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Reviewing the reviewers: The impact of individual film critics on box office performance

Peter Boatwright · Suman Basuroy · Wagner Kamakura

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Abstract Critics and their opinions or critical reviews play a major role in many markets. Marketing research on how critics impact product performance has so far examined an aggregate critic effect. An obstacle in studies examining the relationship of aggregate critical opinion and product sales is the close association between the intrinsic quality of a product and the aggregate opinion regarding the product. Our analysis parses out these two effects, allowing us to distinguish individual critics who are simply good at identifying products with popular appeal from those who act as opinion leaders and engender early product sales. The role of critics is especially prominent in the film business, in which one finds multiple expert opinions about each movie and where critics' endorsements are used in advertising. In the context of the motion picture industry, our research investigates the impact of individual film critics on the market performance of movies, where specific key critics and reviewers may serve as market gatekeepers, and where various critics may have different types of impacts on product performance.

Keywords Entertainment marketing · Motion picture distribution and exhibition · Movie choice · Predictors · Influencers · Wide-release · Platform-release · Movie critics · Stochastic variable selection · Bayesian models · New product research

JEL Classification C01 · C11 · C52 · M31

P. Boatwright (✉)
Tepper School of Business, Carnegie Mellon University, Pittsburgh, PA 15213, USA
e-mail: pbhb@andrew.cmu.edu

S. Basuroy
Florida Atlantic University, Jupiter, FL 33458, USA
e-mail: sumanbasuroy@yahoo.com

W. Kamakura
Fuqua School of Business, Duke University, Box 90120, Durham, NC 27708, USA
e-mail: kamakura@duke.edu

1 Introduction

Critical and expert opinions provide important and crucial information for consumers in many "experience goods" markets—restaurants, shows/theaters, books, movies, etc. (Basuroy et al. 2003; Caves 2000; Eliashberg and Shugan 1997; Greco 1997), because in these markets consumers cannot ascertain product quality prior to actual consumption. For example, Reddy et al. (1998) point out that Broadway show critics such as Frank Rich of the *New York Times* and Clive Barnes of the *New York Post* had significantly greater influence on the longevity of the shows they reviewed than did other critics. Even in markets in which rationality and objectivity is expected to prevail, opinion leaders may play an important role in the acceptance of new products. Stock analysts such as Henry Blodget of Merrill Lynch and Anthony Noto of Goldman Sachs became household names and financial power brokers (Regan 2001). Therefore, the opinion of experts is vital information in the consumption of experience goods, and for such products the opinion of experts is often sought. Our research assesses the specific role of individual expert opinions on market performance after accounting for the effect of product quality.

The literature has inspected two separate roles of experts—influencers and predictors (Basuroy et al. 2003; Eliashberg and Shugan 1997). Critics with opinions that are correlated with early box office sales are defined as influencers, while critics with opinions that are correlated with overall box office sales are defined as predictors. With movies, for instance, the expert (critic) reveals the stars, the director, the sets, and the plotline, in addition to his or her own overall assessment of the film—details that can bring viewers to the theaters or cause them to stay away. As such, a critic may serve the role of *influencer*, influencing early box office sales by disseminating relevant information to the marketplace at the moment the movie is released. On the other hand, the opinion of a critic expressed at the outset of a movie may correlate with its overall box office sales. This correlation could occur if a critic may anticipate a movie's success or potential market size, as has been observed in theatrical performances (Reddy et al. 1998). Alternatively, the correlation could occur if a critic's opinion serves as a bellwether of audience tastes, for instance if the critic and audience have similar preferences. As a label for correlation of critic opinion and overall box office performance, Eliashberg and Shugan (1997) used the term *predictor* (see, Basuroy et al. 2003; Eliashberg and Shugan 1997 for details).

However, this literature and approach to assessing experts' opinions and the nature of their impact has a few major limitations. First and foremost, no empirical study of the role of critical opinion in the marketing literature has accounted for the intrinsic appeal of the experience good. Correlations between ticket sales and aggregate critical acclaim found in the existing literature might be due to a third factor—movie quality. For example, it is entirely possible that good movies sell well because they are good movies, liked by critics and by the public. Because of this confounding factor of movie quality (or appeal), a positive correlation of aggregate reviews and the weekly sales by itself may not reveal the role of critics. We believe that this confound of movie quality raises questions regarding the interpretation of the estimates previously obtained in the literature. Certainly, intrinsic appeal is difficult to measure, because a host of facets of an artistic product join together for a

Gestalt of excellence. Recent research by Kamakura et al. (2006) has provided a measurement of the intrinsic appeal of an experience good after taking into account rater biases and the differences in diagnosticity across critics. Rather than summarizing critical opinion by an average or weighted average across critics, Kamakura et al. (2006)'s technique uncovers and reports the latent dimension that each of the critics are judging—namely, a movie's appeal. Kamakura et al. (2006)'s work underscores the fact that movie appeal and observed critical opinion are correlated, in that critical opinions are themselves measures of movie appeal or aspects of movie appeal. Its framework also implies that correlation of aggregate critic opinion and movie appeal will in general be stronger than the correlation of an individual critic's opinion and movie appeal, because aggregate critic opinion represents the consensus among the majority of experts.

In order to investigate the impact of critics after accounting for movie quality, our model incorporates both the Kamakura et al. (2006) measure as well as opinions by individual critics. As such, our estimates of the impact of individual critics show the incremental impact of the reviews, after accounting for the combined movie quality and critic consensus. In other words, we measure how the unique contributions of individual critics impact box office sales. There may be critics that do not offer any unique insights beyond the readily apparent movie quality and critic consensus; these critics without unique information will not appear to be incrementally influential (with opinions correlated with early sales) or predictive (with opinions correlated with overall sales). By including both the Kamakura et al. (2006) measure and the opinions of individual critics, our model can assess the specific role of critical opinion on market performance after accounting for the effect of movie quality or appeal on market performance.

Our use of individual critics not only allows us to ascertain the role of critics separately from the contribution of movie quality but also yields richer detail on the functioning of the market for experience goods. Eliashberg and Shugan (1997) and others (Basuroy et al. 2003; Ravid 1999) assessed only the aggregate impact of critics, without taking into account the confounding effect of movie quality, rather than measuring the impact of individual critics. In an environment such as the film industry and the financial world, in which certain well-known experts have much greater media reach than others, the impact of the average expert (critic) may not reflect the power of the well-known few. More generally, the nature of the impact of critics may vary by critic—some may be quite powerful influencers, whereas others may be good predictors. Since it is well known that in many industries individual experts or critics play a significant part in shaping consumer behavior, we fill a gap in this literature by using a methodology to identify and understand the incremental role of an individual expert.

The use of individual opinions poses a significant modeling challenge, in that the opinions of the numerous critics greatly expand the number of variables to be incorporated into the model. To account for the large number of critics in the model, we adopt a statistical technology that balances the numerous potential variables with model parsimony. The modeling technology, developed by George and McCulloch (1993) and known as stochastic search variable selection, is well known in the statistics community but does not appear to have been utilized in the marketing literature to date.

For the purpose of differentiating between influence and prediction, we utilize the Bass model, the classic model about how consumers find out about a new product. The Bass model is derived from the assumption that there are two sources of information about a new product. One source of information is external to the pool of consumers, such as advertising. The other source of information is internal to the pool of consumers, such as word of mouth. The sales pattern over time of the new product (box office sales of the movie) depends upon the strength of the impact of the two sources of information. We consider movie critics as an external source of information/persuasion, similar to advertising, that is made available immediately before the movie is released. Therefore, we expect that if critics have influence as defined above, their reviews would be related to the Bass model parameter corresponding to the external source of information (the coefficient of innovation). On the other hand, if critics correctly anticipate which movies will be successful or if their opinions are bellwethers of market preferences, their reviews would be correlated with market potential. It is possible that critics could both influence and predict, in which case their reviews would be correlated with both of the corresponding model parameters.

