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Sales Through Sequential Distribution Channels: An Application to Movies and Videos

This article focuses on the sale of a product across channels that are entered sequentially. Using a two-channel model, the authors derive the optimal time to enter the second channel and then obtain a specific parametric solution for movie distributors regarding theater attendance and subsequent sales to video stores. Using data from 35 movies, the authors estimate exponential sales curves for both theater attendance and video rentals and demonstrate how knowledge of the sales parameters in the first channel (theaters) helps predict sales in the second channel (video rentals). Finally, from the movie distributor's perspective, the authors calculate optimal release times based on the model and its estimated parameters. The results suggest that profits would increase if movies were released to video sooner than is the current practice.

Many products evolve through generations, and technological substitution (Fisher and Pry 1971) has long been an important topic of investigation. Furthermore, the importance of distribution in the diffusion process is well known (Jones and Ritz 1991). In this article, we take a different focus: the adoption of products as they become more widely available across distribution channels, a process we call "sequential distribution."

The essential characteristic of sequentially distributed products is that in stages they become more available to the market. Many products start in limited distribution—for example, in specialty outlets such as health food or sporting goods stores—and then at some point become widely available (and usually lower in price) through supermarkets and mass merchants. Similarly, many pharmaceuticals begin as ethical drugs and then later become available over the counter (e.g., Tagamet, Pepcid). Although some changes in the product occur, the main change has to do with distribution (availability) and price.[1] Consequently, one critical management decision is when to release the product to the next channel. We examine this problem analytically, focusing on goods that are, at least in the short run, bought only once—for example, durables and entertainment products.

A related, and important, characteristic of sequentially distributed products is that sales (and possibly even patterns of sales over time) in one stage of the distribution system may provide a good indication of sales in the next stage of the sequential distribution channel. To the extent that managers can make decisions about how to market sequential products after observing sales patterns at an early stage, improved decision making is possible. We analyze this pattern for one industry, movies, and then use the empirical results to draw conclusions about optimal release timing of videos.

To illustrate our basic structure, we use data from the movie industry. The U.S. movie industry accounted for $5.4 billion in domestic theater revenues in 1995 and was a major exporter as well. It has also been extensively studied (e.g., Eliashberg and Sawhney 1994; Swami, Eliashberg, and Weinberg 1999; Wallace, Seigerman, and Holbrook 1993). However, in addition to the primary movie market itself, a movie is typically released through a sequence of channels and product forms, including pay per view, premium cable channels (e.g., HBO), video stores (for rental and/or sale), and network and local television. Although not all movies go through all stages, distributors' gross revenue from home videos has exceeded that from theater exhibition since the late 1980s (Vogel 1994, p. 79). The subsequent distribution channels are thus critical to the revenues (and profits) of the movie industry. Indeed, some movies would not be made—and many fewer would be profitable—if it were not for the existence of sequential channels. Here, we focus on two distribution channels: box office sales and sales of videos to video stores for rental to consumers.

We focus on two questions with regard to the marketing of sequential products. First, from the point of view of the manufacturer, when should the next sequential distribution channel be opened? That is, how long after the product's introduction should a firm wait to introduce the product into the second channel? Sales in the second channel are assumed to cannibalize sales from the first channel.

[1]Sequential product-markets can cross industry boundaries. For example, successful movies—particularly those targeted at children—can spawn many souvenir products, video games, and CD-ROMs. Likewise, many books have been the basis of films, but often the film is quite different from the book. Our focus, as noted, is sequential distribution in which the core product is similar across the multiple release forms.

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Although the rerelease of the *Star Wars* trilogy demonstrates that some people will go to a movie theater even when a video tape of a movie exists, many people will opt for the cheaper, more widely available version of the product. However, the longer the movie studio waits to release the videotape, the more the impact of the usually extensive (and expensive) introductory marketing campaign decays. This, plus the lack of currency caused by delay and the possibility that consumers of the product in the first channel will not be in the market when it enters the second channel, is likely to reduce sales in the second channel. The time between movie release and video release varies little for major movies; the industry appears to follow a relatively fixed decision rule of waiting approximately six months before releasing the video, though this time has recently decreased somewhat. This relatively consistent timing could result from contractual arrangements with theaters, legal problems in obtaining foreign releases, difficulty in forecasting, or a strategy to make it difficult for customers to delay viewing when they have great interest in the movie (Prasad, Mahajan, and Bronnenberg 1998). Still, given that the "legs" of movies appear to be decreasing (Klady 1997), reconsidering the video release timing decision seems worthwhile.

The second question is empirical, namely, how accurately the sales of the sequential product (e.g., videotape rentals) can be forecast on the basis of the sales of the initial product (e.g., theater attendance). Although new product diffusion models (Parker 1994) have been shown to track sales of new products well, their usefulness as a forecasting instrument is limited because of the number of observations required to prepare an accurate forecast. In contrast, at least for the movie industry, sales data from the first channel are available in time to make both accurate forecasts of sales and decisions about marketing strategies for the second channel. In general, only two or three weeks of data are needed to forecast accurately the overall box office revenue pattern for the movie that, in turn, can be used to forecast video rental revenues.[2] Of course, factors other than the theater attendance pattern for the movie influence rentals of the video, and we attempt to consider these factors as well.

Context

Determination of the best time to launch a new product or a new version of an existing product has been studied in several contexts. Wilson and Norton (1989), using a variant of Bass's (1969) diffusion model, conclude that the optimal time to introduce a product variant is relatively early in a product's life cycle, possibly as soon as it is available. (They also suggest that a product extension that cannibalizes an existing product too severely or does not provide sufficient market growth should not be launched.) We modify their approach by using an exponential decay model for sales in each channel and assumptions appropriate for the sequential distribution situation to derive an analytical solution for the movie industry. Our empirical results show how the specific parameter values determine when a video should be introduced. Other literature has examined such issues as when a firm should replace its existing product or add a line extension (Purohit 1994), whether a firm should replace its existing product early to deter entrance by a new competitor (Nault and Vandenbosch 1996), and whether a firm should defer entry of its new product (a movie; Krider and Weinberg 1998) to avoid a head-to-head confrontation with a competitor. We take the sequential channel structure as given and consider products whose market appeal diminishes over time within a channel. In contrast to Wilson and Norton (1989), our model does not require the first channel to be the most profitable.

This article differs substantially from previous work in the channels area. Much of this work focuses on channel coordination and profit division between retailer and manufacturer. For example, Coughlan (1985) extends the work of McGuire and Staelin (1983) on the marketing strategy of substitute products in a duopoly. Her results suggest that channel integration is inversely related to substitutability of products under profit maximization. Other articles in this stream include Moorthy (1988) and Lal (1990), who focus on franchise contract terms (i.e., royalties) and monitoring.

A related stream of work focuses on the mechanisms for increasing channel coordination (Jeuland and Shugan 1983; Moorthy 1987; Shugan 1985). For example, Jeuland and Shugan (1983, 1988) suggest that coordination can occur without formal mechanisms in cases in which independent pursuit of profit maximization by manufacturers and retailers produces lower profit than a coordinated strategy, for example, one through quantity discounts.

Unlike these two streams of research, we assume that the channel structure is given and consider vertical issues dealing with multiple, different, and partially competing channels. Similar to previous literature, we assume that the manufacturer is the primary decision maker but that the manufacturer's decisions take into account optimal decision making by other channel members.

Model Structure and Analysis

We take the point of view of a manufacturer. To address the optimal time to introduce the product to the second channel, we examine the second channel's optimal decision and use it as an input to the manufacturer's decision. We first state the sequential distribution problem in general terms and show the form of its solution. We then restate the problem in terms of the functional forms and relationships that characterize the movie industry and derive an analytic solution.

We concentrate on the key decision variable that characterizes the sequential decision problem: the time to release

[2]Another critical issue in the movie industry is the price at which the video is sold to video store retailers. Traditionally, two price points are used (though this practice may be changing; see McCollum 1998). Most video versions of movies are sold to video stores at a price of approximately $60 and are primarily targeted at the rental market. However, many videos have a wholesale price of less than $20 and are targeted to both the sell-through and rental markets. Although not common across all sequential distribution decisions, a straightforward economic analysis can be done to determine which of these two price points should be chosen. The more general question of pricing for sequential distribution channels is beyond the scope of the current research.

the product to the next distribution channel.[3] For ease of exposition, we assume that there are only two distribution channels and that industry practice determines which is the prior channel (e.g., theater release before video release).

General Structure

Let $\Pi_1{}^B(t)$ be the profit rate at time t from the first channel (e.g., movie theaters) before the second channel (e.g., video) is opened, and let $\Pi_1{}^A(t)$ be profit rate at time t from the first channel after the second channel is opened, at time t_2. Setting $\Pi_1{}^A(t) = 0$ for $t \geq t_2$ allows for the case in which opening the second channel completely eliminates sales and, consequently, profit in the first channel. Let $\Pi_2(t, t_2)$ for $t \geq t_2$ be the profit rate from the second channel.

For tractability reasons, we present a continuous model here. Similar results emerge from a discrete model. In the example we use, we assume that sales (and consequently profits) in the first channel decrease when the product is released to the second channel, so that

$$\Pi_1{}^B(t) > \Pi_1{}^A(t)$$

and

$$\frac{\delta\Pi_2(t, t_2)}{\delta t_2} < 0;$$

that is, the longer the delay in opening the second channel, the lower is the sales rate in the second channel.

