Forecasting Marketing Mix Responsiveness for New Products

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Abstract

Prior to a new product launch, marketers need to infer how demand will respond to various levels of marketing mix variables in order to set an appropriate marketing plan. A critical challenge in estimating marketing mix responsiveness from historical data is that the observed decisions were affected by private information possessed by managers about the heterogeneous effects of marketing mix variables on sales. We refer to this as the "slope endogeneity" problem. Such endogeneity differs from the “intercept endogeneity” problem, which has been widely acknowledged in the literature. To correct for the slope endogeneity bias, we develop a conceptually simple control function approach that is amenable to multiple endogenous variables and marketing mix carryover effects. We apply the method to forecasting advertising responsiveness in the U.S. DVD market. Results suggest that advertising responsiveness varies substantially across DVD titles and that estimated marketing mix elasticities would be seriously biased if the slope endogeneity problem were ignored. This analysis also yields findings of substantive interest to researchers and managers involved in entertainment marketing.

Key Words: Advertising Budgeting; Marketing Mix Modeling; New Product Introduction; Endogeneity; DVD

Successfully introducing new products or services to the market is vital to the long-term growth of a company (Kotler and Keller 2006). Prior to a new product launch, marketers create marketing programs to maximize the chance of success. This is often a challenging managerial decision because, in order to set the appropriate pricing levels as well as advertising and promotion budgets, managers need to have reliable estimates as to how sales would respond to different levels of a marketing mix variable. In other words, they have to forecast the market responsiveness to various marketing mix variables in the absence of any actual sales data. While there is a substantial literature on new product sales forecasting, there has been scant research related to forecasting marketing mix responsiveness before a new product launch.

To obtain a forecast of how the market will respond to a marketing mix variable, for instance, advertising, one can identify how products with similar attributes historically responded to advertising and then use the model to make a prediction for a new product. A particular methodological challenge in inferring advertising elasticities from historical sales response data is the endogeneity of observed advertising levels. That is, even after controlling for multiple covariates that could affect sales and advertising budgets, (econometrically) unobserved characteristics may still exist (i.e., private information observed and used by that managers to set advertising levels for a particular product). The presence of such private information complicates the task of leveraging data from past product releases to forecast marketing mix responsiveness for new products.

We argue that this endogeneity problem is actually broader than the correction offered by the standard instrumental variable approach, a common method for treating price endogeneity (e.g., Berry et al. 1995; Villas-Boas and Winer 1999; Nevo 2001). For instance, in a simple linear sales response function, $S = \alpha - \beta P$, where P is price and S sales, extant research assumes that econometrically unobserved factors affect the demand level linearly (i.e., intercept α) but not marketing mix responsiveness (i.e., price coefficient β). This assumption may be valid in a market in which marketing mix variables have relatively homogenous effects on demand, but it is problematic in general. A supermarket chain might charge a higher price in markets in response to econometrically unobserved higher preferences for the chain (captured by α) in such markets (i.e., *intercept endogeneity*), but the chain manager's private information about the lower price sensitivity of a market (captured by β) also might lead to a higher than expected price (i.e., *slope endogeneity*). Marketing researchers have paid ample attention to the former problem but little to the latter.

We therefore develop a control function approach based on previous studies in labor economics and econometrics (e.g., Garen 1984; Wooldridge 1997) to address the slope endogeneity issue (in addition to intercept endogeneity). We extend the basic control function model to solve the marketing mix responsiveness forecasting problem. The slope endogeneity issue was independently addressed in Manchanda, Rossi and Chintagunta (2004) and in Petrin and Train (2008). Given their interest in physician-level responsiveness to detailing, Manchanda et al. adopted a hierarchical Bayesian approach using each physician's past prescription and detailing information. Petrin and Train introduced a control function approach for discrete choice models. In comparison, our approach is specifically suitable for the marketing mix responsiveness forecasting problem: it can be estimated with cross-sectional or panel data at the aggregate (product-market) level; it is flexible enough to accommodate multiple endogenous variables and advertising carryover effect; it is also computationally simple and can be easily implemented with commonly used statistical packages with linear regression. As a result, we expect this approach to be widely applied in future work.

We illustrate the approach using data from the U.S. DVD market. Since DVD technology was commercially introduced in 1997, the DVD software market has become an indispensable revenue source for the movie industry. In 2008, DVDs accounted for $21.6 billion in sales and rentals, whereas box office revenues totaled only $9.85 billion. However, the DVD market has received little attention in academic research compared with the extensive literature focused on theatrical movies (e.g., Sawhney and Eliashberg 1996; De Vany and Lee 2001; Eliashberg et al. 2006). By examining the sales drivers and marketing mix effects of the DVD market, we extend the literature in entertainment industry marketing. Further, the empirical setting is ideal to address our research objective because managers in the DVD market are frequently confronted with the challenging task of forecasting marketing mix responsiveness prior to each new DVD release.

An important characteristic of entertainment products such as movies and DVDs is that they have remarkably short lifecycles: demand usually peaks upon product launch and decays exponentially afterwards. Given that the majority of demand occurs within a few weeks, marketers need to make critical advertising (and other marketing mix) decisions before the product is launched because there is little room for post-launch adjustments. Thus a reliable forecast of marketing mix responsiveness is particularly important for short lifecycle products. It should be noted that a large number of product categories such as movies, video games, popular fiction, music albums and fashion goods have short lifecycles.

[Insert Figure 1 about here]

Our key contributions are both methodological and substantive. Methodologically, we address the issue of slope endogeneity and develop a flexible, easy-to-implement estimation approach for multiple endogenous variables (i.e., advertising, release timing, and retail price herein), for which managers may possess private knowledge about marginal returns. Substantively, we introduce the problem of marketing mix responsiveness forecasting to aid marketers' new product launch planning decisions and illustrate the approach with the first empirical analysis of the DVD market. We find that release-week advertising elasticities vary substantially across titles, from as much as .14 to as little as .02, suggesting the forecasting exercise is useful. An optimal advertising schedule based on the model estimates improves profits by 12% on average.

The rest of this article is organized as follows: In the next section, we introduce the data and generate hypotheses about the moderators of advertising responsiveness. Subsequently, we introduce the problem of slope endogeneity and discuss an estimation approach to solve this problem. Finally, we present the results and discuss some future research directions.

DATA AND HYPOTHESES

Data

Our calibration sample includes newly released movie DVDs introduced between January 3, 2000 and October 14, 2003. Theatrically, the movies in the sample opened between June 1999 and June 2003. We exclude DVD titles with box office revenues of less than $5 million, because such films typically are small-budget movies targeted at niche audiences and are marketed differently than Hollywood feature films (e.g., independent distributors typically cannot afford television advertising). For each DVD title, we collect data about box office variables (opening date, number of exhibition screens, revenues, and advertising expenditures), DVD variables (release date, weekly retail price and sales, television GRPs, content enhancements, and distributors), and movie attributes (production budget, genre, Oscar nominations, star power, MPAA rating, production cost, and critical reviews). We also collect monthly data about DVD player penetration rates in the United States to control for the effect of the growing hardware base on software sales. In Table 1, we provide the key descriptive statistics of the sample. Table 2 offers a description of the variables we use in the empirical application.

[Insert Table 1 and Table 2 about here]

Moderators of Advertising Responsiveness

The basic idea behind forecasting advertising responsiveness entails examining how similar products introduced previously responded to varying levels of advertising and then using this to make predictions about a new product. Despite vast research devoted to measuring the effects of advertising on sales, few studies examine the product-specific factors that affect demand responsiveness to advertising. In other words, what factors magnify or attenuate advertising effectiveness for a product? Empirical work that examines such moderators (Batra et al. 1995; Lodish et al. 1995) largely focuses on implementation tactics (e.g., advertisement copy design, media usage) or contextual elements (e.g., category or brand development stages), which offer limited guidance to marketers like movie studios who need to solve their upfront advertising budgeting problems for each individual new product.

Consistent with our objective to generate advertising responsiveness forecasts, we propose hypotheses pertaining to the product-specific characteristics that may influence advertising effectiveness in the DVD market, which we summarize in Table 3. In particular, we posit that advertising elasticity declines from week to week in for DVDs. Previous research in consumer packaged goods industries shows that advertising effectiveness diminishes over the product lifecycle (Shankar et al. 1999). This effect presumably is even stronger for short lifecycle products. Quantifying time-varying advertising effectiveness therefore has important implications for studios' optimal DVD advertising scheduling.

Consumer word of mouth (WOM) may have either positive or negative effects on advertising responsiveness, because these two forms of product-related communication may be either complements or substitutes. That is, a consumer's exposure to interpersonal recommendations from friends and acquaintances could either make advertising exposure superfluous (especially if both exposures are purely informational) or cause the consumer to pay greater attention and attach more credibility to advertising (if advertising also has a persuasive effect). Marketing researchers have begun to measure consumer WOM communication and empirically infer its role in influencing sales (e.g., Chevalier and Mayzlin 2006), but no existing study examines how WOM and advertising interact to influence consumers' purchase decisions. Should the firm invest more or less in advertising for a product if that product has received overwhelmingly positive WOM (versus negative WOM) from consumers? We empirically test these two competing hypotheses using data from the DVD market.

