \Delta \delta_i^{j,0} \quad j = R, B \qquad (33)$$

5. Estimation

5.1. The GMM estimator

Decompose each of $\tilde{U}_{imt}^T$, $\tilde{U}_{im}^R$, and $\tilde{U}_{im}^B$ into one component that is common to all consumers and one component that captures consumer *i*'s deviation from the common component:

$$\tilde{U}_{imt}^T = \eta_{mt}^T (x_{mt}^T, p_m^T, SEASON_{mt}^T, COMP_{mt}^T; \theta_1) + \mu_{imt}^T (v_i) \qquad (34)$$

$$\tilde{U}_{im}^R = \eta_m^R (x_m^{DVD}, p_m^R, W_m; \theta_1) + \mu_{im}^R (v_i) \qquad (35)$$

$$\tilde{U}_{im}^{B} = \eta_m^B(x_m^{DVD}, p_m^B, W_m; \theta_1) + \mu_{im}^B(v_i) \quad (36)$$

Let $\theta_2 = (\Sigma, g, \lambda, \sigma_g^2)$; note that θ_2 governs the distribution of v_i. The partition of the parameters into two vectors, θ_1 and θ_2, is to facilitate interpretation of the estimation procedure detailed below.

The estimation is implemented using generalized method of moments estimation (Berry et al. 1995; Nevo 2001; Sudhir 2001). The GMM identification assumption is given by

$$E[z'\xi] = 0 \quad (37)$$

where $\xi = (\xi_{jt}^T, \xi_j^R, \xi_j^B)$ and z is a set of exogenous (or predetermined) variables that are orthogonal to ξ.

Accordingly, the GMM objective function is defined as

$$G(\theta) = \xi(\theta)' ZAZ' \xi(\theta) \quad (38)$$

where we use the GMM optimal weighting matrix as A to obtain the asymptotically efficient estimator.[18] Since the window length is potentially endogenous, we construct a set of instruments to correct for endogeneity bias. To find such instruments, we need variables that affect actual window lengths set by studios but do not affect demand. A potential source of such instruments is studio-specific characteristics (such as their financial prowess and contractual relations with exhibitors). For instance, if a studio has greater financial leverage of its productions then it may not be as eager to release its DVDs to recoup production and marketing costs as a studio that is less financially endowed. Studio fixed-effects, however, should not affect consumers' decisions since they hardly consider the identity of the movie studio when deciding whether to view a movie or DVD. Thus we include studio dummies, their interactions with production costs, and their interactions with the movie "leg," (computed as in (39)) as instruments for window lengths.

The estimation proceeds as follows:

(Step 0) Simulate *NS* random draws for the individual-specific preference vector; pick an initial value for $\delta \equiv [\delta_m^T, \delta_m^R, \delta_m^B]$, and for $\{s_{im}^T\}_{i=1}^{NS}$, set $\triangle WAIT_{im} = 0$ for all *i* and *m*.

(Step 1) Pick an initial value for θ_2;

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[18] The 2SLS estimates are computed in the first stage by using $A = (Z'Z)^{-1}$, then the resulting parameter estimates are used to compute the optimal weighting matrix, $A = (Z'\xi(\hat{\theta}_{2SLS})\xi(\hat{\theta}_{2SLS})'Z)^{-1}$.

(Step 2) Conditioning on θ_2 and $\{s_{im}^T\}_{i=1}^{NS}$, compute the predicted share, $(\hat{s}_m^B, \hat{s}_m^R)$ given the pair $\delta_m^{DVD} \equiv (\delta_m^R, \delta_m^B)$ through Monte Carlo integration

$$\begin{aligned} \hat{s}_m^R(\delta_1^T;\theta_2) &= \frac{1}{NS}\sum_{r=1}^{NS} s_{im}^R(v_i^r;\theta_2) \\ \hat{s}_m^B(\delta_1^T;\theta_2) &= \frac{1}{NS}\sum_{r=1}^{NS} s_{im}^B(v_i^r;\theta_2) \end{aligned} \qquad (40)$$

where s_{im}^R and s_{im}^B are computed from (19) given δ_m^{DVD}.

(Step 3) Write $\hat{s}_m^{DVD} \equiv (\hat{s}_m^R, \hat{s}_m^B)$, calculate

$$\delta_m^{DVD\prime} = \delta_m^{DVD} + \ln(s_m^{DVD}) - \ln(\hat{s}_m^{DVD}(\delta_m^T, \theta_2)) \qquad (41)$$

(Step 4) Iterate over Step 2 and 3 till convergence; write the convergent value vector as $\delta_m^{DVD}(\delta_m^T, \theta_2)$.

(Step 5) Compute the GMM estimator for $\theta_1^{DVD}(\delta_m^T, \theta_2)$ through

$$\hat{\theta}_1^{DVD}(\delta^{DVD}(\cdot)) = \arg\min_{\theta\in\Theta} \xi(\delta^{DVD}(\cdot))' Z_2 A_2 Z_2' \xi(\delta^{DVD}(\cdot)) \qquad (42)$$

(Step 6) Calculate the value of $\vartriangle WAIT_{im}$ by simulated integration of (23), conditioning on $\hat{\theta}_1^{DVD}$ and θ_2 and compute the corresponding theatrical market shares s_{mt}^T by integration over (24)

$$\hat{s}_{mt}^T(\delta_m^T, \theta_2) = \frac{1}{NS}\sum_{i=1}^{NS} \hat{s}_{imt}^T(\cdot) \qquad (43)$$

(Step 7) Evaluate

$$\delta_{mt}^{T\,\prime} = \delta_{mt}^T + \ln(s_{mt}^T) - \ln(\hat{s}_{mt}^T(\delta_{mt}^T, \theta_2)) \qquad (44)$$

(Step 8) Iterate over Step 2 to Step 7 till convergence.