Our empirical analysis of the role of individual critics and other factors on the market performance of new movies produced three general types of findings. First, our results identify specific individual critics whose opinions correlate with the Bass parameter that reflects the role of external information. For example, critics such as Owen Gleiberman of *Entertainment Weekly*, Manohla Dargis of the *LA Times*, Michael Wilmington of the *Chicago Tribune*, and Lawrence Van Gelder of the *New York Times* wield noticeably more influence than several other critics (after accounting for movie appeal) who have no discernable distinct impact on the diffusion of a new movie. Second, our results show exactly which roles these critics play—influencers or predictors. Although prior literature has concluded that critics in aggregate act as predictors rather than influencers, we find certain individual critics to be "influencers" (i.e., their views correlate with early adoption of the new movie), but no individuals are identified as "predictors" (i.e., their views do not correlate highly with the overall market potential). Third, in contrast to previous generalizations for this product category, we find some effects to depend on the type of movie. One example is the effect of advertising in the initial weeks of the movie's life cycle; we find that advertising is positively correlated with the coefficient of innovation for "platform-release" movies (those released in a limited number of theaters) while inhibiting the typically rapid sales declines for "wide-release" (i.e., blockbuster) movies.

Our article fills a void in the growing literature on critics or opinion leaders by modeling the impact of individual critics and their opinions, both by identifying what role any individual reviewer plays in the diffusion process of a movie and by disentangling the direct effect of product appeal from the individual effect of expert opinion. Although we adopt the basic idea of Eliashberg and Shugan (1997), in which critics can have an influencer and/or a predictor role, we assess the roles of individual critics using a formal diffusion model. By using a model that is based on the definitions of the two potential roles of critics, we are able to parse out and simultaneously measure the predictor and influencer roles. Although we use real-world data from the motion picture industry to provide new empirical evidence and insights on the role of critics and the performance of new products, the methodology developed here can be generalized to any industry in which expert opinion matters.

The remainder of the article is organized as follows. In the next section, we provide a review of the literature on the role of expert opinions. Next, we propose our theoretical model. We then describe the data and present the results of our empirical analyses. Finally, we close with a discussion of the theoretical and managerial implications of our findings, along with suggestions for possible future research directions.

2 Literature review

Scholars from various fields have shown growing interest in recent years in understanding the complex role of expert opinions in many markets—films, theater, books, music, etc. (Caves 2000; Cameron 1995). With regard to empirical evidence on the agreement of ordinary consumers and professional critics, numerous empirical studies have examined the relationship between critical reviews at the aggregate level and box office performance (Basuroy et al. 2003; Litman 1983; Litman and Kohl 1989; Sochay 1994; Litman and Ahn 1998; Wallace et al. 1993; De Silva 1998; Jedidi et al. 1998; Prag and Casavant 1994; Ravid 1999; Holbrook 1999).

One of the fundamental contributions in marketing regarding the role of reviewers is by Eliashberg and Shugan (1997), who contrasted two perspectives on the role of film critics: the influencer perspective and the predictor perspective. An influencer or opinion leader is a person who is regarded by other people or by a group as having expertise or knowledge on a particular subject (Assael 1984; Weiman 1991). In films, critics are typically invited to an early screening of the film and write reviews before the film opens to the public. Therefore, they have more information than the public does in the early stages of the film's run. If critics are primarily opinion leaders, then their views will have a significant impact on early attendance figures and box office revenues but, not necessarily on the final outcome.

Eliashberg and Shugan (1997) proposed an alternative view of critics—the "predictor" role—in which critics' preferences reflect those of the audiences to which they speak. The views of predictor critics are leading indicators of the ultimate success of a movie and do not influence its early run in the box office. In order to test for this role of critics relative to the influencer role, they regressed weekly (early and late) sales of 56 movies against the total number of reviews, the proportion of positive or negative reviews, and the number of screens. For each movie, they had 8 weeks of box office data. They estimated eight independent regressions, one for each week.

It is unclear that the correlation analyses of Eliashberg and Shugan (1997) and others (Basuroy et al. 2003) accurately reflect the role of critics, for these studies did not account for the inherent quality of the movies. As such, their observed correlations between ticket sales and aggregate critical acclaim might be due to a third factor—movie quality. It is entirely possible that good movies sell well because they are good movies, liked by critics and by the public. Because of the confounding factor of movie quality, a positive correlation of aggregate critics with the weekly sales of later or early weeks by itself does not reveal a role of critics.

Another potential problem with the use of aggregate reviews in the prediction of success for a new product is the potential endogeneity in the reviews themselves. For example, a movie based on an excellent screenplay by a famous author and featuring popular actors led by a star director is more likely to be reviewed by a larger number of critics and to generate more positive reviews due to its higher appeal. Consequently, one might see a strong correlation between box-office results and the volume and average valence of the reviews, not because of the critics' predictive power and influence but because of the correlation with a common factor—the overall appeal of the movie. By focusing on the effect of individual reviews, we attempt to at least partially avoid this potential problem, adjusting each individual review in relation to a consensus measure of movie quality obtained across all critics. This way, we consider the impact of each critic's review, after discounting for any possible "bandwagon" effect generated by the aspects intrinsic to the movie.

Second, the analysis of Eliashberg and Shugan (1997) was based upon an assumption about the timing of critical influence, that correlation of critical opinion with early weeks' sales would reflect an influencer role, while correlation with later weeks' sales would reflect a predictor role. One difficulty in this assumption about timing is that early and late box office sales tend to be quite correlated across movies; better movies sell more tickets cumulative and have higher sales both early and late in the product lifetime. A model that ignores this correlation may lack the power to uncover the true roles of critics. Rather than comparing early and late sales, our model estimates the extent to which sales are driven by outside influences and the extent to which individual critics serve as outside influences. Our approach also allows consumers to be influenced by critics later in the lifetime of the movie, not just early, through the dynamics of a diffusion process, which also specifically accounts for the correlation between early sales and cumulative sales.

Third, in analyzing the impact of critics on box office sales, we control for a number of obvious factors that influence sales. For example, movie producers invest heavily in advertising, in the belief that advertising impacts movie sales. Given that advertising informs the public about a movie in a manner not unlike the role of critics, we explicitly account for advertising in our model. For similar reasons, we also account for the movie budget, the recognition of actors and actresses, the number of screens on which the movie opened and other important factors that could influence sales, and we evaluate the impact of critics only after accounting for these factors. Because of the myriad of influences on box office sales that may be simultaneously correlated with critical opinion, an analysis of the role of critics requires a carefully constructed model.

3 Modeling the role of individual critics

We assume the classic formulation of a diffusion process proposed by Bass (1969),

$$y_{it} = p_i(m_i - Y_{it}) + q_i \frac{Y_{it}}{m_i}(m_i - Y_{it}) + \varepsilon_{it} \tag{1}$$

in which movies are indexed by i and weeks by t=1...T_i, and we have added an error term $\varepsilon_{it} \sim N\left(0, \sigma_i^2\right)$. In this notation, p_i is the coefficient of innovation, q_i is that of imitation, m_i is the market potential, y_{it} represents box office sales of movie i in week t, and Y_{it} is cumulative sales.[1]

As discussed in Bass (1969), this new product diffusion model proposes that the timing of product purchase results from one of two buying influences. The parameter q, the coefficient of imitation, reflects the influence of previous buyers on purchase timing. Note in particular that q reflects specifically the impact of previous buyers, such as network effects or "word-of-mouth" and not joint decision making of groups of buyers. A group of friends who decide which movie to watch are making a joint decision, while q reflects the influence of those who have already seen the movie on those who have not. The parameter p, the coefficient of innovation, reflects influences that are not related to the number of previous buyers. In keeping with the diffusion model literature, we take p as representing the probability that a potential buyer adopts the new product through external influences such as advertising, and q as network effects or "word-of-mouth," which depends on the number of current users. A critic's opinion might be related to the early diffusion of the product in the same way that advertising affects adoption. If a critic is merely good at sensing the public's preferences or anticipating the success of a movie, his effect will show in the market potential (m).

