HOW CRITICAL ARE CRITICAL REVIEWS? THE BOX OFFICE EFFECTS OF FILM CRITICS, STAR-POWER, AND BUDGETS

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Abstract

In this paper, we investigate how critics affect box office performance of films, and how their effects may be moderated by stars and budgets. We begin by examining the process through which critics affect box office revenues, i.e., whether they influence the decision of the film going public (their role as influencers), merely predict that decision (their role as predictors), or do both. We find that both positive and negative reviews are correlated with weekly box office revenues over an eight-week period, suggesting that critics may play a dual role i.e., they can influence and predict box office revenues. However, the impact of negative reviews is found to diminish over time (but not that of positive reviews), a pattern more consistent with the influencer perspective. We next compare the positive impact of good reviews with the negative impact of bad reviews and find that film reviews evidence a negativity bias, i.e., negative reviews hurt more than positive reviews help box office performance, but only in the first week of a film's run. Finally, we examine two key moderators of critical reviews – stars and budgets, and find that popular stars and big budgets enhance box office revenues for films that receive more negative than positive critical reviews but do little for films that receive more positive than negative critical reviews. Taken together, our findings not only replicate and extend past research on critical reviews and box office performance, but also offer important insights as to how film studios can strategically manage the review process to enhance box office revenue.

Introduction

Critics seem to play an important role in consumers' decisions in many industries (Austin 1983; Cameron 1995; Caves 2000; Einhorn and Koelb 1982; Eliashberg and Shugan 1997 (henceforth ES); Goh and Ederington 1993; Greco 1997; Holbrook 1999; Vogel 2001; Walker 1995). Investors, for example, closely follow the opinion of financial analysts before deciding which stocks to buy or sell, as the market evidenced when an adverse report by Lehman Brothers Inc. sunk Amazon.com's stock prices by 19% in one day (*Business Week*, July 10, 2000). When advice turns out to be tainted, it leads to nation-wide scandals as the financial markets witnessed in 2002. Readers often defer to literary reviews before deciding on a book to buy (Caves 2000; Greco 1997). For example, rave reviews of *Interpreter of Maladies*, a collection of short stories by the then relatively unknown writer, Jhumpa Lahiri, put the book into the Best Seller Plus list of New York Times (*New York Times*, August 6, 1999). Diners routinely refer to reviews in newspapers and dining guides such as Zagat Survey to decide their selection of restaurants (Shaw 2000).

The role of critics may be most prominent in the film industry (ES 1997; Holbrook 1999; West and Broniarczyk 1998). More than a third of Americans actively seek the advice of critics (*Wall Street Journal*, March 25, 1994; B1), and more importantly, about one out of every three filmgoers says she or he chooses films because of favorable reviews. Realizing the importance of reviews to their films' box office fortunes, studios often strategically manage the review process, excerpting positive reviews in their advertising, and delaying or forgoing advance screenings if they anticipate bad reviews (*Wall Street Journal*, April 27 2001; B1). The desire for good reviews can go even further prompting studios to engage in deceptive practices. For example, Sony Pictures Entertainment admitted inventing a fake critic named David Manning to pump several films in print advertisements, like *A Knight's Tale* and *The Animal* (*Boston Globe*, June 19, 2001; E1).

In this paper we investigate three issues relating to the effects of film critics on box office success. The first issue is the role of critics in affecting box office performance. Critics could have two potential roles - that of *influencers*, if they actively influence the decisions of the consumers in the early weeks, or that of *predictors*, if they merely predict the public's decisions. ES (1997), who were the first to define and test these concepts, found that critics correctly predicted box office performance but did not influence it. Our results are mixed. On one hand, we find that both positive and negative reviews are correlated with weekly box office revenues over an eight-week period, thus showing that critics can do both (i.e., they both influence and predict outcomes). On the other hand, we find that the impact of negative reviews on box office revenues declines over time (but not that of positive reviews), a finding that is more consistent with the influencer perspective

The second question we address is whether positive and negative reviews have comparable effects on box office performance. Our interest in such valence effects stems from two reasons - the first is based on studio strategy while the second is rooted in theory. First, although we might expect the impact of critical reviews to be strongest in the early weeks of the run and fall over time as studio buzz from new releases take over, studios that understand the importance of good reviews are likely to adopt tactics to leverage good reviews and counter bad reviews (e.g., selectively quoting the good reviews in their advertisements). Intuitively, therefore, we should expect the effect of positive reviews to increase over time and those of negative reviews to decrease over time. Second, we expect negative reviews to hurt box office performance more than positive reviews help box office performance. This is based on research on negativity bias in impression formation (Skowronski and Carlston 1989) and work regarding loss aversion in scanner panel data (Hardie, Johnson, and Fader 1993). We find that the negative impact of bad reviews is significantly greater in magnitude than the positive impact of good reviews on box office revenues, but only in the first week of the film's run (when studios, presumably, have not had the time to leverage the good reviews and/or counter the bad reviews).

The final part of our investigation examines how star-power and budgets might moderate the impact of critical reviews on box office performance. We choose these two moderators because we believe that examining their effects on box office revenues in conjunction with critical reviews may provide partial economic rationale for two puzzling decisions in the film industry pointed out in earlier works. The first puzzle is why studios persist in pursuing famous stars when their effects on box office are difficult to demonstrate (De Vany and Walls 1999, Litman and Ahn 1998; Ravid 1999). The second puzzle is why, at a time when big budgets seem to contribute very little to returns (Ravid 1999; John, Ravid, and Sunder 2002), the average budget for a Hollywood movie has steadily increased over the years. Our results show that while star-power and big budgets appear do little for films that receive predominantly positive reviews, they are positively correlated with box office performance for films that receive predominantly negative reviews. In other words, star power and big budgets appear to be able to blunt the impact of negative reviews and thus may be sensible investments to make by the film studios.

The rest of the paper is organized as follows. In the next section we explore the current literature and formulate the key hypotheses. Then, we describe the data and empirical results. Finally, we discuss the managerial implications for marketing theory and practice.

Theory and Hypotheses

Critics: Their Functions and Impact

In recent years, there has been much interest in understanding the role of critics in markets for creative goods – films, theater, books, music, etc. (Caves 2000; Cameron 1995). Critics can serve many functions. According to Cameron (1995), critics provide advertising and information (e.g., reviews of new films, books, and music provide valuable information), create reputations (e.g., critics often spot rising stars), construct a consumption experience (e.g., reviews may be just fun to read by themselves), and influence preference (e.g., reviews may validate consumers' self-image, or promote consumption based upon snob appeal). In the domain of films, Austin (1983) suggests that critics help the public make a film choice, understand the film contents, reinforce previously held opinions of a film, and communicate in social settings (e.g., once you read a review, you can intelligently discuss a film with friends). However, despite a general agreement that critics have a role to play, it is not clear whether the views of critics and audience behavior necessarily go hand in hand. Austin (1983), for example, argues that film attendance will be greater if the public agrees with the critics' evaluations of films compared to cases in which the two opinions differ. More recently, Holbrook (1999) shows that in the case of films, ordinary consumers and professional critics emphasize different criteria when forming their tastes.