(Step 9) Compute the GMM objective function in (38) as a function of θ_2;

(Step 10) Search over the parameter space of θ_2 to minimize the GMM objective function.

The asymptotic standard errors are computed for the efficient GMM estimator.

5.2. Estimating the distribution of consumer heterogeneity from survey data

The major source of computational burden is the variance-covariance matrix of the unobserved individual heterogeneity, v_i. Suppose we have a sum of K random coefficients, then the number of parameters to be estimated in $Var(v_i)$ then amounts to $K(K+1)/2$ (e.g., 21 parameters if $K=6$). Since the variance-covariance matrix is part of the nonlinear parameters, θ_2, to be numerically optimized over, the huge number of parameters is a major challenge in model estimation. One way to circumvent this problem is to impose the assumption that all off-diagonal elements in $Var(v_i)$ are zero (e.g., Berry et al. 1995) and only estimate the diagonal elements. However, such assumptions tend to be inappropriate and lead to biased estimates if consumers' preference parameters are significantly correlated.

One possible approach to solve this problem is to supplement the aggregate-level data with consumer survey data that provides rich information about the distribution of consumer heterogeneity. Harris and Keane (1999) develop an approach to combine attitudinal data with consumer-level revealed preferences to obtain more reliable estimates of consumers' preferences for choice alternatives. Here we propose a method that naturally incorporates the information contained in ordinal-scale attitudinal data into the estimation of market-level data.

Since the survey questions were asked in the form of ordinal variables, we compute a measure of the association between each pair of ordinal variables. The polychoric correlation coefficient suits our need here since this measure specifically addresses situations in which the latent variables of interest are continuous, yet measurement outcomes are ordinal. We can compute a polychoric correlation coefficient between two ordinal variables, X and Y (with M and N categories, respectively), which are related to two latent continuous preference weights, β_k and β_j, by

$$\begin{aligned} X &= x_m \quad if \quad \beta_k \in [\tilde{x}_{m-1}, \tilde{x}_m), \quad m = 1, ..., M \\ Y &= y_n \quad if \quad \beta_j \in [\tilde{y}_{n-1}, \tilde{y}_n), \quad n = 1, ..., N \end{aligned} \qquad (45)$$

Consistent with (31), we assume that β_k and β_j are distributed bivariate normal (with correlation coefficient, ρ_{kj}), we can estimate ρ_{kj}, together with the thresholds, $\tilde{x}_m$'s and $\tilde{y}_n$'s, via maximum likelihood (Olsson 1979; Drasgow 1986). Since the polychoric correlation coefficient computed as such does not depend on the number of rating levels and are scale-free, it can be then plugged into the full covariance matrix of random coefficients.

The estimated correlation matrix is reported in Table 5. The numbers in bold are significant at the 0.05 level.

6. Empirical results

We present the empirical results in three parts. The first part estimates factors impacting movie-DVD window lengths in a first stage, that serves as consumer expectations for movie-DVD release times for the dynamic structural model. Next, we report the estimates of the dynamic structural model. Finally, we present results around the counterfactual analysis to evaluate the optimal movie-DVD release window for the "average" movie from the point of industry revenues.

6.1. Determinants of window lengths and other state variables

In this section, we report the maximum likelihood estimates of the first-stage estimation of the stochastic process that generates the state variables in the DVD period. Table 7 presents the empirical determinants for the theater-to-DVD window length. Leg has a significantly positive effect on the window length; quantitatively, a one-week increase in the leg of a movie's theatrical run leads to approximately 1.1 weeks' increase in the actual window length set by studios. Opening box-office revenue has practically no effect on the window length by itself, but it modifies the marginal impact of Leg. This implies that if a wide-release blockbuster movie's box-office performance decays fast, it tends to be released on DVD even faster than a movie that attracts a smaller audience; on the other hand, if it maintains a relatively high momentum at the box office, than its DVD release tends to take an even longer time, presumably because the studio wants to extract more revenue from the theatrical movie. The viewers' rating of a movie has a significantly positive effect on the window length: a lower-rated movie is released faster on DVD than a higher-rated movie. The trend variable is significantly negative across all specifications, consistent with our previous observation that there has been a general trend towards a shorter theater-to-DVD window at the industry level.[19] Star presence, MPAA ratings and genres do not seem to affect window length (except that drama and science-fiction movies seem to have a longer window than other genres). Among the seven major studios, Studio 1 seems to have the shortest window, whereas Studios 3 and 5 have significantly longer windows than non-majors (whose dummy is normalized to zero). These studio fixed effects may reflect the differences in studios' strategies on setting the

[19] Some industry insiders claimed that the trend towards a faster DVD release is caused by an ever-shortening movie leg at the box-office. Our results indicate that the claim is untrue. First, even controlling for the movie leg, the trend variable has a significantly negative coefficient. Second, we also performed a simple regression of the movie leg against a time trend, and the trend variable is not significant, i.e., there is no evidence that movies' legs have been shortening during our sample period.

theater-to-DVD windows; however, such differences are rather small in magnitude. Given that consumers typically do not pay attention to the identity of the studio when making consumption decisions about movies and DVDs, we exclude these studio fixed effects and report the estimates in the third column. The coefficients are very similar to those in the first column. Since most of the movie covariates are insignificant, we further exclude them and focus on movie's opening strength, leg, viewer rating, and trend; the estimates of this more parsimonious specification are reported in the third column. This small set of estimates is used to compute consumers' expectations about window lengths.