The manufacturing firm's problem, assuming a discount rate ρ, is to maximize cumulative profit

$$(1) \qquad P(t_2) = \int_0^{t_2} \Pi_1{}^B(t)e^{-\rho t}dt + \int_{t_2}^{\infty} \Pi_1{}^A(t)e^{-\rho t}dt + \int_{t_2}^{\infty} \Pi_2(t, t_2)e^{-\rho t}dt$$

by choosing the optimal time (t_2^*) to open the second channel. A further generalization of this structure involves incorporating other decision variables explicitly in the profit objective. In the last section of the article, we incorporate price into the specific case we consider.

Maximization of Equation 1 with respect to t_2 can lead to an implicit expression of the optimal time to open the second channel (see Wilson and Norton 1989). However, to provide more insight into the nature of the optimal policy, we next customize our analysis to the movie industry.

Movie and Video Demand

In this article, we concentrate on box office sales (the first channel) and video rentals (the second channel), as shown in Figure 1. Although other forms of distribution exist (e.g., video sales, television), the two we concentrate on are the major ones for well-known movies. Concentrating on these enables us to both illustrate the general model and capture the major portion of the revenues generated by movies. We also omit issues of discounting, because most revenues occur in the first year and therefore discounting would have little impact.

Anticipating the empirical analysis in the subsequent section and consistent with Krider and Weinberg (1998), we model a movie's revenue in the first channel as an exponential function (Figure 2):

$$(2A) \qquad M^B(t) = m_1{}^B e^{-m_2 t} \qquad 0 \leq t < t_2$$

$$(2B) \qquad M^A(t) = m_1{}^A e^{-m_2 t} \qquad t \geq t_2,$$

where $m_1{}^B > m_1{}^A \geq 0$ and $m_2 > 0$. In other words, a movie opens with a box office sales rate of $m_1{}^B$ (at $t = 0$) and then declines at a rate of m_2. The effect of releasing a video is to decrease the market potential for the movie so that $0 \leq m_1{}^A < m_1{}^B$, but we assume the decay in revenue persists at the same rate, m_2. In practice, theater sales generally drop to approximately zero when a movie is released to video. For the movies studied here, box office revenues when the video was released never exceeded 3% of the first week's revenue. Therefore, we set $M^A(t) = 0$.

We assume that the first channel's sales rate drops from $M^B(t_2)$ to $M^A(t_2)$ exactly when sales in the second channel begin. Other formulations, depending on the characteristics of a particular industry, could be developed that allow for sales to drop earlier, in anticipation of the second channel being opened, or later, allowing for a delay in the second channel's effect. The immediate decay appears to be most appropriate for the movie industry, given the wide availability of video stores.

Video rental demand is also assumed (and shown empirically) to follow a similar exponential decline, so that

$$(3) \qquad V(t, t_2) = v_1(t_2)e^{-v_2{}^A(t-t_2)} \qquad t \geq t_2,$$

where V (t, t_2) represents the video rental rate at time t for a video released at t_2.

The video opens with rentals of $v_1(t_2)$, where $dv_1/dt_2 < 0$. In other words, the longer the video release is delayed, the lower the potential video rentals. This occurs largely because potential customers have either "purchased it" (seen the movie) in the first channel (theaters) or forgotten the intensive communication effort surrounding the movie's introduction.[4] To reflect this compactly, we write

$$(4) \qquad v_1(t_2) = v_1 e^{-v_2{}^B t_2},$$

where v_1 is the (implicit) rental potential of the video if it had been released simultaneously with the movie. We provide further discussion of and support for demand Equations 2 and 3 in the empirical section.

The video rental industry is characterized by two critical elements that require us to modify the formulation in Equation 1. First, an independent retailer must decide how many units to order of a reusable (i.e., rentable) product

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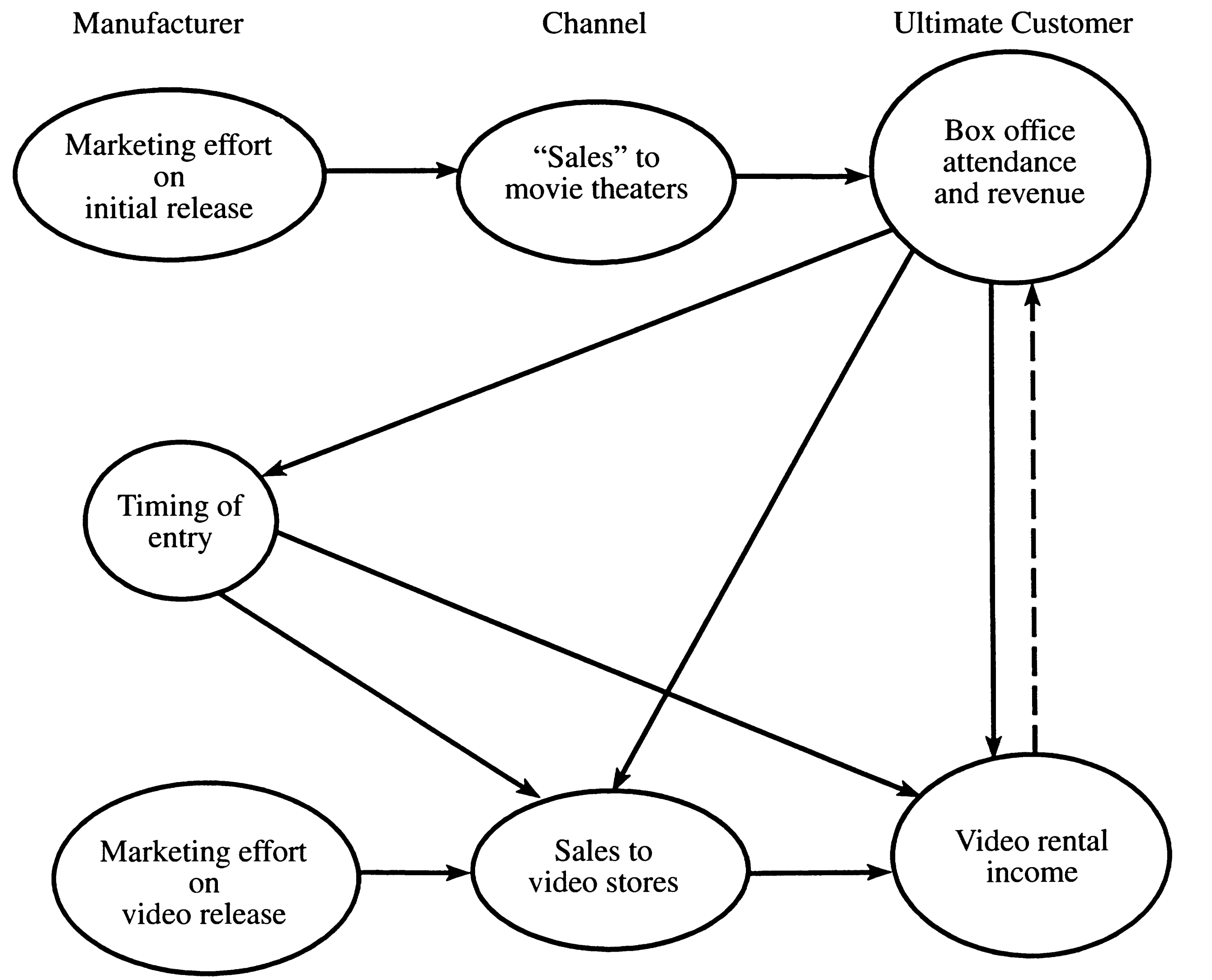
[3]Contractual constraints and channel practices may limit the value that release time can take.

[4]Advertising by the movie producer could increase the potential for the video, but this is, at least at present, a relatively minor factor compared with the initial promotional efforts and marketing budgets for movies.

FIGURE 1
Simplified Movie/Video Structure



whose demand (generally) declines over time.[5] Second, the movie distributor does not usually receive a share of the rental revenue, unlike the case in the theater channel, but instead earns income from the videos purchased by the retailer.[6] However, the number of units the retailer orders should depend on the estimated demand for video rentals (Equation 3). Thus, determining an optimal release strategy first involves determining an optimal ordering policy for the retailer.

The analytical approach followed is thus a backward analysis. That is, we begin with the decisions made by the second channel (i.e., video stores) with respect to purchases. We assume they make optimal decisions based on expected demand for rentals. In addition, this demand (1) is assumed to be predictable on the basis of demand in the first channel (i.e., box office attendance) and (2) depends on entry timing. Once the second channel's optimal behavior is specified, we then address the optimal time for the movie distributor to enter the second channel.

Our model captures just some aspects of the decision problem. Movie producers' multiple concerns include tie-in promotional merchandise sales, relations with independently owned theaters, and timing compared with other releases, as well as relations with video stores. Furthermore, the model does not capture the likely gradual but important

[5]Movie producers also must negotiate with (usually independent) theater owners to obtain screens on which to show their movies. Because our focus is sequential distribution channels, we do not formally model these decisions about the initial release strategy.