Numerous empirical studies have examined the relationship between critical reviews and box office performance (De Silva 1998; Jedidi, Krider and Weinberg 1998; Litman 1983; Litman and Kohl 1989; Litman and Ahn 1998; Prag and Casavant 1994, Ravid 1999; Sochay 1994; Wallace, Seigerman, and Holbrook 1993;). Litman (1983) found that each additional star rating (five stars representing a "masterpiece" and a one star representing a "poor" film) had a significant positive impact on the theatrical rentals. The subsequent Litman and Kohl (1989) study, and later studies by Litman and Ahn (1998), Wallace, Seigerman, and Holbrook (1993), Sochay (1994), and Prag and Casavant (1994), all found the same impact. More recently however, Ravid (1999) tested the impact of positive reviews on domestic revenues, video revenues, international revenues, and total revenues, but did not find any significant effect.

Critics as Influencers or Predictors.

While the above studies investigate the impact of critical reviews on a film's performance, they do not describe the process through which critics may affect box office revenues. ES (1997) were the first to propose and test two differing perspectives of critics - the influencer perspective and the predictor perspective. An influencer or opinion leader is a person who is regarded by a group, or by other people, as having expertise or knowledge on a particular subject (Assael 1984; Weiman 1991). Operationally, if such a person voices an opinion, people should follow. Therefore, we should expect an influencer to have most effect in the early stages of the run, before word of mouth has a chance to spread. A predictor, on the other hand, can use either formal techniques (such as statistical inference) or informal methods to correctly predict the success or failure of a product. In the case of a film, one would expect a predictor to call the entire run (say whether this film will do well or not), or in the extreme case, correctly predict each and every week of the film's run.

Ex-ante, there are reasons to believe that critics may influence the decision of the public to see or not see a film. It is often the case that critics are invited to an early screening of the film and they write reviews before the film opens to the public. Therefore, they not only have more information than the public in the early stages of the film's run, but they are the only source of information at that time. Litman (1983), for example, seems to be referring to the influencer perspective when he argues that critical reviews should be important to the popularity of films (1) in the early weeks before word-of-mouth can take over, and (2) if the reviews are favorable. Litman, however, was unable to directly test this hypothesis because his dependent variable was cumulative box office revenues. To better assess causation, Wyatt and Badger (1984) designed experiments using positive, mixed, and negative reviews and found audience interest to be compatible with the direction of the review. However, because their study was based on experiments, the authors could not use box office returns as the dependent variable.

Inferring critics' roles from weekly correlation data. In our research we follow the procedure established by ES (1997). We study the correlation between positive and negative reviews with weekly box office revenue. However, even with weekly box office data, we argue that it is not easy to distinguish between the influencer and predictor perspectives. We illustrate this point below by considering three different patterns of correlation between weekly box office revenues and critical reviews.

In the first example, suppose that critical reviews are correlated with the box office revenues of the first few weeks, but they are not correlated with the box office revenues of the film's entire run. A case in point is the film *Almost Famous*. The film had great reviews (out of 47 total reviews reported by *Variety*, 35 were positive, and only 2 were negative), a good opening week ($2.4 million on 131 screens or $18,320 revenue per screen), but ultimately did not do very well (grossing only $32 million in about six months). This outcome is consistent with the interpretation that the critics influenced the early run (using ES terminology) but could not correctly forecast the ultimate failure of the film (i.e., could not predict the entire run). We note that, of course, another interpretation would be that critics correctly predicted the early run, without necessarily influencing the public's decision, but they could not predict the ultimate success of the film.

For the second example, suppose that critical reviews are not correlated with the box office revenues in the first few weeks, but they are correlated with the box office revenues of the film's total run. The films *Thelma and Louise* and *Blown Away* appear to fit this pattern. *Thelma and Louise* got excellent reviews, had only moderate first weekend revenues ($4 million), but eventually became a hit ($43 million; ES 1997, p. 72). *Blown Away*, on the other hand, opened successfully ($10.3 million) despite bad reviews, but ultimately did not do well. In the first case, critics correctly foretold the film's successful run (despite a bad opening), and in the second case, critics correctly foretold the film's unsuccessful run (despite a good opening). In both these examples, the performance in the early weeks was counter to the nature of the critical reviews. The interpretation is that the critics could not influence the early run, but were able to correctly predict the ultimate box office fate. The ES study, found precisely such a pattern (i.e., critical reviews are not correlated with the box office revenues of early weeks, but were significantly correlated with the box office revenues of later weeks and with the cumulative returns throughout the run). They concluded that critics are predictors, but not influencers.

The third case is where critical reviews are correlated with weekly box office revenues over the first several weeks (i.e., not just the first week or two) as well as the entire run. Consider the films *3000 Miles to Graceland* (a failure at the box office) and *Lord of the Rings: Fellowship of the Ring* (a box office success). *3000 Miles to Graceland* was trashed by the critics (out of 34 total reviews, 30 reviews were negative), had a dismal opening weekend ($7.16 million on 2545 screens, or about $3,000 per screen), and ultimately bombed at the box office ($15.74 million in slightly more than eight weeks). *Lord of the Rings: Fellowship of the Ring* opened to great reviews (16 out of 20 were positive, and none negative), had a very successful opening week ($66.1 million on 3359 screens, or about $19,000 per screen), and grossed $313 million. In both cases, we can say that the critics either (1) influenced the film's opening and correctly predicted the eventual fate, or (2) correctly predicted the weekly performance over an expanded period as well as the ultimate fate.

From the above three examples, it is evident that distinguishing between the different perspectives (i.e., influencer, predictor, influencer and predictor) based on weekly box office revenues is not an easy task. Very broadly speaking, if critics only influence a film's run at the box office, we should expect to see the greatest impact of critics on early box office revenues (perhaps in the first week or two). On the other hand, if critics only predict the ultimate fate of the film, we would expect their views to be correlated with the later weeks and the entire run, but not necessarily with the early weeks. Finally, if critics influence and predict a film's fate, or correctly predict each and every week of the film's run, we should expect reviews to be correlated with the success or failure of the film in the early and later weeks, as well as with the entire run. Our first hypothesis summarizes these three possible links between the critics' role and box office revenues.