We employ the Bass framework because, derived from principles of new product diffusion, its parameters have straightforward interpretations for the applied problem; for instance, the Bass model identifies and disentangles innovator purchase probability from market potential, an issue of key importance in our study. For many movies, sales decline exponentially. In this case, the Bass model simplifies to a model of exponentially decreasing sales in which the innovator purchase probability measures the speed of decay of the exponential, or how fast public interest curtails. One of our goals is to assess which critics' opinions are correlated with the innovator purchase probability (or decay of movie sales) and which are correlated with market potential. The Bass model also explicitly measures the word-of-mouth effect, which has been found to have a strong effect on movie adoption (Godes and Mayzlin 2004; Sawhney and Eliashberg 1996).

We recognize that the Bass structure is not a perfect match for movies, in that the Bass model was developed for durable goods rather than repeat-purchase products. However, repeat purchase is rare in the movie industry and has been generally deemed safe to ignore in the movie modeling literature (Eliashberg et al. 2000; Sawhney and Eliashberg 1996). An alternative to the Bass model for this data would be the generalized gamma distribution (Ainslie et al. 2005). For exponentially decreasing data, a common sales pattern for movies, the Bass model and the generalized gamma are mathematically identical, in that both simplify to the exponential distribution for exponentially decreasing sales data. Not all movie sales data are exponentially decreasing, so the two models are distinct across movies of varying diffusion patterns.

To allow for variation in the role of critics across different types of products, we specify a model with k product clusters. Within each product cluster, we assume the Bass parameters to be a linear function of exogenous variables such as movie

[1] Although Eq. 1 allows for negative sales, constraints on the space of estimated parameters (e.g. that market potential m_i must exceed cumulative observed sales for movie i) ensure positive sales.

characteristics, critic reviews, and marketing expenditures in promoting and distributing the movie.

$$\begin{aligned} \phi_i|s_i &= W_{si}\theta_s + u_{si} \\ u_{si} &\sim N(0, V_s) \\ \phi_i &= [\mathrm{logit}(p_i), q_i, \log(m_i)] \end{aligned} \quad (2)$$

In Eq. 2, ϕ_i collects the Bass parameters for movie i; we transform the Bass parameters so that the Gaussian error assumption is reasonably accurate. W_{si} is a set of exogenous variables including movie characteristics and other relevant factors for movie i; s_i indexes the movie cluster and takes values 1, 2,...k. Because the composition and dimension of the set of movie variables that affect the Bass parameters may differ by cluster, we index W by cluster as well as by movie. Similarly, we allow the covariance among the Bass parameters to differ by cluster.

In a study of the roles of individual critics, the matrix of exogenous variables W_{is} may be quite large as a result of a large population of individual critics. Furthermore, individual critic's opinions may be correlated with one another and with characteristics of the movies, meaning that W_{is} may be multicollinear. We therefore incorporate a stochastic search variable selection (SSVS) algorithm to identify promising subsets of variables that influence Bass parameters within a movie cluster.

The matrix W_{is} contains not only the critiques of movie reviewers but also the characteristics of movies such as its production and promotion budget. Because empirical work with movies has already identified important movie characteristics, we specify a framework that will incorporate such variables in the model outside the stochastic selection process. To this end, we partition W_s into two subsets, Z_s and X_s, in which those variables in Z_s are included with probability 1, and those variables in X_s are possibly included in the model. Expanding Eq. 2, we have

$$\phi_i|s = Z_{si}\psi_s + X_{si}\beta_s + u_{si} \quad (3)$$

We use a Gaussian prior on vec(ψ_s); note that ψ_s and β_s are matrices of regression coefficients. For our prior on vec(β_s), we use the mixture framework developed by George and McCulloch (1993):

$$\beta_{sj}\Big|\gamma_{sj} \sim (1-\gamma_{sj})N\left(0, \tau_{sj}^2\right) + \gamma_{sj}N\left(0, c_{sj}^2\tau_{sj}^2\right) \quad (4)$$

$$P\left(\gamma_{sj} = 1\right) = 1 - P\left(\gamma_{sj} = 0\right) = \zeta_{sj} \quad (5)$$

where β_{sj} is the jth element of vec(β_s). Here, c_{sj}>1; the intuition is that each coefficient β_{sj} is either close to zero, in which case it can be safely ignored, or not close to zero, in which case it should be part of the model. If β_{sj} are close enough to zero to be ignored, γ_{sj}=0. Because the set of influential critics may vary by movie cluster, we allow γ to vary by cluster s and critic j.

The SSVS algorithm is influenced by tuning parameters c and τ, which are set to reflect the goals of the analysis. For instance, one goal would be model parsimony. Our goal is to identify individual critics that may influence the diffusion process; the most parsimonious model would leave out marginally influential critics, although we at least want to identify critics that have a reasonably large probability of being influential. For details on the relationship between model parsimony and tuning parameters, see George and McCulloch (1993).

Note that the SSVS analysis differs greatly from the standard approach of identifying a best single model and using that model to understand a research problem. The SSVS recognizes uncertainty in identifying a single "true" model and puts probability mass over a distribution of models. The traditional approach assumes that the researcher can identify with certainty the one true model, either by the use of theory or as an outcome of highly informative data. With the nature of our dataset, it is unlikely that the data will clearly identify a single true model. In fact, we know with certainty that there is not adequate information in the data to identify a single true model for one potential situation—if a cluster has fewer observations than it has variables, multiple different models will each fit the data perfectly. The extreme case of fewer observations than variables illustrates an important point: that the more variables one has for model selection, the greater the uncertainty. Because we investigate a large set of critics, it is imperative that we allow for uncertainty of the model.

Because SSVS models are not well known in the marketing literature, we find it important to distinguish SSVS from a more well-known approach in data mining. In data mining, a common analysis method is to use the search tools to identify a single best model. This approach has been criticized because it uses a large set of variables to identify a single model, and it is always possible to find a model that fits data well if one has enough variables for that model. The SSVS approach produces an entirely different outcome—a distribution over a large set of models, not a single model. Rather than conditioning on a single chosen model, as is commonly done elsewhere, we integrate across the whole posterior distribution of models before reporting parameter estimates. The result is a highly conservative approach to identifying important individual critics.

4 Data

We analyze a sample of 466 films released between December 1997 and March 2001. For each of these movies, we collected weekly revenue and screen data from *Variety* magazine. Given our focus on the diffusion process, weekly data are crucial. The data set is fairly large and is comparable to the data that have been used recently in this literature (Basuroy et al. 2003; Elberse and Eliashberg 2003).

Several factors may affect the adoption parameters p_i and q_i and market size m_i for a new movie. To select covariates for our model, we build upon the extant empirical movie modeling research. Below is a description of the variables we include in our study:

- *Budget*: Several authors have shown that the budget of a film is significantly related to its box office performance (Litman 1983; Litman and Kohl 1989; Litman and Ahn 1998; Prag and Casavant 1994; Ravid 1999). The trade term for the budget figure is "negative cost" or production costs. This does not include gross participation, which is ex-post share of participants in gross revenues, nor does it include advertising and distribution costs. The budget data were collected from International Movie Data Base (http://www.imdb.com) and from http://www.baseline.hollywood.com.