[6]Starting around 1997, this practice began to change, and some major video chains—for example, Blockbuster and Hollywood Video—share rental revenues with at least some movie distributors (McCollum 1998).

FIGURE 2
Movie and Video Revenue Patterns

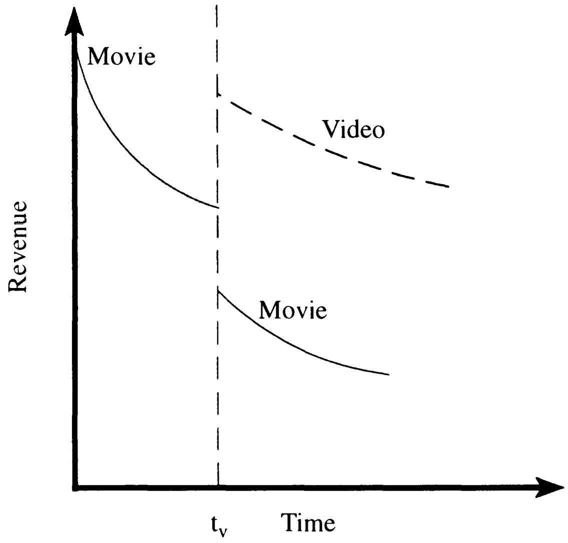
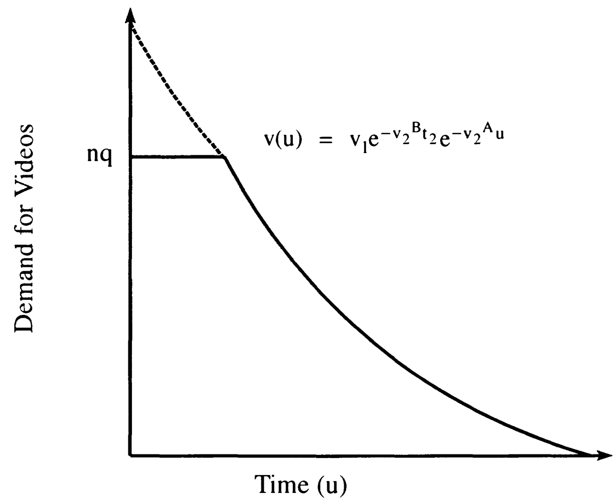


FIGURE 3
Number of Videos to Order



Sales When q Videotapes Are Ordered

adaptation by consumers to release strategies through expectation setting and its consequences. Therefore, our use of the term "optimal" here means optimal with respect to the stated model.

Retailer's Optimal Order Quantity

At the margin, the profit-maximizing video store must trade off, on the one hand, the marginal revenue forgone and the impact on customers of being out of stock and, on the other hand, the additional purchase and holding costs of stocking an additional unit. Although a retailer may in principle reorder at any time, in the face of declining (and deterministic) demand, it is optimal to order a video only once, as soon as the video is available.

We also note that with decreasing demand, a retailer is not likely to order enough videos to satisfy demand in the initial periods. Therefore, the model allows for undercapacity for several periods (τ), as well as out-of-stock cost per period.

More formally, for each video,

- $V(u)$ = rental demand rate per video store at time $u = (t - t_2)$ after the video's release $= v_1 e^{-v_2^B t_2} e^{-v_2^A u}$;
- p = price to retailer per video;
- r = rental fee per copy (assumed to be constant);
- n = number of rental turns per copy each time period, for example, three per week;
- h = holding cost per period per unit;
- l = out-of-stock lost sales cost per period;
- q = number of videotapes ordered;
- τ = time after video's release at which video rental demand equals rental capacity of the store; and
- T = time horizon for which videos are held, at the end of which they have no salvage value.[7]

The time τ after the video's release when demand $[V(\tau)]$ equals the rental capacity, nq (see Figure 3), can be found by solving the following equation for τ:[8]

$$(5) \qquad nq = V(\tau) = v_1 e^{-v_2^B t_2} e^{-v_2^A \tau} = k_1 e^{-v_2^A \tau},$$

where

$$(6) \qquad k_1 = v_1 e^{-v_2^B t_2}.$$

This yields

$$(7) \qquad \tau = \frac{1}{v_2^A} \ell n \frac{k_1}{nq}.$$

The video retailer's cumulative profits from ordering q copies of a video (when the video is released) are defined as follows:

$$(8) \qquad P_R = r\left[\int_0^\tau nq\,du + \int_\tau^T k_1 e^{-v_2^A u}\,du\right] - pq - hqT - \ell \int_0^\tau (k_1 e^{-v_2^A u} - nq)\,du.$$

[7]Although it is beyond the scope of the present article, at some point in time, demand is so low that the retailer should dispose of videos rather than continue to hold them and incur a holding cost. For ease of exposition, we assume a constant and finite holding period for all copies of a video that a retailer purchases.

[8]Unless rental fees are extremely high compared with the price of a retailer's buying a video or because of exogenous factors (e.g., a guarantee that a certain movie will not be out of stock), there will always be a period of time when there is insufficient stock to meet demand.

Notice this formulation assumes that unsatisfied demand due to capacity constraints leads to lost sales.[9]

Integrating Equation 8 yields:

$$(9)\qquad P_R = nrq\tau + \frac{rk_1}{v_2^A}\left(e^{-v_2^A\tau} - e^{-v_2^A T}\right) - pq - hqT - \ell\left[\frac{k_1}{v_2^A}\left(1 - e^{-v_2^A\tau}\right) - nq\tau\right].$$

To maximize profits, the retailer chooses the quantity q^* to maximize Equation 8. Taking the derivative with respect to q and noting that τ is a function of q, we obtain

$$(10)\qquad \frac{\partial P_R}{\partial q} = nrq\frac{\partial\tau}{\partial q} + nr\tau - rk_1\frac{\partial\tau}{\partial q}e^{-v_2^A\tau} - p - hT - \ell k_1\frac{\partial\tau}{\partial q}e^{-v_2^A\tau} + n\ell\tau + n\ell q\frac{\partial\tau}{\partial q}.$$

Note that

$$(11)\qquad \frac{\partial\tau}{\partial q} = \frac{-1}{v_2^A q}.$$

Substituting Equations 7 and 11 into Equation 10 yields, after simplifying terms,

$$(12)\qquad \frac{\partial P_R}{\partial q} = \frac{rn}{v_2^A}\ell n\frac{k_1}{nq} - p - hT + \frac{\ell n}{v_2^A}\ell n\frac{k_1}{nq}.$$

Setting $\partial P_R/\partial q = 0$ and solving for q provides the optimal number of videos to order, q^*, as follows:

$$(13)\qquad q^* = \frac{k_1}{n}e^{-\left[\frac{(p+hT)v_2^A}{(r+\ell)n}\right]}.$$

To concentrate on the critical issues and for clarity, we assume in subsequent sections that there is no holding cost ($h = 0$) or lost sales cost ($\ell = 0$) beyond that of the lost sales revenue, so that the optimal solution to Equation 8 becomes

$$(14)\qquad q^* = \frac{k_1}{n}e^{-\frac{p}{rn}v_2^A} = \frac{v_1}{n}e^{-v_2^B t_2}e^{-\left(\frac{pv_2^A}{rn}\right)}.$$

Manufacturer's (Film Distributor's) Optimal Release Time to the Retailer

Knowing the video store's response to time of release in terms of order quantity, we now turn to the issue of the movie distributor's optimal decision with respect to release time. We assume that each sale achieves a constant gross margin for the distributor of M_T in the first (theater) channel[10] and M_V in the second channel. The gross margin M_V depends on the price at which the movie distributor sells videos to the retailer (see n. 2) and the number (N) of video stores.[11] Combining the previous equations, we write the cumulative discounted (at rate ρ) profit function for the movie distributor:

$$(15)\qquad P(t_2) = \int_0^{t_2} M_T m_1^B e^{-m_2 t}e^{-\rho t}dt + \int_{t_2}^{\infty} M_T m_1^A e^{-m_2 t}e^{-\rho t}dt + M_V\, q^*(t_2, p)e^{-\rho t_2}.$$

If the discount rate is set at $\rho = 0$ for expositional convenience (because it has minimal impact on the results) and if $m_1^A = 0$, the cumulative profit function can be rewritten as

$$(16)\qquad P(t_2) = \underbrace{\left(M_T\frac{m_1^B}{m_2}\right)\left(1 - e^{-m_2 t_2}\right)}_{\text{[Profit from Movie Market]}} + \underbrace{M_V\frac{v_1}{n}e^{-v_2^B t_2}e^{-\left(\frac{pv_2^A}{rn}\right)}}_{\text{[Profit from Video Market]}}$$

Taking the derivative of $P(t_2)$ with respect to t_2, setting it equal to 0, and solving yields

$$(17)\qquad t_2^* = \frac{1}{(m_2 - v_2^B)}\left\{\ell n\left[\frac{m_1^B n M_T}{v_2^B v_1 M_V}\right] + \left(\frac{p}{r}\frac{v_2^A}{n}\right)\right\}.$$

The effect of the parameters on the time to introduce the video follows an intuitive pattern. The bigger and more profitable the movie market is relative to the video market $[(m_1^B M_T)/(v_1 M_V)]$, the greater the optimal delay in the video's release. The more rapid the video's implicit decay is before the release (v_2^B), the earlier the optimal release time. Furthermore, the more the decay of the movie exceeds the (implicit) decay of the video ($m_2 - v_2^B$), the earlier the video should be released. The effect of price on the optimal release time is complex. On the one hand, increasing the price makes the video market more profitable per video sold (recall that M_V increases with p), which decreases the time to release the video. On the other hand, the video stores order fewer videos with higher price, which increases the optimal time to release the video. The video store's ability to increase its rental fee (r) unambiguously leads to more profits for the store, higher orders, and an earlier release date.