[Insert Table 3 about here]

We expect theatrical movie advertising to serve as a substitute for DVD advertising, because advertising in these two sequential channels likely serve similar functions. Furthermore, lower retailer price should magnify market response to advertising, as has been documented for consumer packaged goods (Batra et al. 1995; Kaul and Wittink 1995). A movie's box-office sales may have a negative effect on advertising elasticity. Because movies are experience goods, consumers who have viewed them in theaters rely more on their own experience than on DVD advertising to make their DVD purchase decisions, an experience-dominant effect reported by Ackerberg (2003). Therefore, a greater proportion of experienced consumers in the market should result in lower advertising responsiveness.

The presence of DVD content enhancements (e.g., "behind-the-scenes" documentaries, deleted footage and alternative endings), often prominently featured in DVD advertisements, should increase advertising effectiveness. Finally, we expect the market to be more responsive to DVD advertising during high-demand seasons (e.g., Christmas, Valentine's Day for romantic DVDs), when sales should be more elastic because of the effects of gift buying.

MODEL AND ESTIMATION

Slope Endogeneity Problem

Even after identifying a set of product characteristics that may help us forecast advertising responsiveness, we still face a methodological challenge in estimating the coefficients related to advertising elasticities due to the slope endogeneity problem. Below we introduce this general problem in the context of cross-sectional data and discuss a two-stage control function estimator. We then tailor this approach to our empirical setting with panel data, incorporating the advertising carryover effect and retailer price endogeneity.

Let S_j be the market outcome variable and x_j be the vector of exogenous explanatory variables. A_j and L_j are the two marketing mix variables that affect market outcomes with potential endogeneity problems. (We use notations consistent with our empirical application, to be detailed in the next section, where S_j becomes the logarithm of DVD sales of title j; x_j consists of exogenous variables affecting DVD sales, such as box office revenues and DVD features; A_j becomes the level of advertising goodwill; and L_j is the delay in DVD release.)

Suppose the sales equation that we seek to estimate takes the form:

(1) $$S_j = x_j{}'\beta + \gamma_j^A A_j + \gamma_j^L L_j + \varepsilon_j .$$

The coefficients γ_j^A and γ_j^L are random coefficients composed of a systematic observed component (i.e., function of observed covariates) and an econometrically unobserved component:

(2) $$\gamma_j^A = w_j^{A\prime}\theta^A + \phi_j^A \text{, and}$$

(3) $$\gamma_j^L = w_j^{L\prime}\theta^L + \phi_j^L ,$$

where w_j^A and w_j^L are vectors of observed moderators (including a constant) that influence the marginal effects of *A* and *L* on *S*, respectively. Typically, such moderators also have a direct effect on *S*, so w_j^A and w_j^L are subsets of x_j. With the assumption that the conditional expectations of γ_j^A and γ_j^L are linear in w_j^A and w_j^L, respectively, we have

(4) $$E[\gamma_j^A \mid x_j, w_j] = w_j^{A\prime}\theta^A \text{, and } E[\gamma_j^L \mid x_j, w_j] = w_j^{L\prime}\theta^L ,$$

and therefore can use consistent estimates of θ^A and θ^L to form forecasts, $\hat{\gamma}_j^A$ and $\hat{\gamma}_j^L$, the expected marginal effects of marketing mix variables. (The linearity assumption is not necessarily restrictive, because higher-order terms of the covariates can be included in w_j^A and w_j^L.) By definition,

(5) $$E[\phi_j^A \mid x_j, w_j] = 0 \text{, and } E[\phi_j^L \mid x_j, w_j] = 0 .$$

Substituting Equations (2) and (3) into Equation (1), we obtain

(6) $$S_j = x_j{}'\beta + (w_j^{A\prime}\theta^A)A_j + (w_j^{L\prime}\theta^L)L_j + (\phi_j^A A_j + \phi_j^L L_j + \varepsilon_j) .$$

In the standard random-coefficients model, ϕ_j^A and ϕ_j^L are assumed to be random draws from a population with density $F(\phi)$, which is *independent* of the observed variables including A_j and L_j. With the further assumption that the unobserved demand shifter, ε_j, is conditionally mean independent of observables, we derive

(7) $$E(\phi_j^A A_j + \phi_j^L L_j + \varepsilon_j \mid A_j, L_j, x_j, w_j) = 0 ,$$

and we can estimate the model parameters consistently using ordinary least squares (OLS).

However, problems arise when these assumptions are violated, such as when the decision maker has private information about $(\phi_j^A, \phi_j^L, \varepsilon_j)$, the econometrically unobserved components, and uses that information to choose the levels of the endogenous variables (A_j , L_j). For example, a person tends to know more about the marginal return of education on his or her earning potential than does a researcher and consequently may invest more or less time in education. Similarly, marketing managers may have partial knowledge about how the market will respond to advertising for a particular product, based on their past experience or market research, and this knowledge affects the actual advertising budget they establish. In such cases, the decision maker's marketing mix choice correlates with econometric unobservables (both linear and nonlinear) in the demand equation.

The endogeneity problem has a long tradition in marketing research (e.g., Bass 1969). However, the endogeneity issue in our context goes beyond the standard price endogeneity problem studied extensively in economics and marketing literature (e.g., Berry et al. 1995; Villas-Boas and Winer 1999; Chintagunta 2001). In these studies, the endogenous variable (usually price), is allowed to be correlated with ε_j in Equation (6), which captures the heterogeneity that affects sales *regardless of the levels of endogenous variables*, and the standard instrumental variable (IV) estimator can be used to correct the potential bias. We refer to this type of problem as intercept endogeneity and note that it fails to consider the potential endogeneity arising from the correlation between the slope coefficients and the marketing mix variables, which itself results from what Bjorklund and Moffitt (1987) call the "heterogeneity of rewards." To address the latter case, which we refer to as *slope endogeneity*[1], we allow the

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[1] The term "slope endogeneity" was first used by Villas-Boas and Winer (1995) in the marketing literature but their work was focused on treating the linear, or additive, endogeneity.

unobserved marginal effects (ϕ_j^A and ϕ_j^L) to influence the decision variables A_j and L_j. In the presence of slope endogeneity, not only is the OLS estimator inconsistent, but the standard IV estimator also is (e.g., Verbeek and Nijman 1992; Heckman 1997).

Control Function Approach to Endogeneity Correction

Although the slope endogeneity problem has received little attention in the marketing literature, researchers in labor economics have often been faced with this problem when estimating the return to a particular choice, such as education, employment, or union membership. The well-known Heckman-Lee approach can solve the self-selection problem when the endogenous variable is binary (Heckman 1976; Lee 1978), but this procedure cannot be applied to situations in which the endogenous variables are continuous (e.g., duration of schooling, the quantity of advertising exposures). Garen (1984) proposes a control function procedure to correct for the endogeneity bias in continuous variables in cross-sectional data and uses it to estimate the return to schooling. We relax some of the restrictive assumptions of Garen's model and extend it to incorporate multiple endogenous variables (potentially set by different decision makers, such as manufacturers and retailers), the advertising carryover effect, and panel data. Below we briefly illustrate this model in a cross-sectional context; in the next section, we tailor the model to our empirical setting.

Suppose there exists a set of exogenous (or predetermined) variables, collected in z_j, that influences the firm's choice of endogenous variables:

(8) $$A_j = z_j{}'\lambda^A + \eta_j^A \text{, and}$$

(9) $$L_j = z_j{}'\lambda^L + \eta_j^L .$$

Note that $\phi_j \equiv (\phi_j^A, \phi_j^L, \varepsilon_j)'$ and $\eta_j \equiv (\eta_j^A, \eta_j^L)'$, and suppose the following assumptions hold:

(A1) $$E(\eta_j \mid z_j) = 0 \text{, and}$$

(A2) $$E(\phi_j \mid z_j, \eta_j) = E(\phi_j \mid \eta_j) = \Gamma \eta_j .$$

Assumption A1 implies that η_j has zero conditional mean; it holds as long as the model is specified correctly; that is, the conditional expectations of A and L are linear in z. A2, the key identifying assumption, assumes that ϕ_j is conditional mean independent of z_j given η_j, which is automatically satisfied if z_j is independent of ϕ_j. It also assumes $E(\phi_j \mid \eta_j)$ is linear in η_j (Γ is a 3 × 2 matrix of coefficients that characterize the linear mapping from η_j to $E(\phi_j \mid \eta_j)$). The second part of this assumption does not have to be restrictive; $E(\phi_j \mid \eta_j)$ potentially may be a polynomial approximation that includes higher-order terms of η_j. Assumption A2 is weaker than the bivariate normal distribution assumption imposed on (η_j, ϕ_j) by Garen (1984). Notice that it follows from (A1) and (A2) that $E(\phi_j \mid z_j) = 0$.