- *Advertising*: Ad expenditure data for each movie in our sample were separately collected from various issues of Leading National Advertisers (1998–2001). Our measure of ad expenditure includes spending on all major media, including television, radio, and print.
- *Stars*: Studies by Wallace et al. (1993); Litman and Kohl (1989), and Sochay (1994) found that the presence of stars in the cast had a significant effect on film rentals. On the other hand, Litman (1983) found no significant relation between the presence of a superstar in the cast of a film and its box office rentals. Smith and Smith (1986) found that winning an award had a negative effect in the 1960s but a positive effect in the 1970s. Similarly, Prag and Casavant (1994) report conflicting evidence regarding stars, with star power positively impacting a film's financial success in some samples but not in others. The lack of a star-power effect has been documented in later studies as well (DeVany and Walls 1999; Litman and Ahn 1998; Ravid 1999). For star power we use the proxies suggested by Ravid (1999). For our first definition of a "star," we identified all cast members who had won an Academy Award (Oscar) for Best Actor or Best Actress and all directors who had won for Best Director in years prior to the release of the current film. We created a dummy variable, WONAWARD, which denotes films in which at least one actor/actress or the director has won an Academy Award in years prior to the release of the film. To create an additional similar measure, we defined an additional variable, NOMAWARD, which takes a value of 1 if at least one of the actor/actress/director had been nominated for an award prior to the release of the film.
- *MPAA ratings*: Ratings are considered by the industry to be an important issue. Ravid (1999) found ratings to be significant variables in his regressions. In our analysis, we code the ratings from http://www.mpaa.org using dummy variables. In our sample, the proportions of G, PG, PG13, and R are 4.3, 10.0, 32.2, and 53.5%, respectively. This distribution of all films released between 1999 and 2000 (see http://www.mpaa.org) is as follows: 5% G, 8% PG, 17.6% PG13, and 69% R. We used a dummy variable "<R" to indicate films that had ratings of G, PG, and PG13.
- *Sequel*: One variable that may be of interest is whether or not a film is a sequel (Litman and Kohl 1989; Prag and Casavant 1994; Ravid 1999; Ravid and Basuroy 2004). Although sequels tend to be more expensive and sometimes bring in lower revenues than the original film, they may still outperform the average film if they can capitalize on a successful formula. The SEQUEL variable receives a value of 1 if the movie is a sequel to a previous movie and 0 otherwise.
- *Number of screens*: The number of screens on which a movie plays each week has been reported to have the most significant impact on weekly revenues (Basuroy et al. 2003; Elberse and Eliashberg 2003). We incorporate the weekly screen count provided by Baseline.
- *Movie appeal*: Kamakura et al. (2006) developed an approach that uses information available from every expert, including those who are silent about the product, to obtain a consensus measure of expert opinion on movie quality. Their measure is not simply an aggregate of opinion, because the meaning of an opinion (positive, negative, etc.) varies by critic; for instance, the fact that an expert is silent about a product may imply a positive or a negative review,

depending on the expert. One of their important findings concerned the dimension of the latent space of judgments about the movies. Although their model allows this consensus measure to be multidimensional—where the judged dimensions for movies, books, and plays could be entertainment value, acting, or complexity of the plot—they found the consensus measure in movies to be unidimensional. In other words, critics were fundamentally assessing the same underlying latent factor when writing their opinions. We use the label "appeal" to refer to the univariate latent factor.

- *Individual reviews*: The key issue in our study is to identify individual critics whose reviews impact box office sales. On the first weekend of a film's opening, *Variety* lists the reviews from four major cities: New York, Los Angeles, Washington DC, and Chicago. *Variety* classifies these reviews as "pro" (positive), "con" (negative), and "mixed." The number of reviewers for the sample of 466 films in our data was quite large—more than 150 reviewers, each with a unique valence. We shortened this list to 46 critics, using media circulation statistics to select those critics whose reviews would be most widely accessible. We used all critics whose reviews appear in publications with 2002 circulation that exceeded a half million copies plus a few well-known syndicated critics. We used a single statistic for each critic to measure the valence of a critical review effect of that critic. If the review was positive, we code the critic's effect to be 1. If negative, we code it to be −1. Otherwise, we code it as 0 for a mixed review. An alternative coding would be to use two variables per critic, coding the presence of a review separately from its valence. In this coding, the presence variable would be 1 if the critic reviewed the movie, 0 if the critic was silent about the film. The valence would be equal to 1 if the critic was positive about the film, 0 for a mixed review, and −1 for a negative review. We used the more crude measure so that there would be only 46 variables representing critics, rather than double that number. Out of the 46 critics we used in our analysis, Lawrence Van Gelder (*New York Times*) had the fewest number of reviews, 14, while Peter Travers (*Rolling Stone*) had the largest number of reviews, 358. The most negative critic was Elvis Mitchell (*New York Times*), who gave positive reviews in 10 of 63 films that he reviewed. The most positive reviewer was Kevin Thomas (*LA Times*), who gave 90 positive reviews out of a total of 123 reviews.

In light of the findings of prior empirical work regarding factors known to be relevant to movie sales, we define the Z matrix (see Eq. 3) to be composed of the above factors, except for individual critics, because the Z matrix includes those factors already known to affect movie diffusion. In a later section, when we introduce individual critics into the model, we put the individual critic variables into the X matrix (Eq. 3). By doing so, we estimate the marginal contribution of individual critics beyond that of the covariates identified in the extant literature. In the next section, we describe model estimation and the results.

5 Model estimation and results

Our hierarchical model has two levels of parameters, estimated simultaneously (please refer to the Appendix for the estimation algorithm). The first level of parameters comprises those of the Bass model, parameters which summarize the sales diffusion curve for the movie. The second level of parameters reveals how exogenous variables, such as promotion budget or movie appeal, influence the Bass model parameters. Because of the large number of movies, we do not report the movie-specific parameters (the Bass model parameters) for any of the models we estimate. As for fit statistics for the models of movie sales, the median R^2 across movies is 0.98. Although these parameters provide extremely close fits to the movie sales curves, our focus in this article is neither fit nor prediction of the movie sales diffusion, but rather an understanding of how the diffusion parameters, which themselves are estimates, vary across movies.

We begin by ignoring product differences, in that we assume all movies to belong to the same movie cluster, following the assumptions made in many previous studies. Table 1 contains the estimates for the ψ parameters, measuring the impact of movie characteristics on the diffusion of a new movie. Values of the psi (ψ) parameter that are bolded are those for which the 95% posterior parameter interval does not contain zero (i.e., in classical statistics terminology, the predictor has a "statistically significant" impact on the diffusion process). As discussed earlier, m is the market potential, q is the word-of-mouth parameter, and p in this context (due to the large number of movies with exponentially decreasing sales) reflects both the opening week's sales (as a percentage of total box office sales) and the sales decay rate.

Table 1 Model with no movie clusters or individual critics

Z	Bass parameter	Ψ	std(Ψ)
Intercept	p	**−3.621**	**(0.124)**
Intercept	q	**0.322**	**(0.022)**
Intercept	m	**−1.891**	**(0.116)**
Log screens	p	**0.384**	**(0.023)**
Log screens	q	**−0.029**	**(0.004)**
Log screens	m	**0.124**	**(0.025)**
Log budget	p	0.068	(0.04)
Log budget	q	0.003	(0.005)
Log budget	m	**0.16**	**(0.041)**
<R rating	p	**−0.331**	**(0.061)**
<R rating	q	−0.011	(0.008)
<R rating	m	**0.288**	**(0.069)**
Advertising	p	−0.003	(0.047)
Advertising	q	**−0.03**	**(0.007)**
Advertising	m	**0.59**	**(0.049)**
Appeal	p	**−0.317**	**(0.034)**
Appeal	q	0.002	(0.004)
Appeal	m	**0.283**	**(0.039)**
WonAward	p	−0.019	(0.065)
WonAward	q	−0.006	(0.008)
WonAward	m	0.007	(0.074)
Sequel	p	−0.032	(0.12)
Sequel	q	−0.017	(0.015)
Sequel	m	**0.652**	**(0.14)**

Values in bold indicate that the 95% posterior interval for the parameter does not contain 0. Numbers in parenthesis are posterior standard deviations.