In the next section, we empirically confirm the exponential decay function as a reasonable model for movies and videos. We also explore the relationships between the parameters of the movie and the video.

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[9]An alternative model is one in which lost sales are stockpiled and occur as soon as capacity becomes available. Allowing for some demand to be carried over in this way would result in the retailer reducing q at the optimum. In the subsequent analysis, this would lead to the distributor lengthening somewhat the time until a video was released. This effect is likely to be relatively minor and not explicitly included in the analysis to reduce model complexity.

[10]The movie distributor's contractual share of revenue actually declines over time. Accounting for this would mimic the effect of declining demand over time and is omitted from our model for ease of exposition.

[11]Because the optimal ordering policy is constructed for each store, the model implicitly assumes a market of N identical video stores, all of which purchase the video.

TABLE 1
Descriptive Statistics of Sample (n = 35)

	Mean	Standard Deviation
m_1^B (millions of dollars)	20.70	11.90
m_2	.36	.15
v_1 (rentals per store)	32.70	14.20
v_2^A	.059	.22
If relaunch (1 = yes, 0 = no)	.43	.50
If sell-through price ≤$25	.29	.46
Advertisements (number of pages)	6.09	2.48
Lag (weeks)	23.83	3.48

Application

We focus on situations in which the product class is well defined and the products introduced, though new, are easily understood and fit in the existing mental category structure. For products that are really new, adoption generally will not occur immediately but will gradually diffuse throughout the target market. In contrast, for products such as movies, it is reasonable to expect that the market will take little time to become aware of the product and decide to adopt it or not, so that peak sales will occur very early in the product's life cycle. For movies, this is consistent with the empirical evidence in Krider and Weinberg's (1998) and Sawhney and Eliashberg's (1996) studies. Most major movies decay exponentially, though distribution strategies and competitive effects may cause some deviations from this overall pattern. Although movie attendance patterns have been analyzed in several studies, the sales pattern for videos has not been studied in published work.

Data

Data for this study were compiled from reported theater attendance and video rentals in *Video Business* from January 1994 through August 1995. Each week, *Video Business* reports box office gross revenues in dollars for movies and number of video rentals per store.[12] A convenience sample of 35 movies for which data were available for at least six weeks for both theater sales and video rentals was selected, which provided a sample of recent, successful movies (for summary statistics, see Table 1, and for a list of the movies, see Table 2). Equations 3 and 4 cannot be reliably estimated, so we estimate $v_1(t_2)$ at t_2, that is, potential video demand per store at the time the video is released. We then use the decay parameter to project backward to get $v_1(0)$, that is, v_1 in Equations 4 and 17. We discuss the implications of these assumptions subsequently.

Pattern of Theater Attendance and Video Rentals

We assessed the suitability of the exponential model as a description of theater sales and video rentals over time by estimating this model for each of 35 movies. The overall results appear in Table 3. They demonstrate good fits with an average R^2 of .90 and .86, respectively, for movies and videos.

To test the exponential model further, we also examined a more flexible gamma model. The gamma allows for a buildup in initial sales before a decline. The gamma function is used by Sawhney and Eliashberg (1996) for movies that are not accurately fit by the exponential model. Overall, the gamma model fits slightly better, with an average R^2 of .93 and .91 for theater attendance and video rentals, respectively, which represents improvements of 3% and 5%, respectively.[13]

Distribution strategy helps explain deviations from the exponential decay of revenues. If a variable representing number of screens is added to the set of independent variables, the R^2 increases to .94 for *Dennis the Menace*, .95 for *Schindler's List*, and .93 for *Tombstone*. Another aspect of distribution strategy pertains to rereleasing prints of the movie late in the run. For the 35 movies in the sample, the typical release pattern shows a gradual week-to-week decline in the number of screens showing a movie (after the first two to three weeks). However, for 15 movies, at approximately week 14, the number of screens on which the movie is shown increases by 10% or more. These are movies selected to run at so-called dollar or second-run movie houses. When a dummy variable to represent this effect is also added, the exponential model fits the 35 movies with an average R^2 of .94. On the basis of these results and the greater tractability of the exponential model, we employ the exponential function for normative analysis.

We also considered the effect of supply restrictions on observed demand. Observed video rentals are an underestimate of demand when video stores do not order sufficient stock to satisfy all renters during the first few weeks of a video's release (consistent with our analysis). We expected this restriction not to be severe, in part because demand declines exponentially from week to week. To estimate the magnitude of this effect, we reestimated the exponential model for the videos in our sample starting at week 3 (when stockouts are unusual). For the 25 non–sell-through movies, the decay rate had the same average value (.05) and was correlated r = .91 with the original value. The opening strength (for week 1) was correlated r = .97 with the original value and, as expected, was somewhat higher (28.5) than the value of 27.1 reported in Table 4. The effect of these results, as can be seen in Equation 22, would be to decrease slightly the optimal time for a video's release. Similar results held for the sell-through movies.

[12]Note the lack of dimensional (and numerical) comparability of these terms. In particular, the number of reporting stores for video rentals varies each week. However, these two measures represent the results in each industry well.

[13]Comparing the models on a movie-by-movie basis using a nested model test resulted in 12 of 35 movies' theater attendances fitting the gamma significantly ($p < .05$) better. However, the R^2 value never improved by more than .10, except for *Schindler's List* (from .71 to .88). Similarly, 19 of 35 movies' video rentals are significantly better fit by the gamma. For video rentals, the gamma distribution provided an improvement of .10 in R^2 over the exponential for three titles: *Grumpy Old Men*, *Hard Target*, and *The Piano* (see Table 2).

TABLE 2
Model Fits

	Movies (R^2)				Videos (R^2)	
	Exponential	Gamma	Exponential + Screen	Exponential + Rerelease	R^2 Exponential	R^2 Gamma
Ace Ventura	.88	.89	.96	.98	.97	.98
Beverley Hillbillies	.96	.97	.97	.96	.93	.96
City Slickers	.91	.93	.97	.99	.85	.87
Cool Runnings	.92	.93	.94	.92	.85	.87
D2: Mighty Ducks	.99	.99	.99	.99	.89	.89
Demolition Man	.98	.99	.98	.98	.89	.89
Dennis the Menace	.74	.83	.94	.95	.96	.97
The Firm	.99	.99	.99	.99	.90	.93
Flintstones	.91	.94	.95	.94	.80	.88
Four Weddings and a Funeral	.96	.98	.98	.96	.75	.75
Free Willy	.91	.92	.95	.99	.93	.97
The Fugitive	.99	.99	.99	.99	.92	.92
Grumpy Old Men	.96	.96	.98	.96	.46	.89
Hard Target	.99	.99	.99	.99	.79	.93
In the Line of Fire	.90	.93	.94	.90	.91	.94
Judgement Night	.98	.99	.98	.98	.82	.88
Jurassic Park	.85	.93	.97	.94	.82	.96
Malice	.93	.95	.98	.92	.84	.90
Maverick	.76	.79	.89	.93	.91	.93
Mrs. Doubtfire	.92	.95	.95	.92	.94	.95
Naked Gun 33 1/3	1.00	1.00	1.00	1.00	.92	.96
On Deadly Ground	.83	.89	.97	.98	.97	.98
The Paper	.89	.90	.97	.99	.89	.90
Pelican Brief	.77	.81	.91	1.00	.87	.89
Philadelphia	.95	.95	.96	.95	.94	.94
The Piano	.66	.71	.93	.66	.60	.84
The Program	.98	.98	.98	.97	.87	.91
Rising Sun	.99	.99	.99	.99	.96	.97
Schindler's List	.71	.88	.95	.78	.88	.88
Sleepless in Seattle	.80	.84	.93	.80	.99	.99
Speed	.98	.98	.98	.99	.91	.95
Three Musketeers	.94	.95	.95	.94	.91	.91
Tombstone	.72	.81	.93	.72	.86	.90
Wayne's World	.99	1.00	.99	.99	.83	.83
When a Man Loves a Woman	.86	.92	.98	.89	.83	.83
Mean:	.90	.93	.96	.94	.86	.91

Relations Among Model Parameters

We first examine the simple correlations among the model parameters for theater attendance and video rentals. Table 5 shows several interesting results. Although there is only a small correlation (r = .02, n.s.) between the opening attendance (m_1^B) and decay rate (m_2) for the movies, there is a strong correlation (r = .88, $p < .01$) between v_1 and v_2^A for videos. Videos that open strongly tend to decay more rapidly. However, video rentals decline at a slow rate compared with movies. For the movies studied here, on average theater attendance declines at the rate of 30% ($e^{-.36}$ = .70) per week, whereas videos decline at the rate of 6% ($e^{-.06}$ = .94) per week.

