Firms in many industries release new products in sequential stages. They also launch separate advertising campaigns at each distribution stage. Thus, communication mix elements—advertising and word of mouth (WOM)—can play important, distinct, and yet interdependent roles in stimulating new product demand. Their effectiveness may fluctuate within and across stages and spill over from earlier to later stages. Thus, the authors construct a dynamic linear model to study the dynamic effects of advertising and WOM on demand for heterogeneous products across stages. They further apply the model to examine a canonical example, the theater-then-video sequential distribution of motion pictures, and estimate the parameters using Kalman filtering/smoothing and Markov chain Monte Carlo methods. The results show that advertising and WOM exert dynamic, yet diverse, influences on demand for new products. For example, while increased ad spending is more effective at an earlier stage due to repetition wear-in and synergy with WOM, increased WOM activities at a later stage could become more powerful in driving demand. Subsequent optimization exercises suggest that films of varied characteristics can potentially re-allocate their advertising budgets and reap additional revenues.

Keywords: sequential distribution, new product, Bayesian dynamic linear model, aggregate advertising model, word of mouth

Dynamic Effectiveness of Advertising and Word of Mouth in Sequential Distribution of New Products

Many industries, such as motion pictures, book publishing, fashion, music, and art, distribute their new products in a sequence of stages. The practice, commonly termed “windowing” or “sequential distribution” (Lehmann and Weinberg 2000), is most prevalent for new products with short life cycles. For example, Hollywood studios launch films to theaters and then to rental (e.g., Netflix) and retail (e.g., Wal-Mart) channels, book publishers release hardcover editions before paperbacks, and designer fashions appear at specialty retailers before mass merchants. Sequential distribution has become central to the profitability of many of these industries. For example, on average, Hollywood studios spend $70.8 million to produce and $35.9 million to market a film; yet each film accrues merely $45.7 million on average in theatrical revenues (Motion Picture Association of America [MPAA] 2007). Thus, without additional revenues from sequential distribution, studios might seldom break even. With sequential distribution, a studio (or any firm) can attract consumers with similar preferences for the new product but different preferences for the channel, price, or product format. Consequently, sequential distribution extends the product’s life cycle and improves the firm’s profit.

To help achieve these profits, firms often launch separate ad campaigns at each stage, with advertising for each campaign beginning before product release, peaking at release, and rapidly declining afterward. Given this dramatic fluctu-
tuation in ad spending, it is likely that ad effectiveness, moderated by forgetting (or conversely, carryover) and wear-out (or conversely, wear-in) (e.g., Naik, Mantrala, and Sawyer 1998), differs across stages. Such differences can also result from, for example, deeper knowledge about the advertised product at later stages (Campbell and Keller 2003). Furthermore, ad campaigns in earlier distribution stages may influence demand in not only earlier but also subsequent distribution stages. That is, spillover of advertising across stages may occur. Moreover, given the fashion-able and experiential nature of these new products, consumers’ word of mouth (WOM) could critically influence demand (Liu 2006), albeit with potentially varying strengths at different stages. Its effectiveness could also interact with the effectiveness of the firm’s advertising, resulting in advertisement–WOM interdependence.

Thus, several substantive questions arise: How do ad effectiveness and WOM effectiveness fluctuate across distribution stages? How do they differ and interact? How do they vary across products? Finally, are there more efficient ways to allocate valuable advertising resources? Addressing these questions sheds light on new product advertising that exhibits distinct patterns and poses unique challenges, such as prerelease spending and interplay with WOM (e.g., Bass et al. 2007). It also builds knowledge on advertising strategies, beyond timing and pricing strategies in sequential distributions (e.g., Lehmann and Weinberg 2000). Moreover, it extends the examination of WOM impact beyond a single stage of product distribution (e.g., Liu, 2006).

To accomplish this, we propose a dynamic linear model (DLM) that links a product’s demand to its underlying goodwill stock (Nerlove and Arrow 1962). This stock parsimoniously summarizes the influence of current and past firm advertising and consumer WOM. The model extends prior studies of dynamic advertising by incorporating spillover and differential rates of forgetting and wear-out across stages, dynamic WOM effectiveness, ad–WOM interdependence, and product heterogeneity. We apply the model to a canonical example, the theater-then-video sequential distribution of motion pictures, and estimate the parameters using Kalman filtering/smoothing and Markov chain Monte Carlo (MCMC) methods (e.g., Van Heerde, Mela, and Manchanda 2004).

Our results show that both advertising and WOM exert dynamic influences on demand, but with distinctive patterns across distribution stages. For example, elevated ad expenditure at an earlier theater stage is more effective in driving demand, due to repetition wear-in and synergy with WOM, than at a later video stage, when consumers become knowledgeable about a product. In contrast, more active WOM at a later stage enhances its effectiveness more than at an earlier stage. That is, lively WOM at a later stage potentially delivers a stronger signal of a product’s sustained appeal to consumers who increasingly turn to WOM for information at this stage. Furthermore, the analysis suggests that firms should account for product heterogeneity when planning media strategies. The what-if simulations illustrate that products of distinct characteristics, such as critics’ favorites or action films, could harvest additional revenues with more efficient allocations of their ad budgets.

This work makes four key contributions. First, it generates substantive insights into the critical, yet largely understudied, area of advertising and WOM for sequentially distributed new products. In particular, it shows that (1) advertising can wear in for new products rather than wear out, as is commonly observed for mature categories; (2) the largely diminishing returns to advertising established for mature categories may also operate for new products; and (3) the impact of WOM can elevate over sequential distributions. Second, the current research develops a dynamic modeling framework that integrates cross-media (advertising and WOM) interdependence, cross-stage spillover, and cross-product heterogeneity. As a result, the framework can reveal distinct dynamics of ad and WOM effectiveness, as well as various paths through which either medium can directly and indirectly stimulate demand. Third, and consequently, the study offers managerial guidance to potentially more effective allocations of valuable ad resources within and across distribution stages for each product. Finally, although our findings arise from the movie context, the conceptual and methodological frameworks generalize to many other multi-billion-dollar industries that rely heavily on sequential distribution.

We structure the remainder of this article as follows: We first review the relevant literature and then present the details of the econometric specification. Next, we describe the data, estimation methods, empirical results, and managerial implications. We conclude with an overview of the findings and suggestions for further research.

LITERATURE

This research builds on three streams of literature: sequential distribution, and dynamic ad and WOM effectiveness. We briefly summarize the most relevant studies. For more extensive reviews, see Godes et al. (2005), Little (1979), Mahajan, Muller, and Bass (1995), Tellis (2004), Vakratsas (2005), Vakratsas and Ambler (1999), and the references listed therein.

Sequential Distribution

Since the seminal contribution of Bass (1969), a rich body of work has emerged on new product diffusion. A few studies within this body explore multistage diffusion of new products and related pricing (Clerides 2002) and release timing (Hennig-Thrau et al. 2007; Lehmann and Weinberg 2000; Prasad, Bronnenberg, and Mahajan 2004) decisions. Building on this research, we focus on advertising decisions.