Hypothesis 1a: *If critics are influencers, then critical reviews will be correlated with the box office revenues in the first few weeks only, but not correlated with the box office revenues in the later weeks or the entire run.*
Hypothesis 1b: *If critics are predictors, then critical reviews will be correlated with the box office revenues in the later weeks and the entire run, but not necessarily correlated with the box office revenues in earlier weeks.*
Hypothesis 1c: *If critics play a dual role (both influencers and predictors) or an expanded predictor role, then critical reviews will be correlated with box office revenues in the early and later weeks and also with the entire run.*

Inferring critics' role from the time pattern of weekly correlation. Several scholars, including ES, have argued that if critics are influencers, they should exert the greatest impact in the first week or two of a film's life because little or no word-of-mouth information is available at that time. Thereafter, the impact of reviews should diminish with each passing week as information from other sources becomes available (e.g., people who have already seen the film convey their opinions and as more people see the film), and word-of-mouth begins to dominate (ES 1997; Litman 1983). Even here, the issue is not clear-cut, because if word of mouth agrees with the critics often enough, we may not be able to detect a decline. However, if critics are perfect predictors, no such declining pattern can be expected. In other words, if we do find that there is a decline in the impact of critical reviews over time, this will be consistent with the influencer perspective. Hence we propose:

Hypothesis 2: *If critics are influencers, the correlation of critical reviews with box office revenues should decline with time.*

Valence of Reviews: Negativity Bias

Researchers have consistently found differential impacts of positive and negative information (controlled for magnitude) on consumer behavior. For example, in the domain of risky choice, Kahneman and Tversky (1979) found that utility or value functions are asymmetric with respect to gains and losses. A loss of one dollar provides more dissatisfaction (negative utility) compared to the satisfaction (positive utility) associated with a one-dollar gain, a phenomenon that the authors call *loss aversion*. Kahneman and Tversky extended this finding to multi-attribute settings as well (Tversky and Kahneman 1991). A similar finding in the domain of impression formation is the *negativity bias*, or the tendency for negative information to have a greater impact than positive information (see, Skowronski and Carlston, 1989 for a review).

Based upon these ideas, we may surmise that negative reviews will hurt (negative effect) box office performance more than positive reviews can help (positive effect) box office performance. Two studies lend further support to this idea. First, Yamaguchi (1978) proposes that consumers tend to accept people's negative opinions (e.g., a negative review from a film critic) more easily than positive views (e.g., a positive review from a film critic). Second, recent research suggests that the negativity bias operates in affective processing as early as the initial categorization of information into valence classes (e.g., the film is "good" or the film is "bad;" Ito, Larsen, Smith, and Cacioppo 1998). Hence we propose the following:

Hypothesis 3: *Negative reviews will hurt box office revenues more than positive reviews will help box office revenues.*

Moderators of Critical Reviews: Stars and Budgets

Are there any factors that may moderate the impact of critical reviews on box office performance? We argue that two key candidates are star power and budget. We choose these two moderators because we believe that examining their effects on box office revenues in conjunction with critical reviews may provide partial economic rationale for two puzzling decisions in the film industry pointed out in earlier works. The first puzzle is why studios persist in pursuing famous stars when their effects on box office are difficult to demonstrate (De Vany and Walls 1999; Litman and Ahn 1998; Ravid 1999). The second puzzle is why, at a time when big budgets seem to contribute nothing to returns (Ravid 1999; John, Ravid, and Sunder 2002), the average budget for a Hollywood movie has steadily increased over the years. Our rationale is that popular stars and big budgets may help films by blunting the effect of negative reviews, and thus may be sensible investments on the part of film studios. In the following paragraphs, we elaborate on this issue, by first looking at the literature on star power, and then on film budgets.

Star power has received considerable attention in the literature (De Silva 1998; De Vany and Walls 1999; Holbrook 1999; Levin, Levin and Heath 1997; Litman 1983; Litman and Kohl 1989; Litman and Ahn 1998; Neelamegham and Chintagunta 1999; Prag and Casavant 1994; Ravid 1999; Smith and Smith 1986; Sochay 1994; Wallace, Seigerman and Holbrook 1993). Hollywood seems to favor films with stars (award winning actors, actresses, and directors), and it is almost axiomatic that stars are key to a film's success. However, empirical results of star-power on box office performance have produced conflicting evidence. Studies by Litman and Kohl (1989) and Sochay (1994) found that the presence of stars in the cast had significant effect on film rentals. Similarly, Wallace, Seigerman and Holbrook (1993) concluded that for "certain movie stars do make demonstrable difference to the market success of the films in which they appear" (p. 23). On the other hand, Litman (1983) found no significant relation between the presence of a superstar in the cast of the films and box office rentals. Smith and Smith (1986) found that winning an award has a negative effect on the film's fate in the 1960's, but a positive effect in the 1970's. Similarly, Prag and Casavant (1994) found star power positively impacting a film's financial success in some samples, but not in others. De Silva (1998) found that stars were an important factor in the public's attendance decisions, but stars were not significant predictors of financial success, a finding documented in later studies as well (DeVany and Walls 1999; Litman and Ahn 1998; Ravid 1999).

Like star power, film production budgets too have received significant attention in the literature on motion picture economics (Litman 1983; Litman and Ahn 1998; Litman and Kohl 1989; Prag and Casavant 1994; Ravid 1999) [1]. The average cost of making a feature film was $54.8 million in 2000 (see www.mpaa.org). Large budgets translate into lavish sets and costume, expensive digital manipulations and special effects as seen in films like *Jurassic Park* (budget of $63 million and released in 1993) and *Titanic* (over $200 million, released in 1997). Ravid (1999) and John, Ravid, and Sunder (2002) show that while big budgets are correlated with higher revenues, they are not correlated with returns. In fact, if anything, in these papers, low budget films appear to have higher returns. What then, do big budgets do for a film? Litman (1983) argues that big budgets should reflect higher quality and more popularity at the box office. Similarly, Litman and Ahn (1998) suggest that ".... studios feel safer with big budget films" (p. 182). In this sense, big budgets can serve as an insurance policy (Ravid and Basuroy 2003).

Although the effects of star power and budgets on box office returns may be ambiguous at best, the question remains as to whether these two variables can act jointly with critical reviews to affect box office performance. We believe that they do. For example, suppose that a film receives more positive than negative reviews. If the film starts its run already cast in a positive light, other positive dimensions such as famous stars and big budgets may not further enhance its box office fortunes. However, consider a film that receives more negative reviews than positive reviews. In this case, famous stars and big budgets may help the film by blunting some of the effects of the negative reviews. Levin, Levin and Heath (1997) suggest that popular stars provide the public with a decision heuristic (e.g., *see the film with the famous stars*) that may be strong enough to blunt any negative critic effect. Conversely, when a film receives more positive reviews than negative reviews, it is "less in need of the additional boost provided by a trusted star" (p. 177). Similarly, Litman and Ahn (1998) suggest that budgets should increase a film's entertainment value and hence its probability of box office success, and consequently compensate for other negative traits in a film such as bad reviews. Based on these arguments, we propose:

Hypothesis 4: *For films receiving more negative than positive reviews, star power and big budgets will have a positive effect on box office performance. However, for films receiving more positive than negative reviews, star power and big budgets will have no effect on box office performance.*

Methodology

Data and Variables

Our data include a random sample of 200 films released between late 1991 and early 1993 and much of it is identified in Ravid (1999). This sample was first pared down because of various missing data to 175 films. The data came from two sources: *Baseline Services* in California and

Variety magazine. While some studies have focused on the more successful films, say the top 50 or the top 100 in *Variety* lists (De Vany and Walls 1997; Litman and Ahn 1998; Smith and Smith 1986), our study contains a sample selected completely at random from among the films released in the period in question, and, includes successes as well as failures. Our sample contains 156 MPAA-affiliated films and 19 foreign productions, and covers about a third of all MPAA-affiliated films released between 1991 and 1993 (475 MPAA-affiliated films were released between 1991 and 1993; see Vogel 2001, Table 3.2). In our sample, 3.2 % of the films are rated G, 14.7% are rated PG, 26.3% are rated PG13, and 55.7% are rated R. This distribution closely matches the distribution of all films released between 1991 and 1993 (1.5% G, 15.8% PG, 22.1% PG13, and 60.7% R; see the *Blockbuster Guide to Movies and Videos*).