The decay rate of videos deserves further comment. Aside from two sell-through movies (*Jurassic Park* and *Mrs. Doubtfire*), no movie's video rentals decayed at a rate greater than 10% per week, and the majority declined at a rate of less than 5% per week (see Tables 4 and 6). In contrast, theater revenues decayed at a rate less than 10% per week for only four movies. There is both a demand side and a supply side potential explanation for these results. On the supply side, video store owners need approximately 25 days of video rental demand to pay for a (non–sell-through) video's cost, so they limit their purchases to try to ensure

TABLE 3
Overall Estimation Results for Movies and Videos

	Average R^2 (unadjusted)
Movies (n = 35)	
Exponential (two parameters)	.90
Gamma (three parameters)	.93
Exponential and rerelease (three parameters)	.94
Videos (n = 35)	
Exponential (two parameters)	.86
Gamma (three parameters)	.91

TABLE 4
Parameter Values, Estimates, and Optimal Release Time for Non–Sell-Through Movies

		Movie Parameters		Video Parameters		Video Parameters (Estimation from m_1^B and m_2)			Actual Re-lease	Optimal Re-lease	Profit Differ-ence	Optimal Profits (× H)			Diff–P
Number	Title	m_1^B (millions of dollars)	m_2	v_1	v_2	v_1'	v_2'	$v_1^{R'}$	t_2	t_2^*	$t_2^* - t_2$	Movie	Video	Total	%
1	*Beverley Hillbillies*	11.5	.32	25.9	.04	24.50	.05	79.10	25	6	–19	.59	.74	1.33	33
2	*Cool Runnings*	9.5	.16	26.8	.04	26.56	.05	72.08	21	10	–11	.57	.51	1.08	8
3	*Demolition Man*	24.7	.54	28	.05	27.47	.05	77.43	20	4	–16	.64	.67	1.31	31
4	*The Firm*	41.6	.33	38.2	.06	41.04	.06	176.95	23	4	–19	.51	1.01	1.52	52
5	*Four Weddings and a Funeral*	8.1	.17	21	.04	25.59	.05	78.37	24	8	–16	.54	.62	1.16	16
6	*Grumpy Old Men*	15.3	.23	23.6	.03	28.40	.05	104.18	26	6	–20	.52	.82	1.34	34
7	*Hard Target*	13.5	.55	31.9	.07	21.04	.05	57.22	22	5	–17	.65	.66	1.31	31
8	*In the Line of Fire*	36.3	.37	36.7	.06	37.29	.06	189.21	27	3	–24	.50	1.24	1.74	74
9	*Judgement Night*	6.5	.71	23.2	.05	13.97	.04	30.98	20	4	–16	.67	.56	1.23	23
10	*Malice*	23.9	.40	23.4	.04	29.80	.05	117.96	26	4	–22	.57	.95	1.52	52
11	*Maverick*	32	.38	33.6	.07	34.71	.06	164.56	27	4	–23	.53	1.15	1.68	68
12	*Naked Gun* 33 1/3	18.6	.46	17.2	.04	25.67	.05	88.03	25	4	–21	.61	.82	1.44	44
13	*On Deadly Ground*	14.6	.53	26.7	.05	22.05	.05	61.07	22	5	–17	.64	.67	1.31	31
14	*The Paper*	12.1	.39	21.5	.04	23.44	.05	71.47	24	5	–19	.62	.71	1.33	33
15	*Pelican Brief*	33.9	.40	29.7	.05	35.36	.06	143.92	24	4	–20	.56	.97	1.52	52
16	*Philadelphia*	14.6	.22	26.3	.05	28.21	.05	102.73	26	6	–20	.52	.81	1.33	33
17	*The Piano*	3.2	.07	18	.03	24.85	.05	66.89	22	22	0	.69	.31	1.00	0
18	*The Program*	10.1	.57	19.6	.03	18.76	.04	44.64	20	5	–15	.66	.58	1.23	23
19	*Rising Sun*	21.4	.42	43.5	.08	28.02	.05	95.97	24	5	–19	.60	.81	1.41	41
20	*Schindler's List*	10.3	.16	27.9	.08	27.01	.05	125.39	32	5	–27	.37	1.11	1.48	48
21	*Sleepless in Seattle*	17.6	.18	38.9	.06	30.67	.05	124.28	27	5	–22	.44	.92	1.36	36
22	*Three Musketeers*	19.3	.43	22.7	.05	26.65	.05	88.53	24	5	–19	.61	.79	1.40	40
23	*Tombstone*	9.1	.25	26.7	.04	24.55	.05	74.63	24	7	–17	.58	.66	1.24	24
24	*Wayne's World* 2	21.4	.55	19.6	.05	25.44	.05	84.19	24	4	–20	.63	.81	1.44	44
25	*When a Man Loves a Woman*	10.2	.32	26	.05	23.78	.05	82.68	27	6	–21	.58	.81	1.39	39
	Industry Average	17.6	.36	27.1	.05	26.99	.05	96.10	24	5	–19	.59	.77	1.37	37

Notes: Actual total profit is assumed to be H for each movie as a benchmark point. Mp = .7, Vp = .3; that is, the proportions of total profits brought by movie and video are 70% and 30%. n = 3, assuming that the weekly turnover rate is three times per copy. v_1' is the opening rental estimated at t_2. It is adjusted to $v_1^{R'}$, which is the real opening rate in Equation 22 (see discussion in article). The optimal profits are the percentage of the actual profit (H).

TABLE 5
Correlations

	m_1^B	m_2	v_1	v_2^A	If Re-launched	If Sell-Through	Advertise-ments	Lag
m_1^B	1							
m_2	.02	1						
v_1	.65	−.24	1					
v_2^A	.53	−.11	.88	1				
If relaunch	.00	−.16	.06	.20	1			
If sell-through price (≤$25)	.42	.00	.64	.67	.35	1		
Advertisements	.44	−.40	.30	.16	.05	.09	1	
Lag	.07	−.16	−.05	−.07	.08	−.19	.34	1

TABLE 6
Parameter Values and Estimates for Sell-Through Movies

		Movie Parameters		Video Parameters		Video Parameters (Estimated)		Actual Release
Number	Title	m_1^B (millions of dollars)	m_2	v_1	v_2	v_1'	v_2'	t_2
1	*Ace Ventura*	23.8	.38	52.1	.09	43.63	.08	18
2	*City Slickers*	16.2	.52	19.4	.04	36.62	.07	20
3	*D2: Mighty Ducks*	15.3	.43	33.4	.08	37.91	.07	20
4	*Dennis the Menace*	18.6	.56	45.6	.08	37.16	.07	31
5	*Flintstones*	30.7	.34	29	.06	48.26	.08	22
6	*Free Willy*	20.1	.30	33.8	.07	43.16	.08	27
7	*The Fugitive*	59.6	.34	61.2	.09	64.33	.10	29
8	*Jurassic Park*	38.9	.18	57.1	.11	55.99	.09	16
9	*Mrs. Doubtfire*	34.1	.16	78.3	.11	53.72	.09	21
10	*Speed*	30.8	.29	59.6	.09	49.31	.08	24
	Industry Average	28.8	.35	46.95	.08	47.01	.08	23

profitability.[14] Consequently, they may expect to be out of stock during the first few weeks of the video's release. On the demand side, although there is a segment of the moviegoing population that wants to see "this week's" movie (particularly given the intense amount of hype surrounding a movie's release), this effect is muted when it comes to videos. Given that the average time in our sample between a movie's release and a video's release is 23.8 weeks, much of the movie's initial hype is forgotten by the time the video is released. Moreover, there is limited cachet in claiming, for example, to have seen a video that was just released this weekend.

We next examine the relationship between movie attendance and video rental patterns. As can be seen in Table 5, the opening attraction of a movie (m_1^B) is positively correlated with both the opening week's video rentals (v_1) (r = .65, $p < .01$) and the decay rate (v_2^A) (r = .53, $p < .01$). However, the effect of m_1^B (movie's opening strength) on v_2^A (video decay rate) is entirely mediated by the effect of m_1^B on v_1 (video's opening strength). (A regression analysis with v_2^A as the dependent variable and m_1^B and v_1 as the predictor variables yields $R^2 = .78$, which is not significantly different from $R^2 = .77$ when v_1 is the only predictor variable.) There is no significant relationship between the decay rate (m_2) of a movie and either the video's opening strength (v_1, r = –.24, $p > .10$) or decay rate (v_2^A, r = –.11, $p > .10$). Movies with strong openings in theaters also start fast in the video market (r = .65) but decline more rapidly (r = .53).

[14]According to data for 1992 from Vogel (1994, pp. 80, 305), a video store pays 70% of the retail list price of $89.95 per video tape (not designated for the sell-through market), or approximately $63.00. Also, the average price paid per rental is $2.50, so at least $63/$2.50 = 25 days of rental are required for a retailer to break even. For a sell-through video, the retail list price is $24.95, so similar calculations suggest that only 7 rental days are needed. Most often, studios use a wholesaler to distribute their videos at a charge of 7% of the list price. The studio thus typically receives 63% of the list price.

Marketing Variables and Video Rentals

In 1995, Hollywood movies cost, on average, approximately $40 million to produce and $20 million to distribute and market. In this section, we examine the effects of marketing decisions on the estimated parameters of the exponential models of movie admissions and video rentals, assuming that the movie studio has a completed product.

