The Influence Effect of Critics' Reviews on Foreign and Domestic Movies

Jayoung Jeon and Luxuan Jiao

Professor James W. Roberts, Faculty Advisor

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Abstract

Critics and their reviews provide crucial information for consumers in many "experience goods" markets, and the movie market is one such market. Through their impact on the consumer's film selection, critics' reviews influence the first weekend box office performance (the influence effect). We hypothesize that the influence effect of critics' reviews is different for foreign and domestic movies. Using the U.S. film industry as our empirical setting, we examine the effects of reviews on opening weekend revenues in the U.S. film industry. We find that, when the critics' assessment of domestic movies is positive, people are discouraged from watching the movie. On the other hand, for foreign movies, the impact of positive reviews is found to be positive. We interpret this result as arising from the different target audiences for foreign and domestic movies. Further analysis of our data supports this hypothesis. We also find that people are more influenced to watch movies when they see multiple reviews than only a few of them. This positive impact of the number of critics' reviews is greater for domestic than foreign movies, and greater for domestic art movies than domestic non-art movies.

*JEL classification:*L82; M37

Keywords: Films, Movies, Critics, Reviews, Foreign, Art

1. Introduction to studying the differential effect of critics' reviews

Every year, a handful of high quality foreign movies are produced and imported to the U.S. However, only a few of them gain popularity in the U.S. market. In fact, over the last decade, the size of the American audience for foreign films has steadily declined. However, such trend is not due to a decrease in the number or quality of foreign movies; foreign movie production has grown gradually, whereas production in the U.S. has lost much of its momentum. The decline of foreign movies in the U.S. is even aggravated by the easy access to foreign movies "through alternative venues like Netflix, the internet, and Video on Demand platforms" ("New York", 2010).

In order to encourage foreign film producers to keep producing and exporting their films, a renaissance of foreign movies should be initiated soon. As a contribution to this movement, we examine whether the reviews of critics function differently for foreign movies and, if so, what the implications are for the marketing of those movies. Our findings may help the producers of domestic movies decide how they should promote their movies compared to foreign movies.

"Experience goods" markets are markets in which consumers cannot determine the total value and total cost of products prior to purchase, because they are imperfectly informed about the quality of the products. Examples of experience goods markets are restaurant, show, theater, book and movie markets. For these markets, consumers rely heavily on secondary cues to help them make decisions. Product reviews written by experts are one of the mechanisms that provide consumers with such cues (Basuroy et al., 2003; Eliashberg and Shugan, 1997; Kamakura et al., 2007). We look into the movie industry as one such experience goods market, since reviews have the greatest impact on the film industry, of all the art markets (King, 2007). The Wall Street Journal reported in 2001 that one-third of Americans actively seeks advice from film critics when choosing a film, and approximately one of every three filmgoers consults the reviews of the critics when choosing films. The literature has already verified the legitimacy of this report, in terms of the general trend, even though the details of our results differed from the literature.

Critics are known to function as opinion leaders by writing reviews about movies (Basuroy et al. 2003; Eliashberg and Shugan, 1997; Gemser et al., 2007; Kamakura et al., 2007). Film reviews can actively influence moviegoers to watch a movie or not by disseminating relevant information. Expressed differently, critics function as opinion leaders. This phenomenon is also called *the influence effect* of film reviews. If box office revenues were indeed affected by the influence effect, the influence of reviews would be strongest in the first weekend, since reviews are published before the movie is released, or immediately after the release. However, the influence of reviews should diminish after the first weekend, since reviews are not typically published after then. Thus, the influence effect is manifested by a strong correlation between reviews and box office revenue in the first week and a diminishing correlation afterwards.

There are three main dimensions of critical reviews: nature, size and number. The nature of a review is a continuous variable, which measures how positive or negative the tone of the review is. The size of a review is measured by the fraction of the page the review occupies. The number of reviews tells us how many reviews are written on a single movie. Size and number both indicate the visibility of the review. Many doubt that visibility has a significant influence on people's purchasing behavior. However, we hypothesize that it is as important as the nature of reviews, because visibility raises product awareness. When there are numerous reviews of large size, people tend to pay more attention to them than when there are a few of small ones. The potential audience needs to at least skim the reviews in the first place in order to be influenced by them. If people do not pay attention to the reviews, no matter how positive they are, they will not be able to attract people to watch the movie. Thus, we expect that all three dimensions of reviews will have some impact on consumers' film choices. In our research, we do not control for the size of reviews, since size and number are highly correlated and including both variables would lead to a multicollinearity problem (Gemser et al., 2007). Instead, we look into the nature and the number of reviews and ask how each dimension affects the first weekend box office revenue.

The extant literature also hints at the fact that the type of film may be a relevant determinant of the roles critics play, and the extent to which they influence box office performance. Critics play different roles for mainstream movies [i.e. widely released movies] and art house movies [narrowly released movies] (Gemser et al., 2007; Kamakura et al., 2007). While the reviews of art house movies have an influence effect, those of mainstream movies merely predict the box office performance. Our study classifies movies in a different way, into foreign and domestic, and examines how their revenues are influenced by critics' reviews. Since foreign movies are different from domestic movies along many dimensions like actors/actresses, directors, distributors, number of screens and so on, it is quite plausible that the critics' reviews would have different effects on foreign and domestic movies. In our research, we control for factors that affect revenues and distinguish between foreign and domestic movies, but we presume that inevitably there *should be* some immeasurable, unobservable differences that might produce different effects of critics' reviews on foreign and domestic movies. Thus, we hypothesize that the influence effect of reviews would be different for foreign movies and domestic movies.

Our research makes several primary contributions to the existing literature. First, we study not only the impact of the nature [average ratings in the case of our research] of the reviews, but also the impact of the number of reviews on a film. Second, rather than studying the aggregate effect of reviews, we study the differential effect of critics' reviews according to the type of movie. Classifying movies into foreign or domestic may provide a more precise picture of the reviews' impact. By doing so, we can also make some suggestions about more effective marketing strategies for foreign and domestic movies.

The rest of our study proceeds as follows. In section 2, we describe our project in more detail and discuss a subset of the empirical literature relevant to our topic. In section 3, we provide a theoretical background behind the function of critics' reviews and their influence on box office performance. In section 4, we describe the data. In section 5, we present the empirical methodology and results. In section 6, we argue that not controlling for the production budget does not undermine our regression results. Section 7 presents the managerial implications and we discuss the conclusions and limitations of our study in section 8.

2. Literature Review

2.1 Foreign and Domestic Movies

We classify movies into two types: foreign and domestic. Past literatures employed several different methods to distinguish films into domestic and foreign movies. The first method is to distinguish by language (King, 2007). Films spoken in English language are domestic, whereas those spoken in other languages are foreign. This method would make data gathering easy, since it is easy to tell which language a movie is in. However, it is problematic in dealing with Hollywood movies that are in other languages than English. Even though they are not in English, people rarely consider them to be foreign movies because they come from Hollywood, and thus should be classified as domestic. The second way is to distinguish by the origin of production (Fu, 2006). This method also seems problematic, because there are many domestic movies that are filmed in exotic places. The third method of distinction is by country where the movies had their first premieres (Gemser et al., 2007). We follow the method one of our primary data sources [boxofficemojo.com] uses. This website has complete information on the genres of movies, and they designate "foreign" as one of the genres. They distinguish the foreign movies by language, but they also account for the problem mentioned above, by excluding any Hollywood movies from foreign movies category.