In the context of the movie industry, studios release films domestically to theaters before video rentals and sales, pay-per-view, and so on. We focus on the theater ($9.6 billion annually) and video ($24.2 billion) stages because they generate more than 95% of the revenues (Digital Entertainment Group 2007; Entertainment Industry Market Statistics 2007). Our approach nevertheless extends readily to sequential distributions beyond these two stages. The movie industry is also a primary buyer in the multi-billion-dollar U.S. advertising and media market. For example, during our sampling period, Hollywood studios spent $3.8 billion on theatrical and $1.1 billion on video advertising annually (Kantar Media). Moreover, this industry has a long tradition of employing uniform pricing to highly differentiated films (Orbach and Einav 2007). This feature renders the industry an ideal context to study the advertising effectiveness in the absence of pricing decisions. Thus, a few recent studies have examined the impact of advertising on film demand at
either the theater (Elberse and Anand 2007) or the video (Luan and Sudhir 2010) stage. However, research on multi-stage advertising and ad dynamics remains scant. Moreover, previous researchers have made calls for better understanding of advertising over sequential distribution (Elberse and Anand 2007; Elberse, Leenders, and Stewart 2006). Our work takes a step in this direction.

Dynamic Ad Effectiveness

The advertising literature has explored dynamic ad effectiveness, interactions between advertising and other marketing-mix elements (e.g., pricing), and the allocations of ad budgets, all primarily for mature categories (for reviews, see Vakratsas and Ambler 1999). However, several more recent game-theoretic (Krishnan and Jain 2006; Nguyen and Shi 2006) and empirical (Elberse and Anand 2007; Luan and Sudhir 2010) studies have begun to examine advertising for new products. Our research broadens this domain of inquiry to multistage advertising strategies in sequential distributions of new products.

Moreover, recent studies reveal that ad effectiveness indeed fluctuates over time. Naik, Mantrala, and Sawyer (1998), Bass et al. (2007), Bruce (2008), Kolsarici and Vakratsas (2010), and Aravindakshan and Naik (2011) all show that ad effectiveness may decline or rise over time for mature categories. These findings suggest that ad dynamics may also operate for new products, especially over the course of their sequential distributions. At least three reasons support this notion. First, ad spending fluctuates dramatically over time for new products, both within a distribution stage and across stages. Consider the movies shown in Figure 1 as examples: Advertising for them (and many other new products, such as those in the music industry) often commences before release, peaks at release, diminishes swiftly after release, and repeats a similar pattern at a later stage, often with a distinct magnitude. Because different ad spending levels signal divergent product qualities (Erdem, Keane, and Sun 2008) and firm support, create varying scopes of audience reach, and generate diverse levels of interests among audiences in purchasing the product or spreading WOM, the ad effectiveness is likely to vary over time.

Second, several underlying factors shown to drive dynamic ad effectiveness, such as forgetting and wear-out (e.g., Naik, Mantrala, and Sawyer 1998), could also differ across stages. Specifically, as a new product rapidly moves from introduction to decline and into a different distribution stage, its fashionable nature induces consumers to become less interested in, or more likely to forget about, the product or its ad. For example, as more people become aware of and familiar with The Aviator at the video stage, its advertising becomes less powerful at informing or persuading viewers (Vakratsas and Ambler 1999). Indeed, repeated airing of its ad could aggravate viewers, risking wear-out or reduction of ad effectiveness (Campbell and Keller 2003; Pechmann and Stewart 1990). Furthermore, ad copy changes; for example, a theatrical ad featuring Harry Potter flying on a broom is far more entertaining and memorable than a video ad simply informing the DVD’s release date.

Third, as WOM becomes more or less effective over time (e.g., Liu 2006; Moe and Trusov 2011), ad effectiveness may also be enhanced or reduced. For example, as WOM for The Passion of the Christ becomes increasingly power-
aggregate sales response function, while allowing the coefficients (i.e., effectiveness) of advertising and WOM to vary over time. It also offers a flexible approach to account for heterogeneity across products and spillover from an earlier to a later stage.

**Aggregate Demand and Goodwill Stock**

Given our interest in examining the aggregate effects of advertising and WOM on demand, we construct an aggregate sales response model. It is built on the discrete time analog of Nerlove and Arrow's (1962) model (hereinafter, the N-A model). The N-A model is widely adopted in the advertising literature due to its parsimony (Bass et al. 2007; Naik, Mantrala, and Sawyer 1998) and theoretical consistency with individual consumers' response to advertising (Blattberg and Jeuland 1981; Rao 1986). In particular, to capture the dynamic advertising effects, Nerlove and Arrow suggest the use of "goodwill stock," which essentially summarizes the effects of current and all past advertising on demand.

To demonstrate this more clearly in the movie context, we use the following as an example: A movie i's weekly advertising and consumers' WOM build the goodwill stock...
(G) toward the movie. In turn, this goodwill drives the demand for the movie, operationalized as the logarithm of the weekly revenue ($y_{jt}^0$) at week $t$ of distribution stage $j$ ($j = 1$ for theater and 2 for video). That is,

$$y_{jt}^0 = G_{jt}^0 + \beta_j^0 X_{jt}^0 + \epsilon_{jt}^0,$$

where $\epsilon_{jt}^0 \sim N(0, \sigma^2_j)$.

The vector $X_{jt}^0$ comprises control variables that may also affect the demand for the movie, such as holiday opening and competition, which we describe in greater detail in the "Data" section.

Consistent with the N-A specification, the film’s goodwill (G) decays in proportion to the lagged goodwill, while it is maintained by the studio’s ad spending (A) and consumers' WOM captured by their online ratings (R), as follows:

$$y_{jt}^0 = G_{jt}^0 + \beta_j^0 X_{jt}^0 + \epsilon_{jt}^0,$$

where $\epsilon_{jt}^0 \sim N(0, \sigma^2_j)$.
For example, due to the short life cycle and fashionable appeal of The King’s Speech, its goodwill diminished with the passage of time. Meanwhile, as the studio continued to advertise and the public continued to chatter, more consumers became interested in seeing it. Specifically, its goodwill decayed over time as consumers gradually forgot about the film, and thus the aggregate brand awareness declined. This process is captured by the forgetting rate ($\delta$), in other words, only the $(1 - \delta)$ portion of the prior goodwill stock is carried over to the next period (Mahajan, Muller, and Sharma 1984; Nerlove and Arrow 1962). As advertising and favorable WOM cultivate goodwill, their effectiveness is captured by $\theta_1$ and $\theta_2$, respectively. Consistent with the literature, we also apply a semilog transformation of ad spending, $g(A) = \ln(1 + A)$, to account for the diminishing return of advertising (Naik, Mantrala, and Sawyer 1998; Simon and Arndt 1980).

Dynamic Advertising and WOM Effectiveness

After linking a film’s demand to its goodwill stock, driven by ad and WOM, we next examine how the ad, and then WOM, effectiveness could vary over time. Our specification is guided by the literature, which reveals several factors that could enhance (wear in) or diminish (wear out) ad effectiveness. Ad wear-out arises from two sources: copy wear-out and repetition wear-out (Naik, Mantrala, and Sawyer 1998). Copy wear-out occurs due to passage of time, regardless of the levels of ad frequency or spending. Consider that when an ad for Pirates of the Caribbean: On Stranger Tides first airs, it usually informs viewers of, for example, the film’s lead actor/actress and release date. Its impact diminishes, however, when viewers acquire this knowledge (Assmus, Farley, and Lehmann 1984). In addition, possibly, as the novelty of specific advertising techniques, such as a 60- instead of 30-second feature commercial, wears off or is copied by competitors, the perceived contrasts among ads reduce and competition for consumers’ attention intensifies (e.g., Axelrod 1980), reducing the original ad’s effectiveness.