Despite advertising's obvious importance in building an audience for a movie, there appears to be little published empirical research relating advertising levels to opening strength, decay rate, total revenue, or other measures of a movie's performance. (Two exceptions are Mahajan, Muller, and Kerin [1984], who study advertising levels in the context of positive and negative word of mouth in a diffusion of innovations framework, and Zufryden [1996].) Here, we examine advertising's effect on movie performance. We operationalize advertising as number of pages of advertising in the *New York Times* before the movie's release. We use the *New York Times*'s advertising pages as a proxy for national advertising.[15]

The impact of decision variables can be captured by allowing m_1^B and m_2 to be functions of these variables (X) in a varying-parameter framework:

$$m_1^B = m_{10} + m_{11}X_1, \tag{18}$$

and

$$m_2 = m_{20} + m_{21}X_1. \tag{19}$$

Because the vast majority of marketing expenditures occur before a movie is released, X_1 is assumed to be a one-time prelaunch advertising expenditure.

The carryover effect from sales in the first channel to sales in the second is captured by allowing v_1 and v_2^A to depend on decision variable X_2, as well as m_1^B and m_2:[16]

$$v_1 = v_{10} + v_{11}m_1^B + v_{12}m_2 + v_{13}t_2 + v_{14}X_2, \tag{20}$$

and

$$v_2^A = v_{20} + v_{21}m_1^B + v_{22}m_2 + v_{23}t_2 + v_{24}X_2. \tag{21}$$

As expected, the number of advertising pages is positively correlated with opening strength, m_1^B, (r = .44, $p < .01$) and negatively correlated with decay rate, m_2, (r = –.40, $p < .05$). However, the direction of causality is unclear. Although the advertising occurs before the opening of a movie, Hollywood studios do an extensive amount of research to estimate the popularity and likely theater attendance of their movies before they are released (Dutka 1992). Therefore, it is quite plausible that movies that are expected to be popular receive more advertising. However, studios appear to focus more on opening weekend results than on decay rate, so the correlation between increased advertising pages and a slower decay rate provides some support for the view that increased advertising has a direct impact on attendance.

When the movie's run commences, several strategies can be employed to extend it. As noted previously, for 15 of the 35 movies we studied, the number of screens on which the movies were shown increased substantially late in the run of the movie as dollar theaters were used. Although we expected that more successful movies would be associated with the use of this strategy, this was not case. Neither m_1^B nor m_2 was significantly ($p < .05$) correlated with the use of this strategy. Similarly, the use of this strategy had no significant relationship with v_1 and v_2^A.

We examine two marketing decisions pertaining to the release of a film on video. The first is the time between the movie's release and the video's release. As discussed previously, a longer delay until the video's release reduces the likelihood that the movie's sales will be cannibalized by the video. Pressure for delay is mirrored by the common practice in the book industry of delaying the paperback's release until the hardcover version has relatively small sales. However, when sequential product entry is delayed substantially from the release of the original product, advertising and publicity effects that surrounded the release of the movie will have largely dissipated.

Despite the potentially strong effects of a delay in a video's release on video rentals, there appears to be little variation in the length of time between the movie's release and the video's release. The average for the 35 movies in our study was 23.8 weeks, and the standard deviation was 3.5 weeks, which resulted in a coefficient of variation much lower than that for any of the other variables studied here. Moreover, the lag is minimally correlated with either m_1^B (r = .07, $p > .10$) or m_2 (r = –.16, $p > .10$), which suggests that movie studios do not change their release strategy for videos even after they have knowledge of the sales pattern of their movies. Most important, perhaps because of the attenuation in range, release time is significantly related to neither v_1 (r = –.05, $p > .10$) nor v_2^A (r = –.07, $p > .10$).

A second variable of interest when a video is released is pricing. In practice, two price points appear to be used. The first, a wholesale price of $60 or more to video stores, is designed with the expectation that the primary market for the video will be rentals. The second, however, a wholesale price of $20 or less, is designed to encourage the sell-through market. Originally used for movies marketed to children, this strategy is now expanding to include some movies with more adult-oriented themes, such as *The Fugitive* and *Speed* in our sample.

Conventional wisdom suggests that children's/family movies are more likely than others to be priced for the sell-through market (children enjoy watching the same movie over and over again). In our data, the opening strength of a movie, m_1, is significantly related to the use of a sell-through video price (r = .42, $p < .05$); decay rate (m_2) is not (r = –.04, $p > .10$). It thus appears that Hollywood management uses opening strength as another guide to determine whether to use a sell-through price strategy; movies that have high opening box offices are more likely to employ a sell-through strategy.

Not surprisingly, the use of a sell-through strategy is significantly correlated with v_1 (r = .64, $p < .01$) and v_2^A (r = .67, $p < .01$). Moreover, as shown in Table 7, adding a variable for the presence or absence of a sell-through price significantly increases the explained variance for both v_1 and v_2^A without changing the significance of m_1^B and m_2.[17] Namely, m_1^B has a significant effect on both v_1 and v_2^A, but m_2 does not. Consistent with the economic analysis presented previously, sell-through videos tend to open higher

[15]Published estimates of advertising expenditures for a particular movie appear to merge spending both before and after a movie's release. Because New York is a major market and preopening advertisements are paid for by the movie's distributor, we believe that these advertisements are a reasonable indicator of national advertising.

[16]We can also assume that v_1, v_2 depend on cumulative theater sales. However, because our goal is to make early forecasts of video sales, we use m_1^B and m_2, which can be reliably estimated early in a movie's run.

[17]For v_1, $F(1, 31) = 13.78$, $p < .01$, for adding sell-through to the model involving m_1^B and m_2; for v_2, $F(1, 31) = 15.17$, $p < .01$.

TABLE 7
Regression Predictions for Video Demand Parameters

Dependent Variable			Predictors		Adjusted R^2
	Intercept	m_1B^*	m_2	Sell-Through	
v_1	24.29	7.79 (t = 5.11)	21.19 (t = 1.75)	—	.45
v_1	24.46	5.56 (t = 3.91)	19.86 (t = 1.93)	13.48 (t = 3.63)	.60
v_2^A	.044	9.66 (t = –3.59)	.014 (t = –.66)	—	.25
v_2^A	.044	5.57 (t = –2.25)	.011 (t = –.66)	.025 (t = –3.92)	.48

*Coefficient scale by 10^{-1} and 10^{-4} for v_1 and v_2^A, respectively.
Notes: Neither lag nor advertisements is significant ($p \geq .10$) when it is added to the explanatory variable set either individually or collectively.

and decay more rapidly (for empirical support for this, see Tables 4 and 6).

Optimal Release Policy for Individual Movies

Equation 17 provides the optimal time to release a video. Using that expression requires an estimate of the relative profitability of the two markets (M_T/M_V). In addition, the parameter v_2^B is not observable, so we set $v_2^B = v_2^A = v_2$, omitting the superscript for expositional ease. With these assumptions, Equation 17 can be restated as follows:

$$(22) \quad t_2^* = \left(\frac{1}{m_2 - v_2}\right)\left\{\ell n\left[\frac{nm_1{}^B M_T}{v_2 v_1 M_V}\right] + \left(\frac{p}{r}\frac{v_2}{n}\right)\right\}.$$

The optimal time to release a movie depends on p, and a joint optimization problem involving both price and time to release can be constructed. However, the price decision depends on several product positioning decisions, as well as on industry practice, that go beyond the scope of this article (see n. 6). Consequently, we focus on time and assume that price is set exogenously. For our calculations, we therefore set p = \$63.00 and r = \$2.50, consistent with industry data for non–sell-through movies (Vogel 1994).

The ratio $m_1{}^B/v_1$ represents the relative size of the potential (opening) movie and video market. These parameters, though differing in units of measurement, can be estimated from our data, as can m_2 and v_2.

The ratio M_T/M_V depends on the relative profitability to the movie studio of the theater and video markets. Given the well-known mysteries of Hollywood accounting (Cones 1997; Vogel 1994), it would be difficult to determine a precise estimate of the profitability to Hollywood of the two markets. Returning to Equation 16, the first term in the last expression represents the profits from the movie market, and the second term the profits from the video market. Calculating the optimal time to release a video depends on the ratio of those two terms. However, when we know the ratio of movie to video profits under current procedures, the ratio of M_T/M_V can be determined. Figure 4 illustrates that, for a movie and a video with the average parameters in our sample, the optimal time to release a video depends on the relative profitability. As the video market's relative profitability increases, the optimal time to release the video declines, as expected. As shown, if video profits contribute 50% of combined movie and video profits, the average video should be released with only two weeks delay. (We discuss consumer expectations and industry structure constraints on such a conclusion subsequently.) Conversely, if video contributes just 10% of profits, the optimal release time would be nine weeks. It is interesting to note that the practice of waiting approximately half a year to release a video began when videos accounted for only a tiny fraction of total profits. The continuing decline in time to video release (see Prasad, Mahajan, and Bronnenberg 1998) is consequently not surprising.

To demonstrate how the approach would work for an individual movie, we assume that video rentals account for 30% of combined theater and video profits for the studio.[18] Although total video rentals are higher in terms of dollars than the theater box office, a larger portion of movie revenues flows directly back to the distributor. Other assumptions would yield directionally similar results to those presented here.