Weekly domestic revenue. Every week *Variety* reports the weekly domestic revenues for each film. These numbers served as the dependent variables. Most studies cited so far do not use weekly data (see, e.g., De Vany and Walls 1999; Litman and Ahn 1998; Ravid 1999). Given our focus and the context of ES study, this is critical.

Valence of reviews. Variety lists reviews for the first weekend in which a film opens in major cities - New York, Los Angeles, Washington and Chicago. We collected the number of reviews from all these cities to be consistent with the ES study. *Variety* classifies reviews as “pro” (positive), “con” (negative), and “mixed.” It does so by generally calling each reviewer and asking how s/he rated a particular film, with a choice between positive, negative, or mixed. We use these classifications to come up with measures of critical review assessment similar to ES (1997). Unlike Ravid (1999), and consistent with ES, we collected the total number of reviews

(TOTNUM) from all four cities. For each film, POSNUM (NEGNUM) is the number of positive (negative) reviews a film received, POSRATIO (NEGRATIO) is the number of positive (negative) reviews divided by the number of total reviews.

Star Power. For star power we use the proxies suggested by Ravid (1999) and Litman and Ahn (1998). For each film, *Baseline Services* provided a list of the director, and up to 8 main cast members. For our first definition of a "star," we identified all cast members who had won a Best Actor or Best Actress Award (Oscar) in *prior* years (prior to the release of the current film). We create a dummy variable, WONAWARD, that denotes films in which at least one actor/actress or the director has won an academy award in previous years, prior to the release of the film. Based on this measure, out of the 175 films in our sample, 26 films have star power (i.e., WONAWARD = 1). For our second measure, we create a dummy variable, TOP10, which receives a value of one if any member of the cast or the director had participated in a top-ten grossing film in the previous years (Litman and Ahn1998). Based on this measure, out of the 175 films in the sample, 17 films possess star power (i.e., TOP10 = 1). For our third and fourth measures, we collect Best Actor/Actress/Director award nominations for each film in the sample. Two variables are defined, NOMAWARD and RECOGNITION. The first variable, NOMAWARD, receives a value of one, if one of the actor/actress/director had previously been nominated for an award. The NOMAWARD measure increases the number of films with star power to 76 out of 175. The second variable, RECOGNITION, as the label suggests, measures recognition value. For each of the 76 films in the NOMAWARD category, we sum the total number of awards and the total number of nominations. This method effectively creates a weight of 1 for each nomination and doubles the weight of an actual award to 2 (in other words, if say, an actress was nominated twice for an award RECOGNITION is 2. If she also won in one of these cases, the value increases to 3). Each of the 76 films is thus assigned a numerical value, ranging from a maximum of 15 (for Cape Fear, directed by Martin Scorcese and starring Robert DeNero, Nick Nolte, Jessica Lange, and Juliette Lewis) to 0 for the films with no nominations.

Budgets. Baseline Services provided the budget (BUDGET) of each film. The trade term for this is "negative cost" or production costs (Litman and Ahn 1998; Prag and Casavant 1994; Ravid 1999). This does not include gross participation, which is ex-post share of participants in gross revenues. It does not include advertising and distribution costs, or guaranteed compensation, which is a guaranteed amount paid out of revenues if revenues exceed this amount.

Other Control Variables. We use several control variables. Each week, *Variety* reports the number of screens a film was shown on that week. ES (1997) and Elberse and Eliashberg (2002) found the number of screens to be a significant predictor of box office revenues. Hence, we use SCREEN as a control variable. Another variable of interest is whether or not a film is a sequel (Litman and Kohl 1989; Prag and Casavant 1994; Ravid 1999). The SEQUEL variable receives a value of 1 if the movie is a sequel to a previous movie and zero otherwise. There are 11 sequels in our sample. Ratings are considered by the industry to be an important issue (Litman 1983; Litman and Ahn 1989; Ravid 1999; Sochay 1994). In our analysis, we code ratings using dummy variables. For instance, a dummy variable G receives a value of one if the film is rated G and zero otherwise. Some films are not rated at all for various reasons and those receive a value of zero. Finally, our last control variable is release date. In some studies (Litman 1983; Litman and Kohl 1989; Sochay 1994; Litman and Ahn 1998), release dates are used as dummy variables, on the theory that a Christmas release should attract greater audiences, and a release in a low attendance period should be bad for revenues. However, since there are several peaks and troughs in attendance throughout the year, we use information from Vogel (2001 figure 2.4) to produce a more sophisticated measure of seasonality. Vogel constructs a graph, which depicts normalized weekly attendance over the year (based upon 1969-1984 data). This figure assigns a number between 0 and 1.00 for each date in the year (where Christmas attendance is 1.00 and early December is 0.35 for high and low points of the year respectively). We match each release date with this graph and assign a variable which we call RELEASE to account for seasonal fluctuations.

Results

Table 1 reports the correlation matrix for the key variables of interest. The ratio of positive reviews, POSRATIO, is negatively correlated with the ratio of negative reviews, NEGRATIO, that is to say, not too many films received many negative and many positive reviews at the same time. The most expensive film in this sample cost $70 million (*Batman Returns*) and is also the film with the highest first week's box-office revenue ($69.31 million), opening to the maximum number of screens nationwide (3700). In our sample, the average number of first week screens is 749, the average box office return for the first week is $5.43 million, and the average number of reviews received is 34 (43% positive, and 31% negative). Based on a sample of 56 films, the ES study reported 47% positive reviews and 25% negative reviews (ES, p. 74). The highest revenue per screen in our sample went to *Beauty and the Beast* ($117,812 per screen, for two screens) which also has the highest total revenue ($ 426 million).

INSERT TABLE 1 HERE

The Role of Critics

Hypotheses H1 and H2 discuss the role of critics as influencers, or predictors or both. To test these hypotheses, we run three sets of tests. First, we replicate the ES model by running separate regressions for each of the eight weeks and including only three predictors (POSRATIO or NEGRATIO, SCREEN, TOTNUM). In the second test, we expand the ES framework by including our control variables in the weekly regressions. In the third test, we run time series cross-section regression combining both cross-sectional and longitudinal data in one regression, specifically to control for unobserved heterogeneity.

The replications of ES results are reported in Tables 2a and 2b. The coefficients of both positive and negative reviews are significant at .01 level for each of the eight weeks and seem to support H1c. Critics both influence and predict box office revenues, or they predict consistently across all weeks.

INSERT TABLES 2a AND 2b HERE

Next, we added the control variables to the regressions – ratings, star-power, release time, sequel-status, and budget. Table 3a and 3b report the results of this set of regressions [2]. The results confirm what we found in Table 2. The critical reviews, both positive and negative, remain significant for each and every week. For the first four weeks, SCREEN appears to have the biggest impact on revenues followed by BUDGET and POSRATIO (or NEGRATIO). After four weeks, BUDGET becomes insignificant, and critical reviews become the second most important factor behind screens. The R-squares and the adjusted R-squares are generally higher than those in Tables 2a and 2b suggesting enhanced explanatory power of the added variables.