This specification allows the coefficients for A_j to be correlated with observed L_j and vice versa, which represents a desirably flexible formulation because firms usually design their marketing mix variables simultaneously rather than singularly. With these assumptions,

(10) $$\begin{aligned} E(\phi_j^A \mid A_j, L_j, x_j, \eta_j) &= E[E(\phi_j^A \mid A_j, L_j, z_j, x_j, \eta_j) \mid A_j, L_j, x_j, \eta_j] \\ &= E[E(\phi_j^A \mid z_j, \eta_j) \mid A_j, L_j, x_j, \eta_j] \\ &= E[g_{1,1}\eta_j^A + g_{1,2}\eta_j^L \mid A_j, L_j, x_j, \eta_j)] \\ &= g_{1,1}\eta_j^A + g_{1,2}\eta_j^L \end{aligned} ,$$

where the second equation follows because (A_j, L_j, x_j) are functions of (z_j, η_j). $g_{1,1}$ and $g_{1,2}$ are the first-row elements of Γ. It follows that

(11) $$E(\phi_j^A A_j + \phi_j^L L_j + \varepsilon_j \mid A_j, L_j, x_j, \eta_j) = (A_j, L_j, 1)\, \Gamma \eta_j .$$

Because $E[\eta_j \left| A_j, L_j \right.] \neq 0$, the OLS estimator is inconsistent, but if we first obtain consistent estimates for η_j from a first-stage estimation of Equations (8) and (9) and then use the resulting estimates, $\hat{\eta}_j$'s, to replace η_j's in the sales equation, we should be able to obtain consistent estimates for the demand equation parameters. In the case of two endogenous variables, Equation (6) can be rewritten as

$$\begin{aligned} S_j &= x_j{}'\beta + (w_j^{A\prime}\theta^A)A_j + (w_j^{L\prime}\theta^L)L_j + g_{1,1}\hat{\eta}_j^A A_j + g_{1,2}\hat{\eta}_j^L A_j \\ &\quad + g_{2,1}\hat{\eta}_j^A L_j + g_{2,2}\hat{\eta}_j^L L_j + g_{3,1}\hat{\eta}_j^A + g_{3,2}\hat{\eta}_j^L + \tilde{\varepsilon}_j. \end{aligned} \tag{12}$$

Note that the standard IV estimator does not eliminate endogeneity bias: even assuming $E(\phi_j \mid z_j) = 0$, the endogeneity problem persists unless $E(\phi_j^A A_j + \phi_j^L L_j \mid z_j)$ is orthogonal to z_j, which is generally untrue without further conditional homoskedasticity assumptions (Heckman and Vytlacil 1998).

Empirical Specification of DVD Sales

In this subsection, we tailor the model to our empirical application with panel data and show how the framework easily accommodates the advertising carryover effect. Suppose we have a panel of *J* DVD titles, each with *T* weeks of sales and marketing mix data. Equation (6) thus can be written as:

$$\ln S_{jt} = x_{jt}{}'\beta + (w_{jt}^{A\prime}\theta^A)A_{jt} + (w_j^{L\prime}\theta^L)L_j + (\phi_j^A + \Delta\phi_{jt}^A)A_{jt} + \phi_j^L L_j + \varepsilon_j + \Delta\varepsilon_{jt}, \tag{13}$$

where S_j is the unit sales of DVD title *j* in week *t*, x_{jt} is the vector of exogenous explanatory variables that affect weekly sales (e.g., DVD characteristics, competition), A_{jt} is the level of advertising goodwill for title *j* in week *t*, and L_j is the lag between DVD *j*'s release and its initial theatrical opening. Advertising goodwill is time-variant, but release delay is not. Finally, $\Delta\phi_{jt}^{A}$ and $\Delta\varepsilon_{jt}$ capture the weekly deviations from the title-specific mean errors ϕ_{j}^{A} and ε_{j}.[2]

Studio's decision variables. Here we focus on two decision variables set by studios for each DVD titles: (1) advertising, A_{jt}, and (2) DVD release delay, L_j. (We discuss how to model retailers' pricing decisions subsequently.) Advertising goodwill stock, A_{jt}, is a discounted sum of the weekly advertising levels (in logs):

$$A_{jt} = \sum_{\tau=1}^{t} \delta^{\tau-1} \ln(AD_{j\tau}), \tag{14}$$

where AD_{jt} is television advertising GRPs for DVD title *j* in week *t*. Due to the presence of zero advertising, we add 1 to all advertising GRPs to ensure this measure is well defined. Note that this carryover structure allows for pre-release advertising to enter the sales model.

Although the effect of advertising on sales is well known, few sales response models have captured the effect of product release timing. However, the institutional structure of the motion picture industry necessitates incorporating DVD release timing into the sales function. A DVD typically gets released four to eight months after the movie opens in theaters. Such inter-release delays have evolved as a convention among movie studios to protect the revenues from theatrical releases. The length of the delay may influence DVD demand, because, as is widely acknowledged in the industry, the faster the DVD release, the higher consumers' awareness and purchase intent. The coefficient of L_j is intended to capture the degree to which a movie's "buzz" at the box office dissipates when the DVD release gets postponed.

[2] Note that past sales are not included in the model. Models that use past sales to explain current sales typically use it as a proxy for certain underlying mechanisms when direct measures of these mechanisms are unobtainable, such as consumer word of mouth, advertising carryover, and unobserved demand shifters. Since our model incorporates most of these structural variables, it would be superfluous to include past sales in the model. Doing so would also be impractical for our forecasting task (since no past sales data are available prior to launch).

We formulate an empirical measure for L_j that adjusts for the varying patterns of theatrical performance by using the log of the number of days between when the theatrical movie gains 75% of its total box office revenue and when the DVD is released. Because our data contain only weekly (i.e., discrete-time) box office receipts over the first nine weeks (i.e., right-truncated), we estimate the 75 percentile thresholds using a two-parameter Weibull density function and use the resulting estimates to construct L_j:

(15) $$f_j(t \mid p_j, q_j) = \frac{p_j}{q_j} t^{p_j - 1} e^{-t^{\frac{p_j}{q_j}}},\ t \geq 0, p_j > 0, q_j > 0.$$

Instruments. Suppose the studio's advertising and timing decisions for DVD *j* are influenced by a set of pre-determined variables, z_{jt}. We can write

(16) $$\ln(AD_{jt}) = z_{jt}{}'\lambda^A + \eta_j^A + \Delta\eta_{jt}^A; \text{ and}$$

(17) $$L_j \equiv \ln(DELAY_j) = \overline{z}_j{}'\lambda^L + \eta_j^L,$$

where z_{jt} includes all exogenous variables in x_{jt} (not including retail price, which itself may be endogenous) and a set of excluded variables that affect the supply-side (i.e., distributor's advertising and timing) decisions but not the unobserved heterogeneity components in the demand equation. Note that the advertising decision is made each week while the release timing decision is made once for each DVD. Accordingly, $\overline{z}_j$ includes the across-week mean for each element in z_{jt}. η_j^A is the disturbance common to all observed advertising levels for title *j*, $\Delta\eta_{jt}^A$ is the mean-zero week-specific deviation from the mean, and η_j^L is the disturbance associated with the release delay for DVD *j*.

A natural source of the exclusion variables comes from supply-side factors such as advertising costs and interest rates. If studio *f* enjoys lower advertising costs for DVD *j*, its observed advertising level would likely reach higher than that for another DVD of similar characteristics; however, such supply-side shocks should not affect consumer behavior. We therefore include the following exclusion variables in z_{jt}: (1) studio dummies, (2) production costs, (3) number of screens during the movie's theatrical run, (4) holiday-season release-clustering indicators, and (5) interaction terms of these instruments with the variables in x_{jt}. We explain the rationale behind each set of instruments next.

The DVD market is an oligopolistic market, dominated by a number of major distribution labels, such as Warner Home Videos (owned by Warner Brothers), Buena Vista (Disney), Universal (Vivendi), Fox, Columbia/TriStar (Sony), Paramount (Viacom), and MGM, which collectively own over 90% of the DVD market. Different studios are likely to have different cost structures for their DVD advertising production and placement for two reasons: first, the studios' in-house marketing divisions, rather than advertising agencies, usually create DVD advertisements; second, major studios, most of which are part of media conglomerates, leverage their connections with their sister television networks to get deals on spot commercials (so-called "house ads"). While studio fixed effects may explain some of the variation in observed advertising levels, consumers usually are either unaware of the distributor label or indifferent between labels[3] Studios also may vary in their financial leverage on the capital market, such that if studio *f* has higher interest rates on its borrowed investment to produce a movie, it may release

[3] This assumption may not hold if the advertising created by different studios varies systematically in quality, but this variation is unlikely for DVD advertisements, most of which consist of a trailer from the movie and do not feature any other creative elements.

it faster on DVD to recoup the cost and avoid higher debts. Consequently, studio dummies may correlate with DVD release timing as well.

After controlling for a movie's box office performance, we recognize that its production cost may affect the studio's DVD marketing mix decisions. Suppose two movies earn similar box office returns but one incurred a much higher cost to produce. In this case, the studio of the more expensive movie suffers greater financial constraints on its DVD promotion and may speed up its DVD release to recoup production expenses. Therefore, the production cost should correlate with the observed advertising and timing outcomes. Because a typical consumer does not know the production costs (and we control for various observable movie characteristics, such as box office revenue and star power), these supply-side costs represent a valid instrument. Similarly, the number of screens during the movie's theatrical run may affect the studio's timing decision, because a movie with wider theatrical distribution probably leads the studio to defer its DVD release for fear of damaging relationships with exhibitors, which may still be showing the film.