At the time when a decision about when to release a video (t_2) is made, the distributor has sufficient information to determine the values of $m_1{}^B$ and m_2. However, the parameters of the exponential decay model for video rentals are not yet known and must be estimated through the regression equation in Table 7. For non–sell-through movies in particular, the regression equations are (omitting error terms)

$$(23A) \qquad v_1 = 24.46 + .556m_1{}^B + 19.86m_2$$

and

[18]Lukk (1997) provides two detailed examples of movies that grossed \$100 million or more at U.S. and Canadian theaters. Both are consistent with this assumption. *Goldeneye* was released on November 17, 1995, and "it went to the video rental market, which means the distributor sells it wholesale for \$60 to \$65 ... [and] distributed 475,000 units of the video" (Lukk 1997, p. 53). *Pulp Fiction* grossed \$107 million domestically and sold 715,000 units to the rental market (Lukk 1997, p. 29).

(23B) $$v_2 = .04 + .000557m_1^B + .01m_2.$$

To illustrate our approach, we discuss the optimal release times for two movies. (See Table 4 for the optimal release times for the 25 videos that were released for the non–sell-through market.) *Cool Runnings* had a relatively weak opening (compared with other movies) but a slow decay in the movies. However, its performance in the video market was typical of that for the non–sell-through movies in our sample. We estimate that the optimal time to release *Cool Runnings* would be 10 weeks after its movie release, 11 weeks earlier than its actual release time of 21 weeks.

As shown in Table 4 (last column), this would have had an effect of increasing the studio's profit by 8%. That is, the actual release pattern was assumed to result in a profit level that we arbitrarily denote as H. Seventy percent of H is due to the movie, 30% to the video. If the video were to be released earlier, as the optimization routine suggests, movie profits would decline to 57% of H, but the video attracts more customers than before, and its profit increases to 51% of H (that is, video profits increase by 70%, .51H/.30H). Figures 5 and 6 illustrate the difference between current release time and optimal release time for *Cool Runnings*.

As another example, consider the movie *Philadelphia*. The video's release date was 26 weeks, slightly higher than average. However, our model suggests that early release of that movie could have resulted in a substantially higher profit. In particular, a video release at the calculated optimal time of 6 weeks would have resulted in an estimated 33% increase in overall profits to the movie studio.

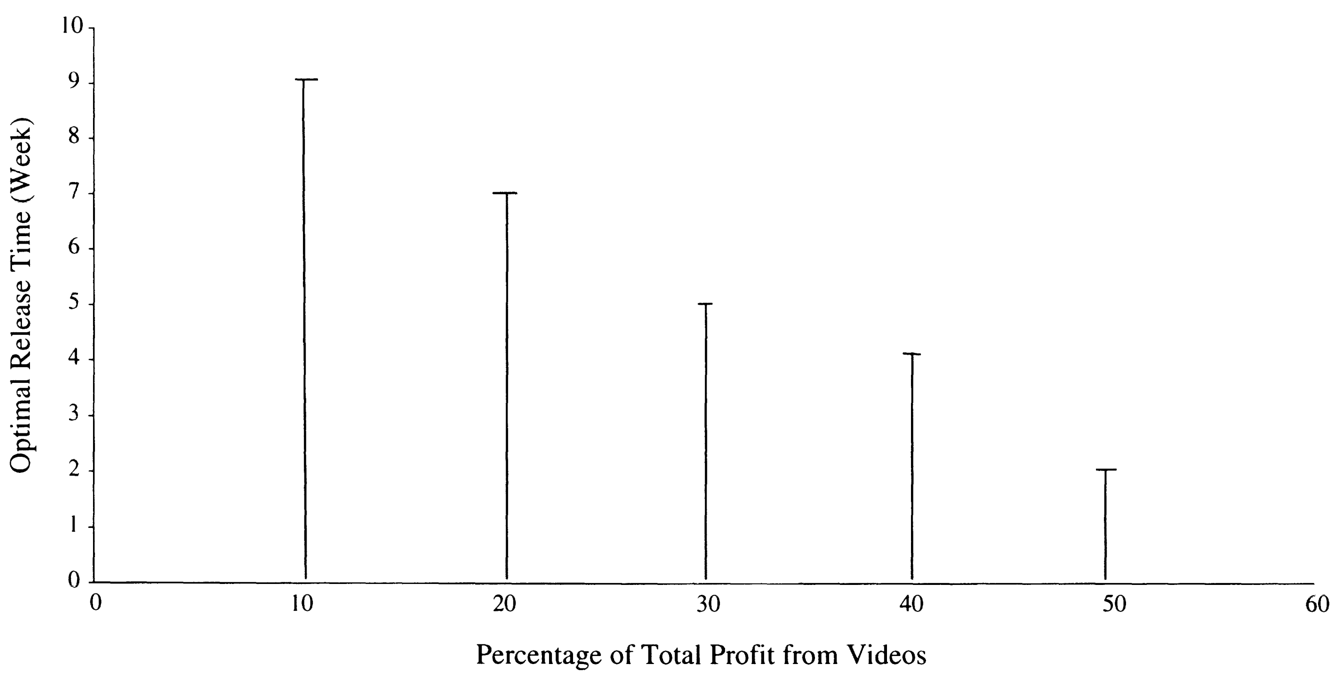
As can be seen in Table 4 with one exception, the general recommendation is to release videos earlier and allow for variation in video release times of between three and ten weeks (omitting one outlier). The particular parameter values for each movie determine the appropriate release date. Institutional restrictions, legal constraints, and consumer expectations may limit the feasibility and reasonableness of decreasing the time to video release as fully as suggested in Table 4, but the directional implications are quite strong.

Table 4 illustrates how sensitive the optimal release time is to the parameters of a movie. Stronger movies (those with higher m_1^B or lower m_2) should delay release in the secondary channel. Because these parameters to a large extent can be readily estimated after a few weeks of a movie's run, there is considerable opportunity for improved profitability from varying video release patterns.

When the video is targeted for the sell-through market, the video retailer buys for both the rental and video markets at the same (low) price. On the basis of the data in Vogel (1994) (see n. 14), the contribution to the studio is approximately \$53 (calculated at 63% of the list price of \$89.95, less a cost of \$4 per tape) for the rental market and \$12 per tape for the sell-through market. Although our data (see Table 7) suggest that the lower price increases the initial rental market by slightly more than 50% on average, the profitability of using a sell-through strategy, as expected, depends critically on the existence of a substantial sell-through market for the movie. Because our data (see Table 8) are not sufficient to reliably estimate video sales in the sell-through market,[19] we do not make specific calculations

[19]Perhaps again because of small sample size (n = 8), m_1^B and m_2 were not significantly related to either s_1 or s_2.

FIGURE 4
Industry-Wide Optimal Release Time for Non–Sell-Through Movies



for the optimal time for the video release of sell-through movies.

Limitations and Future Research

One obvious limitation is that the empirical results are confined to one industry. Even for the movie industry, there are problems of limited data, particularly because industry practice limits our ability to gather data on important parameters in our model. Because videos are almost never released until widespread theatrical play of the movie has ended, and usually at a relatively fixed time after release, the effects of cannibalization could not be directly estimated. Although the directionality and impact of our results seem clear, experiments—say, consisting of early release of videos in some markets—would be helpful. Other industries, such as book

FIGURE 5
Actual Box Office Revenue and Optimal Video Release Schedule for *Cool Runnings* (Movie)