Repetition wear-out, in contrast, stems from excessive levels of ad spending and consumers’ subsequent repeated exposure to an ad (Calder and Sternthal 1980; Grass and Wallace 1969; Greenberg and Suttoni 1973). When viewers gain no novel information or entertainment from seeing the ad repeatedly, they become bored, less attentive, or even irritated and thus become unmotivated to process the ad. The ad effectiveness then declines as a result of reduced recall or unfavorable attitude toward the ad or product (Belch 1982; Cacioppo and Petty 1979; Lodish et al. 1995). Significantly, the opposite of repetition wear-out—namely, wear-in—prevails in some cases (Pechmann and Stewart 1990). For example, when a firm rotates its ads across different themes, such as price offer versus reassurance (Bass et al. 2007), ad repetition may create positive effects on viewers who perceive the ads as fresh. Wear-in could also occur for movie ads because they often embed rich stories and imageries that viewers enjoy (Pechmann and Stewart 1990).

The literature further reveals that ad effectiveness could be restored during periods of no advertising because of consumer forgetting ($\delta$). That is, when the ad for Black Swan goes off the air for a while, the public tends to forget about the details of the ad message and/or the movie. When the ad resumes, viewers perceive it as being “like new” and devote more attention to it (Calder and Sternthal 1980; Grass and Wallace 1969; Greenberg and Suttoni 1973). Thus, the greater the forgetting, the stronger is the regenerating effect of an ad after its hiatus.

In light of these empirical findings, we model the ad effectiveness ($q_1$) to wear out in proportion to copy wear-out ($o_1$) and repetition wear-out ($o_2$), to restore when the ad is off (i.e., $I(A) = 0$) in proportion to the rate of forgetting ($\delta$), and to interact (through $q_2$) with the WOM effectiveness ($q_2$) as follows:

$$q_{1t}^o = (1 - o_1)q_{1t-1}^o + \theta_1 (1 - I(A_{it})) \left(1 - o_2q_{2t-1}^o\right),$$

where $o_1^o \sim N(0, W_1^o)$.

By multiplying $\delta$ by $(1 - o_2q_{2t-1}^o)$, this specification also allows the less effective ads to benefit from a stronger regeneration of its ad effectiveness (for other appealing properties of the specification, see Naik, Mantrala, and Sawyer 1998). In addition, while prior studies focus on how advertising interacts with WOM volume ($Q$) or valence ($R$) (Luan and Sudhir 2010; Monahan 1984; Moon, Bergey, and Iacobucci 2010), we focus on the intriguing, yet understudied, relationship between the ad and WOM effectiveness. In other words, will Black Swan’s ad attract more attention when its WOM becomes more persuasive, and vice versa?

Next, we turn our attention to the WOM literature, which suggests that WOM effectiveness could also be dynamic (e.g., Liu 2006). Thus, we propose the following formulation to capture its evolution:

$$q_{2t}^o = (1 - o_2q_{2t-1}^o)q_{2t-1}^o + \theta_2 (1 - I(A_{it})) \left(1 - o_2q_{2t-1}^o\right)$$

$$+ \theta_2 I(A_{it}) q_{2t-1}^o + o_3^o q_{2t-1}^o, \text{ where } o_3^o \sim N(0, W_3^o).$$

That is, similar to the ad effectiveness, the WOM effectiveness ($q_2$) may decline with the passage of time and in proportion to its wear-out rate ($o_2$). It may also be influenced (through $q_2$) by the ad effectiveness ($q_1$) and potentially enhanced by its volume ($Q$). Therefore, we use the term $w_2$ to refer to the rate of WOM wear-in. By multiplying $Q$ by $(1 - q_2)$, this specification permits the less effective WOM to produce a stronger effect of its volume ($Q$) on its effectiveness ($q_2$).

Note that the movie literature shows that WOM affects demand for films, though the findings are mixed on whether WOM volume or valence offers a better predictor (Chintagunta, Gopinath, and Venkataraman 2010; Dellarocas, Zhang, and Awad 2007; Duan, Gu, and Whinston 2008; Liu 2006). Thus, we account for both by linking the goodwill ($G$) to WOM valence ($R$) in Equation 2 and the WOM effec-
tiveness ($q_t$) to WOM volume ($Q$) in Equation 4. This formulation suggests that a large volume of WOM, which may result from either positive or negative reviews, influences its effectiveness, whereas favorable WOM with positive valence boosts goodwill and purchase. Subsequent tests of alternative formulations for WOM valence, volume, or both in these equations also support this specification.

**Heterogeneity**

Besides varying over time within a single stage, the effects of advertising and WOM may further differ across stages and products as, for example, the informational and emotional contents of advertising and WOM change (see Tellis 2004, p. 154; see also Rennhoff and Wilbur 2011; Zhu and Zhang 2010). Thus, we also acknowledge such potential heterogeneity by linking the demand parameters ($\beta_t$, forgetting rate ($\delta_t$), weart-out/ear-in rates ($\sigma_t$), and ad-WOM interdependence parameters ($\psi_{ij}$)) from Equations 1–4 to a set of film characteristics, such as genre and sequel ($Z_t$):

$$
(5) \quad \beta_t, \delta_t, \sigma_t, \psi_{ij} = Q_t Z_t + \xi_t,
$$

where $\xi_t - N(0, \Omega_t)$.

In summary, Equations 1–5 constitute the proposed model, given current knowledge of ad and WOM dynamics applied to the movie example. The model captures the dynamics of a product's demand within and across distribution stages as driven by current and past ads and WOM through the goodwill stock. It also accounts for dynamic ad and WOM effectiveness due to forgetting, wear-out/wear-in, and ad–WOM interdependence. Last, it allows these effects to differ across stages and products. Next, we describe the data, estimation methods that also account for spillover across stages, empirical findings, and managerial implications.

**EMPIRICAL STUDY**

The data draw on a random sample of 360 films of diverse genres, MPAA ratings, and studios. The genres include, among others, action (12%), comedy (36%), and dramas (24%); 62% of the movie had an MPAA rating less than R; and 68% were released by major studios. In the sample, 8% movies were nominated for Academy Awards in one of the major categories (i.e., Best Picture, Best Director, Best Actor/Actress, and Best Support Actor/Actress), 12% are sequels, and the average volume and valence of critics' reviews are 130 and 5.4 out of 10, respectively. On average, the studios behind these films spent $43 million on their weekly total production budgets), competitive new theatrical releases (as the logarithm of competitive new theatrical releases (as the logarithm of their weekly total production budgets), competitive new video releases (as the logarithm of their weekly total cumulative theatrical revenues), and holiday release dummies for President's Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas, or New Year's Day.