2.2 Film critics: opinion leaders?

Film critics offer basic information and individual evaluations on films. Past researchers have termed the function of critics' reviews as the "influence effect" when critics exert influence on the box office performance of films through the reviews they write (Eliashberg and Shugan, 1997; Basuroy et al., 2003: Reinstein and Snyder, 2005).

Examining the impact of film reviews on early box office revenue can indicate whether reviews have the influence effect. If there existed the influence effect of reviews, the relation between reviews and box office revenue would be the strongest in the first week and after that it would diminish (Eliashberg and Shugan, 1997). Thus, we examine how the critics' reviews are correlated with the first weekend revenues, rather than with total revenues. Some papers find that film critics could predict the response of the audience, but fail to shape audiences' preference (Eliashberg and Shugan, 1997). Others argue that film critics are more opinion leaders than predictors, although they can be both (Basuroy et al., 2003). Some papers demonstrate that film critics are both opinion leaders and predictors (Gemser et al., 2007). There are also some papers that discredit any association between critics' reviews and box office performances (Holbrook and Addis, 2008). Since the results of current literatures are mixed, we examine the issue ourselves.

For more information on past research, look at **Table 1** in **Appendix**. It is built upon a table borrowed from a research conducted by Zhu and Zhang (2009).

2.3 Film reviews and visibility

Many previous studies have examined the impact of film reviews only in terms of the nature of reviews (how positive or negative reviews are in content or tone). However, as mentioned in the introduction, there are two more dimensions to film reviews: size and number. These two dimensions signify the visibility of film reviews and we believe these could have a significant impact on box office performances. The results from past researches are mixed. Gemser et al., (2007) found that the number and size of the film reviews are important variables that influence the box office revenues, whereas the nature of reviews does not play a significant role. On the other hand, Eliashberg and Shugan (1997) argue that the total number of reviews is not very predictive of a movie's performance, while the nature of them can predict the performance.

2.4 Non-cinema evidence for the influence effect

In other experience goods markets, such as CD and book markets, reviews by experts also have influence effects. Silva and Silva found (2010) that the national public radio music critics have the power to persuade people. They demonstrated that listening to an NPR music critic's favorable review influenced listeners' opinions of songs. They were, however, not the first ones to report music critics' ability to influence listeners' opinions of songs.

Sorensen£ and Rasmussen (2004) reported similar results for the book market. They found that, in the case of book reviews, any publicity is good publicity, and thus even negative reviews lead to increases in sales. They also found that the book reviews by critics serve largely to inform consumers about a book's content and characteristics, including the book's existence.

The findings above support the view that critics are more than mere reflectors or predictors of public opinions.

3. Theories on the role of critics

There are two main functions of critics' reviews. First, they help increase the awareness of movies. They can inform readers that the movies, which are reviewed, exist, and thus function as advertisements in themselves. When people repeatedly come across multiple reviews of a movie, that movie does not drift away from their minds easily. Thus, when they go to the theater, the movie remains in their set of movie choices. No matter how good a movie might be, if it were not included in consumers' consideration set, they would not be able to recall the movie and thus would fail to choose it. This function of reviews is captured by the **ln(Number)** variable. The second prominent function of critics' reviews is that they inform the readers of the quality of movies. They praise the movies that they consider to be of high quality, while criticizing those they consider to be unsophisticated or too hedonistic. By doing so, they deliver their assessment of the quality of movies to readers, thereby influencing them to watch or not to watch the movies. The **ln(Nature)** variable captures this function of critics' reviews.

The following theories explain why the potential consumers of movies consult the reviews of critics, and why they are influenced by what the critics write.

Transaction cost economics, developed by Oliver Williamson, states that people try to minimize the costs incurred in economic exchanges. Such transaction costs occur because people have limited cognitive processing capabilities and cannot consider all possible scenarios in economic decision-making (bounded rationality). When people make film choices, they lack the time or ability to consider all aspects of movies. Another factor that incurs transaction costs is the human instinct to be untruthful about any benefits when given a chance to cheat (opportunism attributable to information asymmetry). When the movie studios promote their movies through advertisements, they tend to exaggerate their merits. Since people are aware of this tendency, they do not believe everything the advertisements say and sometimes expend some time and effort to collect further information.

Uncertainty reduction theory also explains the influence effect of critics' reviews. This theory states that people seek to reduce the uncertainty when the available information is not sufficient and asymmetric. Product uncertainty is commonplace in "experience goods" markets, e.g. movie markets. Only after actually watching a movie can consumers learn whether what they bought is similar to or different from what they perceived it to be during the movie selection process. Advertisements and other sources of information cannot overcome the lack of information, because the individual himself knows his preferences the best, and even he cannot be certain if he will like the movie or not until he actually watches it. Thus, consumers engage in uncertainty reduction efforts in order to mitigate and reduce the risks of purchase and to maximize the outcome value.

Signaling is the idea that a party or an object sends a signal about itself. Critics' reviews can send signals about movies, whether they are good, bad or mediocre. When the readers receive such signals, their selections of movies are influenced.

To summarize, in order to reduce transaction costs and the uncertainty of a movie selection, people read the reviews of movie critics, which send them signals and help them make their film choices.

4. Data Description

4.1 Data sources for movies

We collected the sample of 1388 films released in the United States between January 2008 and August 2011. Our dataset is appropriate for several reasons. First, the size of the dataset is larger than that used in past studies. To list a few, Kamakura et al. used a sample of 466 movies, and Basuroy et al. studied 200 movies. Thus, the problem of having non-comprehensive data is less of an issue for our dataset. Thus our data set is more comprehensive than those in prior studies. We still might be missing some extremely unpopular/unadvertised movies, but presumably few of those. Second, the two main sources of our data, boxofficemojo.com and metacritic.com are referenced by a film industry expert, Sriram Venkataraman, who also used these sources in his own research. Thus, we are not drawing data from some unverified sources, but from sources that have been repeatedly used in film studies and acknowledged to be reliable. Third, the time scope of our dataset is the recent past. The more recent the dataset is, the more helpful it is in assessing the managerial implications for the current and future film industry. In addition, the factors that influence the first weekend revenues might be different for recent movies and old movies. For example, about 10 years ago, the Internet was not as widely accessible as it is today and thus the effect of online word-of-mouth values would diverge greatly for relatively new movies and for old movies. Thus, collecting both old and new movies and running regressions with the same control variables would be misleading.