Table 8 presents the coefficient estimates for DVD retail price. Opening box-office revenue has a significantly negative effect on price, which may result from the fact that retailers are more likely to use popular DVDs as loss leaders to boost store traffic. DVDs of the action movies are priced (about 2%) lower than DVDs of other genres on average. There is also a significant trend towards lower DVD retail prices: each new quarter leads to about 1% decrease in price.

Table 9 reports the estimates for the box-office gross revenue. Since consumers tend to infer the quality (or mass appeal) of the movie from its total theatrical demand, we empirically estimate the effects of the movie covariates that influence the eventual demand and use them to generate consumer expectations during the theatrical run. As expected, the opening-weekend box-office revenue strongly determinants the overall revenue of a theatrical movie; one percent increase in the opening-weekend revenue leads to 0.9% increase in the overall revenue. A movie's leg also has a substantial impact on the overall market demand: one week's increase in a movie's leg leads to about 19% (exp(0.176)-1) increase in its total theatrical demand. Viewers' ratings also positively influence a movie's theatrical demand. R-rated movies tend to have lower demand in general. Comedy movies seem to attract a larger audience, whereas dramas tend to attract a smaller audience, compared to movies of other genres.

6.2. Estimates of the dynamic structural model

Table 10 presents the current-period utility parameters for viewing theatrical film. Studios' marketing strategies such as the number of exhibitor screens (capturing the "availability" of a movie) and movie advertising expenditure have substantial effect on a movie's appeal to consumers. Star power rating has a significantly positive effect, as expected. Critical review seems to have a negative effect while the viewer rating has a significant effect. Seasonality factors are also important. Among various film genres, thrillers, horror movies, and comedies appear most popular for movie-goers. There is considerable amount of heterogeneity across consumers in their preference strength for stardom. The decay rate is estimated to be highly negative, but the dispersion parameter is statistically significant, indicating that consumers' have very heterogeneous valuations for the "newness" of the movie.

Table 11 presents the utility parameters for DVD rental and for DVD purchase (for collection). As predicted, the box-office gross of a movie has a significantly positive effect on both the renting and buying utilities of the DVD. This is consistent with the industry observation that theatrical release is a marketing exercise for the DVD. This is further manifested by the fact that theatrical revenue has a larger effect on collection utility than on viewing utility.

Consistent with the perishability hypothesis, a longer window reduces both renting and buying utility. The coefficients correspond to a monthly 7.3% and 5.6% discount rate for renting utility and buying utility, respectively; for instance, a four-month decay in DVD release can reduce the value of DVD rental by 26% and that of DVD purchase by 22%.

Star power has a significant effect on renting utility but has no effect on buying utility. R- and PG13-rated movies appear to be more attractive to DVD viewers, as compared to G- and PG-rated movies. However, while R-rated movies are more likely to be bought than G- and PG-rated movies, PG13-rated movies are not. Interestingly, sequels actually offer lower DVD viewing and buying utility. Among the various movie genres, thrillers and war movies have greater appeal, while dramas have the lowest appeal.

Among the content enhancement provided on the DVD, deleted scenes seem to be valued by both viewers and collectors. Music videos, on the other hand, mainly appeal to collectors. Price coefficient is estimated to be significantly negative. Filmmaker commentary and children's games increase the likelihood of buying but have no effect on the likelihood of renting.

Table 12 reports the estimates for parameters that dynamically link the theatrical period and the DVD period utilities. The five estimates are related to the substitution effect (SE). The constant is estimated to be significantly positive, indicating that, on average, the consumer's utility from the DVD would be *reduced* after having viewed it in theater, suggesting that DVD is at least partially substitutable with the theatrical movie. Viewers' rating, however, has a significantly negative sign, suggesting that a highly rated movie is less substitutable. The animation genre also has a negative sign, meaning that animation movies on average induce less satiation after theatrical viewing. R-rated movies, on the contrary, are more substitutable, i.e., once consumers have viewed these in theater, they are unlikely to view it on DVD again. There is substantial amount of consumer heterogeneity in the degree to which consumers view the sequential releases as substitutable. The forward-looking parameter, λ, is estimated to be significantly positive, suggesting that the consumers are indeed *forward-looking* in their movie consumption decisions. Therefore, a change in the theater-to-DVD window would affect consumers' movie-going decisions since they tend to optimize their utilities over time rather than behave myopically.

6.3. Policy Analysis: The Optimal Theater-to-DVD window

Given the structural demand parameters, we perform a policy analysis, where we simulate the market demand for theatrical movies and DVDs under industry-wide shorter windows. The other variables, such as product attributes, advertising and prices, are fixed exogenously at the observed value in the sample. The consumer expectations are assumed to be adaptive to the new window regime, as described in the model section. When simulating for the new windows, we reduce the average window by 3 to 18 weeks while still allowing for the movie-specific variation in window length and also in consumers' expectations across movies, through the change in a movie's box-office sales pattern.