INSERT TABLES 3a AND 3b HERE

For the final test, we run time series cross section regressions (Baltagi 1995; Hsiao 1986, p. 52) [3] - see Table 4. In this equation, the variable SCREEN varies across films as well as across time, the other predictors and control variables vary across films but are invariant over time, and we create a new variable WEEK which takes the value from 1 to 8 and thus varies across time, but not across the films. In this regression, we add an interaction term (POSRATIO*WEEK, or NEGRATIO*WEEK) to assess the declining impact of critical reviews over time. The results support H1c, and partially support H2. The coefficient of positive and negative reviews remains highly significant ($\beta_{Positive} = 3.32$, $p < 0.001$; $\beta_{Negative} = -5.11$, $p < 0.001$), pointing to the dual role of critics (H1c). However, the interaction term is not significant for positive reviews, but is significant for negative reviews, suggesting a declining impact of negative reviews over time, a finding partially consistent with the influencer perspective.

INSERT TABLE 4 HERE

The above results are somewhat different from the ES findings (where critics are just predictors) as well as the Ravid (1999) results (i.e., there is no effect of positive reviews). There are several reasons why our results differ from those of ES. First, while ES included only those films that had a minimum of eight-week run, our sample includes films that ran for less than eight weeks as well. We did so to accommodate films with short box office lives. Second, the size of our data set is three times as large as the ES data set (175 vs. 56). Third, our data set covers a longer time period (late 1991 through early 1993) than the ES data which only covered films between 1991 and early 1992. Fourth, the films in our data set are selected completely at random whereas ES's sample, as they note, is more restrictive. Similarly, our results may differ from those of Ravid's (1999) given that (1) we include reviews from all cities reported in *Variety* and not just New York, and (2) we use weekly revenue data instead of the entire revenue stream.

Negative Versus Positive Reviews.

Hypothesis 3 predicts that negative reviews should have a disproportionately greater negative impact on box office reviews compared to the positive impact of positive reviews. Since the percentage of positive and negative reviews are highly correlated (see Table 1, r = -0.88), they cannot be put in the same model. Instead, we use the number of positive (POSNUM) and negative (NEGNUM) reviews as they are not correlated with each other (Table 1, r = 0.17) and hence both variables can be put in the same regression model. We expect the coefficient of NEGNUM to be negative, and hence, there might be some evidence for the negativity bias if $|\beta_{NEGNUM}| > |\beta_{POSNUM}|$. Table 5 reports the results of our time series cross-section regression.

INSERT TABLE 5 HERE

Although β_{NEGNUM} is negative and significant ($\beta_{NEGNUM} = -0.056$, $t = -2.29$, $p < 0.02$) and β_{POSNUM} is positive and significant ($\beta_{POSNUM} = 0.032$, $t = 2.34$, $p < 0.01$), their difference, $|\beta_{NEGNUM}| - |\beta_{POSNUM}|$, is not ($F_{1, 1108} < 1$). In some sense this pattern is expected since we found that negative reviews diminish in impact over time, but not positive reviews. A stronger test for the negativity bias should then focus on the early weeks (the first week in particular) when the studios have not had the opportunity engage in damage control. As expected, the negativity bias is strongly supported in the first week. β_{NEGNUM} is negative and significant (β_{NEGNUM} = -0.209*, t* = -3.42*, p* < 0 .0001), β_{POSNUM} is not significant (β_{POSNUM} = 0.052*, t* = 1.60*, p* = *ns*), and their difference, $|\beta_{NEGNUM}| - |\beta_{POSNUM}|$, is significant ($F_{1, 151} = 3.76$, $p < 0.05$). Separate weekly regressions on the subsequent weeks (Week 2 onwards) do not produce a significant difference between the two coefficients. The combined data for the first two weeks show evidence of negativity bias (Table 5).

It is possible that the negativity bias is confounded by perceived reviewer credibility. When consumers see a positive review, they may feel that the reviewers have a studio bias. A negative review, on the other hand, is more likely to be independent of any studio influence. In order to separate the effects of credibility from negativity bias, we ran an analysis that includes only the reviews of two, presumably universally credible critics - Siskel and Ebert [4]. We were only able to locate their joint reviews for 72 films from our data set. Thirty-two films received two thumbs up, 10 received two thumbs down, and 23 received one up and one down reviews. We coded three dummy variables – TWOUP (for two thumbs up), TWODOWN (for two thumbs down), and UP&DOWN (one thumb up). In the regressions we used two of these dummy variables – TWOUP and TWODOWN. The results confirmed our previous findings. The coefficient of TWODOWN is significantly larger than that of TWOUP both in the first week ($\beta_{TWODOWN}$ = -6.51, β_{TWOUP} = 0.32; $F_{1, 57} = 4.95$, $p < 0.03$) as well as for the entire eight-week run ($\beta_{TWODOWN}$ = -2.28, β_{TWOUP} = 0.42; $F_{1, 501} = 3.46$, $p < 0.06$).

Star Power, Budgets and Critical Reviews

Hypothesis 4 predicts that star power and big budgets can help films that receive more negative than positive reviews, but will do little for films that receive more positive than negative reviews. Since we make separate predictions for the two groups of films (POSNUM-NEGNUM ≤ 0 and POSNUM-NEGNUM > 0), we split the data into two groups. The first group contains 97 films for which the number of negative reviews is greater than or equal to that of positive reviews, while the second group contains the remaining 62 films for which the number of positive reviews exceeds that of negative reviews. We ran time-series cross-section regressions separately for the two groups and Table 6 shows the results.

INSERT TABLE 6 HERE

Table 6 shows that when negative reviews outnumber positive reviews, star power's effect on box office returns approaches statistical significant effect on box office returns when measured with WONAWARD ($\beta = 1.117$, $t = 1.56$, $p = 0.12$), and is statistically significant in the case of RECOGNITION ($\beta = 0.224$, $t = 2.09$, $p < 0.05$). In each case, BUDGET has a positive and significant effect as well. However, when positive reviews outnumber negative reviews, neither the budget, nor any definition of star-power has any significant impact on the box office revenues of films. These results appear to suggest that star power and the budget may act as countervailing forces against negative reviews, but do very little for films that receive more positive than negative reviews.

Discussion and Managerial Implications

Critical reviews play a major role in many industries – theater and performance arts, book publishing, recorded music, art, bond ratings, and many others. In most cases, there is not enough data to identify the role of critics in these industries. Are they good predictors of the public tastes, do they influence and determine behavior, or do they do both? Our paper sheds light on critics' role in the context of a film's box office performance. We further assess the differential impact of positive versus negative reviews, and how they might operate jointly with star power and the film's budget.