We also use a set of film characteristics to explain heterogeneity (i.e., $Z_t$ from Equation 5). These characteristics, commonly used in the movie literature, are derived from a variety of sources, such as Nielsen EDI, Rotten Tomatoes, and Oscars.org. They include one studio dummy (which is 1 for a film released by one of the top studios such as Sony), the volume and valence of critics' reviews from Rotten Tomatoes, an MPAA dummy (which is 1 for a less-than-R-rated film), genre dummies (which is 1 for an action, animated, comedy, drama, science fiction, or suspense film), the length of a film in minutes, an Oscar dummy (which is 1 for a film nominated for the aforementioned major categories), and the production budget. At the video stage, we observe that theatrical advertising often begins within three months before theatrical release, peaks at the release, and rapidly decays afterward. Video ad spending exhibits a similar pattern, though it tends to be at a lower level. The films’ WOM data come from the online consumer reviews at Yahoo Movies (movies.yahoo.com) and IMDB (imdb.com), the two primary sources of film WOM data used by prior studies (Dellarocas, Zhang, and Awad 2007; Duan, Gu, and Whinston 2008; Liu 2006). The time-stamped ratings range from 1 (the lowest evaluation) to 10 (highest) on IMDB and from F (lowest) to A+ (highest) on Yahoo. To make the two data sources comparable, we follow Duan, Gu, and Whinston’s (2008) approach by equating the 13 Yahoo letter ratings with 1 to 13 and then dividing them by 1.3. From before theatrical release to video, we measure the WOM volume by weekly number of consumer ratings and WOM valence by weekly volume-weighted average ratings from both websites. Subsequent tests of alternative metrics, such as the percentages of positive and negative WOM, support the selected approach.

Overall, the weekly WOM volume ranges from zero to more than a few thousand. As we also expected, it peaks at theatrical release and declines afterward. In contrast, WOM valence exhibits a more random pattern over time, both within a stage (Liu 2006) and across stages. It can also fluctuate greatly within the same film. Figure 1 shows four examples of weekly revenues, ad spending, and WOM valence at the theater (top panel) and video (bottom panel) stages, respectively (week 0 = release week). The figure also offers preliminary evidence that the impact of advertising and WOM on demand can vary over time.

In addition to advertising and WOM, other covariates that may affect a film’s demand at each stage (i.e., $X_t^i$ in Equation 1) include competitive advertising (as the logarithm of weekly ad spending by all other films at both stages), competitive new theatrical releases (as the logarithm of their weekly total production budgets), competitive new video releases (as the logarithm of their weekly total cumulative theatrical revenues), and holiday release dummies for President’s Day, Memorial Day, Independence Day, Labor Day, Thanksgiving, Christmas, or New Year’s Day.

2We choose the reduced-form measures of competitive advertising in light of prior findings of a much smaller effect of competitive than own advertising on demand (Dubé and Manchanda 2005). Nonetheless, further research could investigate dynamic ad competition over sequential distribution with a more structural approach.
also include a logarithm of the film’s cumulative theatrical revenues.

Finally, to help capture the goodwill evolution before theatrical release when no revenues are observed, we employ data from the Hollywood Stock Exchange, an online market where millions of online users trade virtual stocks of upcoming films with virtual currency. A film’s stock price at any time (e.g., $50 per share) reflects the public’s expectation of its first four weeks’ theatrical revenues (e.g., $50 million). Thus, we divide the weekly average trading prices by 2.8, as the Hollywood Stock Exchange suggests, to measure the prerelease expectations of its opening week theatrical revenue. Previous research has shown that these prices provide accurate demand forecast (Elberse and Anand 2007; Foutz and Jank 2010; Spann and Skiera 2003).

Estimation

To describe the estimation procedure used in this study, it is convenient to recast Equations 1–4 in formal state-space notation. Specifically, Equation 6 represents the observation equation and Equation 7 represents the state equation:

\[
\begin{align*}
\text{(6)} & \quad y^0_t = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} G^0_{0t} \\ q^0_{1t} \\ q^0_{2t} \end{bmatrix} + \beta^0 X^0_t + \epsilon^0_t, \quad \text{and} \\
\text{(7)} & \quad \begin{bmatrix} G^0_{1t} \\ q^0_{2t} \\ q^0_{3t} \end{bmatrix} = \\
& \begin{bmatrix} G^0_{1t-1} \\ q^0_{2t-1} \\ q^0_{3t-1} \\ \phi^0_t \end{bmatrix}, \\
& \begin{bmatrix} \Sigma^0_{1t} \\ \Sigma^0_{2t} \\ \Sigma^0_{3t} \end{bmatrix} = \\
& \begin{bmatrix} (1-\delta^0_t) g(A^0_t) R^0_t \\ 0 \\ 0 \end{bmatrix} \\
& \begin{bmatrix} 0 \\ (1-\phi^0_t) w^0_t Q^0_{1t} - \delta^0_t [1-I(A^0_t)] \phi^0_t \Sigma^0_{1t} \\ 0 \end{bmatrix} \phi^0_t \Sigma^0_{1t} \\
& \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \phi^0_t \Sigma^0_{1t} \\
& \begin{bmatrix} H^0_{1t} \\ H^0_{2t} \\ H^0_{3t} \end{bmatrix} \begin{bmatrix} G^0_{1t-1} \\ q^0_{2t-1} \\ q^0_{3t-1} \end{bmatrix} + \\
& \begin{bmatrix} \delta^0_t [1-I(A^0_t)] \\ \delta^0_t [1-I(A^0_t)] \end{bmatrix} \phi^0_t \Sigma^0_{1t} \\
& \begin{bmatrix} \omega^0_{1t} \\ \omega^0_{2t} \\ \omega^0_{3t} \end{bmatrix} \phi^0_t \Sigma^0_{1t}.
\end{align*}
\]

Here, the constant vector \( \Phi \) reflects the impact of the goodwill, as driven by current and past advertising and WOM, on film demand. The unobserved state vector \( \theta^0_{It} \) contains three state parameters: the goodwill, ad effectiveness, and WOM effectiveness of film \( i \) during week \( t \) of stage \( j \). The \( 3 \times 3 \) transition matrix \( H^0_{It} \) captures the time-varying effects of ad spending, WOM, wear-out/wear-in, forgetting, and ad–WOM interdependence on the state vector \( \theta^0_{It} \). In addition, we assume the error terms \( \epsilon^0_t \) and \( \omega^0_t \) to be independent normal random variables with zero mean.

Thus, we can further rewrite Equations 6 and 7 to obtain a more compact notation of the standard Bayesian DLM of West and Harrison (1997) as follows:

\[
\begin{align*}
\text{(6')} & \quad y^0_t = \begin{bmatrix} F^0_t \end{bmatrix} \theta^0_{It} + \beta^0 X^0_t + \epsilon^0_t, \quad \text{where } \epsilon^0_t \sim N(0, \Sigma^0_{rt}), \\
\text{(7')} & \quad \theta^0_{It} = H^0_{It} \theta^0_{I(t-1)} + \omega^0_{It}, \quad \text{where } \omega^0_{It} \sim N(0, W^0_{It}).
\end{align*}
\]

Recall that Equation 5 groups all time-invariant nonstate parameters from the preceding equations into a quintuple \( \{\beta^0, \phi^0_t, \sigma^0_{rt}, \sigma^0_{rt}, \sigma^0_{rt}\} \) and links them to product characteristics \( Z_i \). Therefore, Equations 6’, 7’, and 5 constitute our final DLM.