Table 13 presents the predicted market outcomes; the implication for revenue is graphed in Figure 4. We find that industry revenues are a convex function in the window length reduction, with an optimum at around 12 weeks. Since the average window length in our sample is 5.5 months, a 12-week reduction in window length would imply an optimal industry-level average window of about 2.5 months.

Our analysis thus yields insights about the tradeoffs involving optimal inter-release times. On the one hand, for the period of the data, it shows that proponents of the theory that studios have gone too far in reducing window lengths are incorrect. On the other hand, the argument proposed by certain industry executives that there is very little cannibalization and therefore studios should simply release movies and DVDs simultaneously is flawed as well. We find that, because of the prominent role played by consumers' rational expectations, the studios should wait a few weeks after the movie has typically gone out of the theater before releasing the movie on DVD. However, given that the cannibalization problem is more than balanced by the reduction in buzz that affects DVD sales in the current scheme, it does not make sense to delay DVD releases as much as the average in the data of about 4.5 months.

7. Conclusion and Discussion

In this paper we develop a structural demand model to empirically solve the inter-release timing problem between sequentially introduced products. The model incorporates consumers' forward-looking choice behavior with rational, adaptive expectations, the possibility of multiple purchases, as well as a rich structure of consumer heterogeneity.

Methodologically, we propose a parsimonious approach to augment the market-level aggregate data with consumer-level attitudinal (survey) data to improve model identification. In addition, we extend Berry (1994)'s contraction mapping algorithm from a static demand context to a dynamic setting to ensure that the individual's choice probabilities are dynamically consistent within the estimation framework.

We apply the model to the motion picture industry to address the issue of the inter-release time between a theatrical movie and its DVD version. We obtain several insights from the estimates of the structural model that informs movie-DVD release timing. First, we find that indeed consumers are forward-looking and have adaptive expectations about inter-release times. As studios shorten inter-release times, consumers do adjust their behavior, supporting the notion that shrinking windows cause DVD sales to cannibalize theatrical demand. Second, consumers dynamically adjust their expectations in a Bayesian learning fashion specifically incorporating new information about movie inter-release times. Countering the loss of box-office demand due to the shrinking windows is the stronger buzz for DVDs with the shorter window; as buzz decays at a rate of about 5.6% a month for DVD rentals and 7.3% a month for DVD sales. Finally, based on the structural estimates, a policy analysis shows that given current consumer preferences, the theater-to-DVD window that maximizes the industry revenue is about 2.5 months on average.

There are several future research directions that appear promising. First, in this paper we focus on the theatrical market and home-video market; the two channels combined currently generate nearly 90% of the studios' revenues from feature movies at the time of the sample. With the rise of streaming, many new questions arise. For example, our model treats the evolution of DVD hardware installation base as exogenous; i.e., we do not explicitly model the consumer's decision to adopt the DVD player in order to view DVDs at home. Since our focus is on the effect of inter-release time on sequential product demand, such a modeling simplification should not be problematic.[20] Karaca-Mandic (2004) and Inceoglu and Park (2003) address the indirect network externalities of DVD player adoption and DVD software availability and uses data from the early years of DVD introduction. Since our data cover a later period of 2001-2003, almost all major-studio feature movies were released on DVD; therefore, such network effect is less of a concern if the DVD release is a given and only its timing is uncertain. However, treating the hardware adoption and software consumption in an integrated fashion would be desirable in an evolving market. Interestingly, given the adoption of streaming, hardware adoption will be replaced by subscriptions to services such as Netflix and Amazon Prime, but now, the purchase price is no longer relevant for many movies with streaming as the movies are available with subscription. Our model needs to be adapted to consider the time-cost of watching streaming home video along with purchase and rental prices for movies.

Second, we focus on the inter-release time between a movie and its DVD version, but we do not explicitly model the competition between various DVDs. Since a DVD not only faces competition from other DVDs released around the same time, but also faces competition from contemporaneous box-office releases (Luan and Sudhir 2006), solving a full equilibrium model of the release timing decision of DVDs, which should both account for the optimal inter-release time and for time-varying competitive sets, becomes exceptionally difficult. This issue becomes even more significant in the streaming context. We hope this paper will serve as a starting point to solve a variety of managerially relevant problems given the rapid changes in home distribution of movies.

[20] Leaving the hardware adoption decision out of the current framework might be problematic if the trend towards a shorter theater-to-DVD window induces consumers to adopt the DVD player earlier than they otherwise would, which subsequently increases the demand for DVD software titles. However, this effect is not identifiable with our current data.

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Tables

Table 1

Key Descriptive Statistics[a]

Variable	Mean	Median	Std. Dev.	Max.	Min.
Theater-to-DVD Window (days)	165.37	158.00	41.44	405	88
DVD Sales, 4 Weeks (mils.)	0.72	0.32	1.20	8.97	0.01
DVD Sales, 6 Months (mils.)[b]	0.99	0.50	1.50	11.29	0.01
DVD Retail Price ($)	19.84	19.60	1.89	33.98	14.16
DVD Rentals, 4 Weeks (mils.)[c]	2.87	2.55	1.67	7.68	0.35
DVD Advertising (TV GRPs)	273.2	94.5	415.9	2560	0
Box-Office Revenue ($ mils.)	55.05	34.56	58.20	404.76	5.11
Theatrical Release Advertising ($ mils.)	19.65	18.69	9.80	63.35	0
Number of Opening Screens	2255	2480.5	844.6	3876	41
Production Budget ($ mils.)	41.46	35.00	31.01	200	0.16
Star Power Rating (0-100)[d]	56.52	59.09	27.63	100	0
Viewer Rating[e]	6.07	6.10	1.14	8.9	2.4
Critical Rating[f]	5.42	5.00	2.14	9.40	1.10
Oscar Nominations	0.57	0	1.73	13	0
Oscar Awards	0.12	0	0.58	6	0

[a] Sample consists of 526 new DVD titles released between 2000/1 and 2003/10.