Our first set of results shows that for each of the first eight weeks, both positive and negative reviews are significantly correlated with box office revenues. The pattern is consistent with the dual perspective of critics (i.e., they are influencers and predictors). At the simplest level, this would suggest that any marketing campaign for a film should carefully integrate critical reviews, particularly in the early weeks. If studios expect positive reviews, the critics should be encouraged to preview the film in advance in order to maximize their impact on box office revenues. However, if studios expect negative reviews, the wise strategy would be either to forgo the initial screenings for critics altogether, or invite only select, "friendly" critics to the screening. If negative reviews are unavoidable, then studios can use their stars to blunt some of the effects by encouraging appearances of the lead actors and actresses on television shows like *Access Hollywood* and *Entertainment Tonight* (*Wall Street Journal*, April 27, 2001, B1, B6).

Our second set of results shows that negative reviews hurt revenues more than what positive reviews can do to help in the early weeks of a film's release. This would suggest that whereas studios like positive reviews and hate negative reviews, the impact is not symmetric, and in the context of a limited budget, more should be spent for damage control then to promote positive reviews. In other words, some of the following may be more cost effective than, say, spending money on ads that tout the positive reviews: (1) forgoing critical screenings fearing negative attention. For example, *Get Carter* and *Autumn in New York* did not offer advance screenings for critics leading the prominent critic Roger Ebert to comment that "the studios have concluded that the films are not good and will receive negative reviews" (*Los Angeles Guardian*, October 11, 2000); (2) selectively invite "soft" reviewers; (3) delay sending their press kits to reviewers. Press kits generally contain publicity stills and production information for the critics, and since newspapers do not run the reviews without at least one press still from the film, it gives the film an extra week to survive without bad reviews.

Our third set of results suggests that stars and budgets can moderate the impact of critical reviews. While star power may not be needed if a film gets good reviews, it can significantly lessen the impact of negative reviews. Similarly, big budgets add little if a film has already received positive reviews, but they can significantly lessen the impact of negative reviews. Thus in some sense, big budgets and stars serve as an insurance policy. Since success is hard to predict in the film business (see for example, DeVany and Walls 1999) and so is the quality of reviews, executives can hedge their bets by employing stars or by using big budgets (e.g., expensive special effects). It will not be needed and on average, it may not help the returns, but should the critics pan the film, big budgets and stars can serve to moderate the blow, and perhaps save the executive's job (Ravid and Basuroy 2003).

Implications for Other Industries

While the current analysis is based on the film industry, we believe that the results may be applicable to other industries where consumers are unable to accurately assess the qualities of these products before consumption (e.g., theater/performance arts, book publishing, recorded music, financial markets). The critics may influence consumers, or consumers may seek out those critics who, they believe, accurately reflect their taste (the predictor perspective). For example, in the dance and theater industry, critics' influence amount to "life and death power" over ticket demand (Caves 2000); for Broadway shows critics appear to both influence as well as predict the public's taste (Reddy, Swaminathan, and Motley 1998). Similarly, research in the bond market shows there is very little market reaction to bond rating changes when the rating agency simply responds to public information (i.e., the rating agencies are simply predicting what the public has done already). On the other hand if the rating change is based on projections or some inside research, then the markets react to the news (see Goh and Ederington 1993).

In addition to the role of critics, all the other questions that we have raised in this paper (e.g., negativity bias, moderators of critical reviews) should be of significance in these industries as well. For example, bad reviews can doom a book in the publishing business, (Greco 1997, p. 194). But just as in the case of films, readers' reliance on the book critics is reduced when the book features a popular author compared to books with unknown authors (Levin, Levin, and Heath 1997). Once enough data is available, there is ample opportunity to extend our framework in assessing the revenue fortunes of such similar, creative businesses.

Footnotes

[1] In investigating the role of budgets on a film's performance, we have to disentangle the effects of star power from budgets, since one can argue that expensive stars may make the budget a proxy for star power. In our data however, there is extremely low correlation between the measures of star power and budget suggesting that the two measures are unrelated to each other.

[2] Although we report the results using one of the four possible definitions of star power, WONAWARD, re-running the regressions using the other three measures of star power does not change the results.

[3] We thank an anonymous reviewer for this suggestion.

[4] We thank an anonymous reviewer for this suggestion.

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TABLE 1
Variables and Correlations

	Budget	**Release**	**Posratio**	**Negratio**	**Totnum**	**Posnum**	**Negnum**	**Wonaward**
Budget mean=15.68 s.d.=13.90	1.00							
Release mean=.63 s.d.=.16	.004	1.00						
Posratio mean=.43 s.d.=.24	-.131	.017	1.00					
Negratio mean=.31 s.d.=.22	.042	-.068	-.886	1.00				
Totnum mean=34.22 s.d.=17.46	.605	.150	.252	-.341	1.00			
Posnum mean=15.81 s.d.=12.03	.283	.056	.740	-.704	.760	1.00		
Negnum Mean=9.23 s.d.=7.06	.498	.124	-.579	.556	.448	-.179	1.00	
Wonaward Mean=.15 s.d.=.36	.358	.077	.126	-.139	.430	.379	.169	1.00

TABLE 2a
Replication of ES Regression Results With Percent of Positive Reviews

Week	R-sq (Adjusted R-sq.)	Posratio		Totnum		Screen		F-ratio (p-value)
		Unstandardized Coefficient (Standardized Coefficient)	t-statistic (p-value)	Unstandardized Coefficient (Standardized Coefficient)	t-statistic (p-value)	Unstandardized Coefficient (Standardized Coefficient)	t-statistic (p-value)	
Week 1 (n=162)	.7268 (.7217)	5.114 (.14017)	2.96 (.0036)	.037 (.07176)	1.49 (.1394)	.00890 (.85073)	17.49 (<.0001)	141.03 (<.0001)
Week 2 (n=154)	.7229 (.7174)	4.02465 (.15252)	3.15 (.0020)	.0498 (.13428)	2.70 (.0076)	.00593 (.81576)	16.22 (<.0001)	131.32 (<.0001)
Week 3 (n=145)	.6542 (.6469)	3.2968 (.15427)	2.79 (.0060	.03661 (.12538)	.2.17 (.0315)	.00451 (.77171)	13.23 (<.0001)	89.56 (<.0001)
Week 4 (n=139)	.7174 (.7111)	2.15975 (.14426)	2.91 (.0042)	.01495 (.07051)	1.32 (.1891)	.00361 (.82838)	1.32 (.1891)	115.07 (<.0001)
Week 5 (n=137)	.7325 (.7265)	1.709 (.14897)	3.14 (.0021)	.00566 (.03552)	.69 (.4927)	.00302 (.84327)	16.72 (<.0001)	122.33 (<.0001)
Week 6 (n=132)	.7079 (.7011)	1.58248 (.15050)	3.06 (.0027)	-0.00147 (-.01003)	-0.19 (.8502)	.00299 (.84839)	16.15 (<.0001)	104.22 (<.0001)
Week 7 (n=130)	.5763 (.5663)	2.28437 (.20870)	3.56 (.0005)	-0.00396 (-0.02546)	-0.41 (.6858)	.00299 (.76491)	12.13 (<.0001)	57.59 (<.0001)
Week 8 (n=122)	.7013 (.6938)	1.20016 (.16071)	3.17 (.0019)	-0.00551 (-.05212)	-0.95 (.3432)	.00262 (.8577)	15.62 (<.0001)	93.14 (<.0001)