Another instrument entails the studios' tendency to release blockbuster movies or DVDs in high-demand seasons (Chiou 2005; Einav 2007). For example, a movie theatrically released in June typically should be released on DVD in November; however, the studio may want to delay the DVD launch until December to benefit from a holiday-season demand boost. The discrepancy between actual release and predicted release dates (which may be positive or negative) should correlate with the DVD release delay but not with the unobserved components in demand (we already control for seasonality dummies and box office performance). In other words, if one holiday DVD release experiences a longer than expected delay and another has a shorter than expected delay, the difference may be caused by supply-side shocks (arising from variation in theatrical openings) but not demand-side differences between the two DVDs. To extract these instruments, we undertake a two-step procedure: We first regress $\ln(DELAY_j)$ on all other exogenous variables and obtain $\tilde{\eta}_j^L$. Next, we create two additional variables, PRE_CHR and PRE_VAL as follows, and include them to estimate Equation (17):

(18) $$PRE\_CHR_j = 1\{\text{DVD } j \text{ is released during Christmas}\} \cdot 1\{\tilde{\eta}_j^L > 0\}; \text{ and}$$

(19) $$PRE\_VAL_j = 1\{\text{DVD } j \text{ is released around Valentine's Day}\} \cdot 1\{\tilde{\eta}_j^L > 0\}.$$

Because studios make advertising and timing decisions simultaneously, the instruments for release timing can be used for advertising and vice versa. We also include a set of interaction terms among studio dummies, exhibition screens, production costs, and several variables (e.g., box office revenue, DVD penetration rate) as instruments.

Let $\overline{\phi}_j \equiv (\phi_j^A, \phi_j^L, \varepsilon_j)'$, $\Delta\phi_{jt} \equiv (\Delta\phi_{jt}^A, \Delta\varepsilon_{jt})'$, $\overline{\eta}_j \equiv (\eta_j^A, \eta_j^L)'$, and $\Delta\eta_{jt} \equiv (\Delta\eta_{jt}^A, 1)$. Assume

(20) $$E(\overline{\phi}_j \mid \overline{\eta}_j, z_{jt}) = \Gamma_1 \overline{\eta}_j, \text{ and,}$$

(21) $$E(\Delta\phi_{jt} \mid \Delta\eta_{jt}, z_{jt}) = \Gamma_2 \Delta\eta_{jt}.$$

Note that the advertising carryover structure does not affect how we correct for the correlated random coefficients; whereas A_{jt} includes lagged advertising GRPs, the error term for the current-period elasticity, $\Delta\phi_{jt}^A$, is assumed to be solely a function of $\Delta\eta_{jt}^A$ (i.e., not a function of $\Delta\eta_{jt-1}, \Delta\eta_{jt-2}, \ldots$, conditional on $\Delta\eta_{jt}^A$). In other words, $\Delta\phi_{jt}^A$ gets revealed to the studio only at time *t*, not before. Consequently, any change in A_{jt} that results from the studio's knowledge of $\Delta\phi_{jt}^A$ is reflected only in AD_{jt}.

After we obtain $\hat{\eta}_{jt}^A$ and $\hat{\eta}_j^L$, we can replace η_j^A with $\frac{1}{T}\sum_{t=1}^{T}\hat{\eta}_{jt}^A$, $\Delta\eta_{jt}^A$ with $(\hat{\eta}_{jt}^A - \frac{1}{T}\sum_{t=1}^{T}\hat{\eta}_{jt}^A)$, and η_j^L with $\hat{\eta}_j^L$ and estimate

$$\ln S_{jt} = x_{jt}'\beta + (w_{jt}^{A\prime}\theta^{A})A_{jt} + (w_{j}^{L\prime}\theta^{L})L_{j} + \Gamma_{1}\hat{\eta}_{j}(A_{jt}, L_{jt}, 1) + \Gamma_{2}\Delta\hat{\eta}_{jt}(A_{jt}, 1) + v_{jt}. \tag{22}$$

The pooled OLS estimator that we therefore compute is consistent under the orthogonality and linearity assumptions previously specified.[4] The pooled OLS estimator does not impose any structure on the second moments of the errors (except that they be well-defined) and allows for arbitrary serial correlation, cross-equation correlation, and heteroscedasticity. Because v_{jt} is generally heteroscedastic, heteroscedasticity-robust standard errors and test statistics should be applied.

Retail prices. In the model described above, we focus on studios' two decision variables for DVDs, namely, advertising and release delay. In contrast, DVD retail prices usually are not influenced by studios, which typically sell the DVDs to retailers at a constant wholesale price ($17–18); the retailers set the final prices. Nevertheless, retailers' private knowledge about the linear demand shifter and the (heterogeneous) price elasticity for each DVD title, if not accounted for, might lead to inconsistent estimates of the price coefficient. Therefore, it is important that we also correct for price endogeneity (both in the intercept and slope coefficients) in the demand estimation.

Retailers usually set DVD prices after observing the studio's advertising and release timing decisions, so the same set of instruments we use for advertising and release timing can apply to retail prices, because they affect the retailer's pricing (through the studios' marketing mix decisions) but not demand-side unobservables. After obtaining the residuals $\hat{\eta}_{j}^{P}$ and $\Delta\hat{\eta}_{jt}^{P}$ from a first-stage regression of the log price, P, on the instruments, we add four additional terms — $\hat{\eta}_{j}^{P}$,

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[4] In our empirical application, we relax the linearity assumption and test several specifications including higher-order terms of first-stage residuals. These specifications do not result in a significantly improved fit, so we retain the simpler model and report the results from this specification.

$\Delta\hat{\eta}^P_{jt}$, $\hat{\eta}^P_j P$, and $\Delta\hat{\eta}^P_{jt} P$ — to Equation (22) to correct further for price endogeneity. We do not need to introduce the interactions between price residuals and studio decision variables explicitly because, given the assumptions in Equations (20) and (21), price residuals do not have extra information (beyond advertising and delay residuals) about the unobserved marginal effects of A and L on sales.

Operationalization of WOM. Rather than use proxies such as online consumer reviews (Chevalier and Mayzlin 2006), we compute an empirical measure for WOM based on a movie's box-office sales over time. Box office sales patterns reveal information about consumers' WOM communication and thereby affect the "playability" (or "longevity") of a movie. To construct this measure, we use a regression method similar to that recommended by Elberse and Eliashberg (2003):

(23) $$\ln(BO\_REV_{jt}) = \alpha_0 + \alpha_1 \ln(SCREENS_{jt}) + \alpha_{2,j} \ln(SCR\_REV_{jt-1}) + e_{jt}, \quad t = 2,3,...T,$$

where BO_REV_{jt} is the box office revenue for movie *j* in week *t*, $SCREENS_{jt}$ is the number of total screens allocated to movie *j* in week *t*, and SCR_REV_{jt-1} is the revenue per screen for movie *j* in week *t-1*.[5] The parameter $\alpha_{2,j}$ captures how the movie's performance in the previous week affects its current performance and thus constitutes an intuitive measure of the WOM effect: A low $\alpha_{2,j}$ suggests poor WOM, whereas high $\alpha_{2,j}$ indicates favorable WOM. Elberse and Eliashberg estimated this coefficient by pooling all movies; in contrast, we estimate it for each individual movie and use the standardized value of $\hat{\alpha}_{2,j}$ as the empirical WOM index.

[5] *SCREENS* may be an endogenous decision variable set by exhibitors. We chose not to correct for this potential endogeneity because the average marginal return of exhibition screens is not central to our analysis.

Operationalization of competition. Previous research reveals the importance of modeling competition between theatrical movies when studying box office sales (e.g., Ainslie et al. 2005). However, no previous research has studied competition for DVDs, which tends to be more complicated than competition among movies for several reasons. First, what constitutes the competitive set? It may consist of not only other DVDs released around the same time but also movies playing in theaters. Second, the extent of competition between contemporaneous DVD releases is unclear, because a consumer drawn by a DVD advertisement to the store may end up buying multiple new releases on the shelf (hence, a sales *cross-over* effect).

We construct two time-variant variables of competition to test these effects empirically. The first measure, $COMP\_DVD_{jt}$, captures competition from other new DVD releases, operationalized by the logarithm of the sum of theatrical revenues of all other DVDs released within two weeks of the *t*-th week after DVD *j*'s release date. The second measure, $COMP\_THEATRICAL_{jt}$, the logarithm of total box office revenues for all movies playing in theaters in the *t*-th week after DVD *j*'s release date, captures the competition from movies playing at the box office.

RESULTS

Determinants of Endogenous Variables

Methodologically, the first-stage regression attempts to obtain endogeneity correction terms that can be used in a second-stage estimation. However, the first-stage results reported in Table 4 are of substantive interest in their own right because they suggest how studios currently set their advertising levels and DVD release delays as well as how retailers price DVDs.

[Insert Table 4 about here]

As we expected, the advertising level that a studio sets for a DVD relates positively to its box office performance (*BO_REV)*; specifically, a 1% increase in box office revenue leads to an approximately .53% increase in DVD advertising. Advertising expenditures for the theatrical movie (*MOVIE_AD*) do not have significant main effects on DVD advertising, but they reveal a positive interaction effect with WOM; thus, *ceteris paribus*, theatrical and DVD advertising budgets positively correlate only when the movie has received good WOM. We find that R- and PG13-rated DVDs receive less advertising (by over 50%) than more family-friendly G- and PG-rated DVDs. Holiday-season (Christmas–New Year's Day) DVD releases receive approximately double the amount of advertising support than non-holiday releases, but romantic DVDs released around Valentine's Day do not receive higher advertising support. Competition does not have a significant effect on either advertising or release delay.