Our data comes from three main online sources. We collected data regarding reviews (both nature and number) from metacritics.com, and other characteristics of films from boxofficemojo.com. We collected data for actors/actresses from imdb.com.

4.2 Box office revenues: the opening weekend

The adjusted box office revenue of the opening weekend is our dependent variable. We collected the data for revenues from boxofficemojo.com. We then adjusted the revenues using the annual average ticket prices, using the year 2011 as the base year. Accordingly, all the revenues are in the units of the year 2011 dollar. Adjusted revenues help purge the effect of ticket price changes and make our estimation more precise.

ln(Openrev_adj): Opening weekend box office revenues include revenues from Friday through Sunday of the first week of release. We take the log of opening weekend revenues in order to estimate the percentage change instead of the change in dollar value. The reason why we prefer to estimate the percentage change is because marginal effects thus become comparable across movies.

4.3 Critics' reviews of movies

Our dataset contains critics' reviews published in newspapers, magazines and/or websites, and/or broadcast on radio. Our data source, metacritics.com, collects reviews from various sources. Some reviews are published in newspapers, such as the New Orleans Times-Picayune, Orlando Sentinel, Los Angeles Times, St. Petersburg Times, Miami Herald, USA Today, San Francisco Chronicle, Philadelphia Inquirer, Chicago Sun-Times, Chicago Tribune, Wall Street Journal, Arizona Republic, New York Post, St.

Louis Post-Dispatch, Boston Globe, The New York Times, or the Chicago Reader and in many others. Others are published on magazines, such as Entertainment Weekly, Rolling Stone, Variety, The New Yorker, Time, The Hollywood Reporter, Austin Chronicle (alternative weekly), Washington Post, New York Observer (weekly), Village Voice (Weekly), New York Daily News, Time Out New York, or the Boxoffice Magazine, etc. A few come from online sources, such as Movieline and Salon.com.

In order to assess the influence effect of reviews, it is better to leave out reviews from online sources, because they might be read much after the release of movies, whereas, by the definition of the influence effect, we need to look at the effect of reviews within one week of the release of movies. However, there were only a few online reviews, compared to those from other media sources. Thus, we proceed with the assumption that the results are not confounded too much by the reviews from online sources.

Nature: the average of ratings given by the film critics; it is measured on the scale of 0 to 100 (0= lowest evaluation, 100= highest evaluation). We expect to see a positive effect for **Nature**, since people might conceive of high ratings as a cue for high quality movies. In turn, they might become interested in the movie and even be influenced to go watch the movie. In other words, by conveying the quality of movies, the nature of reviews might influence the potential audience. Metacritic.com gathers critics' reviews from a variety of sources, and translates written comments to numerical scores. If critics gave numerical scores instead of/in addition to verbal reviews, metacritics.com simply recalculate numerical scores on a scale of 0 to 100. There might be worries over the seemingly arbitrary translation of written comments to numerical scores, and over potentially inconsistent grading standards across different critics.

Unfortunately, without knowing when and how the arbitrariness and inconsistencies happen, it is not possible to control for this. However, as long as the over-evaluation or under-evaluation of movies happens randomly, the error term in our regression is sufficient to account for them, and we cannot think of a reason why it should happen in a non-random fashion. We take the log of **Nature**, **ln(Nature)**, when we run regressions.

Number: how many critics' ratings there are for a single movie. People are less likely to forget about a movie when they see multiple reviews on it rather than only a few. Thus, even though critics might have castigated the movie severely in the reviews, it might still remain in the consideration set of movies when people go to the theater. There is at least some chance that people will consider a movie if they can recall it. On the other hand, if they forget about it, they would not choose that movie, regardless of how much critics praised it. Thus, the number of critics' reviews might have a positive effect on the likelihood people will watch the movie and thus affect the box office performance, by increasing the awareness of a movie. Metacritics.com might fail to collect every single review that exists, and the number of reviews might be underestimated. However, it is the relative number of reviews that is important, not the absolute number. Since underestimation is a potential for any movie, the relative number of reviews across different movies would change little. We use **ln(Number)**, log of **Number**, when we run regressions.

4.4 Foreign and domestic movies

We define foreign movies as movies in languages other than English, but categorize all Hollywood movies as domestic movies, including those that are not in English. Domestic movies include all movies in English and Hollywood movies

Foreign: a dummy variable, which has a value of 1 if the movie is foreign, 0 if the movie is domestic.

Foreign×ln(Nature): an interaction term between **Foreign** and the log of **Nature**. A significant coefficient of **Foreign×ln(Nature)** would indicate that the nature of critics' reviews has a differential influence on the box office performances of domestic and foreign movies.

Foreign×ln(Number): an interaction term between **Foreign** and the log of **Number**. A significant coefficient of **Foreign×ln(Number)** would indicate that the number of critics' reviews has a different influence on the box office performances of domestic and foreign movies.

4.5 Other control variables

Other factors that might possibly affect the opening weekend revenues are included in the regressions. In order to avoid endogeneity problems, we collected data on more control variables than any of the past studies on the influence effect of critics' reviews, to our knowledge.

Yr2008/Yr2009/Yr2010/Yr2011: year dummies, in order to control for year-specific effects on box office revenues. Since our data is time-series data, it is especially important to control for time effects.

Jan/Feb/Mar/Apr/May/Jun/Jul/Aug/Sep/Oct/Nov/Dec: month dummies, in order to control for month-specific effects on box office revenues. Some months might attract more viewers than others. For example, February might be able to raise more revenue than other months because many couples go to the movies on Valentine's Day (February 14th).

WOMscore: the **W**ord **O**f **M**outh **score** stands for the average ratings of a movie given by the consumers on metacritic.com and is measured on a scale of 0 to 10. A number of previous studies have reported that the word of mouth value plays a non-negligible role in consumer film selections.

WOMnumber: the **number** of **W**ord **O**f **M**outh values is the number of consumer ratings on metacritic.com. Like the number of critics' reviews, **WOMnumber** might positively influence box office performance by raising awareness of a movie.

Star-First-Tier: a dummy variable for the top 10 stars. If any of the lead actors/actresses of a movie are on the list in the **Appendix**, then the movie is considered to have some star power, and this dummy variable takes the value of 1. Otherwise, its value is 0. This list is ranked by the total gross revenue each actor/actress has raised throughout his/her career.

Star-Second-Tier: a dummy variable for the top 11-50 stars. If any of the lead actors/actresses are ranked 11-50th on the list in the **Appendix**, then the movie is considered to have a star power.

Director: a dummy for whether the director(s) of a movie has/have star power or not. It has a value of 1 if it does, 0 if it does not. Directors on the list in the **Appendix** are considered to have star power. This list is also ranked by the total gross revenue each director has raised throughout his/her films. We classify directors with star power as those ranked in the first 15.

Budget: the size of production budget. Gemser et al. (2007) and Kamakura et al. (2007) suggested that there is a significant correlation between the budget of a film and its box office performance. The production budget is measured in units of dollars.