Dependent variable is weekly revenues
Method is separate regressions for each week

TABLE 2b
Replication of ES Regression Results With Percent of Negative Reviews

Week	R-sq (Adjusted R-sq.)	Negratio		Totnum		Screen		F-ratio (p-value)
		Unstandardized Coefficient (Standardized Coefficient)	t-statistic (p-value)	Unstandardized Coefficient (Standardized Coefficient)	t-statistic (p-value)	Unstandardized Coefficient (Standardized Coefficient)	t-statistic (p-value)	
Week 1 (n=162)	.7290 (.7239)	-6.05792 (-0.1525)	-3.18 (.0018)	.0285 (.05479)	1.10 (.2738)	.00888 (.84904)	.17.80 (<..0001)	142.58 (<.0001)
Week 2 (n=154)	.7273 (.7219)	-5.10837 (-0.17391)	-3.53 (.0005)	.04204 (.11328)	2.22 (.0276)	.00598 (.82294)	16.51 (<.0001)	134.26 (<.0001)
Week 3 (n=145)	.6518 (.6444)	-3.39389 (-0.14618)	-2.59 (.0105)	0.03451 (.11819)	1.98 (.0496)	.00447 (.76423)	13.16 (<.0001)	88.59 (<.0001)
Week 4 (n=139)	.7118 (.7054)	-1.97242 (-0.12094)	-2.38 (.0187)	.01486 (.07007)	1.26 (.2090)	.00355 (.81431)	15.37 (<.0001)	111.95 (<.0001)
Week 5 (n=137)	.7298 (.7237)	-1.78567 (-0.14178)	-2.89 (.0044)	.00418 (.02621)	.49 (.6252)	.003 (.83882)	16.60 (<.0001)	120.63 (<.0001)
Week 6 (n=132)	.7065 (.6997)	-1.73476 (-0.14911)	-2.95 (.0038)	-0.00368 (-0.02515)	-0.46 (.6465)	.00299 (.84649)	16.10 (<.0001)	103.52 (<.0001)
Week 7 (n=130)	.5604 (.5500)	-2.10310 (-0.1672)	-2.76 (.0066)	-0.00606 (-0.03903)	-0.60 (0.5503)	0.00296 (.7576)	11.79 (<.0001)	53.97 (<.0001)
Week 8 (n=122)	.6945 (.6868)	-1.20867 (-0.13982)	-2.68 (.0083)	-0.00704 (-0.06662)	-1.18 (.2408)	.00261 (.85507)	15.39 (<.0001)	90.20 (<.0001)

Dependent variable is weekly revenues
Method is separate regressions for each week

TABLE 3a
Effect of Critical Reviews on Box Office Revenues:
Weekly Regression Results With Percent of Positive Reviews and Other Control Variables

	Constant	Wonaward	G	PG	PG13	R	Totnum	Release	Sequel	Budget	Posratio	Screen	R-sq	Adj. R-sq	F-ratio
Week 1 (n=162)	-6.59a	.255 (.0106)	-5.101b (-.109)	-.857 (-.035)	-.445 (-.0218)	-0.1210 (.0067)	-0.032 (.0609)	3.035 (.0545)	5.223a (.149)	.1763a (.278)	6.796a (.186)	0.007a (.938)	.791	.776	51.92a
Week 2 (n=154)	-4.50a	.927 (.0547)	-1.38 (.0428)	.05574 (.0032)	-.634 (-.043)	-0.186 (-.015)	.009 (.026)	.549 (.014)	1.889c (.078)	0.097a (.217)	4.670a (.177)	.005a (.697)	.757	.738	40.44a
Week 3 (n=145)	-2.416	.966 (.075)	-0.310 (-.013)	1.485 (.109)	-1.042 (-.093)	-0.059 (-.006)	-0.003 (-.011)	-0.914 (-.030)	.228 (.012)	.105a (.310)	3.590a (.168)	.0035a (.601)	.728	.706	32.64a
Week 4 (n=139)	-1.92	.521 (.058)	-0.360 (-.019)	1.204 (.127)	-0.515 (-.065)	.438 (.0634)	-0.005 (-.024)	-0.159 (-.007)	-0.716 (-0.054)	.039b (.164)	2.424a (.162)	.003a (.753)	.758	.738	36.51a
Week 5 (n=137)	-1.929b	.776b (.114)	-0.727 (-.051)	.603 (.085)	-0.101 (-.017)	.3575 (.068)	-0.008 (-.055)	1.084 (.067)	-0.578 (.057)	.005 (.027)	1.867a (.163)	.003a (.866)	.768	.748	37.97a
Week 6 (n=132)	-1.413	.564c (.091)	.228 (.018)	.202 (.031)	.132 (.024)	.191 (.040)	-0.006 (-.044)	.744 (.050)	-0.718 (-0.075)	-.008 (-0.050)	1.416b (.135)	.003a (.892)	.727	.702	29.30a
Week 7 (n=130)	-1.608	.477 (.076)	2.265c (.176)	.134 (.020)	.248 (.045)	.286 (.057)	.00011 (.0007)	.285 (.018)	-0.874 (-0.084)	-.0109 (-.065)	1.792a (.163)	.003a (.766)	.614	.578	17.19a
Week 8 (n=122)	-0.937	.511b (.118)	.359 (.042)	-0.135 (-.029)	.072 (.018)	.081 (.023)	-0.004 (-.037)	.678 (.064)	-0.219 (-0.032)	-.018c (-.152)	.867b (.116)	.003a (.921)	.733	.706	27.65a

Dependent variable is weekly revenues
Method is separate regressions for each week
a: Significant at .01 level; b: Significant at .05 level; c: Significant at .10 level
Standardized Betas are reported in the parentheses

TABLE 3b
Effect of Critical Reviews on Box Office Revenues:
Weekly Regression Results With Percent of Negative Reviews and Other Control Variables