With regard to pricing, DVD retailers seem to set lower prices for DVDs with higher box office revenue and higher theatrical advertising and also during the first week after release, which is consistent with a loss-leader pricing strategy that takes advantage of the release of popular DVDs to boost store traffic.[6]

The lower half of Table 4 presents coefficients related to the excluded instruments. First, we note the substantial differences among major studios in their advertising and release timing behavior. Among the seven major labels, five spend significantly more than the non-majors (used as the baseline), especially Studios 3, 4, and 7. Studio 6 advertises significantly less. Second, in terms of release timing, Studio 1 seems to have the shortest DVD release schedules (in addition to its relatively low advertising budgets), and Studios 4 and 5 indicate the longest

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[6] Retailers such as Wal-Mart and Target typically pay studios $17 or $18 wholesale for new-release DVDs and sell them to consumers at $16–19 to attract consumers into stores.

delays. Such differences may underline supply-side factors, such as advertising production and broadcasting cost and financial leverage.

Advertising Response Estimates and Model Comparison

We report the estimation results for the marketing mix responsiveness and endogeneity correction terms in Table 5 and use Table 6 to report the remainder of the second-stage estimates. The first column in Table 5 shows the results from the full model (which corrects for both intercept and slope endogeneity). As benchmarks, we also report results from a model with no endogeneity correction (i.e., OLS) in the second column and from one with intercept endogeneity correction only (equivalent to the standard IV approach) in the third column.

[Insert Table 5 about here]

For differences in the estimates of advertising responsiveness (captured by the coefficient of the constant since all moderators are demeaned) between the proposed model and the two alternative models, we find that release-week advertising elasticity (non-holiday) is .030 in the full-correction model, compared with .041 and .023 in the no- and partial-correction models, respectively. This difference indicates a 37% overestimation by the OLS estimator and 23% underestimation by the standard IV estimator. Because the alternative models are nested in the full model, we can use an F-test to compare model fit. The full-correction model provides superior fit compared with the no-correction ($F = 6.0$, $p < .01$) and the partial-correction ($F = 4.9$, $p < .01$) models.

The estimates pertaining to the moderators of advertising responsiveness show that advertising elasticity exhibits a significant decline (by 30% weekly) after the DVD release week. It dwindles to nearly zero in Week 4, which affirms the industry's current practice where DVD advertising rarely extends beyond the first month. These estimates do not differ significantly across the three specifications.[7]

The WOM coefficient is significantly positive, which implies that DVD advertising is more effective for movies with stronger WOM and suggests a complementary (rather than substitutable) relationship between advertising and WOM. Quantitatively, one advertising dollar for a DVD movie with a one-standard-deviation positive WOM is 1.6 times as effective as that for a movie with a one-standard-deviation negative WOM. In contrast to the common presumption that firms can reduce advertising in the presence of strong favorable WOM, our results suggest that, if a movie receives favorable WOM, the studio should increase its DVD advertising budget. Theatrical advertising (*MOVIE_AD*), in contrast, negatively affects DVD advertising elasticity, which suggests substitutability between these sequential channels. As we hypothesized, the presence of DVD content enhancements (*BONUS*) increases advertising effectiveness, which is consistent with previous research that suggests advertising is more effective for higher-quality products (Batra et al. 1995).

Retail price negatively affects advertising responsiveness, pointing to a synergistic relationship between price promotion and advertising. Because DVD advertising does not tend to focus on price, we confirm the well-known interaction effect between price and non-price advertising on sales (Kaul and Wittink 1995). Our results suggest that studios should coordinate with retailers' promotions by increasing their advertising intensity. Box office revenue (*BO_REV)* has a negative coefficient on advertising elasticity but is not statistically significant. High-demand seasons, such as Christmas and Valentine's Day (for romantic movies) are considerably

[7] The carryover coefficient, δ, is estimated using a grid search over the minimized sum of squared residuals of Equation (22). The range between .70 and .85 indicates virtually no difference in model fit, whereas values outside this range lead to inferior model fit. Thus, we use .75 in the final results.

more responsive, presumably due to gift buyers' susceptibility to advertising. The Christmas holiday nearly doubles advertising elasticity, and Valentine's Day increases the advertising responsiveness of romantic DVDs threefold.[8]

Because DVD release delay has a significantly negative effect on sales, we find support for the time-sensitive nature of DVD release. The proposed model estimates price elasticity as -1.84, substantially greater than the OLS estimate (-1.39) and similar to the IV estimate (-1.86).

The estimates for the correction terms confirm our conjecture that marketing mix variables, such as advertising and pricing, are endogenously determined and thus correlated with the unobserved marginal effects of these variables. The estimates also provide insight into the nature of such correlations. The coefficient of $\hat{\eta}_j^A A$ is significantly positive, which suggests a positive relationship between ϕ_j^A, the heterogeneity in DVD *j*'s advertising elasticity, and $\hat{\eta}_j^A$, which is the residual in the advertising equation. Therefore, firms appear to have private knowledge about product-specific advertising effectiveness and take that knowledge into account when setting advertising levels. Namely, more advertising is given to DVDs that are more responsive to advertising. In addition, $\Delta\hat{\eta}_{jt}^A A$ has a positive yet much smaller coefficient, which suggests that studios have limited knowledge about week-specific deviations in advertising responsiveness or that they do not act on such information (presumably because most advertising schedules are set in the upfront media buying market and cannot be adjusted on a weekly basis). Also, $\eta_j^P P$ has a significantly positive coefficient, which means that more price-sensitive DVDs are indeed priced lower. This finding, combined with the results pertaining to the determinants of retail prices,

[8] We also test a specification with *DVD_BASE* as an additional moderator. However, the coefficient of DVD_BASE on advertising elasticity is insignificant (coefficient = .21, t = .88), so we do not report the results from this specification.

indicates that retailers adopt a combination of a loss-leadership strategy and profit maximization in pricing DVDs. They give deeper discounts to popular DVD titles (box office successes, prominent theatrical advertising support) but also adjust individual prices on the basis of title-specific price sensitivity.

The control terms related to release delay, $\hat{\eta}_j^L A$, $\hat{\eta}_j^L L$, $\hat{\eta}_j^A L$, and $\hat{\eta}_j^L$, are all insignificant. Therefore, either studios possess little knowledge about title-specific demand responsiveness to release delay or, compared with advertising, DVD release timing is a less flexible strategic instrument for studios, perhaps due to the pressure to conform to industry conventions.

In summary, our findings confirm the presence of slope endogeneity. At least partially, firms observe marketing mix effectiveness and tailor their strategies to such private knowledge. It is therefore critical to correct for endogeneity bias in estimating marketing mix responsiveness.

Determinants of DVD Sales

In Table 6, we present the remaining second-stage estimation results from the full model. Not surprisingly, a movie's box office performance (*BO_REV*) is the most important predictor of its DVD sales: a 1% increase in box office revenue corresponds to a roughly .96% increase in DVD sales.

[Insert Table 6 about here]

WOM has a significantly positive main effect on sales. Although theatrical advertising (*MOVIE_AD*) has no significant effect on DVD sales on average, its interaction with WOM is significantly positive, which offers important implications for firms that face a sequential channel marketing problem. In a parallel context, Erdem and Sun (2002) show that advertising has a spillover effect for umbrella brands in consumer packaged goods categories; however, to our knowledge, no empirical study examines whether advertising spillover (or trickle-down) exists for products marketed in sequential channels (e.g., hardcover and paperback books, movies and DVDs, couture and ready-to-wear fashion). Our finding suggests that advertising in the first channel trickles down to the second channel but only when the product receives favorable WOM in the first channel.

Various DVD extras seem to improve sales significantly. “Making-of” documentaries, deleted scenes, and music videos each increase sales by approximately 10%, and children’s games raise demand by almost 50%, reflecting the extreme popularity of such materials with the target audience.

Even after controlling for box office performance, we find that movie star presence (*STAR*) increases DVD sales, which supports the attraction power of well-known actors and actresses for DVD consumers. Therefore, the rising prominence of DVD revenues relative to box-office receipts should generally warrant higher (not lower) compensations for stars. Critical reviews (*CRITIC*) result in a negative coefficient in the DVD sales equation. Surprising as it may seem, this result apparently indicates that movie critics and the average DVD consumer have divergent preferences (Eliashberg and Shugan 1997) A similar argument may explain the negative sign on Oscar nominations. In addition, R-rated DVDs sell better than DVDs of other ratings (G, PG, and PG13), indicating that DVDs appeal to a more mature audience.

Competition from other newly released DVDs (*COMP_DVD*) and from the theatrical market (*COMP_THEATRICAL*) both negatively affect DVD sales, though the magnitude of between-DVD competition is quite small. A 1% increase in between-DVD competition leads to a mere .05% decrease in sales, whereas a 1% change in theatrical competition leads to a .22% decrease in DVD sales. This finding supports the viewpoint espoused by some industry observers that the DVD market supports more "biodiversity" than the theatrical market (e.g., Cellini and Lambertini 2003), because DVDs allow (often different members of) a household to inventory and watch multiple DVDs at convenient times. The major competition for DVD releases instead comes from movie theaters, suggesting that studios should avoid releasing their DVDs in the same week as box office blockbusters. A holiday release does not increase DVD sales significantly; however, as we discussed previously, it substantially increases DVD advertising responsiveness. That is, studios must support their holiday DVD releases with large-scale adverting campaigns if they wish to take advantage of the gift-buying seasons.