Distributor: a dummy variable for whether a film is distributed by a major film distributor. We define major distributors as the top 6 distributors that raised the most revenues from year 2008 to year 2011. The list of these distributors is in the **Appendix**. Movies distributed by major distributors seem to be more successful, whether it is because the major distributors choose movies well or because people prefer movies distributed by them. This dummy variable is equal to 1 if it is distributed by a major film distributor, and 0 if it is not.

Screen: the number of screenings on the opening weekend. Gemser et al. (2007) found the number of screens on the opening weekend to be a reliable proxy for the marketing budget. Even intuition tells us this proxy is reasonable because studios with large budgets tend to release movies more widely in the first weekend than those with small budgets do. The amount and/or quality of advertising in turn would have some impact on the first weekend revenues.

G/PG/PG-13/R/Unrated: dummy variables for MPAA ratings. The value of the **Unrated** variable is equal to 1 when the movie is not given any MPAA rating.

Horror/Comedy/IMax/Foreign/Documentary/Fantasy/Adventure/Drama/Animation/Action/Family/Thriller/Romance/Crime/War/Western/Musical/History/Sport/Sci-Fi/Concert/Period: dummy variables for the genres of movies. People have different tastes for different movie genres. Thus, certain genres might appeal to a wider range of audiences than other genres, and thus generate higher opening weekend revenues.

5. Methodology and Results

5.1 Overview of collected movies

The table below presents the descriptive statistics of the pooled data. Pooled data includes all the movies we collected, regardless of movie type, domestic or foreign.

Table 2

The Overview of Pooled Data

	Mean	S.D.	Min	Max
Openrev_adj	8447654	19200000	100.8267	199000000
ln(Openrev_adj)	12.25178	3.488612	4.613403	19.10845
Foreign	.1280277	.3342652	0	1
Nature	57.10467	16.99265	7	95
Number	21.39619	10.43863	2	43
Star-First-Tier	.0294118	.1690309	0	1
Star-Second-Tier	.08391	.2773728	0	1
Director	.0233564	.1510981	0	1
Distributor	.2032872	.4026186	0	1
Screen	208.9581	173.7509	1	519

From January, 2008, to August, 2011, the film that yielded the highest opening weekend revenue was *A Christmas Carol* (raised $ 199000000), and *The objective* yielded the lowest opening weekend revenue (raised only $100.8267). Again, the revenues are given in units of year 2011 dollars. The average critics' rating of the movies in our dataset is 57.10467 on a scale of 0 to 100 and the number of critical reviews varies from 2 to 43, with a mean of 21.40272. Approximately 10% of the movies have actors/actresses with star power in their casts, whereas only about 2% are directed by star directors. About 13% of the movies are foreign movies and the rest are domestic. The number of screens on the first weekend was 208.9581, on average.

We also present separate statistics for the two types of movies: domestic and foreign.

Table 3 Overview of Separate Data: Foreign Movies and Domestic Movies

	Foreign Movies		**Domestic Movies**		**T-test**	
	Mean	S.D.	Mean	S.D.	F	P
Openrev_adj	532541	5745697	9609793	20200000	-5.42	0.000
ln(Openrev_adj)	9.79309	1.686628	12.61278	3.539059	-9.53	0.000
Nature	68.10811	13.03169	55.48909	16.91124	8.71	0.000
Number	16.80405	8.2878	22.19441	10.43091	-5.81	0.000
Star-First-Tier	.0067568	.0821995	.0327381	.1780386	-1.75	0.081
Star-Second-Tier	.0202703	.1414019	.093254	.2909324	-3.00	0.003
Director	0	0	.0267857	.1615368	-2.02	0.044
Distributor	.0135135	.1158516	.2311508	.4217779	-6.24	0.000
Screen	185.3194	192.3102	212.4387	170.6792	-1.75	0.080

Table 3 shows the statistics of foreign and domestic movies and the t-test results. The t-tests demonstrate that foreign movies are significantly different from domestic movies in several respects. The average opening weekend revenue of domestic movies is significantly higher than that of foreign movies. Domestic movies also tend to have more star actors/actresses and star directors than foreign movies do, and they are more frequently distributed by major distributors than foreign movies are. In terms of critics' reviews, foreign movies tend to have more positive reviews than domestic movies do. However, the number of critics' reviews is greater for domestic movies than for foreign movies. The number of screens on the opening weekend also is greater for domestic movies than foreign movies, which correspondingly implies that the marketing budget would be greater for domestic movies. Although not listed in the table, the **WOMscore** and **WOMnumber** variables are also significantly different for foreign and domestic movies.

The differences mentioned above are not a comprehensive list of the differences between foreign and domestic movies. There might be some unobservable and/or immeasurable differences and also some observable and/or measurable differences that we failed to note. Leaving out these factors is likely to cause the effect of critics' reviews to differ for foreign movies and domestic movies.

5.2 Regressions and Results

Due to skewed distributions, we take the log of the **Nature** and **Number** variables: **ln(Nature)**, **ln(Number)**. There are many missing values for the **WOMscore**, **WOMnumber**, and **Budget** variables. Since including these control variables reduced our sample size drastically, we do not include them in our regressions.

Regression 1

$$\begin{aligned}\ln(Openrev\_adj) = {} & \alpha + \beta_1 \times \ln(Nature) + \beta_2 \times \ln(Number) + \beta_3 \times Foreign \times \ln(Nature) \\ & + \beta_4 \times Foreign \times \ln(Number) + \beta_5 \times Foreign + \beta_6 \times Screen + \beta_7 \times Distributor \\ & + \beta_8 \times Director + \beta_9 \times Star - First - Tier + \beta_{10} \times Star - Second - Tier \\ & + \sum_{g=1}^{22} \omega_g \times Genre + \sum_{mp=1}^{5} \gamma_{mp} \times MPAArating + \sum_{m=1}^{12} \theta_m \times Month + \sum_{y=1}^{4} \tau_y \times year + u\end{aligned}$$

Following is the result of the specification above.

Table 4

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	Coefficient	t-statistic	p-value
ln(Nature)	-1.830404	-7.59	0.000***
ln(Number)	2.718746	17.61	0.000***
Foreign×ln(Nature)	2.097242	3.05	0.002***
Foreign×ln(Number)	-1.741061	-4.76	0.000***
Foreign	-4.855959	-1.83	0.068*
Screen	.222925	7.75	0.000***
Distributor	2.222579	13.13	0.000***
Director	.316427	1.10	0.271
Star-First-Tier	-.2522081	-0.89	0.375
Star-Second-Tier	1.178803	5.79	0.000***