We estimate the model using MATLAB programming on the entire observed data series from before theatrical release to video for each movie. The procedure nests a Kalman filter/smoother inside an MCMC Gibbs sampler with conjugate priors (Gelfand and Smith 1990; West and Harrison 1997). The primary goal is to estimate the joint posterior distribution of the state and nonstate parameters for each movie and stage. By using the conjugate priors, we can analytically derive and directly sample the conditional posteriors of the state parameters given the nonstate parameters, and vice versa (Carter and Kohn 1994). Specifically, the conditional posterior of the state parameters given the nonstate parameters is a linear state-space model with known hyperparameters and thus can be sampled with the standard Kalman filter/smoother algorithm. Conversely, given the state parameters, the system becomes a multivariate linear model with hierarchical priors, and thus we sample directly using the standard MCMC methods (Rossi and Allenby 2003). Simply put, whereas the Kalman filter/smoother updates the evolution of the state parameters in \( \theta^0_{It} \) conditional on the remaining nonstate parameters, the MCMC Gibbs sampler updates the nonstate parameters given the state parameters. Thus, we obtain a sample from the joint posterior distribution of the two.

During the estimation procedure, we further account for the goodwill spillover from the theater to video stage. Specifically, similar to Van Heerde, Mela, and Manchanda (2004), we continue to update the goodwill evolution from the end of the ten theatrical weeks up to video release, as driven by advertising and WOM during this period when no sales are observed. Then, the resulting goodwill at the time of video release becomes the initial goodwill at the video stage. In addition, we conducted Hausman (1978) tests, which show insignificant results for the weekly competitive advertising \( (\chi^2(1) = .4196) \), own advertising (.0014), WOM valence (3.05), and WOM volume (.30). These suggest that endogeneity may not be a serious concern in our data (Leeffang et al. 2000, p. 382). Moreover, because the scales on ad spending, WOM volume, and WOM valence largely differ, we further rescale ad spending by $1 million and WOM volume by 1000. Finally, because the data contain a large number of films and film characteristics, we adopt a two-step empirical Bayes approach to construct Equation 5 (Raudenbush and Bryk 2001, p. 268). That is, conditional on Equations 6’ and 7’, we first estimate the intercept vector \( \hat{\Omega}^0 \) in Equation 5 and form the residual \( \hat{\epsilon}^0_t \). We then run a stepwise regression of the residual \( \hat{\epsilon}^0_t \) against the film char-

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\(^3\)The state-space approach is convenient for handling multivariate data and provides significant advantages over traditional time-series techniques (see, e.g., Durbin and Koopman 2001, pp. 51–53).
acteristics $z_i$ (Litman 1983; Sawhney and Eliaishberg 1996). We then include the surviving characteristics Equation 5.

**Model Comparison**

We benchmark the proposed model against ten alternatives based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Table 1). In Web Appendix A (www.marketingpower.com/jmr_webappendix), we report additional comparisons with alternative demand models commonly used in the movie literature—namely, the generalized Bass model (Bass, Krishnan, and Jain 1994), BOXMOD (Sawhney and Eliaishberg 1996), and Ainslie, Drèze, and Zufryden’s (2005) model. Model 1 assumes static ad and WOM effectiveness (i.e., $q_{12}^1 = q_{12}^2 = q_{22}^1 = q_{22}^2$; thus, Equations 3 and 4 disappear) but accounts for heterogeneity across movies and stages in the ad and WOM effectiveness and remaining parameters (e.g., $\beta_1^0$ and $\beta_2^0$). Models 2–4 assume no movie heterogeneity, no stage heterogeneity, or neither in the nonstate parameters (e.g., forgetting, wear-out/wear-in, and ad–WOM interdependence). Model 5 suggests equal observation variances across stages ($\sigma_{y1}^2 = \sigma_{y2}^2$) and equal system variances across stages ($W_{11}^1 = W_{22}^1$). Models 6 and 7 delineate the dynamic evolution of the WOM effectiveness as due to either random walk or ad–WOM interdependence. Model 8 ignores goodwill spillover from theater to video. Model 9 relaxes the assumption of interdependent ad and WOM effectiveness. Last, Model 10 investigates an alternative specification of goodwill spillover in which we assume the goodwill at video release to be proportional to that at theater release, when the goodwill likely stands at its highest level.

Overall, both AIC and BIC consistently and clearly favor the proposed Model 11. This furnishes additional evidence of the key assumptions of the proposed model: The ad and WOM effectiveness are dynamic and interdependent, forgetting and wear-out/wear-in differ across stages and products, and goodwill spills over from theater to video. Figure 2 displays the predicted versus actual demand at the theater (top panel) and video (bottom panel) stages, respectively. They further illustrate that the proposed model offers a good fit with the data.

**Parameter Estimates**

Tables 2 and 3 report the posterior means, standard deviations, and 95% highest probability density intervals (HPDI) of the parameters in the proposed model. A parameter is significant if its HPDI excludes zero. Web Appendix B (www.marketingpower.com/jmr_webappendix) provides a discussion of the estimates of the film characteristics that contribute to the heterogeneous ad and WOM effectiveness across stages and products. First, consider the estimates related to the demand factors ($\beta_1^1$, $\beta_2^2$) and the forgetting rates ($\delta_1^1$, $\delta_2^2$) at both stages. As we expected, competitive advertising induces a negative effect on demand. Notably, new theatrical and video releases generate a positive and significant lift on video demand. That is, new releases may serve as a prime that activates the broader film category in memory through spreading activation (Neely 1977). This increase in accessibility of the film category prompts higher demand (Higgins, Rhoses, and Jones 1977). Forgetting is positive and significant at both the theater ($\theta_2$ and video ($\theta_1$) stages and within the previously reported range (Naik, Mantrala, and Sawyer 1998). The higher rate of forgetting at the theaters suggests that brand awareness diminishes faster at theaters, perhaps because a higher proportion of theatrical audiences prefer to watch a film at its release.

Next, consider wear-out/wear-in of advertising and WOM at the theatrical stage (Table 2). The significant and positive ad copy wear-out $o_{11}^1$ ($0.959$) and WOM wear-out $o_{21}^1$ ($1.155$) suggest that the effectiveness of advertising and WOM indeed decays with the passage of time. Such decay occurs when audiences become more knowledgeable about the product (Calantone and Sawyer 1978), less interested in the product (Liu 2006) or its ad, or used to other products’ ads with similar contents or rendition techniques (Corkindale and Newall 1978).