[b] The correlation coefficient between the first four-week sales and 6-month sales is 0.992.

[c] Rental volumes are only available for 265 titles; from *Video Business* magazine

[d] From Hollywood Reporter (2002)

[e] From www.imdb.com.

[f] From www.metacritic.com.

Table 2

Description of Categorical Variables		
	Variable	**Mean**
Genres	Action	0.23
	Adventure	0.13
	Animation	0.06
	Comedy	0.44
	Crime	0.15
	Documentary	0.01
	Drama	0.42
	Fantasy	0.06
	Horror	0.10
	Music/Musical	0.02
	Romance	0.17
	Sci-Fi	0.10
	Thriller	0.27
	War	0.03
MPAA Ratings	R	0.43
	PG 13	0.41
	PG	0.12
	G	0.04
DVD Extras	Making-of Documentary	0.69
	Filmmaker Commentary	0.74
	Deleted Scenes	0.52
	Music Video/Isolated Score	0.32
	Interactive Features/Games	0.13
Sequel		0.10

Table 3

DVD Market Shares

Studio	Total sales (billions)	Market share
Warner Home Video	$4.21	20.2%
Buena Vista	$3.38	16.2%
Universal	$3.07	14.7%
Fox	$2.76	13.2%
Sony	$2.63	12.6%
Paramount	$1.96	9.4%
MGM	$1.11	5.3%
Others	$1.77	8.5%

Source: *Video Business* (2004)

Table 4

Consumer Survey Data: Descriptive Statistics		
Variable	**Category**	**Mean**
(1) Preference for movie-going	"Like Very Much"	0.30
	"Like Somewhat"	0.41
	"Don't Like it Very Much"	0.14
	"Do Not Do It At All"	0.15
(2) Preference for video-watching	"Like Very Much"	0.38
	"Like Somewhat"	0.43
	"Don't Like it Very Much"	0.09
	"Do Not Do It At All"	0.10
Polychoric correlation coefficient b/w (1) and (2)[a]		0.45
Favorite movie genres	Action/Adventure	0.60
	Animated	0.18
	Comedy	0.68
	Drama	0.49
	Horror/Suspense	0.28
	Musical	0.20
	Romance	0.31
	Science Fiction	0.28
	Foreign	0.06
Importance for choose movies	Stars/director	2.00
	Advertising	1.92
	Critic Review	1.61
	WOM	2.33
	Awards/Nominations	1.58
Importance for choose videos	Stars/director	2.06
	Advertising	1.77
	WOM	2.26
	Awards/Nominations	1.54
Likelihood of repeat watching	"Rarely"	0.33
	"Sometimes"	0.45
	"Frequently"	0.22

[a] The Pearson correlation coefficient is 0.40.

Table 5

Polychoric Correlation Coefficients between Attribute Weights						
	Star	Ads	WOM	Rewatch	Movie	DVD
Star	**1**					
Ads	**0.498**	**1**				
WOM	**0.571**	**0.563**	**1**			
Rewatch	**-0.143**	**-0.083**	-0.063	**1**		
Movie	**0.166**	**0.135**	**0.14**	-0.024	**1**	
DVD	**0.274**	**0.245**	**0.203**	**-0.067**	**0.398**	1

Table 6

A Sample of Movie Legs and Windows (in weeks)		
Title	**Leg[a]**	**Window**
Charlies Angels (2000)	1.9	20.6
Formula 51	0.9	15.6
Gladiator	3.4	28.6
Green Mile	4.4	26.6
Lara Croft: Tomb Raider	1.6	21.6
Meet The Parents	3.8	21.6
Mission Impossible 2	1.7	23.9
Nowhere In Africa	8.6	29.6
Perfect Storm	2.1	19.6
Quiet American, The	5.2	35.6
Rules Of Attraction, The	1.2	18.6
Runaway Bride	2.5	25.6
Scary Movie	2.0	22.6
Sixth Sense	5.5	33.6
Stuart Little	3.4	17.6
Tarzan	2.6	32.9
Wash, The	1.6	16.9
What Lies Beneath	2.9	27.6
X-Men	1.6	18.6

Note: [a] Maximum-likelihood estimates for the scale parameter of Weibull distribution are taken as measure of movie leg, as shown in Eq. (27).