*** significant at 1% level * significant at 10% level

Significant coefficients for **ln(Nature)** and **ln(Number)** indicate that critics' reviews have an influence effect on the first weekend box office revenues. Their effects are different for foreign and domestic movies, however, as the significant coefficients on **Foreign×ln(Nature)** and **Foreign×ln(Number)** indicate. For foreign movies, positive critic ratings influence people to watch the movie and increase the first weekend revenue. Highly visible reviews have the same effect for foreign movies. Domestic movies, on the other hand, are influenced differentially by the nature and number of reviews. The number of reviews positively influences the first weekend revenues of domestic movies by a greater magnitude than it influences those of foreign movies, but the nature of the reviews has a negative impact on revenue. Although some might find this negative influence effect of nature doubtful, we are unsurprised by this finding, because we had already expected such a result during the data collection process. **Figure 5.2.1** in the **Appendix** roughly shows that **ln(Nature)** and **ln(Openrev_adj)** are negatively correlated Those American movies with which we are familiar and which generated high revenues seemed not to have high ratings. Rather, many of them had negative reviews, although almost all of them had larger-than-average number of reviews. For example, *Transformers: Revenge of the Fallen*, which raised the third largest total revenue among the movies in our dataset, was rated only 35, on average, by the critics. Another movie from the Transformers series, *Transformers: Dark of the Moon*, raised smaller total revenue but was rated higher by critics. *A Christmas Carol*, which raised the highest opening weekend revenue, scored only 55 in the average critics' ratings. *The Twilight Saga: New Moon*, which raised the fourth highest amount of revenue, was rated only 44 by the film critics. We are not the first ones to find such positive effects of negative publicity (King, 2001; Kennedy, 2008). In a recent study by Berger et al. (2010), negative reviews increased the sales of books. They contend that negative publicity can increase purchase likelihood and sales by increasing product awareness. Although they find this result to be true for relatively unknown products, such as books by unknown authors rather than established ones, there is no reason to believe it does not apply to American movies. In addition, if we remind ourselves of the common wisdom that any publicity is good publicity, our finding is not totally unexpected.

Nevertheless, we examined the **ln(Nature)** variable further, using the categorical dummies, **Nature_low** and **Nature_high**.

Nature_low: a dummy variable for movies with average critics' ratings in the lowest 10 percentile of the movies in our dataset.

Nature_high: a dummy for movies with average critic ratings in the highest 10 percentile.

We use these dummies instead of employing the continuous variable **ln(Nature)**, because mediocre critic ratings might not have a visible influence and might just confound the result. For example, when people see the average rating of 60, they are not strongly influenced by it because the score 60 is just not strong enough to influence people, even though it is above average (=57.17672). On the other hand, when the critics' ratings are extremely good/bad, people might find it hard to ignore them. Thus, we ran the regression including these two dummy variables instead of **ln(Nature)** and including **Foreign×Nature_low** and **Foreign×Nature_high** instead of **Foreign×ln(Nature)**.

Foreign×Nature_low: an interaction term between **Foreign** and **Nature_low**

Foreign×Nature_high: an interaction term between **Foreign** and **Nature_high**

All other control variables remain the same along with the constant and the error term. The specification looks like the following.

Regression 2

$$\begin{aligned}\ln(Openrev\_adj) = {} & \alpha + \beta_1 \times Nature\_low + \beta_2 \times Nature\_high + \beta_3 \times \ln(Number) \\ & + \beta_4 \times Foreign \times Nature\_low + \beta_5 \times Foreign \times Nature\_high \\ & + \beta_6 \times Foreign \times \ln(Number) + \beta_7 \times Foreign + \beta_8 \times Screen + \beta_9 \times Distributor \\ & + \beta_{10} \times Director + \beta_{11} \times Star - First - Tier + \beta_{12} \times Star - Second - Tier \\ & + \sum_{g=1}^{22} \omega_g \times Genre + \sum_{mp=1}^{5} \gamma_{mp} \times MPAArating + \sum_{m=1}^{12} \theta_m \times Month + \sum_{y=1}^{4} \tau_y \times year + u\end{aligned}$$

This specification also captures the distribution of the data better, because the relationship between **ln(Openrev_adj)** and **ln(Nature)** is not linear. Look at **Figure V.II.II** in the **Appendix** for the graph that illustrates this relationship [x: **ln(Nature)**, y: **ln(Openrev_adj)**]

Following is the result of the specifications above.

Table 5

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	Coefficient	t-statistic	p-value
Nature_low	1.40739	5.05	0.000***
Nature_high	-.5965385	-2.88	0.004***
ln(Number)	2.43965	16.98	0.000***
Foreign×Nature_low	-1.949161	-1.63	0.103*
Foreign×Nature_high	.7260136	2.30	0.022**
Foreign×ln(Number)	-1.527399	16.98	0.000***
Foreign	2.960088	-4.22	0.004***
Screen	.0012799	3.46	0.001***
Distributor	2.362847	13.78	0.000***
Director	.166939	0.58	0.563

Star-First-Tier	2.362847	13.78	0.000***
Star-Second-Tier	1.149662	5.45	0.000***

*** significant at 1% level ** significant at 5% level * significant at 10% level

The regression result is almost the same as that of **Regression 1**. Accordingly, the interpretation remains consistent across two specifications. For domestic movies, extremely good reviews have a negative impact, whereas extremely bad reviews have a positive impact on the likelihood of watching the movie and the opening weekend revenues. For foreign movies, extremely good reviews have a positive impact, while extremely bad reviews have a negative impact.

We interpret such results as arising from different audience bases for foreign and domestic movies, and the resulting difference in the aspects of critics' reviews that the consumers of foreign and domestic movies seek. We argue that the main audiences for domestic movies watch movies for fun, whereas those for foreign movies watch movies to appreciate them as works of art. People generally perceive foreign movies as art movies. For instance, the famous film review aggregator, Rotten Tomatoes, puts foreign movies and independent movies (i.e. art movies) in the same category. Thus, those who are interested in watching art movies would be more attracted to foreign movies, while those who want some enjoyable rest would prefer domestic movies. Holbrook and Addis (2008) also find that movies provide "two very different values to two very different kinds of targets". They contend that some audiences watch movies to find finer things in life, while others enjoy movies with "big-budget mass-marketed spine-tingling blockbuster-type special effects that thrill them on the big screen". We argue that the former make up the majority of foreign movie audiences, while the latter make up the majority of domestic movie audiences, because people perceive foreign movies to be art movies but do not perceive domestic movies as art. Indeed, our data also demonstrate that almost all foreign movies are art movies by our definition of an art movie (movies in the genres of History and/or Documentary), while only a minority of domestic movies are art movies.