**Table 1**

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>AIC</th>
<th>BIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>No dynamic advertising or WOM effectiveness ($q_{12}^1 = q_{12}^2 = q_{22}^1 = q_{22}^2$)</td>
<td>$-7,553$</td>
<td>$-7,072$</td>
</tr>
<tr>
<td>2</td>
<td>No movie ($i$) or stage ($j$) heterogeneity*</td>
<td>$-8,863$</td>
<td>$-8,764$</td>
</tr>
<tr>
<td>3</td>
<td>No movie ($i$) heterogeneity</td>
<td>$-10,592$</td>
<td>$-10,401$</td>
</tr>
<tr>
<td>4</td>
<td>No stage ($j$) heterogeneity</td>
<td>$-11,018$</td>
<td>$-10,700$</td>
</tr>
<tr>
<td>5</td>
<td>Observation, system variances equal across stages ($\sigma_{y1}^2 = \sigma_{y2}^2$, $W_{11}^1 = W_{22}^1$)</td>
<td>$-11,414$</td>
<td>$-10,791$</td>
</tr>
<tr>
<td>6</td>
<td>WOM effectiveness modeled as random walk</td>
<td>$-9,990$</td>
<td>$-9,396$</td>
</tr>
<tr>
<td>7</td>
<td>WOM effectiveness modeled as ad effectiveness</td>
<td>$-12,211$</td>
<td>$-11,560$</td>
</tr>
<tr>
<td>8</td>
<td>No goodwill across stages</td>
<td>$-12,601$</td>
<td>$-11,972$</td>
</tr>
<tr>
<td>9</td>
<td>No ad–WOM interdependence ($q_{13}^0 = 0; q_{23}^0 = 0$)</td>
<td>$-12,694$</td>
<td>$-12,086$</td>
</tr>
<tr>
<td>10</td>
<td>Goodwill spillover as proportional to goodwill at theater release</td>
<td>$-12,774$</td>
<td>$-12,137$</td>
</tr>
<tr>
<td>11</td>
<td>Proposed model</td>
<td>$-17,140$</td>
<td>$-16,532$</td>
</tr>
</tbody>
</table>

*All heterogeneities listed in Table 1 are with respect to the nonstate parameters (e.g., wear-out/wear-in, forgetting, ad–WOM interdependence).
could experience more difficulty navigating and seeking information, thus reducing the WOM effectiveness.

It is now worthwhile to compare the theater and video stage estimates (Table 3). Notably, although repeated advertising wears in at the theater stage, it wears out at the video stage ($w_{T}^{(2)} = 1.023$). In other words, repeated video advertising reduces, not strengthens, its effectiveness. Consistent with the literature, this finding shows that at the video stage, advertising provides limited entertainment or new information, and thus elevated spending does not translate into increased consumer attention or interest (Belch 1982; Cacioppo and Petty 1979; Lodish et al. 1995). This result may partly explain why studios tend to reduce ad spending at the video stage. For example, in our sample, all but two films advertised more at the theater stage than at the video stage.

Another significant result is that although increased WOM activities at the theater stage reduce their effectiveness, the opposite is true at the video stage ($w_{V}^{(2)} > 0$). This may stem from consumers’ increasing reliance on online WOM, instead of advertising, at this stage for information and recommendations (Basuroy, Desai, and Talukdar 2006). Then, more active chattering could also provide a stronger indicator of persistent interests in the film even at a later distribution stage, as well as arrival of wealthier novel information such as behind-the-scenes DVD features.

Ceteris paribus, increased theatrical ad spending not only drives demand directly but also enhances its own effectiveness, builds goodwill, and generates demand by augmenting the WOM effectiveness indirectly. In other words, elevated advertising, the lion’s share of which occurs before release, provides a prime source of information to potential audiences and drives the largest portion of theatrical revenues at opening weekends (Elberse and Anand 2007). After release, strong campaigns continue to convey studio support and fuel the power of WOM. However, repeated video ads offer little novel information and risk aggravating viewers. Thus, the diminishing ad effectiveness or return on ad spending over a product’s life cycle shown in consumer packaged goods (Shankar, Carpenter, and Krishnamurthi 1999) also applies to short-life-cycle new products such as movies over their sequential distributions.

In comparison, more WOM does not mean it is more effective early on. At a later stage, when firm advertising diminishes and online WOM surfing and product purchasing often take place simultaneously, viewers, largely late
adopter, increasingly turn to online WOM for suggestions. As a result, it becomes a more prevalent meter of a product's sustained appeal. More chattering at this stage might also indicate disseminations of new information, such as new formatting, packaging, or pricing at a new stage of distribution, thus increasing the WOM effectiveness. Figure 3 displays examples of the ad (top panel) and WOM (bottom panel) effectiveness at both stages.

Cross-Validation
To investigate whether the proposed model provides useful guidance to studio managers when introducing a new movie, we further conducted a cross-validation analysis. Specifically, we randomly split the 360 movies into an estimation sample of 300 and a holdout sample of 60. We used the estimation sample to calibrate the parameters, which we then used to calculate the mean absolute deviation (MAD) and root mean square error (RMSE) on the holdout sample. We repeat the above steps 100 times and in each repetition employ a new random split of the estimation and holdout samples. These 100 sets of MADs and RMSEs allow us to exploit their variability and test whether they differ across the estimation and holdout samples.

Although, unsurprisingly, the holdout metrics are worse than the estimation metrics, the average difference between the two samples remains small (MAD = 4.29%; RMSE = 10.64%). Further t-tests also show the null hypothesis that the MADs or RMSEs differ across the two samples cannot be rejected (t = .06, d.f. = 198, and t = .99, d.f. = 171, respectively). This analysis offers supportive evidence that the proposed model yields satisfactory forecasting performance and potentially offers valuable guidance to media planning.

Managerial Implications
We now illustrate the applications of the proposed model to potential re-allocations of ad budgets, given the observed budget levels and WOM. In accordance with the current practice that studios manage theatrical releases and home videos through independent divisions, we allocate the theatrical ad budget first; then, given the predicted resulting theatrical demand, we allocate the video ad budget. Specifically, we re-allocate the stage ad budget (b_{i}^{s}) across each week t for film i. The objective is to maximize the total expected log revenues across weeks at this stage \( \sum_{t} E(y_{i}^{s}) \). Thus, we solve the nonlinear optimization problem as follows:
Table 2
PARAMETER ESTIMATES: THEATER STAGE

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Competitive advertising $b_1$</td>
<td>-.002</td>
<td>.013</td>
<td>-.041</td>
<td>.036</td>
</tr>
<tr>
<td>New theater releases $b_2$</td>
<td>-.003</td>
<td>.004</td>
<td>-.012</td>
<td>.007</td>
</tr>
<tr>
<td>New video releases $b_4$</td>
<td>.004</td>
<td>.005</td>
<td>-.002</td>
<td>.011</td>
</tr>
<tr>
<td>Holiday $b_5$</td>
<td>.012</td>
<td>.001</td>
<td>-.033</td>
<td>.056</td>
</tr>
<tr>
<td>Forgetting $g_1$</td>
<td>.028</td>
<td>.022</td>
<td>.005</td>
<td>.053</td>
</tr>
<tr>
<td>Initial goodwill $G_1$</td>
<td>15.252</td>
<td>2.203</td>
<td>10.371</td>
<td>18.145</td>
</tr>
<tr>
<td>Observation variance $\sigma_1^2$</td>
<td>.578</td>
<td>.152</td>
<td>.199</td>
<td>2.466</td>
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<tr>
<td>System variance on goodwill $\sigma_0^2$</td>
<td>.586</td>
<td>.219</td>
<td>.218</td>
<td>2.148</td>
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</table>

**Advertising**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
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<tbody>
<tr>
<td>Copy wear-out $o_1$</td>
<td>.959</td>
<td>.036</td>
<td>.699</td>
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<tr>
<td>Repetition wear-out $w_1$</td>
<td>-.549</td>
<td>.365</td>
<td>-.1613</td>
<td>-.153</td>
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<tr>
<td>Initial effectiveness $q_1$</td>
<td>.008</td>
<td>.053</td>
<td>-.086</td>
<td>.099</td>
</tr>
<tr>
<td>System variance $\sigma_2^2$</td>
<td>.117</td>
<td>.044</td>
<td>.076</td>
<td>.789</td>
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</table>