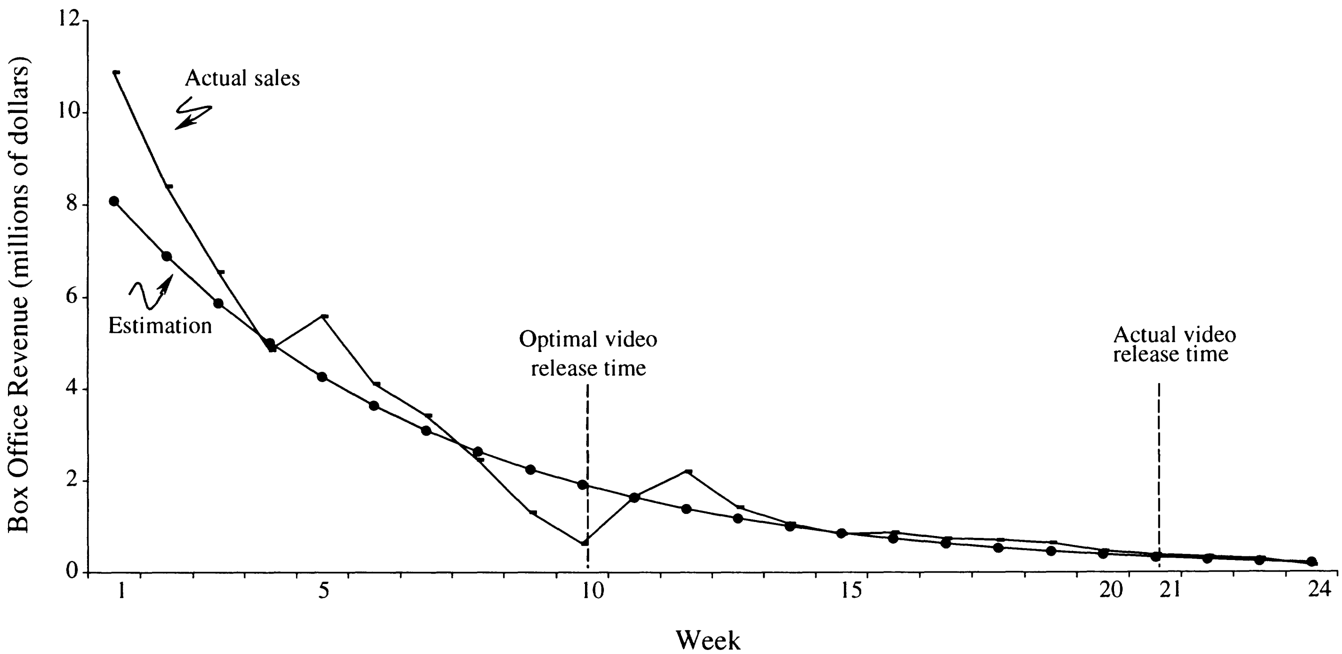
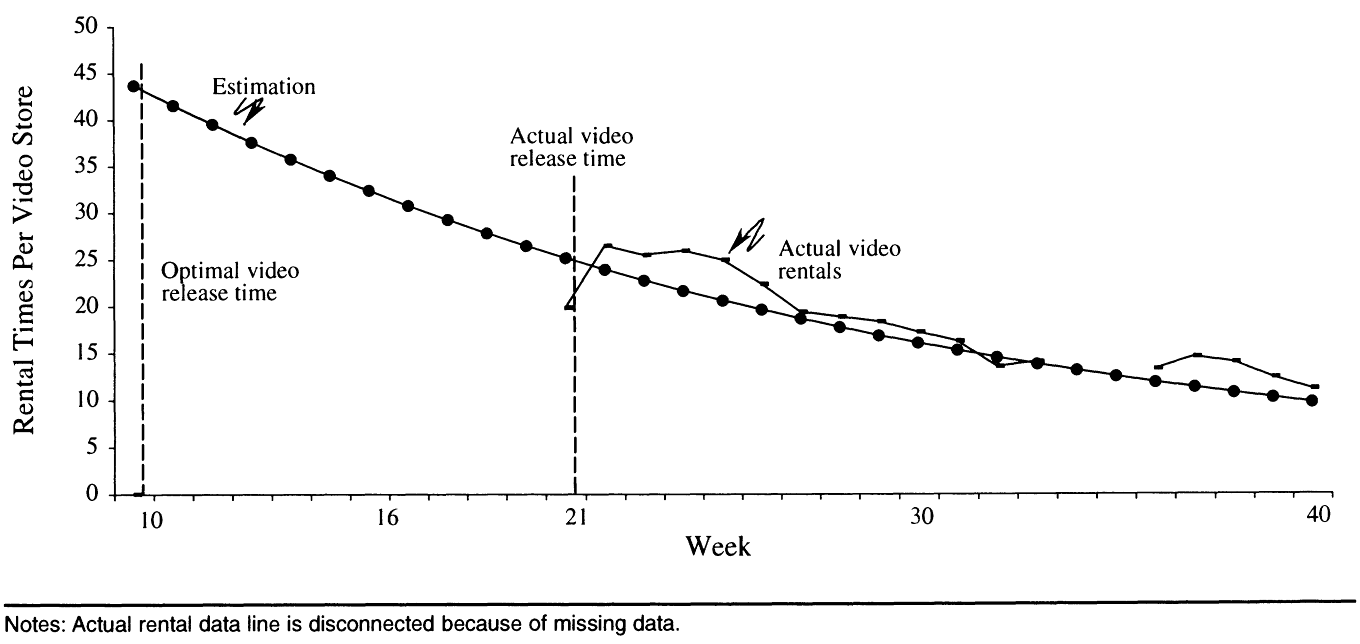


FIGURE 6
Actual Video Rentals and Optimal Video Release Schedule for *Cool Runnings* (Video)



Notes: Actual rental data line is disconnected because of missing data.

TABLE 8
Estimation for Video Tape Sales (Sales = $s_1e^{-s_2t}$) for Eight Movies in Sample Available at Sell-Through Price*

Movie	s_1^{**}	s_2^{**}	Adjusted R^2
Ace Ventura	4.43	.021	.65
D2: Mighty Ducks	4.45	.018	.62
Flintstones	3.98	.039	.68
Free Willy	4.22	.013	.97
The Fugitive	3.99	.021	.66
Jurassic Park	6.50	.015	.39
Mrs. Doubtfire	5.01	.015	.57
Speed	5.45	.026	.38

*Sales per store per week (*Video Business*).
**All significant at $p < .001$.
Notes: Sales data for *City Slickers II* and *Dennis the Menace* were not available.

publishing and fashion goods, seem to be similar, though the structural arrangements of each industry vary. Each poses interesting modeling challenges, but analyzing them would lead to a better understanding of the determinants of success in the management of sequential distribution channels.

In the industry we study, we analyze only two sequential channels and assume that the sequence is known. Although adding more channels to our model is relatively straightforward, the problem of determining the appropriate sequence of channels is more complex, especially with regard to different patterns of cannibalization across channels. (Combinatorial analysis provides an inelegant but effective way to consider different orders analytically.) In addition, structural constraints such as contractual obligations and channel relationships (Vogel 1994) need investigation.

Going further, if the timing of release of products to sequential markets changes radically, the issue of customer expectations must be considered. For example, consumers typically expect paperback versions of books to be released after at least a year and a video to be released well after a movie finishes its theatrical run. If potential moviegoers know that a movie is likely to be released only five weeks after its theater release, the likelihood that they will go to a theater to see the movie may decrease. Prasad, Mahajan, and Bronnenberg's (1998) game theoretic analysis suggests that one reason for the relatively uniform release time for videos is to avoid strategic behavior in which competing firms, anticipating consumer response, move up release times so that movie and video release times eventually become simultaneous. Industry practice in the movie industry appears to be changing. In the summer of 1997, in contrast to historical practice, movies were released with a much larger number of initial screens, which resulted in relatively high opening weekends but fast decay rates and less time in theatres. If such policies persist, different sequential distribution strategies will be needed. Already, the average time between movie release and video release is declining.

Our models assume that the time of theater release is fixed and that the video release timing decision can be made sequentially. An approach that simultaneously considers the optimal timing of release in the initial and sequential channels is an interesting area for extension. If the potential value of information from sales in one channel for determining sales in other channels is included in the models, interesting and managerially important modeling challenges emerge.

One key implication of the high correlations between the theater and video parameters is that good estimates of the video's two parameters are possible early in the sales curve for theaters. These estimates would undoubtedly be even more accurate if we used a meta-analysis of parameters for other movies, along with the data, to estimate the parameters (e.g., through Goldberger–Theil's mixed-estimation procedure, as in Sultan, Farley, and Lehmann [1990]). Furthermore, the estimated parameters would change in mean and variance after each period, and the variance would tend to decrease. Therefore, an interesting research (and managerial) question pertains to the decision whether to postpone releasing a video until more information about theater revenues becomes available. That is, to decide whether to introduce the product to the second channel after each period of data, we must compute the expected profits of staying in theaters and moving to videos. The profits, in turn, are a direct function of the parameters. The parameters of the sales curves could be assumed to come from a multivariate normal distribution with a mean equal to the expected value and standard deviation (or variance) taken from the variance–covariance matrix of the parameter estimates.

Several other specific extensions are also possible. For example, in the retailer's model, some fraction of unmet demand might be assumed to carry over to the next period, which makes being out of stock less damaging and lowers the retailer's optimal order level. More generally, incorporating uncertainty explicitly in the demand functions and allowing for heterogeneity across retailers (e.g., a ma and pa versus megastore segmentation) may also prove interesting. Still, because our focus is sequential channels in general, the exact extensions needed are likely to vary by the product category under study.

Conclusions

Just as successful management of the supply chain has become an important business activity, the analogous management of sequential distribution channels is a potentially important source of profits for many businesses. In this article, we focus on the time to begin marketing a product in sequential channels and show that data available from sales in the first channel can be used to improve the profitability of subsequent decisions.

In particular, we derive an expression for determining the optimal time to open a sequential channel and, for a particular setting, derive a closed-form solution. Using data from the movie industry, we provide empirical support for our modeling assumptions. The results lead us to question current industry practice. We find that the optimal time to release a videotape varies depending on the opening strength and decay rate of a movie, parameters that can be determined early enough in a movie's run to be used in making the video release timing decision. This runs counter to current practice, because our data indicate that videos are released at a relatively constant delay of 24 weeks from the movie's release. Although factors other than those included in our model influence the optimal timing decision, our results suggest the potential for increased profitability from making sequential channel decisions dependent on early results.

Our focus is the time to open a sequential distribution channel based on results from the initial channel. Other decisions, such as pricing, can also be based on the results obtained in the first channel, as we briefly discuss. Combined with managerial judgments and information gleaned from meta-analysis of results for related products, our model provides an initial attempt to manage products optimally as they move successively through channels to (typically) reach a wider set of consumers.

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