Table 7

Determinants of the Theater-to-DVD Window

Intercept	24.974**	(1.314)	26.336**	(1.120)	26.404**	(0.578)
Leg	1.154**	(0.172)	1.143**	(0.175)	1.184**	(0.169)
ln(OpeningBoxOffice)	0.021	(0.297)	0.104	(0.304)	0.079	(0.242)
ln(OpeningBoxOffice)*Leg	0.209**	(0.059)	0.201**	(0.060)	0.195**	(0.059)
Viewer Rating	0.885**	(0.294)	0.941**	(0.303)	0.918**	(0.225)
Trend	-0.236**	(0.051)	-0.240**	(0.053)	-0.242**	(0.051)
Star	-0.026	(0.099)	-0.033	(0.102)		
Critic	0.018	(0.133)	0.015	(0.136)		
MPAA_R	-0.027	(0.848)	-0.542	(0.864)		
MPAA_PG13	-0.170	(0.787)	-0.515	(0.803)		
Sequel	0.082	(0.797)	0.309	(0.816)		
Action	-0.665	(0.613)	-0.850	(0.631)		
Fantasy	1.203	(0.945)	1.124	(0.972)		
Romance	0.446	(0.652)	0.640	(0.669)		
Thriller	-0.049	(0.631)	-0.003	(0.647)		
Comedy	0.237	(0.596)	0.251	(0.615)		
Drama	0.176	(0.600)	0.411	(0.617)		
Animation	0.059	(1.157)	0.312	(1.186)		
War	-0.995	(1.356)	-1.029	(1.390)		
Drama	4.166*	(2.353)	5.045**	(2.383)		
Horror	0.262	(0.872)	0.183	(0.892)		
SciFi	1.551*	(0.793)	1.576*	(0.817)		
Studio 1	-1.806*	(0.954)				
Studio 2	1.041	(0.901)				
Studio 3	2.309**	(1.000)				
Studio 4	1.765*	(1.038)				
Studio 5	2.603**	(0.908)				
Studio 6	1.524	(1.046)				
Studio 7	1.789	(1.229)				
$\hat{\sigma}_W^2$	4.948		5.110		5.112	

Notes: * p<.1; **p<.05. Standard errors are in parentheses.

Table 8

Determinants of DVD Price[a]

Intercept	3.088**	(0.017)
ln(OpeningBoxOffice)	-0.011**	(0.004)
Star	0.001	(0.002)
Critic	0.000	(0.002)
Viewer_Rating	0.005	(0.004)
MPAA_R	0.004	(0.014)
MPAA_PG13	-0.003	(0.013)
Sequel	0.012	(0.013)
Action	-0.021**	(0.010)
Fantasy	-0.011	(0.015)
Romance	0.003	(0.011)
Thriller	-0.017	(0.010)
Comedy	0.001	(0.010)
Drama	0.004	(0.010)
Animation	-0.001	(0.019)
War	-0.017	(0.022)
Drama	-0.045	(0.038)
Horror	0.005	(0.014)
Sci_Fi	-0.008	(0.013)
Trend	-0.010**	(0.001)
σ_P	0.081**	(0.021)

Notes: Dependent variable is the logarithm of DVD retail price. * p<.1; **p<.05. Standard errors are in parentheses.

Table 9

Determinants of Box-Office Gross[a]		
Intercept	3.612**	(0.064)
ln(Opening Box Office)	0.902**	(0.017)
Leg	0.176**	(0.006)
Viewer_Rating	0.105**	(0.017)
Trend	0.000	(0.003)
Star	0.009	(0.006)
Critic	0.000	(0.008)
MPAA_R	-0.148**	(0.049)
MPAA_PG13	-0.048	(0.046)
Sequel	0.005	(0.046)
Action	-0.013	(0.036)
Fantasy	0.004	(0.055)
Romance	0.032	(0.038)
Thriller	0.018	(0.037)
Comedy	0.079**	(0.035)
Drama	0.028	(0.035)
Animation	-0.033	(0.068)
War	-0.022	(0.079)
Drama	-0.256*	(0.135)
Horror	0.043	(0.051)
Sci_Fi	-0.047	(0.046)
σ_B	0.291**	(0.106)

Notes: Dependent variable is the logarithm of box-office gross revenue. * p<.1; **p<.05. Standard errors are in parentheses.

Table 10

Theatrical-Movie Utility Parameters

Intercept	-13.256**	(0.141)
ln(Ad_Spend)	0.248**	(0.034)
Star	0.080**	(0.008)
Critic	-0.017*	(0.010)
Viewer_Rating	0.042**	(0.020)
MPAA_R	-0.101*	(0.061)
MPAA_PG13	-0.021	(0.056)
Sequel	-0.084	(0.052)
Action	-0.073	(0.046)
Fantasy	-0.097	(0.059)
Romance	-0.173**	(0.048)
Thriller	0.132**	(0.046)
Comedy	0.215**	(0.042)
Drama	0.048	(0.043)
Animation	0.114	(0.076)
War	-0.122	(0.103)
Documentary	-0.235	(0.197)
Horror	0.125**	(0.061)
Sci-Fi	0.050	(0.056)
Spring	0.251**	(0.055)
Summer	0.179**	(0.049)
Fall	0.101*	(0.052)
Holiday	0.236**	(0.059)
ln(Screens)	1.124**	(0.015)
Decay_Rate	-0.438**	(0.008)
Heterogeneity dispersion		
Constant	0.177	(0.141)
Star	0.115**	(0.017)
Decay_Rate	0.265**	(0.011)