**WOM**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wear-out $o_2$</td>
<td>1.155</td>
<td>.004</td>
<td>1.089</td>
<td>1.229</td>
</tr>
<tr>
<td>Wear-in $w_2$</td>
<td>-.172</td>
<td>.068</td>
<td>-.305</td>
<td>-.006</td>
</tr>
<tr>
<td>Initial effectiveness $q_2$</td>
<td>-.017</td>
<td>.092</td>
<td>-.189</td>
<td>.183</td>
</tr>
<tr>
<td>System variance $\sigma_3^2$</td>
<td>.117</td>
<td>.049</td>
<td>.053</td>
<td>.349</td>
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</tbody>
</table>

**Ad-WOM Interdependence**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>WOM on ad $\phi_1$</td>
<td>.030</td>
<td>.053</td>
<td>-.102</td>
<td>.156</td>
</tr>
<tr>
<td>Ad on WOM $\phi_2$</td>
<td>.089</td>
<td>.011</td>
<td>.013</td>
<td>.219</td>
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</table>

Table 3
PARAMETER ESTIMATES: VIDEO STAGE

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Competitive advertising $b_1$</td>
<td>-.498</td>
<td>.004</td>
<td>-.644</td>
<td>-.307</td>
</tr>
<tr>
<td>New theater releases $b_2$</td>
<td>.166</td>
<td>.014</td>
<td>.109</td>
<td>.210</td>
</tr>
<tr>
<td>New video releases $b_4$</td>
<td>.136</td>
<td>.014</td>
<td>.082</td>
<td>.179</td>
</tr>
<tr>
<td>Holiday $b_5$</td>
<td>.037</td>
<td>.006</td>
<td>-.046</td>
<td>.134</td>
</tr>
<tr>
<td>Forgetting $g_1$</td>
<td>.016</td>
<td>.003</td>
<td>.008</td>
<td>.046</td>
</tr>
<tr>
<td>Initial goodwill $G_1$</td>
<td>15.082</td>
<td>1.239</td>
<td>12.169</td>
<td>16.988</td>
</tr>
<tr>
<td>Observation variance $\sigma_1^2$</td>
<td>.938</td>
<td>.134</td>
<td>.239</td>
<td>6.265</td>
</tr>
<tr>
<td>System variance on goodwill $\sigma_0^2$</td>
<td>3.498</td>
<td>1.539</td>
<td>.919</td>
<td>12.919</td>
</tr>
</tbody>
</table>

**Advertising**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Copy wear-out $o_1$</td>
<td>1.124</td>
<td>1.194</td>
<td>-.949</td>
<td>3.142</td>
</tr>
<tr>
<td>Repetition wear-out $w_1$</td>
<td>1.023</td>
<td>.002</td>
<td>.592</td>
<td>1.368</td>
</tr>
<tr>
<td>Initial effectiveness $q_1$</td>
<td>.022</td>
<td>.015</td>
<td>.009</td>
<td>.061</td>
</tr>
<tr>
<td>System variance $\sigma_2^2$</td>
<td>.281</td>
<td>.036</td>
<td>.091</td>
<td>1.457</td>
</tr>
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</table>

**WOM**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wear-out $o_2$</td>
<td>1.133</td>
<td>.025</td>
<td>1.051</td>
<td>2.126</td>
</tr>
<tr>
<td>Wear-in $w_2$</td>
<td>.185</td>
<td>.001</td>
<td>.013</td>
<td>.298</td>
</tr>
<tr>
<td>Initial effectiveness $q_2$</td>
<td>.050</td>
<td>.019</td>
<td>.033</td>
<td>.080</td>
</tr>
<tr>
<td>System variance $\sigma_3^2$</td>
<td>.177</td>
<td>.031</td>
<td>.071</td>
<td>.625</td>
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</tbody>
</table>

**Ad-WOM Interdependence**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>SD</th>
<th>2.5th HPDI</th>
<th>97.5th HPDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>WOM on ad $\phi_1$</td>
<td>.109</td>
<td>.023</td>
<td>-.125</td>
<td>.242</td>
</tr>
<tr>
<td>Ad on WOM $\phi_2$</td>
<td>-.018</td>
<td>.018</td>
<td>-.122</td>
<td>.099</td>
</tr>
</tbody>
</table>

(8) \[
\max \sum_t \sum_s E(y^{(s)}_t), \text{ s.t. } \sum_s A^{(s)}_t \leq b^{(s)}_t \text{ and } A^{(s)}_t \geq 0.
\]

Note that the solution is not necessarily a global optimum but nevertheless proposes a more efficient ad allocation. In other words, the revenue improvement as a result of this exercise represents a conservative estimate of the potential revenue improvement.

Figure 4 displays the average observed and recommended weekly ad spending across all films in the sample at the theater (top panel) and video (bottom panel) stages, respectively. Consistent with Horsky and Simon (1983) and Mahajan, Muller, and Kerin (1984), optimal advertising begins high when a new product is introduced and decays over time. Specifically, at the theatrical stage, our optimization shows that nearly all films in the sample could reallocate their ad budgets to increase the total log revenues by 1%–15%. In addition to obtaining a new weekly allocation scheme, the weekly spending can be aggregated to shed additional light on the pre- versus postrelease budget split. For example, the new plan suggests that 55% of the films designate a higher-than-currently-observed portion of their budgets before release, while the remaining films benefit from the opposite. Further regression analysis reveals that several factors contribute to the heterogeneous allocation recommendations. For example, critics’ favorites such as Fahrenheit 9/11 and Ray could allot a greater-than-present share of the budget prerelease, potentially to take advantage of their theatrical performance.
of the high-quality cast, performance, and plot in their ads to stage a strong opening weekend and then enjoy the push from positive WOM after release. In contrast, action films such as *Agent Cody Banks* and *Flight of the Phoenix* may be better-off reducing the percentage of prerelease ad spending. This is consistent with our finding that repeated ads for action films wear out the audiences and thus potentially undermine the opening weekend box office (see Web Appendix B at www.marketingpower.com/jmr_webappendix).

Similarly, at the video stage, when the actual or predicted theatrical revenue is revealed, all but 10% of the films in the sample could garner extra total log revenues by 1%-16%. For example, 44% of the films in the sample could allocate a higher-than-current-share of their video ad budgets before release. Intuitively, those with higher cumulative theatrical revenues, such as *Finding Nemo* and *Cold Mountain*, could shift more ad dollars than present levels from pre- to post-video release. This is potentially because the public are more likely to be aware of and remember these films from the theatrical stage, and thus less advertising is needed before these films’ video releases (for additional illustrations of these results, see Web Appendix C at www.marketingpower.com/jmr_webappendix).

Next, given the recent discussions in Hollywood about possibly coordinating the media planning between the theater and video stages (Zeidler 2010), we also conducted a one-step exercise to allocate the total theater-plus-video ad budget. Our analysis shows that, if the two stages are indeed coordinated, 95% of the movies in our sample could enjoy greater overall theatrical and video revenues, with 1%-18% increases in the total log revenues. This exercise also illustrates the ready applications of the proposed approach to other industries that coordinate media planning across sequential stages of distribution.