Responsiveness Forecasting and Optimal Advertising Budgeting

We use the estimates from the proposed model to perform advertising responsiveness forecasting for a holdout sample of 52 DVDs; we report a sample of the weekly advertising elasticities estimated for these titles in Table 7. The first-week advertising elasticity varies from as much as .14 (*Winged Migration*) to as little as .02 (*Charlie's Angels: Full Throttle*). Therefore, marketers' decisions likely will be suboptimal if they do not fully account for product-specific characteristics. Advertising responsiveness forecasting, in contrast, helps marketers determine optimal advertising budgets on a title-by-title basis.

[Insert Table 7 about here]

To compare the elasticity estimates between models, we report the median and standard deviation of the predicted advertising elasticity estimated by each model in Table 8. The left panel refers to the first-week (i.e., short-term) elasticity, $\hat{\gamma}_{j1}^{A}$, whereas the right pertains to first-month elasticity with the carryover effect, as captured by $\sum_{t=1}^{4} \delta^{t-1} \cdot \hat{\gamma}_{jt}^{A}$, which represents the long-term effect of first-week advertising. The two benchmark models reveal a 14–36% bias in the average elasticity estimates compared with the proposed model. The results is consistent with previous research suggesting that the average long-term effect of advertising is approximately double its initial effect (Hanssens et al. 2001).

[Insert Table 8 about here]

To illustrate how the proposed model might be used to derive optimal advertising schedules for new products, we compute profit-maximizing advertising plans for the holdout sample based on estimates from our model. Technical details are described in the Appendix, and we assume a constant wholesale margin of $15.50 for each DVD and, for the sake of simplicity, a constant advertising cost of $4,200 per GRP.[9]. We report the optimal advertising plans for a sample of DVD titles and the resulting profit improvement over the actual advertising plan in Table 9. According to our model, some DVDs that studios did not advertise at all, such as *Winged Migration*, *Spellbound*, and *How to Deal*, could have benefited substantially (20–80% increase in profitability) from a moderate advertising budget. Among the DVDs that received some advertising support, studios could have gained profits by increasing advertising for some titles (e.g., *Under the Tuscan Sun*, *Bad Boys 2*, *Pirates of the Caribbean*) but saving the advertising dollars expended on others (e.g., *Jeepers Creepers 2*, *American Wedding*). The proposed advertising plans lead to a 12.2% improvement in profits for an average DVD, or $2.1 million.

[Insert Table 9 about here]

CONCLUSIONS

In this article, we introduce the marketing mix responsiveness forecasting problem and illustrate how it can help marketers improve the productivity of their marketing investments. We also account for the methodological problem of slope endogeneity and thereby extend the current literature that has focused on intercept endogeneity. Our solution is a simple and intuitive control

[9] According to our interviews with industry experts, this estimate falls in the reasonable range of advertising costs for a 15-second spot, which is the dominant form of DVD advertising.

function model that corrects for marketing mix responsiveness endogeneity explicitly. Although the control function framework, on which our model is based, has been used previously, we extend it by incorporating multiple endogenous variables and advertising carryover, which makes the proposed model particularly useful for solving marketing problems. Through an optimal advertising scheduling exercise, we demonstrate how the proposed model can help marketers optimize their advertising planning for new products and improve profitability.

The simplicity of this approach also should aid in the use of endogeneity correction methods in marketing literature when appropriate. In our application, we find that firms possess private information (unobservable to the researcher) about advertising and pricing responsiveness and that the failure to correct for such endogeneity leads to considerable bias in advertising and pricing elasticity estimates.

Another option to estimate the demand equation would be to impose structural assumptions on the supply side and estimate it jointly with the demand-side model (Berry et al. 1995; Sudhir 2001). Although this approach could improve the efficiency of the estimator if the structural assumptions are valid (i.e., firms act optimally), it would result in inconsistent demand-side estimates if the supply-side model is misspecified. In comparison, our control function estimator is more robust, because we do not impose optimality assumptions on supply-side behavior. Because a broad spectrum exists between "possessing private managerial knowledge" and "acting optimally" in the real world, we believe that our model provides a more flexible conceptual platform to infer and forecast marketing mix responsiveness. Our empirical study also provides evidence that managers use their private information in advertising budgeting but that their advertising levels remain suboptimal.

Our analysis yields several qualitative findings regarding advertising effectiveness and entertainment marketing. We highlight a few key insights: First, we find that DVD advertising is more effective when the consumer WOM is strong and favorable. This suggests that WOM complements advertising rather than act as a substitute. Hence DVD advertising is ineffective in propping up a movie that generates poor WOM. Second, retailers engage in a combination of loss-leadership and profit maximization strategies when setting DVD prices. Also, when a popular DVD is used a loss-leader by the retailer, it makes sense for the studio to increase advertising. Finally, the competition for DVDs is greater with contemporaneous theatrical releases than with DVDs released in the same week. Thus studios should avoid releasing DVDs head to head with major box office releases. Competition between DVDs is much less intense than between theatrical movies presumably because people can purchase multiple DVDs at once and watch it at leisure, allowing for greater "biodiversity."

There are several limitations to the current study. First, our empirical implementation assumes that the studios set their theatrical-stage marketing mix variables (e.g, *MOVIE_AD*) without considering the marketing mix effects in the DVD sales model, thus treating them as predetermined. While this assumption is based on the current movie industry practice, this may not be generally true in other markets where firms are strategically forward-looking in planning sequential releases. In the latter case, the endogenous marketing mix variables in both the first and the second release channel need be modeled simultaneously. Similarly, we treat the DVD features as predetermined. Although this assumption is generally valid in the movie industry since the DVD extras are typically determined well in advance of the airing of DVD ads (e.g., creating behind-the-scene documentaries and alternative endings takes place at the theatrical production stage), we realize that product characteristics, in general, should ideally be modeled in conjunction with marketing mix variables in a coherent framework. Lastly, our model treats the market size as exogenous. It does not explicitly capture the fact that marketing mix variables may influence consumers' purchase timing decisions, which is particularly relevant in the durable goods market (e.g., Nair 2007). Future research should investigate how to improve the current forecasting approach with endogenous market size evolution.

In summary, "heterogeneity of rewards" and "private managerial information" is a common characteristic of most resource allocation decisions. Firms allocate consumer and trade promotions to products and across time periods where they believe would be most effective for raising sales. More salespeople (or more capable salespeople) get allocated to territories in which managers believe they would obtain greater "bang for the buck." Retailers give more space to those categories and brands that generate greater profits when allocating shelf space. To estimate unbiased marginal effects of each of these resources, researchers must account for the potential slope endogeneity bias. We offer this research as a flexible solution to this general challenge and hope further research continues this effort.

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Table 1: Key Descriptive Statistics[a]

Variable	Mean	Median	Std. dev.	Max.	Min.
DVD sales, 4 weeks (mils.)	0.72	0.32	1.20	8.97	0.01
DVD sales, 6 months (mils.)	0.99	0.50	1.50	11.29	0.01
TV GRPs, 2 weeks before release date	7.80	0	37.71	567	0
TV GRPs, 1 week before release date	75.18	0	127.66	584	0
TV GRPs, Week 1	117.93	41	156.87	690	0
TV GRPs, Week 2	46.18	0	94.23	612	0
TV GRPs, Week 3	10.75	0	42.56	461	0
TV GRPs, Week 4	7.26	0	33.75	522	0
Total TV GRPs	265.90	85	400.80	2484	0
Theatrical-to-video window (days)	165.37	158.00	41.44	405	88
DVD retail price ($)	19.84	19.60	1.89	33.98	14.16
Box office revenue ($ mils.)	55.05	34.56	58.20	404.76	5.11
Production budget ($ mils.)	41.46	35.00	31.01	200	0.16
Theatrical movie advertising ($ mils.)	19.7	18.7	9.8	63.3	0
Exhibition screens[b]	1293.2	1204.3	695.4	3273.1	29.6
Star power rating (0–100)[c]	56.52	59.09	27.63	100	0
Critical rating (1–10)[d]	5.42	5.00	2.14	10	1
Oscar nominations[e]	0.21	0.00	0.75	6	0

[a] Sample consists of 526 new DVD titles released between January 2000 and October 2003.

[b] Average number of screens in the first nine weeks of theatrical exhibition. Source: *Variety* Magazine.

[c] Source: Hollywood Reporter.

[d] Source: Metacritic.com.

[e] Only includes major categories: Best Picture, Best Director, Best Leading Actor, and Best Leading Actress.