The estimates reported in Table 1 lead to the following conclusions regarding the diffusion process for all movies:

- The initial number of screens accounts for variation of all three Bass parameters. The greater the number of opening screens, the more rapid the decline of sales, because the effect on p is positive. In addition, movies with a greater number of opening screens have less of a word-of-mouth effect (negative effect on q) and a greater total market potential (positive effect on m).
- Movies with greater advertising support are those with larger market potentials and less of a word-of mouth effect. Whenever theater capacities limit initial sales, advertising cannot increase early weekly box office sales (a positive effect on Bass parameter p) but rather should slow the sales decay (a negative effect on p) of the movie. In this model, the coefficient is estimated to be close to zero, indicating no significant impact of advertising on p.
- The role of movie appeal on initial sales should be similar to advertising, either directly stimulating early sales (see the discussion earlier of the coefficient of innovation) or slowing the sales decline, depending upon the type of movie. In this model, we find that sales fall off less rapidly (negative effect on p) for movies with greater appeal, and that movies with greater appeal have larger market potentials.
- Movies with greater market potential are those with larger budgets, sequels, greater advertising support, a large number of opening screens, of greater appeal, and those with an MPAA rating other than “R”; the latter also have sales curves that decay less rapidly.

6 Accounting for product differences

In order to investigate product differences, we next allow for more than one cluster of movies. The literature discusses two types of movies, “wide-release” and “platform-release” (Ainslie et al. 2005; Sawhney and Eliashberg 1996). These two movie types correspond to two different release strategies. In the wide-release strategy, movies open in a large number of theaters, whereas platform movies open in select theaters that are frequented by the movie’s target demographic. These two strategies can clearly be seen in the bimodal distribution shown in Fig. 1, which shows a histogram of the number of opening screens for the 466 movies in our data. Seeing that the platform-release data are well below 500 opening screens and the wide-release movies are well above 500 opening screens, we use 500 screens to define the two clusters: that is, a movie is defined as platform release if it opened on less than 500 screens. This classification of movies into two categories is so clear-cut that an attempt to cluster-analyze our data based on all movie characteristics led to essentially the same classification as the one we report here.

Descriptive statistics of the clusters are contained in Table 2. By definition, the clusters differ in the number of opening screens (2,272 vs 54). More generally, the clusters differ in scale; the wide-release cluster’s 317 movies tend to have high box office sales, larger budgets ($48.1 million vs $11.7 million), and more advertising ($16.7 million vs $3.5 million). All of the sequels are in the wide-release cluster,

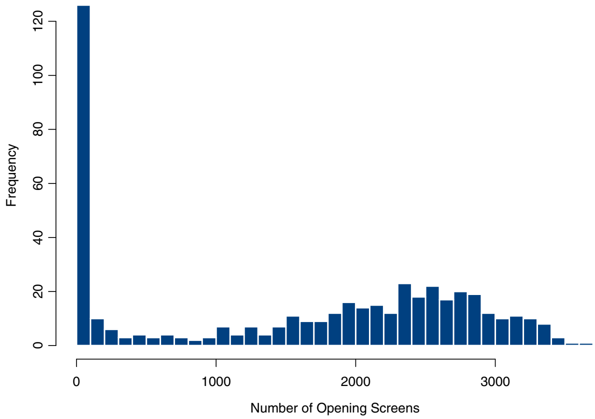

Fig. 1 Histogram of number of opening screens. *The spike* near 0 in this chart reflects the large number of films with fewer than 100 opening screens (see Table 2). All films in our data open in greater than 0 screens

possibly because sequels tend to be made for previously successful films. In general, critics are more positive when rating movies in the platform-release cluster (61% positive ratings) than in the wide-release cluster (32% positive ratings), although ratings exhibit high variability. These statistics suggest that critics have preferences that do not agree with those of the viewing public (Holbrook 1999; Kamakura et al. 2006). Many of the films in the platform-release cluster cater to a smaller segment of viewers by design; it may be that critics also tend to like such films more than those designed for the "masses" (Holbrook 1999). Our model results (see below) find agreement between critics and the masses, in that the critical consensus is positively correlated with the market potential.

Another important distinction between the two clusters is the shape of the time series sales function. The wide-release cluster has a greater proportion of sales

Table 2 Descriptive movie statistics by cluster

Class	Statistic	Platform-release	Wide-release
	Number	149	317
	% sequels	0%	8%
	Number of weeks	14.0 (7.4)	13.6 (6.0)
Ratings	G	2.7%	5.0%
	PG	6.0%	12.0%
	PG13	18.1%	38.8%
Awards	WonAward	24.2%	34.7%
	NomAward	46.3%	53.3%
Scale	Budget (millions)	11.7 (14.3)	48.1 (33.1)
	Advertising (millions)	3.5 (5.8)	16.7 (7.8)
	Opening screens	54 (95)	2,272 (672)
Critics	Number of reviews	12.8 (3.8)	14.3 (4.2)
	Perc pos reviews	61% (23%)	32% (26%)
Sales	Sales (millions)	8.2 (1.4)	10.6 (0.9)
	First week (%)	11.4% (15.8%)	37.2% (14.9%)

Values within parentheses are standard deviations.

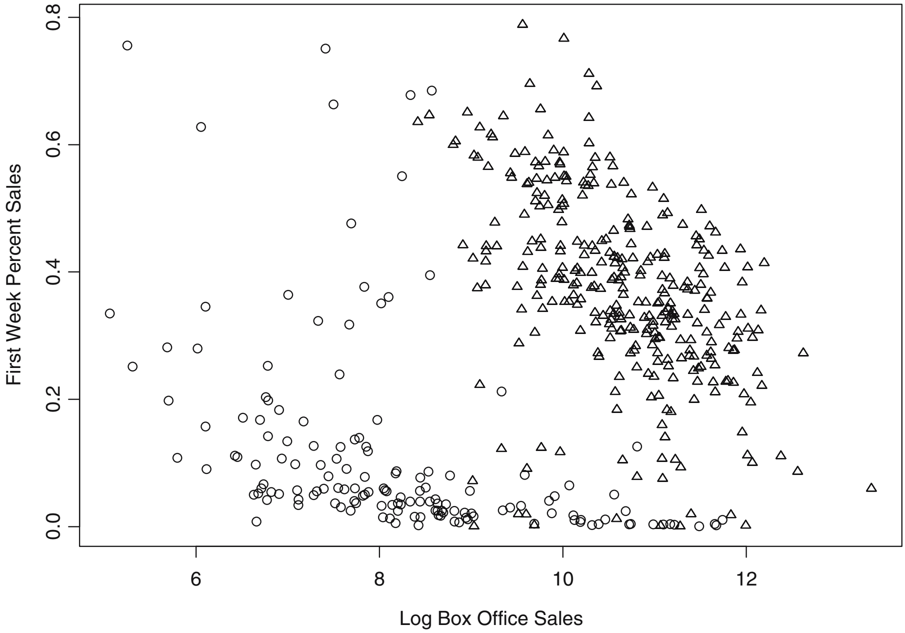

Fig. 2 Initial and total box office sales. *Triangles* are movies that opened in at least 500 screens; *circles* represent movies that opened in fewer than 500 screens

(37.2% vs 11.4%) occurring in the opening week. An examination of the sales curves revealed that 128 of the 149 movies in the platform-release cluster were sleeper movies (those for which the mode of weekly sales occurs after the second week) (86%), whereas only 41 of 317 (13%) of movies in the wide-release cluster were of the sleeper shape. The difference in diffusion shape is important for the interpretation of the coefficient of innovation p, as discussed earlier in the model section. In the wide-release category, which is dominated by exponentially decreasing sales diffusion curves, the coefficient of innovation p reflects this exponential sales decay; in the platform-release category, that parameter maintains the typical interpretation of the coefficient of innovation in the Bass model. Although a high p is generally viewed in this industry as undesirable,[2] a high p is desirable for sleeper movies, because it triggers the diffusion of the movie through contagion or imitation. It is for movies with exponentially declining sales that p is undesirable, in that movies with a high p die more quickly.

In Fig. 2 we show a scatter plot of total sales versus first-week sales, in which a triangle plotting symbol was used for wide-release movies and a circle for platform-release movies. The cluster of platform-release movies runs along the bottom of the plot, because its first-week sales are a relatively small percentage of total sales. The wide-release cluster appears in the upper right; movies in this cluster have both higher total sales (shown in log scale in the figure) and higher first-week sales. Among other things, Fig. 2 reveals the importance of our modeling assumptions: (1)

[2] Noted by one of the anonymous referees.

that coefficient of innovation p and market potential m are correlated, and (2) that correlations of p (which will roughly correspond to first-week percent sales) and m (which will roughly correspond to total sales) might differ by cluster. Put more succinctly, V_s is non-diagonal and could be cluster dependent, and models should account for the correlation of p and m rather than assuming that early and late sales are independent of each other.