Furthermore, because the industrial rule of thumb of setting the ad budget to one half the production cost (Quelch, Elberse, and Harrington 2010, p. 9) is not necessarily optimal, we relax the budget constraint in Equation 8 and investigate whether different ad budgets may be allocated at each stage.4 Specifically, at the theater stage, because the average revenue-to-ad ratio is 3, we vary the ad budget from 10% to 300% of the observed budget for each film in incre-

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4We thank the associate editor and an anonymous reviewer for their suggestion to examine alternative levels of ad budgets and the relationship between the sizes of the theater-to-video window and the ad budgets.
ments of 10%. At each budget level, we then reconduct the entire optimization exercise. We further link the recommended budget level of each film to its characteristics such as genre and critics' reviews. The results show that 29.4% of the films in the sample could allocate less than observed theatrical ad budget, whereas 69.2% could increase the budget to accrue greater revenues. In particular, films attracting a large number of critics' reviews, such as *21 Grams*, and science fiction films, such as *The Day After Tomorrow*, are more suited for an augmented ad budget. These results are consistent with our findings that (1) a larger number of critics' reviews forestall forgetting, potentially because films attracting more critics' reviews also enjoy broader and prolonged public awareness, appeal, and fascination and (2) science fiction films enjoy an increased advertising wear-in (Web Appendix B at www.marketingpower.com/jmr_webappendix). In other words, advertisers for films that enjoy reduced forgetting and increased ad wear-in could consider allocating more ad budgets at the theater stage.

We executed a similar analysis at the video stage. The results show that 16.9% of films could designate a lower-than-observed video ad budget, and 72.8% could designate a higher budget. Intuitively, films that enjoy greater cumulative theatrical revenues, such as *Meet the Fockers*, could allocate higher ad budgets at the video stage. These additional exercises further illustrate the managerial usefulness of the proposed framework. Not only can we improve a film's week-to-week (or aggregately, pre- vs. postrelease) allocation of the current ad budget, we can also determine whether a better overall budget level exists. Both provide valuable decision tools to managers.

Last, given the industrial trend of shrinking the size of the theater-to-video window (varying from 10 to 62 weeks, with an average of 21.3 weeks in our sample), we take three steps to explore how the window size may be related to more efficient ad budget allocations. First, we conduct regression analyses of the observed ad budgets on window sizes. The results show that a shorter window, after controlling for other movie characteristics, is associated with (1) a lower video ad budget both in absolute dollar value and as a percentage of the theater-plus-video ad budget and (2) a lower prerelease video ad budget both in absolute dollar value and as a percentage of the video ad budget. Second, running similar regressions of the recommended ad spending on window sizes, we draw identical conclusions. Note
that the recommended video ad spending used to draw conclusion 1 results from the one-step ad allocation across the theater and video stages and that used to draw conclusion 2 results from the theater-then-video two-step ad allocation exercise. Third, we further conduct regression analyses of the recommended minus observed ad budgets on window sizes while controlling for movie characteristics. Again, we find that a shorter window is associated with a recommendation of a less-than-observed percentage of the theater-and-video ad budget allocated to the video stage and a less-than-observed percentage of the video ad budget allocated to pre-video release period.

All these results are statistically significant at the \( p < .05 \) level. Overall, these findings make intuitive sense because viewers tend to remember a film and its theatrical advertising better when the video is released sooner. In other words, the residual goodwill from the end of the theater stage tends to be higher for films with faster video releases. Thus, less prerelease video advertising and less overall video ad spending are needed. Notably, these results provide additional support to the industrial trend of shortening the theater-to-video window.

Managerial Misallocation or Model Misspecification

The preceding analysis illustrates the potential benefits of improved media planning. However, managers applying the proposed method need to bear in mind that any new allocation is associated with a specific modeling framework. For example, if the model is misspecified or a different framework, such as that which Naik, Prasad, and Sethi (2008) implement, the ensuing recommendations regarding, for example, specific budget levels or particular percentages of pre versus postrelease split of a stage budget, could vary. As such, further research comparing different modeling paradigms will illuminate more definitive recommendations on media planning.

Nonetheless, the stated effort illustrates the value of gauging dynamic ad and WOM effectiveness over sequential distributions of new products. It also demonstrates that opportunities exist for more efficient allocations of resources. For many industries relying on sequential distributions (the film industry alone spends $34 billion in domestic theaters and videos), the suggested improvement could lead to substantial economic benefits.

CONCLUSION

Sequential distribution or releasing new products in multiple stages is vital to the profitability of many industries—publishing, fashion, art, music, motion picture, and technology being a few exemplars. To help achieve these profits, firms often launch separate advertising campaigns at each distribution stage, in which consumer WOM may also influence demand. In this study, we construct a model to quantify the dynamic effects of advertising and WOM due to forgetting, wear-out/wear-in, and ad–WOM interdependence while accounting for spillover across stages and heterogeneity across stages and product. We estimate the proposed state-space model, applied to the theater-then-video distribution of films, with Kalman filtering/smoothing nested within MCMC methods. As a result, we are able to investigate a crucial yet underexplored area—namely, the dynamic effects of advertising and WOM on the demand for sequentially distributed products—and the implications of these effects on media planning.

We believe that several novel findings emerge from this work. First, it supplies empirical evidence that the dynamic, and largely diminishing, impact of advertising on demand operates not only for mature categories (Bruce 2008; Naik, Mantrala, and Sawyer 1998) but also for new products over their sequential distributions. Second, in addition to the commonly observed repetition wear-out of advertising, wear-in can also take place for new products such as movies. In other words, repeated advertising with entertaining and informational value could increase, not decrease, advertising effectiveness. Third, advertising and WOM

5We thank another anonymous reviewer for suggesting the addition of this discussion.
exert independent yet interdependent influences on demand. Consequently, advertising promotes demand through multiple avenues, both directly and indirectly through enhancing the ad and WOM effectiveness. Fourth, the influence of advertising and WOM exhibits distinct patterns: Whereas higher ad spending increases the ad effectiveness at the theater but not video stage, the reverse is true for increased WOM activities. Finally, although our study focuses on the movie industry, the findings underscore the value of investigating cross-communication (ad and WOM), cross-stage (dynamic), and cross-product (heterogeneous) effects. It also suggests that opportunities exist for more efficient media planning in industries that profit from sequential distributions. The proposed conceptual and modeling frameworks also generalize to these industries.

Notwithstanding these contributions, this research has limitations that could lead to future inquiries. For example, we examine advertising and WOM here given the observed release timing. Further research could jointly examine advertising, WOM, and release-timing decisions. A deeper understanding might then result with regard to, for example, how a shorter gap between stages may alter the ad and WOM effectiveness and, thus, media budgeting. Furthermore, the proposed model and the ad budgeting exercises are conditional on the observed WOM and online WOM solely. Future studies could investigate different measures of online and offline WOM, their dynamic formations over multiple distribution stages, and their relationship with other aspects of consumer behavior, such as observational learning, or firm decisions, such as participation in stimulating WOM (Godes and Mayzlin 2009) or whether to provide review platforms (Chen, Wang, and Xie 2011; Chen and Xie 2008).

REFERENCES


Dynamic Effectiveness of Advertising and Word of Mouth