	Constant	Wonaward	G	PG	PG13	R	Totnum	Release	Sequel	Budget	Negratio	Screen	R-sq	Adj. R-sq	F-ratio
Week 1 (n=162)	-0.390	.381 (.016)	-5.415b (-.116)	-1.234 (-0.051)	-1.055 (-.051)	-.612 (-.034)	-0.036 (-.069)	2.543 (.046)	4.938a (.141)	.172a (.271)	-7.173a (-.181)	.007a (.689)	.789	.774	51.50a
Week 2 (n=154)	.019	1.106 (.065)	-1.742 (-.054)	-0.360 (-0.020)	-1.115 (-.075)	-.623 (-.050)	.004 (.011)	.215 (.005)	1.655 (.068)	.091a (.205)	-5.476a (-.186)	.005a (.710)	.759	.741	41.06a
Week 3 (n=145)	.822	1.097 (.0855)	-0.441 (-.0181)	1.215 (.0899)	-1.380 (-.123)	-.330 (-.034)	-0.004 (-.011)	-1.266 (-.0416)	.0998 (.005)	.0996a (.292)	-3.573a (-.154)	.004a (.602)	.726	.703	32.21a
Week 4 (n=139)	.185	.5999 (.066)	-0.229 (-.012)	1.083 (.114)	-.698 (-.089)	.281 (.040)	-0.005 (-.024)	-0.363 (-.017)	-.802 (-.060)	.038b (.157)	-2.310a (-.142)	.003a (.740)	.754	.733	35.73a
Week 5 (n=137)	-0.280	.838 (.123)	-.619 (-.044)	.538 (.076)	-.213 (-.035)	.273 (.052)	-0.010 (-.063)	.942 (.058)	-.669 (-.066)	.004 (.021)	-1.952a (-.155)	.003a (.862)	.767	.746	37.64a
Week 6 (n=132)	-0.0526	.604c (.097)	.255 (.020)	.119 (.017)	.020 (.004)	.094 (.019)	-0.008 (-.058)	.625 (.042)	-.826 (-.086)	-.008 (.0513)	-1.607a (-.138)	.003a (.891)	.728	.704	29.48a
Week 7 (n=130)	.056	.513 (.082)	2.30 (.173)	-0.084 (-0.013)	-.018 (-.0033)	.055 (.011)	.00029 (.002)	.133 (.0087)	-.988 (-.096)	-0.013 (-.082)	-1.645b (-.1308)	.0029a (.764)	.607	.571	16.72a
Week 8 (n=122)	-0.133	.524 (.122)	.348 (.040)	-0.226 (-.0488)	-.043 (-.011)	-.015 (-.004)	-0.004 (-.039)	.616 (.058)	-.280 (-.040)	-.018b (-.163)	-.840c (-.097)	.0028a (.921)	.729	.703	27.27a

Dependent variable is weekly revenues
Method is separate regressions for each week
a: Significant at .01 level; b: Significant at .05 level; c: Significant at .10 level
Standardized Betas are reported in the parentheses

Table 4
Effect of Critical Reviews on Box Office Revenues (Fuller-Battese Estimations)

	Using Percent of Positive Reviews			**Using Percent of Negative Reviews**		
Variable	**Coefficient**	**t-value**	**Significance (p-value)**	**Coefficient**	**t-value**	**Significance (p-value)**
Constant	-1.42	-.98	.33	2.14	1.33	.18
Wonaward	.58	1.46	.14	.69	1.59	.11
G	-1.18	-1.07	.28	-1.46	-1.19	.23
PG	.102	.10	.91	-.33	-.31	.75
PG13	-.042	-.04	.96	-.48	-.46	.64
R	.22	.24	.81	-.16	-.16	.86
Totnum	-.006	-.52	.60	-.007	-.59	.55
Release	1.02	1.21	.22	.77	.82	.41
Sequel	.73	1.30	.20	.55	.89	.37
Budget	.032	2.24	.02	.023	1.47	.14
Posratio	3.321	3.33	.00			
Negratio				-5.11	-4.41	.00
Screen	.005	22.06	.00	.005	21.79	.00
Week	-.436	-2.23	.02	-.55	-2.38	.01
Posratio*Week	-.023	-.14	.89			
Negratio*Week				.42	2.17	.03
R-square	.47			.43		
Hausman Test for random effects	M=1.00		.60	M=2.00		.36

Dependent variable is weekly revenues
Method is time series cross section regression
N = 159

TABLE 5
Tests for Negativity Bias

	Fuller-Battese Estimation	Week 1 regression	Week 1+Week 2 regression
Constant	.53 (.38)	-2.94 (-1.34)	-2.47 (-1.56)
Wonaward	.55 (.1.39)	.08 (.07)	.41 (.56)
G	-1.65 (-1.50)	-6.21 (-2.46) a	-4.43 (-2.47) a
PG	-.58 (-.62)	-2.09 (-1.00)	-1.39 (-.93)
PG13	-.71 (-.78)	-1.50 (-.74)	-1.45 (.99)
R	-.46 (-.51)	-1.22 (-.63)	-1.13 (-.81)
Release	1.10 (1.31)	3.55 (1.70) c	2.45 (1.67) c
Sequel	.64 (1.14)	4.85 (3.37) a	3.45 (3.51) a
Budget	.03 (2.17) b	.18 (5.05) a	.15 (5.76) a
$\mathbf{b_{POSNUM}}$	.032 (2.34) b	.052 (1.60)	.055 (2.40) a
$\mathbf{b_{NEGNUM}}$	-.056 (-2.29) b	-.209 (-3.42) a	-.148 (-3.49) a
Screen	.005 (22.70) a	.007 (12.82) a	.006 (15.46) a
Week	-.446 (-2.33) a	-	-
F value for $\mathbf{\lvert b_{NEGNUM} \rvert - \lvert b_{POSNUM} \rvert}$	.54 ns	3.76 a	2.71 c
N	159	162	317
R-square	.471	.798	.736

Dependent variable is weekly revenues
Methods are time series cross section regression and weekly regressions (Week 1 and Weeks 1 + 2)
a: Significant at .01 level; b: Significant at .05 level; c: Significant at .10 level
t-values are reported in the parentheses

TABLE 6
Effects of Star Power and Budget on Box Office Revenues

	When Posnum-Negnum ≤ 0 (i.e., Negative Reviews Outnumber Positive Reviews) (n=62)		When Posnum-Negnum > 0 (i.e., Positive Reviews Outnumber Negative Reviews) (n=97)	
Variable	**Star Power is Wonaward**	**Star Power is Recognition**	**Star Power is Wonaward**	**Star Power is Recognition**
Constant	1.540 (1.06)	1.234 (.86)	1.238 (.77)	1.250 (.78)
Wonaward	1.117 (1.56)	N/A	.529 (.99)	N/A
Recognition	N/A	.225 (2.09) b	N/A	-.069 (-.95)
G	-2.372 (-1.86) c	-2.679 (-2.11) b	-1.651 (-1.21)	-1.451 (-1.05)
PG	-.131 (-.19)	-.340 (-.49)	-.522 (-.47)	-.436 (-.39)
PG13	-.818 (-1.54)	-.978 (-1.82) c	-.743 (-.69)	-.723 (-.67)
R	*	*	-.503 (-.49)	-.387 (-.38)
Release	-1.358 (-.90)	-.779 (-.53)	1.331 (1.15)	1.212 (1.04)
Sequel	-.501 (-.63)	-.480 (-.61)	1.531 (1.56)	1.057 (1.10)
Budget	.053 (3.01) a	.047 (2.65) a	-.030 (-1.49)	-.017 (-.82)
Screen	.003 (10.97) a	.003 (11.09) a	.006 (19.03) a	.005 (19.00) a
Week	-.447 (-2.20) a	-.446 (-2.20) a	-.482 (2.23) a	-0.480 (2.22) a
R-square	.377	.380	.486	.487
Hausman Test for random effects	M = 7.37 a	M = 7.13 a	M = 8.87a	M = 8.25 a

Dependent variable is weekly revenues
Method is time series cross section regression
t-values are reported in the parentheses
a: Significant at .01 level; b: Significant at .05 level; c: Significant at .10 level
* This set did not have any unrated films, and hence, dropped the R-rating during estimation