The difference in the main audiences, in turn, makes a difference in what kind of information consumers seek from the reviews of critics, and how they are influenced by the reviews. The consumers of foreign movies would like to watch high quality sophisticated movies and they know that their tastes align closely with those of the critics. The consumers of foreign movies and the critics both enjoy movies that are "challenging by virtue of their abstract qualities of cinematic style, deviations from conventional values (graphic sex and violence), departures from familiar settings (foreign languages, older vintage), and/or emphasis on subtle complexities (Holbrook, 1999)." Thus, they look for experts' assessment of the quality of movies, hoping the experts' appreciation and taste in art will be resonant with their own. Of course, coming across the critics' reviews and reading them helps the potential audience know that the movies, which reviews are on, exist. However, for the consumers of foreign movies, critics' reviews do more than that; they inform the readers of the quality of a movie. On the other hand, reviews function differently for the consumers of domestic movies. Critics' reviews are more important to let the potential consumers know that such movies exist. Art critics tend to prefer very sophisticated and sometimes obscure movies, which might be educational but not necessarily enjoyable. In fact, the general audience would find such movies boring and hard to understand. Thus, when the consumers of domestic movies go to theaters to have fun, they tend to avoid movies the critics praise as great works of art and instead choose movies that they can enjoy mindlessly. If this interpretation were true, we would see the same effect for the reviews of domestic art movies and foreign movies because they both target a highbrow art-seeking audience. Also, these movies would be different from non-art domestic movies. Indeed, the research by Austin (2008) indicates that the main audiences for such “artsy” movies [foreign movies and non-art domestic movies] are more likely to plan their attendance at least one week in advance, are more interested in learning about the films, and express only a moderate preference for American movies over foreign movies than the audience for non-art movies. Austin’s finding hints that art movies and non-art movies have different audience bases that might render the effects of critics’ reviews different for art and non-art movies. In order to test this, we ran a regression with a dummy for domestic movies that are art movies and its interaction terms.

Art_domestic: a dummy for domestic movies that are considered art movies.

Art_domestic×ln(Nature): an interaction term between **Art_domestic** and **ln(Nature)**.

Art_domestic×ln(Number): an interaction term between **Art_domestic** and **ln(Number)**.

Including the terms above to Regression 1, we ran the following regression.

Regression 3

$$
\begin{aligned}
\ln(Openrev\_adj) = {} & \alpha + \beta_1 \times \ln(Nature) + \beta_2 \times \ln(Number) + \beta_3 \times Foreign \times \ln(Nature) \\
& + \beta_4 \times Foreign \times \ln(Number) + \beta_5 \times Foreign + \beta_6 \times art\_domestic \times \ln(Nature) \\
& + \beta_7 \times art\_domestic \times \ln(Number) + \beta_8 \times art\_domestic + \beta_9 \times Screen \\
& + \beta_{10} \times Distributor + \beta_{11} \times Director + \beta_{12} \times Star - First - Tier \\
& + \beta_{13} \times Star - Second - Tier + \sum_{g=1}^{22} \omega_g \times Genre + \sum_{mp=1}^{5} \gamma_{mp} \times MPAArating \\
& + \sum_{m=1}^{12} \theta_m \times Month + \sum_{y=1}^{4} \tau_y \times year + u
\end{aligned}
$$

Following is the regression result.

TABLE 6

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	**Coefficient**	**t-statistic**	**p-value**
ln(Nature)	-1.918199	-7.44	0.000***
Foreign×ln(Nature)	2.211653	3.20	0.001***
Art_domestic×ln(Nature)	.6276897	1.02	0.307
ln(Number)	2.978888	16.68	0.000***
Foreign×ln(Number)	-2.034031	-5.39	0.000***
Foreign×ln(Number)	-1.371782	-5.26	0.000***
Foreign	-4.434829	-1.66	0.096*
Art_domestic	-.2639899	2.557178	0.918
Screen	.0013426	3.69	0.000***
Distributor	2.064418	11.96	0.000***
Director	.2680705	0.93	0.351
Star-First-Tier	-.2597808	-0.91	0.363

Star-Second-Tier	1.134688	5.51	0.000***

*** significant at 1% level * significant at 10% level

For our interpretation to hold, we need to see positive coefficients for **Foreign×ln(Nature)** and **Art_domestic×ln(Nature)** and negative coefficients for **Foreign×ln(Number)** and **Art_domestic×ln(Number)**. In fact, we do see these coefficients in the result. The coefficient of .6276897 on the **Art_domestic×ln(Nature)** variable indicates that the effects of reviews are differential for domestic art movies and domestic non-art movies. We acknowledge that the p-value of 0.307 is a bit high to guarantee the significance of the **Art_domestic×ln(Nature)** variable. Even though the regression result does not constitute conclusive evidence for our interpretation, it does demonstrate that it is a possibility.

The Number variables [**Foreign×ln(Number)** and **Art_domestic×ln(Number)]** seem to provide more solid support for our interpretation. The positive effect of the number of critics' reviews is greater for non-art domestic movies than for foreign movies and domestic art movies, as the positive coefficients on **Foreign×ln(Number)** and **Art_domestic×ln(Number)** indicate. This implies that the critics' reviews of domestic non-art movies primarily function to let the potential audience know that the movies exist, thereby increasing their awareness of movies. On the other hand, merely increasing the awareness would not influence the consumers of foreign movies or art movies as much, or convince them to watch the movies.

The regression result and the analysis stay the same even when we change the definition of art movies. Since an unambiguous definition of art films does not exist, we repeated the regression using a different definition (i.e. redefining art movies as those not produced by the 6 major distributors in the US market). They all give qualitatively the same results.

Through three different specifications, some of the control variables consistently remained significant. First, the coefficient on **Screen** is positive and significant. As mentioned earlier, the number of screens in the opening weekend is a proxy for the marketing budget. Our regression result suggests that the amount/quality of advertisements on a movie, which is largely determined by the size of the marketing budget, influences people's likelihood of watching the movies. Major **distributor**s are also found to influence the performance of movies. Finally, the top 11-50 stars have highly significant and positive impacts on box office revenues. Interestingly, the top 1-10 stars have insignificant effects on box office performance. This might be the case because the sample of movies in which they appear is very small. The top 10 stars also tend to be old, which makes sense because we classified stars by the total revenues they raised throughout their career and it takes time to raise high cumulative revenues even though each movie they appeared in might have been extremely successful. Their being old would lose some of their ticket power due to factors like loss of attractiveness and loss of their main fan base. They might also take more secondary roles rather than leading roles, in which case the consumers would not be influenced as much to watch the movie.

6. Justifying the exclusion of the production budget

When running the regressions in section 5, we did not control for the production budget, because the **Budget** variable has many missing values and thus including this variable greatly reduces the sample size. However, some might find objectionable our leaving out the **Budget** variable. They might insist that the production budget of movies has a great impact on the first weekend revenues, and thus should be controlled for. These people also might infer from our finding in the previous section that critics tend to rate movies with high production budgets poorly, because they consider them to be generally non-art movies, implying the possibility of the negative correlation between **Budget** and **Nature**. However, three pieces of evidence extinguish such concerns.

First of all, the scatter plot and correlation between **Nature** and **Budget** show that there is no notable association between these two variables. The scatter plot is shown in the **Appendix** (**Figure 6.1**). The plots seem to be scattered randomly, with the fitted line barely having a slope. The correlation between **Nature** and **Budget** is -0.1250, which implies there is a negligibly small correlation between them. Thus, we can carefully dismiss the possibility that movie critics might rate high-budget movies poorly, and rate low-budget movies highly. In addition, the correlation between **Number** and **Budget** is negligible (0.0194). The scatter plot is in the **Appendix** (**Figure 6.2**). Thus, when we ran regressions without a **Budget** variable, the error term took care of its impact on the box office performance, without raising the endogeneity issue between the **Nature**/**Number** regressor and the error term. The correlation also seems negligible when we use **ln(Nature)** and **ln(Number)**, instead of **Nature** and **Number** (Look at **Figure 6.3** and **Figure 6.4** in the **Appendix**).