Table 11

DVD Utility Parameters				
	Rental		*Collection*	
Intercept	-0.972**	(0.400)	1.931**	(0.834)
ln(OpeningBoxOffice)	0.624**	(0.016)	1.106**	(0.020)
Window	-0.075**	(0.029)	-0.061**	(0.012)
Star	0.031**	(0.005)	-0.010	(0.006)
Critic	-0.015**	(0.007)	-0.015*	(0.008)
Viewer_Rating	-0.015	(0.019)	-0.043**	(0.017)
MPAA_R	0.577**	(0.046)	0.171**	(0.049)
MPAA_PG13	0.466**	(0.043)	-0.110**	(0.044)
Sequel	-0.356**	(0.042)	-0.143**	(0.044)
Action	-0.066**	(0.027)	0.172**	(0.033)
Fantasy	0.080*	(0.048)	0.271**	(0.055)
Romance	-0.091**	(0.038)	-0.187**	(0.041)
Thriller	0.199**	(0.030)	0.084**	(0.040)
Comedy	0.026	(0.030)	-0.103**	(0.038)
Drama	-0.027	(0.027)	-0.024	(0.033)
Animation	-0.638**	(0.121)	0.012	(0.105)
War	0.153**	(0.062)	0.235**	(0.063)
Drama	-0.436**	(0.120)	-0.160**	(0.071)
Horror	0.013	(0.038)	0.057	(0.051)
Sci_Fi	0.037	(0.037)	0.009	(0.047)
Commentary	0.038	(0.028)	0.092**	(0.033)
Del_Scenes	0.071**	(0.023)	0.066**	(0.027)
Music	-0.102**	(0.028)	0.172**	(0.030)
Games	0.209	(0.136)	0.300**	(0.131)
Trend	-0.257**	(0.010)	-0.524**	(0.015)
ln(Price)	-2.302**	(0.288)		
d_0	-0.022*	(0.013)		
c_0	0.151**	(0.07)		

Table 12

Dynamic Linkage Parameters	
Substitutability parameters (SE)	
Constant	0.153 ** (0.213)
Viewer Rating	-0.120 ** (0.034)
Animation	-0.312 ** (0.135)
R-Rated	0.110 * (0.065)
σ_g^2	0.113 ** (0.050)
Forward-looking parameter	
λ	-5.739 ** (1.985)

Table 13

Simulated Effects of Window Reduction

Reduction in the Average Window (Weeks)	Change in theater admission per movie (000)	Change in DVD Sales	Change in DVD Rentals	Industry Revenue
0	**0.00**	**0.00**	**0.00**	0.00
3	-35.82	45.80	32.50	42.48
6	-79.21	88.50	68.30	77.59
9	-133.83	133.50	99.21	98.88
12	-206.75	190.55	122.10	105.90
15	-310.28	240.30	159.39	89.41
18	-380.40	261.90	170.20	51.70

Table 14

Windowing Schedule of a Typical Movie

Version	Release Time
Theatrical Exhibition	Initial debut
Home Video	5 months later
Pay-Per-View (or Video-on-Demand)	8 months later
Pay-TV (e.g., HBO)	12 months later
Network/Syndication	2-3 years later

Figures

Figure 1

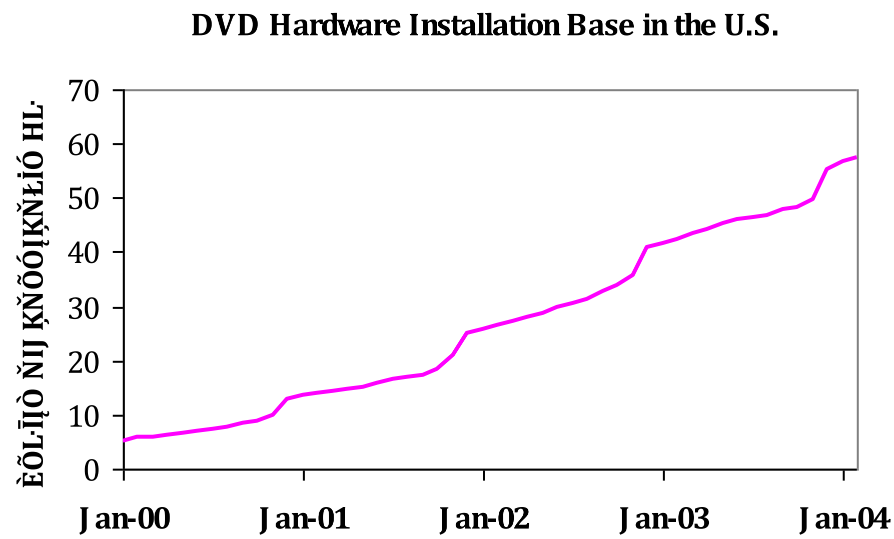
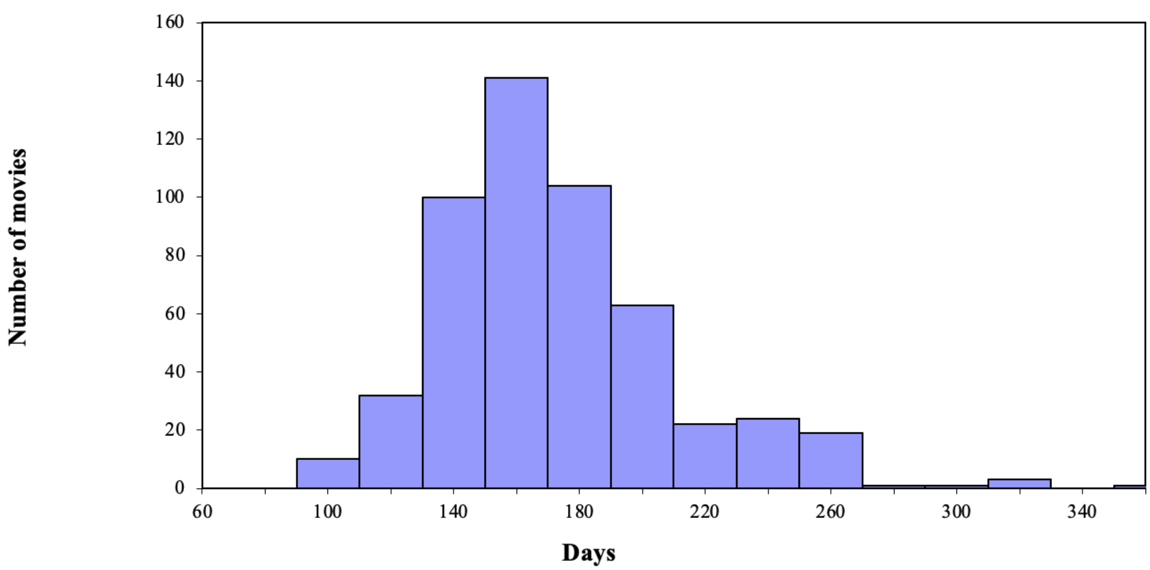