After accounting for product differences, we obtain different estimates (shown in Table 3) from the previous ones, as well as a richer description of the movie sales diffusion process. Before accounting for product differences, movies with greater advertising support proved to be those with larger market potentials and less of a word-of-mouth effect, and there was no relationship between advertising and the coefficient of innovation (p). After allowing for product differences, we found for the wide-release cluster that advertising was negatively correlated with p. For the wide-release cluster, the dominant model is exponentially decreasing sales, and advertising is found to dampen the decay rate of the sales. For the platform cluster, we did not find a strong effect of advertising on the coefficient of innovation (p), but the more heavily advertised films ended up with less of an effect from word of mouth. For both types of movie, those with greater advertising support had greater market potentials.

Table 3 Model with clusters, no individual critics

Z	Bass parameter	Platform cluster		Wide-release cluster	
		Ψ	std(Ψ)	Ψ	std(Ψ)
Intercept	p	**−3.788**	**0.359**	−0.955	0.679
Intercept	q	**0.431**	**0.071**	**0.376**	**0.082**
Intercept	m	**−1.239**	**0.220**	**−9.529**	**0.812**
Log screens	p	**0.160**	**0.079**	0.095	0.104
Log screens	q	**−0.048**	**0.018**	**−0.046**	**0.012**
Log screens	m	0.035	0.053	**1.295**	**0.125**
Log budget	p	0.162	0.115	0.032	0.047
Log budget	q	**0.130**	**0.025**	−8E-05	0.005
Log budget	m	−0.116	0.068	0.084	0.057
<R rating	p	**−0.507**	**0.217**	**−0.241**	**0.056**
<R rating	q	**−0.094**	**0.050**	−4E-04	0.006
<R rating	m	**0.384**	**0.169**	**0.182**	**0.069**
Log advertising	p	0.172	0.120	**−0.126**	**0.055**
Log advertising	q	**−0.163**	**0.022**	−0.001	0.006
Log advertising	m	**0.719**	**0.077**	**0.229**	**0.068**
Appeal	p	−0.097	0.178	**−0.266**	**0.029**
Appeal	q	−0.014	0.035	0.001	0.003
Appeal	m	**0.304**	**0.121**	**0.298**	**0.036**
WonAward	p	−0.192	0.232	−0.013	0.057
WonAward	q	−0.093	0.068	−0.002	0.006
WonAward	m	0.284	0.192	0.022	0.071
Sequel	p	–	–	0.102	0.099
Sequel	q	–	–	−0.010	0.010
Sequel	m	–	–	**0.368**	**0.123**

Values in bold indicate that the 95% posterior interval for the parameter does not contain 0. Numbers in parenthesis are posterior standard deviations.

In the wide-release cluster where the dominant model is exponentially decreasing sales, the role of movie appeal exactly followed that of advertising; movies with greater appeal had not only a larger market potential, but also a less pronounced decay in sales (negative coefficient on p). In the platform cluster, greater appeal again led to larger market potentials but did not affect the diffusion of the new movie. We had expected movies with greater appeal to receive more word of mouth, but we did not find movie appeal to be significantly related to the word-of-mouth parameter (q) in either of the two clusters.

Although our model without product differentiation found movies with larger production budgets to have greater market potential, the movie budget no longer had an effect on market potential after accounting for product differences. The earlier result was driven by differences in the type of movie; platform movies tended to have both lower overall sales and lower budgets than wide-release movies. This result shows the importance of accounting for different products or marketing strategies, in that the former model attributed an effect to a movie budget that actually turned out to be an effect of the product release strategy. We also found that platform movies with greater budgets had a larger word-of-mouth effect, a relationship that disappeared once we included individual critics (discussed later).

The initial number of screens was the only factor in the first model (without product differentiation) that accounted for variation of all three diffusion parameters. After controlling for product differences, the number of screens was no longer associated with all three Bass parameters in either cluster. In both clusters, movies with a greater number of opening screens had less of a word-of-mouth effect. In the wide-release cluster, movies with a greater number of screens had greater market potential, a result not reflected in the platform-release cluster. In contrast, movies in the platform-release cluster with a greater number of opening screens had greater initial sales.

In the platform-release cluster, the MPAA ratings accounted for variation in all three Bass parameters. Movies with ratings other than “R” opened with lower sales, had lower word-of-mouth effect, but had greater overall market potential. In the wide-release movie cluster, movies with other than “R” rating had both higher market potential and a sales curve that did not decay as rapidly. Finally, there were no sequels in the platform-release cluster, and the result from the previous model (sequels have greater market potential) was confirmed in this model for the wide-release cluster.

One overall conclusion from our examination of summary statistics is that it is important to account for product differences when studying the diffusion of new movies. For example, we found that advertising and movie appeal affected both sales decay and total market potential in the wide-release cluster but affected only market potential in the platform cluster. More generally, we found that the use of clusters allows for accurate and meaningful parameter interpretation.

7 Product differences and individual critics

The addition of individual critics resulted in few changes in existing parameters, as can be seen by comparing the full model (Table 4) with the previous results

Table 4 Model with clusters and individual critics

Z	Bass parameter	Platform cluster		Wide-release cluster	
		Ψ	std(Ψ)	Ψ	std(Ψ)
Intercept	*p*	**−4.359**	**(0.411)**	−1.308	(0.676)
Intercept	*q*	**0.543**	**(0.134)**	0.173	(0.193)
Intercept	*m*	**−1.280**	**(0.216)**	**−9.472**	**(0.794)**
Log screens	*p*	**0.256**	**(0.094)**	0.150	(0.104)
Log screens	*q*	**−0.070**	**(0.028)**	−0.014	(0.029)
Log screens	*m*	0.017	(0.055)	**1.281**	**(0.122)**
Log budget	*p*	0.203	(0.114)	0.016	(0.045)
Log budget	*q*	0.026	(0.031)	−0.010	(0.011)
Log budget	*m*	−0.003	(0.062)	0.095	(0.055)
<R rating	*p*	−0.488	(0.26)	**−0.225**	**(0.056)**
<R rating	*q*	−0.131	(0.08)	0.010	(0.015)
<R rating	*m*	0.393	(0.17)	**0.165**	**(0.068)**
Log advertising	*p*	**0.204**	**(0.109)**	**−0.131**	**(0.057)**
Log advertising	*q*	**−0.072**	**(0.036)**	−0.002	(0.014)
Log advertising	*m*	**0.666**	**(0.075)**	**0.238**	**(0.069)**
Appeal	*p*	−0.129	(0.178)	**−0.253**	**(0.03)**
Appeal	*q*	0.003	(0.056)	0.008	(0.008)
Appeal	*m*	**0.336**	**(0.12)**	**0.291**	**(0.036)**
WonAward[a]	*p*	–	–	–	–
WonAward	*q*	–	–	–	–
WonAward	*m*	–	–	–	–
Sequel	*p*	–	–	0.088	(0.098)
Sequel	*q*	–	–	−0.031	(0.025)
Sequel	*m*	–	–	**0.372**	**(0.122)**

Results for individual critics appear in the following table. Values in bold indicate that the 95% posterior interval for the parameter does not contain 0. Numbers in parenthesis are posterior standard deviations.
[a] Because WonAward is consistently insignificant, it was dropped from this model.

(Table 3). As alluded to earlier, for the platform-release cluster, movie budget in the final model is no longer correlated with the word-of-mouth parameter. Possibly the budget accounted for some additional aspects of movie appeal not fully covered by our measure of appeal but reflected in the reviews of individual critics. Also in the platform-release cluster, where seating capacity constraints are less binding, greater advertising was shown to increase early sales. Finally, whereas the MPAA ratings affected all three diffusion parameters in the previous model, none remained significant in this model.[3] In the wide-release cluster, the only change in the results was that the opening number of screens was no longer associated with the word-of-mouth parameter.