Second, when we ran the same regression only with movies that have data on the production budget, the regression results retained most of their significance. We wondered whether the availability of information on production budgets could imply something about the movies; these movies might be popular or well-advertised movies, with qualities that make them intrinsically different from other movies. However, when we ran **Regression 1** and **Regression 3** with only these movies, the coefficients still seemed similarly significant. Such similar results indicate that the movies with budget data are not intrinsically different from those without them. Some minor changes in the significance of some variables are worth noting, however. After running **Regression 1** only with movies with budget data, **the Foreign×ln(Number)** variable becomes insignificant, with a p-value of 29.8. The **Screen** variable also loses significance with a p-value of 66.6. This is particularly surprising, because the **Screen** variable remains highly significant throughout previous regressions. The loss of significance from the **Screen** variable might imply that the number of screens accounts for the effect of the production budget when the **Budget** variable is excluded, gaining its significance by correlation with the production budget. **Regression 3** shows the differences in the same variables in the same direction: less significant **Foreign×ln(Number)** and **Screen** variables. Look at **Table 7** and **Table 8** in the **Appendix** for the regression results.

Third, when we include the **Budget** variable in **Regression 1** and **Regression 3**, the coefficients and their significance do not change notably, although there are some changes. **Regression 4** and **Regression 5** in the **Appendix** are the regressions with the **Budget** variable included to, respectively, **Regression 1** and **Regression 3**. In **Regression 4**, **Foreign×ln(Number)** and **Screen** become insignificant when the **Budget** variable is included. **Regression 5** experiences more changes than **Regression 4**; in addition to **the Foreign×ln(Number)** and **Screen** variables, the **Art_domestic×ln(Number)** variable becomes insignificant. Yet, these variables still remain the same in terms of their direction (positive/negative) of impact on the box office performance. Moreover, for both regressions, the **Budget** variable does not seem significant, which implies that this variable might not have any notable impact on the box office performance. If that were the case, it would be misleading to include it in the regressions. Look at **Table 9** and **Table 10** in the **Appendix** for the regression results.

Therefore, not controlling for the production budget of movies does not have a significant influence on the regression results and the corresponding interpretation.

7. Applications to the film industry

With the economy in recession, people are turning to cheaper forms of entertainment, one of which is movies. However, even though there are more people to entertain, there are many other modes of entertainment, which compete with movies. Thus, the marketing aspect of movies is growing more important. Without an effective marketing strategy in hand, the movie industry could lose the opportunity to raise huge profits to these other modes. Our findings have some managerial implications that might be helpful to the movie industry.

Our results show that the reviews of critics do influence people's film choices, but differentially for different types of movies. Specifically, domestic non-art movies are influenced negatively by the nature of the reviews, but positively by the number of reviews. For these movies, the mere existence of reviews is more important than the content or tone of those reviews. Since having many reviews augments box office revenues, movie studios should encourage critics to write more reviews when they distribute their movies. They can do so by holding many pre-screenings and inviting many critics. They can also ask critics to hold interviews with the actors/actresses starring in movies, which might encourage the critics to write more reviews. If they still have only a few reviews, they might also try to re-edit the movie in order to attract more critics to write reviews. Shooting multiple scenes in the production process would help address the problem of only a few critics showing interest in a movie. Since having positive critics' reviews actually undermines box office revenues, film studios should avoid incorporating positive comments from critics in their advertisements. One of the common marketing strategies is to have favorable quotations from critics in advertisements. However, this could actually undercut box office revenues.

On the other hand, foreign movies are positively influenced by good reviews and negatively by bad reviews. We expect the domestic art movies to be influenced in a similar way, even though our regression result does not provide conclusive evidence for this, but merely a suggestion. Although having more reviews also helps box office performance, the content of the reviews matters for these types of movies. Thus, the marketing strategy should be different from domestic non-art movies. The mere existence of reviews would not help as much. The movie studios should strive to get good reviews, even though they can get only a few of them. One way to achieve this is to selectively invite “soft” reviewers to critical screenings (Eliashberg and Shugan, 1997). When producers expect bad reviews from critics, they can even choose to forgo the screenings altogether. They could also delay sending press kits to reviewers, since these contain publicity stills and production information. Because newspapers rarely run reviews without at least one press still from the movie, withholding the kit enables the movie to survive an extra week without a bad review (Basuroy et al., 2003). When producers advertise these artsy movies on social networking websites, it would be more effective to use grouped networks like Twitter, because those producers are targeting a specific type of audience [those who are interested in art movies], not a general audience.

8. Conclusions and Limitations

We find that the reviews of critics play a significant role in shaping consumer film selections. However, they work differently for different types of movies. For domestic non-art movies, which make up the majority of domestic movies, positive reviews negatively influence box office performance. On the other hand, foreign movies, the majority of which are art movies, are positively influenced by good reviews. All movies are positively influenced when there are many critics writing reviews about them, but the influence is greater for domestic non-art movies than for foreign or domestic art movies.

We interpret such result as arising from the fact that different types of movies create a different target audience. Many people consider foreign movies to be art movies and many of those who prefer domestic art movies also prefer foreign to domestic non-art movies. The regression result indicates that domestic non-art movies are influenced negatively by good reviews and such negative effect is smaller for domestic art movies. Thus, we cautiously conclude that domestic art movies are intrinsically different from domestic non-art movies in terms of the values they provide and the main audience they target, and that they are similar to foreign movies.

It seems that people self-select into two quasi-separate markets: 1. the market for domestic non-art movies, and 2. the market for domestic art movies and foreign movies. The consumers in the type 1 market tend to watch movies for fun and thus the critics' reviews primarily function to merely let them know that the movie exists. Due to the systematic divergence between the preferences of critics and the main audiences for these movies, positive reviews hurt box office performance. According to Holbrook (1999), critics tend to give higher ratings to relatively complex, abstract, and intellectually demanding art movies. However, a consumer in the type 1 market might not find such movies particularly amusing. On the other hand, consumers in the type 2 market tend to watch movies to appreciate them as works of art and are likely to do some research on movies beforehand in order to choose high quality movies. Thus, critics' reviews do more than merely raising product awareness for these people. They actively figure out what the experts say about the quality of a given movie. Our finding can contribute to the formulation of effective marketing strategies for foreign as well as domestic movies. They might help restore the popularity of foreign movies in the U.S. market.