Figure 2: Histogram of Theater-to-DVD Windows



The sample consists of DVDs of feature movies released between Jan. 2000 and Oct. 2003. (N=526)

Figure 3: Weibull Fitting of Box-Office Sales

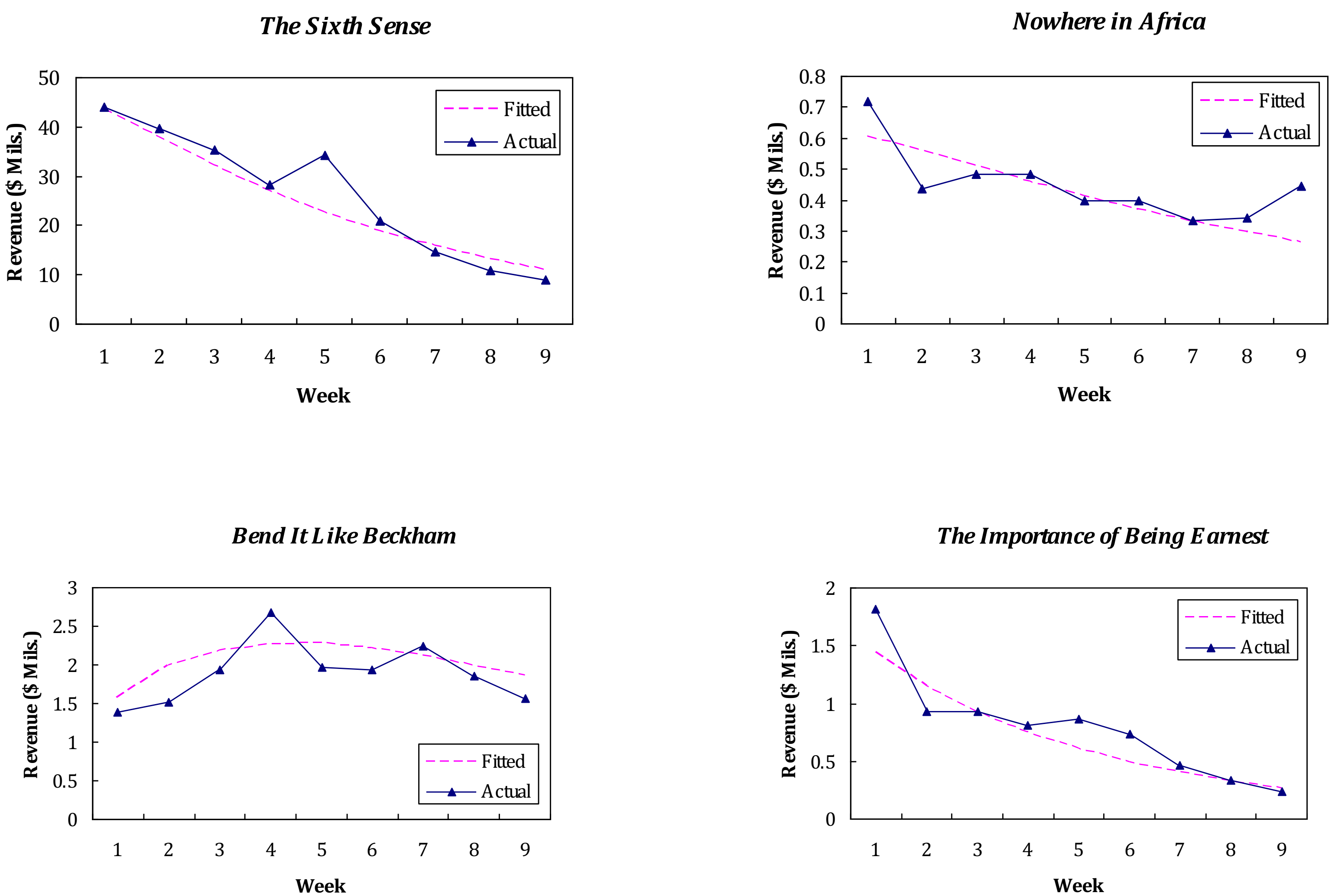


Figure 4

Effect of Window Reduction on All Movies