In this final model we also investigated which critics offer unique views that impact box office sales (i.e. which were influential after taking into account the general consensus). Because the aggregate set of critics was used to determine the latent appeal of a movie, these results (Table 5) for individual critics reflect their relative (beyond the consensus) impacts rather than absolute impacts on the sales diffusion. There may be critics that do not offer any unique insights beyond the

[3] The coefficient estimates and standard errors are very close to previous values but no longer "significant," in that 95% posterior intervals in this final model contain 0.

Table 5 SSVS results for individual critics

Cluster	Critic	Bass param.	$\overline{\gamma}_{sj}$	β	std(β)
Platform	Petrakis	p	0.534	**1.045**	**(0.495)**
Platform	Wilmington	p	0.563	**0.466**	**(0.182)**
Platform	Dargis	p	0.753	**0.552**	**(0.199)**
Platform	Feeney	p	0.754	**0.726**	**(0.271)**
Platform	Gleiberman	p	0.909	**−0.620**	**(0.193)**
Wide-release	Howe	p	0.597	**−0.107**	**(0.032)**
Wide-release	Van Gelder	p	0.756	**0.217**	**(0.067)**

Numbers in parentheses are posterior standard deviations.

readily apparent movie quality and critic consensus; these critics without unique information will not appear to be influential or predictive in our analysis, because their impact is already embedded in the consensus.

Unlike the elements of the ψ vector, which correspond to movie characteristics determined by previous research to influence movie sales, the prior for elements of the β vector is a mixture model (Eq. 4)—a mixture of two distributions—which reflects two cases: (1) that the impact of critic j on movies in cluster s is negligible, in which case $\gamma_{sj}=0$; and (2) that the impact of critic j on movies in cluster s is substantial, in which case $\gamma_{sj}=1$.

Empirically, γ_{sj} will be between 0 and 1; this is the probability that critic j influences movies in cluster s. For any single model, γ_{sj} is either 0 or 1. The average across models is a marginal probability that reflects a critic's influence across the distribution of possible models. Table 5 lists all cases for which γ_{sj} exceeds 0.5. If $\gamma_{sj}>$ 0.5, the evidence shows that that critic j most likely influenced the diffusion process in cluster s; otherwise, the evidence reveals that the critic most likely did not influence the diffusion process. Also note that each γ_{sj} corresponds to a particular β_{sj}, and β_{sj} influences one or more specific Bass parameters. As implied in the format of Table 5, which reports both γ_{sj} and β_{sj}, the γ_{sj} values reveal the nature of each critic's relationship to the diffusion process—that is, whether the critic's opinion correlates with the coefficient of innovation p, the coefficient of imitation q, or overall market potential m.

In the platform-release cluster the dominant sales pattern is the 'sleeper' diffusion pattern, and higher p's engender earlier sales, thereby triggering the diffusion process via imitation. John Petrakis is among those that appear to be influential ($\overline{\gamma}>0.50$). The positive estimate of β shows that Petrakis' reviews correlate positively with the innovation coefficient p, suggesting that a positive opinion about a movie leads to an increase in early ticket sales for the movie. Michael Wilmington, Manohla Dargis, and FX Feeney are even more closely related to the diffusion process, because their $\overline{\gamma}$ estimates are higher than that of Petrakis. As in the case of Petrakis, their reviews are positively correlated with the coefficient of innovation. The data quite strongly show the relevance of Owen Gleiberman's opinion, in that $\overline{\gamma}$ for Gleiberman is estimated to be 0.909. Gleiberman's opinions run counter to the tastes of the viewing public—it is when his reviews are negative that early ticket sales increase.

As discussed earlier, the role of the innovation coefficient p in the wide-release movie cluster is distinct from the other cluster. Due to the exponentially declining sales pattern, typical of "blockbuster" movies, advertising and movie appeal were found to slow the sales decay of a movie (to correlate negatively with p) rather than to bring higher early sales. In this cluster, Desson Howe and Lawrence Van Gelder were found to be influencers. A positive opinion from Howe would slow the decline of early sales (a negative β coefficient). A positive opinion from Van Gelder hastened the sales decline, indicating that Van Gelder's preferences, like Gleiberman's, run counter to the market.

It is important to recognize that the views of every relevant individual critic were found to be associated with the coefficient of innovation rather than with market potential. For market potential m, none of the critical reviews' $\overline{\gamma}_{sj}$ exceeded 0.5; the largest marginal posterior mean was a 0.20.[4] The evidence indicates that the marginal information from individual critics is not correlated with market potential. In the terminology of Eliashberg and Shugan (1997), our results show that a few critics are influencers; none in our data are predictors.

In the theoretical framework of Eliashberg and Shugan (1997), critics that are predictors may have opinions that correlate with the tastes of the readers of their critiques. Our results indicate that critics may be influential even while having opinions that are opposite of those of their audience. In writing their reviews, critics provide information about movies that allows their consumers to form their own quality expectations apart from the overall opinion of the critic, allowing critics to be influential in a market whose tastes do not correlate with their own.

In addition, we found more influential critics for platform movies than for wide-distribution movies. Although the discrepancy between five influential critics for the platform cluster and two for the wide release cluster is relatively small, one would expect critics to have greater informational value for the less advertised platform-release movies. Possibly the larger number of influential critics for the platform cluster reflects the need for information for that type of movie.

8 Discussion and managerial implications

Marketing research on critics' impacts on box office performance has so far examined the aggregate effect of critics, which is problematic because the aggregate critic effect is confounded with the underlying appeal of the movie. In order to assess the role of critics as well as account for the underlying appeal of the movie, this research investigated the impacts of individual film critic's reviews on box office performance of motion pictures after controlling for the appeal by using the latent appeal measure of Kamakura et al. (2006). This correction for the overall appeal of a movie is important, because some individual critics might be more likely to write positive reviews of movies with broader appeal, producing a spurious correlation between their opinions and ticket sales. Because the latent appeal measure of Kamakura et al. (2006) is the consensus of the set of critics, our estimates for individual critics reveal how unique contributions of individual critics marginally impact box office sales. We find that certain critics in their role as opinion leaders are correlated with the coefficient of innovation in the Bass model framework, a view

[4] For q, the largest was 0.12.

analogous to the influencer perspective (Eliashberg and Shugan 1997). Overall, we find critics to be influencers, and not predictors—conclusions that are opposite of those of Eliashberg and Shugan (1997) and closer to those of Basuroy et al. (2003).

Rather than separately investigating how early box office sales and total box office sales are influenced by covariates as in previous studies, our model accounts for the information sources in the marketplace about new products, using the well-known Bass model for the diffusion of innovations. Whereas the marketing literature already contains extensive research applying diffusion theory to the study of the spread of new ideas and products in a wide variety of settings, research exploring the impact of information from opinion leaders on the diffusion process has been limited. Recently, however, researchers in public policy and health have considered different methods of accelerating the diffusion of innovations using opinion leaders (Valente and Davis 1999).

Another distinguishing aspect of our approach that sets it apart from previous work is that incorporating the covariates—movie appeal and individual critic's impact—allows us to distinguish between the two types of movies while at the same time accounting for the possibility that both ticket sales and critics' opinions might be correlated with movie quality. The Bass diffusion model has three parameters and thus can speak to more than simply early and late sales. In particular, the diffusion model has a parameter that can be interpreted as a word-of-mouth effect (q). Most of our results show impacts on either initial sales or market potential, confirming the validity of the framework proposed by Eliashberg and Shugan (1997), in which initial sales and late sales (total sales) are the dominant features.