Table 2: Description of Variables

Variable	Description
Marketing and sales variables	
BOX_REV	Box office revenue
AD	Weekly TV GRPs of DVD advertising
PRICE	Weekly DVD retail price (weighted average across retailers)
DELAY	DVD release delay
MOVIE_AD	Ad expenditure for theatrical release
PROD_COST	Movie production cost
SCREENS	Number of exhibition screens (average during the first 9 weeks)
Movie characteristics	
WOM	Word of mouth
CRITIC	Critic review (from metacritic.com)
OSCARS	Number of Oscar nominations
STAR	Star power rating
R	R-rated (by MPAA)
PG13	PG13-rated (by MPAA)
SEQUEL	Sequel
ACTION	Action genre
ANIMATION	Animation genre
DOCUMENTARY	Documentary genre
DRAMA	Drama genre
FANTASY	Fantasy genre
HORROR	Horror genre
ROMANCE	Romance genre
SCI-FI	Sci-fi genre
THRILLER	Thriller genre
WAR	War genre
DVD content enhancements ("extras")	
MAKING_OF	"Behind-the-scenes"/"making-of" featurettes or documentary
COMMENTARY	Filmmaker commentary
DEL_SCENES	Deleted scenes and/or alternative endings
MUSIC_VIDEO	Music videos and/or isolated scores
INTERACTIVE	Interactive features such as DVD-ROM games
CHILDREN_GAME	Games such as "sing-alongs" for children
Market environment variables	
DVD_BASE	Number of households with DVD hardware installed
COMP_DVD	Competition from other new DVD releases
COMP_THEATRICAL	Competition from theatrical films

Table 3: Moderators of Advertising Elasticity

Variable	Predicted Sign	Hypothesis
TREND	-	Ad response is highest immediately after DVD release and diminishes over time.
WOM	+/-	Advertising and WOM may be complements or substitutes.
MOVIE_AD	-	Theatrical advertising and DVD advertising can be substitutes.
BONUS	+	DVD content enhancement increases ad response.
PRICE	-	Ads are more effective when combined with lower prices.
BOX_REV	-	Ad elasticity is lower for bigger box office hits.
CHRISTMAS	+	Ad response is higher during the Christmas-New Year holiday season.
VALENTINE*ROMANCE	+	Ad response for romance DVDs is higher around Valentine's Day.

Table 4: Determinants of Endogenous Variables

	ln(AD)		***ln(DELAY)***		***ln(PRICE)***	
Constant	2.726	(1.152) **	5.093	(0.443) **	0.136	(0.053) **
ln(BOX_REV)	0.526	(0.199) **	-0.098	(0.067)	-0.027	(0.009) **
ln(MOVIE_AD)	-0.161	(0.117)	-0.050	(0.039)	-0.010	(0.005) *
WOM	-0.047	(0.068)	-0.040	(0.023) *	0.015	(0.003) **
ln(MOVIE_AD)*WOM	0.186	(0.058) **	-0.038	(0.020) *	0.009	(0.003) **
ln(DVD_BASE)	0.237	(0.184)	-0.081	(0.062)	-0.028	(0.008) **
STAR	0.033	(0.041)	-0.025	(0.014) *	0.000	(0.002)
CRITIC	-0.010	(0.019)	0.010	(0.006)	0.003	(0.001) **
R	-0.645	(0.145) **	0.050	(0.049)	0.007	(0.007)
PG13	-0.654	(0.132) **	0.028	(0.044)	0.000	(0.006)
SEQUEL	0.040	(0.132)	0.002	(0.044)	-0.002	(0.006)
OSCARS	0.003	(0.056)	0.018	(0.019)	-0.003	(0.003)
SPRING	0.179	(0.134)	-0.098	(0.045) **	-0.002	(0.006)
SUMMER	0.115	(0.120)	-0.002	(0.041)	0.023	(0.006) **
FALL	0.156	(0.132)	0.050	(0.045)	0.005	(0.006)
HOLIAY	0.715	(0.187) **	-0.282	(0.066) **	0.039	(0.009) **
VALENTINE*ROMANCE	0.174	(0.505)	-0.497	(0.169) **	0.034	(0.023)
WEEK 2	-1.044	(0.095) **			0.041	(0.004) **
WEEK 3	-2.136	(0.095) **			0.056	(0.004) **
WEEK 4	-2.363	(0.095) **			0.060	(0.004) **
COMP_DVD	-0.121	(0.079)	0.017	(0.038)	0.004	(0.004)
COMP_THEATRICAL	0.010	(0.185)	-0.029	(0.072)	-0.034	(0.009) **
Genre variables[a]	Yes		Yes		Yes	
DVD extras variables[a]	Yes		Yes		Yes	
ln(PROD_COST)	-0.126	(0.170)	0.010	(0.057)	-0.015	(0.008) **
ln(SCREENS)	0.215	(0.320)	0.203	(0.107) *	0.040	(0.015) **
ln(PROD_COST)*ln(SCREENS)	0.120	(0.055) **	-0.024	(0.018)	0.003	(0.003)
STUDIO 1[b]	-0.014	(0.160)	-0.104	(0.054) *	0.026	(0.007) **
STUDIO 2	0.400	(0.156) **	0.087	(0.052) *	0.015	(0.007) **
STUDIO 3	0.791	(0.165) **	0.081	(0.055)	0.077	(0.008) **
STUDIO 4	0.614	(0.190) **	0.109	(0.064) *	0.117	(0.009) **
STUDIO 5	0.267	(0.152) *	0.128	(0.051) **	0.064	(0.007) **
STUDIO 6	-0.427	(0.183) **	0.086	(0.061)	0.047	(0.008) **
STUDIO 7	1.075	(0.209) **	0.069	(0.070)	0.019	(0.010) **
PRE_CHRISTMAS	0.043	(0.218)	0.480	(0.073) **	-0.002	(0.010)
PRE_VALENTINE	0.551	(0.454)	0.546	(0.152) **	-0.025	(0.021)
Interaction terms[a]	Yes		Yes		Yes	
R^2	0.50		0.51		0.52	

* $p < .1$; ** $p < .05$. Heteroscedasticity-robust standard errors are in parentheses.

[a] Coefficients suppressed because of the large number of variables. The full set of results is available from the authors.

[b] The seven studio dummies are Warner, Buena Vista, Universal, Fox, Columbia, Paramount, and MGM. The exact studio identities are disguised for confidentiality.

Table 5: Elasticity Estimates and Endogeneity Corrections

	Full Correction		No Correction		Intercept Correction	
Advertising elasticity						
Constant[a]	0.030	(0.003) **	0.041	(0.004) **	0.023	(0.003) **
Trend[b]	-0.009	(0.003) **	-0.009	(0.002) **	-0.006	(0.003) **
WOM	0.007	(0.003) **	0.007	(0.003) **	0.007	(0.003) **
ln(MOVIE_AD)	-0.026	(0.007) **	-0.024	(0.007) **	-0.024	(0.007) **
BONUS[c]	0.004	(0.002) **	0.003	(0.002) *	0.004	(0.002) **
ln(PRICE)	-0.084	(0.025) **	-0.051	(0.024) **	-0.065	(0.024) **
ln(BOX_REV)	-0.006	(0.004)	-0.006	(0.004)	-0.006	(0.004)
CHRISTMAS	0.022	(0.008) **	0.025	(0.008) **	0.023	(0.008) **
VALENTINE*ROMANCE	0.084	(0.012) **	0.086	(0.012) **	0.084	(0.012) **
Delay elasticity	-0.095	(0.057) *	-0.119	(0.023) **	-0.113	(0.039) **
Price elasticity	-1.843	(0.209) **	-1.387	(0.171) **	-1.860	(0.210) **
Endogeneity correction terms						
$\hat{\eta}_j^A A$	0.010	(0.003) **				
$\Delta\hat{\eta}_{jt}^A A$	0.004	(0.002) *				
$\hat{\eta}_j^L A$	-0.004	(0.009)				
$\hat{\eta}_j^L L$	0.013	(0.038)				
$\hat{\eta}_j^A L$	0.062	(0.059)				
$\hat{\eta}_j^P P$	2.263	(0.899) **				
$\Delta\hat{\eta}_{jt}^P P$	-1.574	(1.337)				
$\hat{\eta}_j^A$	0.038	(0.020) *			0.055	(0.018) **
$\Delta\hat{\eta}_{jt}^A$	0.012	(0.011)			0.028	(0.009) **
$\hat{\eta}_j^L$	-0.022	(0.064)			-0.005	(0.059)
$\hat{\eta}_j^P$	0.694	(0.250) **			0.714	(0.258) **
$\Delta\hat{\eta}_{jt}^P$	0.941	(0.339) **			0.877	(0.401) **

* $p < .1$; ** $p < .05$. Heteroscedasticity-robust standard errors are in parentheses.

[a] This coefficient indicates the average advertising elasticity in the release week.

[b] The coefficient indicates the weekly trend in advertising elasticity relative to the release week.

[c] BONUS is the total number of DVD bonus features (see Table 2).