After accounting for the relationship of early sales and total sales, and after recognizing that this relationship varies across platform-release and wide-release movies, we find that the roles of covariates differ for these two types of movie. Note that because our model accounts for the interrelationship of m and p, we are able to estimate effects on both m and p in spite of their high correlation with each another. Our results show that advertising hastens adoption (p) and increases the market potential (m) for platform-release movies, whereas for wide-release movies, advertising delays the decay process (p) and enhances the market potential (m). Along similar lines, we find more critics to be influential in platform-release movies than in wide-release movies, a result that fits with the greater availability of information about wide-release movies, which translates into less potential reliance on information from critics. There is some anecdotal evidence in the mainstream media that corroborates these findings. Writing about wide-release movies, movie critic Richard Corliss wrote "Hollywood's marketers have become tremendously efficient at getting their core audiences to see their big movies. They don't need critics for that." (Corliss 2007). As for platform release movies, Joe Morgenstern, film critic of the *Wall Street Journal*, has noted "...movie critics still play a crucial role in supporting independent films. We [critics] may well be more useful than ever in that regard, because the independent film movement is struggling more desperately than ever to find production money, publicity budgets, and access to multiplex screens" (Morgenstern 2006).

Earlier results with aggregated effects of critics were unable to distinguish the differential impacts of covariates between different types of movies. For wide-release movies, the diffusion curve of the vast majority of films exponentially decreased, and the word-of-mouth effect was trivial. Even so, movie appeal had a statistically significant, albeit small, effect on word of mouth in the wide-release cluster, for the results show that positive acclaim increased word of mouth. Word of mouth is non-trivial for the platform-release movies, for which positive acclaim lessened the word-of-mouth effect. These results reveal that high positive acclaim has an effect similar to advertising across movie clusters.

Although we relied upon extant research to identify different movie types, future research may simultaneously estimate movie clusters and identify influential individual critics. Simultaneously identifying data clusters and selecting model variables poses a modeling and data challenge. Clustering algorithms generally rely on some stable criterion (such as a likelihood) and identify data structures that fulfill the criterion. Variable selection models rely on fixed datasets and identify models (again, a likelihood) that best fit the data. Therefore, to cluster and select variables simultaneously presents a research challenge, in that clustering and variable selection rely on opposing assumptions. Additionally, our model conditions on certain variables such as the number of opening screens that might be endogenously determined, so the coefficients associated with these variables are biased away from what their values would be in a full specification. To the extent that other analyses may require more accurate estimates for these estimates, future research can augment the modeling framework accordingly.

Given the nature of our estimates, where influential critics are those that offer distinct and relevant information beyond the readily apparent movie quality, it is not clear *a priori* which critics will be found to be influencers. It is quite possible that widely circulated reviews offer no information beyond the readily apparent movie quality (and consensus viewpoint). Such an outcome could be consistent with strategy literature studies on first movers and followers that find that those with dominant market shares have incentive to imitate rather than innovate, even for information goods (Hidding and Williams 2002; Lieberman and Montgomery 1988). It is also possible that it is the unique and compelling insights of the well-known critics that have led to their wide market circulation. We do not specifically examine leader–follower strategies of well known critics (e.g. Roger Ebert) who did not appear in Table 5. For such critics, our results even so are not in support of the latter hypothesis, in that we do not find evidence that such critics had unique insights that influenced box office sales. Our results do identify specific critics that appear incrementally influential, suggesting the best targets to be coddled by producers. Further research may reveal that specific critics have demographic-specific influence (appealing to youth, for instance), because our research did not consider that certain reviewers may be more influential than others for specific movie genres.[5]

Finally, while our analyses focused on the impact of movie critics on the diffusion of new movies, we must re-iterate that our framework is not limited to the movie industry; it is applicable to the broad category of "experience" goods such as music,

[5] In some of our preliminary modeling, we examined differences across genres of films, not finding differences between genres. One plausible explanation is sample size, that even with our relatively large set of films (466), the number of films in the 17 genres (action, adventure, animation, comedy, crime, documentary, drama, family, fantasy, foreign, horror, musical, mystery, romance, sci-fi, thriller, and western) in the 2 clusters is on average 13. We also combined the 17 genres into 9 more general genres, still not finding differences between them.

restaurants, wines, video games, books, etc. where consumers seek the opinion of experts and vendors use critical acclaim as a promotion tool.

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Appendix

In this appendix we specify the prior distributions of the model parameters. Because we estimate model parameters with the Gibbs sampler, we also describe the conditional posterior distributions. Convergence of the MCMC chains was assessed with BOA version 1.0.1 (see Best et al. 1995).

For our prior on V_s, we use the covariance prior of Barnard et al. (2000), decomposing V_s into a vector of standard errors (ξ_s) and a correlation matrix R_s. We use an independent inverse gamma prior on each element of the standard error vector, $\xi_{sl}^2 \sim IG\left(v_{\xi s}, \kappa_{\xi s}\right)$, and we use a uniform prior over the space of positive definite correlation matrices for the prior on R_s. To complete the specification of our cluster-specific priors, we assume $\sigma^2 \sim IG(v_\sigma, \kappa_\sigma)$ and $\psi_\sigma \sim N\left(\mu_{\psi\sigma}, \omega_{\psi\sigma}\right)$.

We estimate model parameters using Gibbs sampling, drawing from the full set of conditional distributions. The conjugate priors on σ^2, ψ_s, and β_s lead to well-known conditional distributions (inverse gamma and normal) for the following conditional posteriors:

$$\begin{aligned}&\left[\sigma_i^2|\phi_i, \nu_\sigma, \kappa_\sigma\right],\\&\left[\psi_s\middle|\{\phi_i\}_s, s, \beta_s, V_s, \mu_s, \omega_s, \gamma_s\right], \textit{ and}\\&\left[\beta_s\middle|\{\phi_i\}_s, s, \psi_s, V_s, c_s, \tau_s, \gamma_s\right].\end{aligned}$$

To simplify the structure of the algorithm while allowing the dimension of W_s to vary across clusters, we simply condition on certain elements of ψ_s and/or β_s as equal to zero; the conditional distributions of the remaining elements are still multivariate normal, and draws are easily obtained.

Our prior for γ_{sj} is

$$f(\gamma) = \prod\prod \zeta_{sj}^{\gamma_{sj}} (1 - \zeta_{sj})^{\left(1-\gamma_{sj}\right)}$$

Although this prior implies independence, this assumption has been found to work well in practice (George and McCulloch 1993). The discrete conditional posterior distribution $\left[\gamma_{sj}\middle|\beta_s, \{\phi_i\}_s, s, \psi_s, V_s, c_s, \tau_s, \zeta_s\right]$ is Bernoulli where

$$p\left(\gamma_{sj} = 1\right) = \frac{\left[\beta_s\middle|\{\phi_i\}_s, s, \psi_s, V_s, c_s, \tau_s\gamma_{sj} = 1\right]\zeta_s}{\left[\beta_s\middle|\{\phi_i\}_s, s, \psi_s, V_s, c_s, \tau_s\gamma_{sj} = 0\right](1 - \zeta_s) + \left[\beta_s\middle|\{\phi_i\}_s, s, \psi_s, V_s, c_s, \tau_s\gamma_{sj} = 1\right]\zeta_s}$$

The conditional distribution of the ϕ vector $\left[\phi_i\middle|\sigma_i^2, \eta_i, \theta_s, V_s\right]$ is not conjugate, and we use a Metropolis Hastings algorithm to obtain draws of each ϕ_i. To make the draws, we transformed the third parameter from $\log(m_i)$ to $\log\left(m_i - Y_{iT_i} - y_{iT_i}\right)$, because we know that sales potential must exceed observed sales. Not only did this transformation allow us to incorporate relevant information in the draws of m_i, but it also ensured that predicted sales from the Bass model would be non-negative. We used the multivariate *t* distribution as our proposal density, with a location set equal to the previous draw of ϕ_i and a covariance matrix equal to $a_\phi V_s,$ where a_ϕ is a tuning constant.

Finally, we used the Griddy Gibbs algorithm (Ritter and Tanner 1992) to simulate from the conditional distribution of V^s

$$\left[V_s \middle| \phi, \eta, \theta_s, \nu_{\xi s}, \kappa_{\xi s}, s\right]$$

as was done by Barnard et al. (2000).

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