Table 6: Estimates for the Sales Equation

General sales predictors		
Constant	9.765	(0.726) **
ln(BOX_REV)	0.961	(0.025) **
ln(MOVIE_AD)	0.008	(0.030)
WOM	0.064	(0.016) **
ln(MOVIE_AD)*WOM	0.057	(0.018) **
ln(DVD_BASE)	0.837	(0.025) **
Wk2	-0.559	(0.029) **
Wk3	-1.037	(0.033) **
Wk4	-1.405	(0.034) **
DVD content enhancements		
MAKING_OF	0.134	(0.022) **
COMMENTARY	0.022	(0.023)
DEL_SCENES	0.084	(0.020) **
MUSIC_VIDEO	0.099	(0.021) **
INTERACTIVE	-0.001	(0.026)
CHILDREN_GAME	0.371	(0.088) **
Movie attributes	0.076	(0.013) **
STAR	0.076	(0.013) **
CRITIC	-0.009	(0.005) *
R	0.280	(0.041) **
PG13	0.050	(0.036)
SEQUEL	-0.135	(0.033) **
OSCARS	-0.081	(0.015) **
ACTION	0.274	(0.025) **
ANIMATION	0.133	(0.073) *
DOCUMENTARY	0.154	(0.104)
DRAMA	-0.040	(0.022) *
FANTASY	0.210	(0.038) **
HORROR	0.160	(0.035) **
ROMANCE	-0.155	(0.030) **
SCI-FI	0.087	(0.031) **
THRILLER	0.100	(0.024) **
WAR	0.250	(0.049) **
Environmental and seasonality factors		
COMP_DVD	-0.052	(0.021) **
COMP_THEATRICAL	-0.221	(0.049) **
SPRING	-0.035	(0.035)
SUMMER	-0.024	(0.030)
FALL	-0.337	(0.035) **
HOLIDAY	0.058	(0.058)
VALENTINE*ROMANCE	0.084	(0.080)

* $p < .1$; ** $p < .05$. Heteroscedasticity-robust standard errors are in parentheses.

Table 7: Sample of Predicted Weekly Advertising Elasticities

Title	Week 1	Week 2	Week 3	Week 4
Winged Migration	0.135	0.120	0.110	0.101
My Boss's Daughter	0.125	0.115	0.104	0.094
Spellbound	0.114	0.105	0.097	0.088
Intolerable Cruelty	0.108	0.095	0.081	0.072
Whale Rider	0.061	0.052	0.042	0.033
American Wedding	0.057	0.036	0.022	0.012
X2: X-Men United	0.051	0.030	0.012	0.002
Bruce Almighty	0.043	0.028	0.014	0.004
Legally Blonde 2	0.043	0.029	0.016	0.038
Grind	0.038	0.028	0.016	0.007
Charlie's Angels: Full Throttle	0.024	0.009	0.000	0.000
Mean[a]	0.053	0.040	0.028	0.021

[a] The average elasticities are computed over 52 DVD titles in the holdout sample.

Table 8: Predicted Advertising Elasticity for Holdout Sample

	First Week (Short-Term)		***First Month (Long-Term)***	
	Median	Std. Dev	Median	Std. Dev
Full-correction model	0.048	0.029	0.085	0.079
No-correction model (OLS)	0.058	0.029	0.116	0.081
Partial-correction model	0.040	0.028	0.073	0.077

Table 9: Profit Improvement with Proposed Advertising Schedules

	Optimal Ad Plan (GRPs)				**Actual Ad Plan (GRPs)**				***Profit Increase (%)***
Title	*Week 1*	*Week 2*	*Week 3*	*Week 4*	*Week 1*	*Week 2*	*Week 3*	*Week 4*	
Winged Migration	109	59	32	14	0	0	0	0	83.7%
Spellbound	31	19	10	4	0	0	0	0	40.9%
Alex & Emma	16	7	3	1	229	2	1	0	41.1%
Sinbad: Legend of the Seven Seas	135	78	53	37	593	0	0	0	24.6%
How to Deal	62	22	8	3	0	0	0	0	23.3%
Intolerable Cruelty	494	263	120	48	400	5	0	0	22.7%
Under the Tuscan Sun	966	510	252	103	431	115	0	0	19.9%
Adam Sandler's 8 Crazy Nights	26	9	2	0	247	0	0	0	15.1%
Jeepers Creepers 2	165	80	34	13	349	0	0	1	14.0%
Spy Kids 3D: Game Over	218	48	3	0	869	447	241	214	12.7%
Legally Blonde 2	181	82	56	59	349	0	0	0	11.1%
Medallion, The	97	42	16	5	228	0	0	0	8.5%
American Wedding	445	119	35	9	766	2	0	0	5.3%
28 Days Later	183	95	47	16	160	74	0	0	4.0%
Freaky Friday	388	104	27	6	986	224	0	0	4.0%
Cabin Fever	159	56	23	8	74	62	0	0	3.7%
Dumb and Dumberer	33	14	5	1	48	0	0	0	3.2%
Seabiscuit	281	62	11	0	666	137	110	13	3.1%
Terminator 3	214	14	0	0	410	111	45	0	2.9%
Freddy vs. Jason	483	123	24	3	275	6	0	0	2.8%
Santa Clause 2, The	540	201	58	17	913	371	1	0	2.7%
Lara Croft Tomb Raider 2	349	114	33	9	194	56	0	1	2.1%
Bad Boys 2	1004	263	44	6	440	209	0	0	1.7%
Pirates of the Caribbean	1540	316	55	10	1106	553	342	149	1.4%
S.W.A.T.	602	183	47	10	495	141	0	0	1.3%
Bruce Almighty	768	229	52	8	737	122	0	0	1.2%

Figures

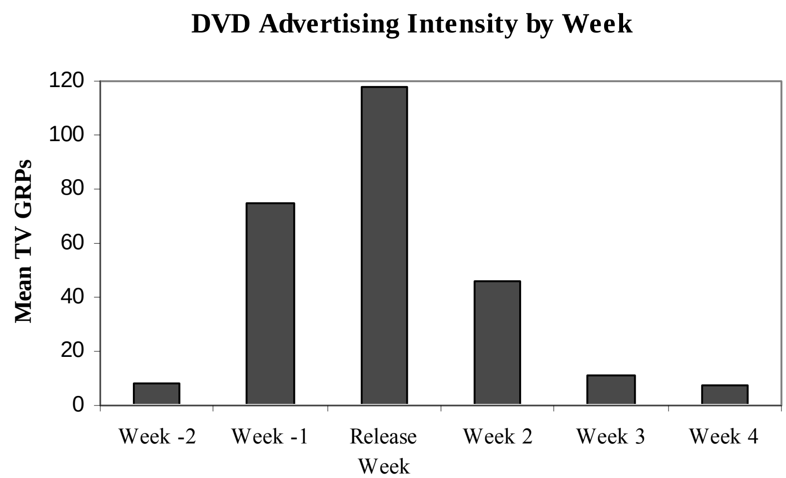

Figure 1

Appendix

OPTIMAL ADVERTISING BUDGETING EXERCISE

In this appendix, we describe the details of the optimal advertising budgeting exercise based on the model estimates. We take the other marketing mix variables (product features, retail prices, and release timing) and contextual variables (competition and seasonality) as given and focus on deriving the optimal weekly advertising schedules.

Suppose studio *s*'s profit from DVD *j* is the sum of weekly profits,

(A1) $$\pi_j = \sum_{t=1}^{T} [S_{jt} \cdot wm_j - a_s \cdot AD_{jt}],$$

where wm_j is the wholesale gross margin of DVD *j*, and a_s is studio *s*'s advertising cost (per GRP). Because DVD sales s_{jt} cannot be predicted perfectly, we write it as the sum of a predicted value (based on the estimated coefficients, collected in $\hat{\theta}_1$), $\hat{s}_{jt}$, which is a function of all current and previous weeks' advertising levels, and an unobserved demand shock (hidden from the studio at the time of planning), whose distribution is governed by θ_2:

(A2) $$\ln S_{jt} = \ln \hat{S}_{jt}(AD_{j1},..., AD_{jt}; \hat{\theta}_1) + e_{jt}, \;\; e_{jt} \sim F(\theta_2).$$

The studio's problem is to find the advertising plan, $(AD_{j1}, AD_{j2},..., AD_{jT})$, that maximizes the expected profit:

(A3) $$\max_{(AD_{j1},...,AD_{jT})} \int_e \sum_{t=1}^{T} [(\hat{S}_{jt}(AD_{j1},..., AD_{jt}; \hat{\theta}_1) + e_{jt}) \cdot wm_j - a_s \cdot AD_{jt}] dF(e_{jt}; \theta_2)$$

Given Equations (13) and (14), we can derive the first-order condition for a given θ_2 as:

(A4) $$AD^*_{jt}(e_{jt}) = \frac{wm_j}{a_s} \sum_{\tau=t}^{T} \hat{\gamma}^A_{j\tau} \delta^{\tau-t} \hat{S}_{j\tau}(AD^*_{j1},..., AD^*_{j\tau}; e_{jt}).$$

We can then numerically solve this system of nonlinear equations (A2) and (A4) for t = 1, 2, 3, 4, conditional on e_{jt}. For our empirical application, we assume $e_{jt} \sim N(0, \sigma_e^2)$ and estimate the variance from the differences between the actual and predicted log sales in the calibration sample. We compute the optimal advertising plan for each title using the simulated average of 500 draws (i.e., NS = 500)[1]:

(A5)
$$AD_{jt}^{*} = \frac{1}{NS} \sum_{ns=1}^{NS} AD_{jt}^{*}(e_{jt}^{(ns)}) \, .$$

We assume a constant wholesale margin of \$15.50 for each DVD and, for the sake of simplicity, a constant advertising cost per GRP. Because this cost is not observed, we calibrate this parameter based on the premise that, on average, the studios set their advertising levels optimally for the set of DVDs in our sample.

[1] An alternative simulation approach is to sample from the empirical distribution of the residuals from the calibration sample. In our exercise, we found that the normal approximation yielded almost identical predictions and was much faster in computation. We thank an anonymous reviewer for this suggestion.