Our research has several limitations. First, because of the difficulty of data collection, we could not directly control for advertising expenditures. However, we doubt that this represents a serious concern, since the number of screens allocated on the opening weekend (which we have data for) is a reasonable proxy for advertising expenditures (Gemser et al., 2007). Second, because of many missing values, we failed to control for production budgets. Although this does not change the main conclusions of our study, as demonstrated in the previous section, the regression result would have been improved if we had complete information on all production budgets. Third, because of time constraints, we did not collect movies from all time periods. However, even if time might not be an issue, we would choose not to collect movies released too long ago, because they may be irrelevant when giving suggestions for how to distribute current and future movies.

Although our empirical study is limited to the movie industry, we believe that our findings can be extrapolated to other types of experience goods markets. Future research could study whether our findings can be replicated in other markets. One of the potential markets for future study is the book market, because people read books written by American writers but also translated books that are originally written by foreign writers. Readers often consult critics' reviews when they decide which book to purchase.

Above all, however, the biggest limitation of our research is the failure to find a significantly positive influence effect of critics' reviews on the box office performance of domestic art movies. Although we do observe more positive influence for them than for domestic non-art movies, the impact is still negative and not highly significant. Future research should examine this issue further, and examine other possible reasons why we fail to see a significantly positive impact of critics' reviews on domestic art movies, even though our intuition and research tells us that domestic art movies are more similar to foreign movies than to domestic non-art movies.

Appendix

List of Actors/Actresses with Star Power

First Tier Stars

1	Tom Hanks
2	Eddie Murphy
3	Harrison Ford
4	Robin Williams
5	Morgan Freeman
6	Johnny Depp
7	Tom Cruise
8	Samuel L. Jackson
9	Cameron Diaz
10	Bruce Willis

Second Tier Stars

11	Robert DeNiro	31	Kathy Bates
12	Julia Roberts	32	Mel Gibson
13	Will Smith	33	Tommy Lee Jones
14	Emma Watson	34	Ian McKellen
15	Jim Carrey	35	Shia LaBeouf
16	Matt Damon	36	Ralph Fiennes
17	Rupert Grint	37	Antonio Banderas
18	Daniel Radcliffe	38	Adam Sandler
19	John Travolta	39	Jon Voight
20	Orlando Bloom	40	Ewan McGregor
21	Ben Stiller	41	Liam Neeson
22	Michael Caine	42	Denzel Washington
23	Owen Wilson	43	Leonardo DiCaprio
24	Gary Oldman	44	Natalie Portman
25	Helena Bonham Carter	45	Jack Nicholson
26	Mike Myers	46	Elijah Wood
27	Sigourney Weaver	47	Alec Baldwin
28	Nicolas Cage	48	Keanu Reeves
29	Dustin Hoffman	49	Robert Downey Jr.
30	Brad Pitt	50	Tim Allen

List of Directors with Star Power

1	Steven Spielberg
2	Robert Zemeckis
3	James Cameron
4	Michael Bay
5	Ron Howard
6	George Lucas
7	Chris Columbus
8	Tim Burton
9	Gore Verbinski
10	Peter Jackson
11	Sam Raimi
12	David Yates
13	Clint Eastwood
14	Lee Unkrich
15	Christopher Nolan

List of Major Distributors

1	Paramount
2	Warner Bros.
3	Buena Vista
4	Sony/Columbia
5	Universal
6	20th Century Fox

Table 1: Past Research on the Function of critics' reviews

Study	Method	Data	Key Findings
Litman (1983)	Multiple regression	Movies 1972-1978	Critics' ratings play a significant role in explaining box office revenues
Sawhney and Eliashberg (1996)	Forecasting model, Generalized gamma	Movies 1990-1991	Critics' reviews help forecast box office revenues
Eliashberg and Shugan (1997)	Correlation analysis	Movies 1991-1992	Critics predict, rather than influence box office performances
Basuroy et al. (2003)	Multiple regression	Movies 1991-1993	Critics influence and predict box office revenues.
Reinstein and Snyder (2005)	Differences-in-differences	Movies early 1990s	The influence effect of critics' reviews is smaller than previous studies suggested, but still is significant
Zhang and Dellarocas (2006)	Multiple regression	Movies 2003-2004	The influence effect of critics' reviews is larger than previously suggested, especially in the early weeks after the release of a movie
Boatwright et al. (2007)	Diffusion model	Movies 1997-2001	Some critics are more influential than others in shaping consumer film selections
Gemser et al. (2007)	Multiple regression	Movies 1998-2003	The number and size of critics' reviews influence box office revenues, whereas the nature of reviews does not play a significant role.
Holbrook and Addis (2008)	Two-path model	Movies 2003	There is no notable association between critics' reviews and box office performance

Figure 5.2.1 Scatter plot of **ln(Nature)** against **ln(Openrev_adj)**

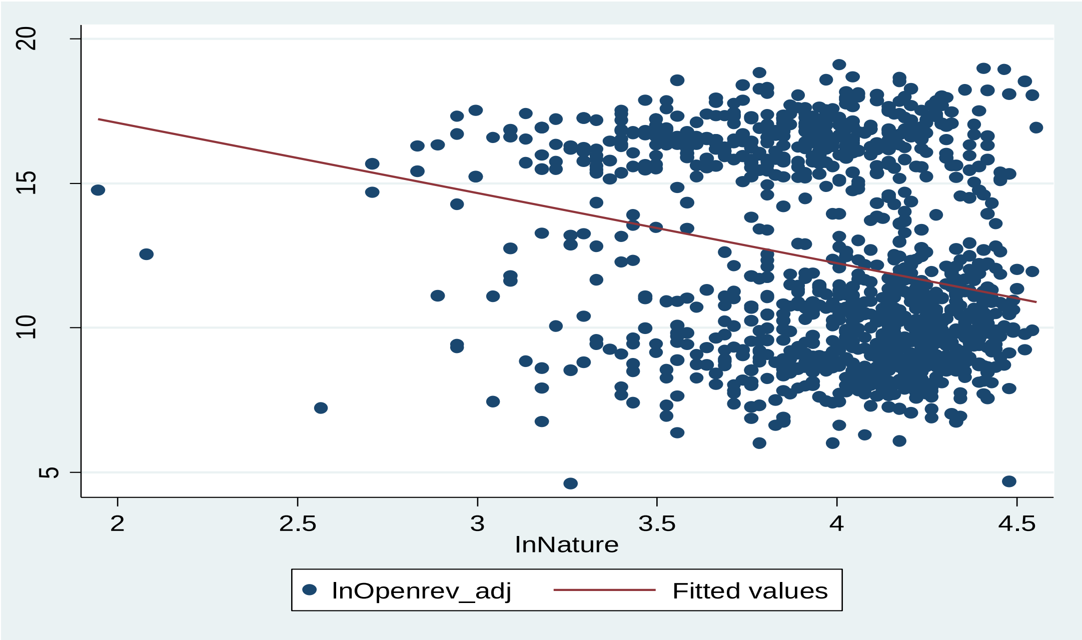

Figure 5.2.2 Non-monotonicity of the **ln(Nature)** variable [x: **ln(Nature)**, y: **ln(Openrev_adj)**]

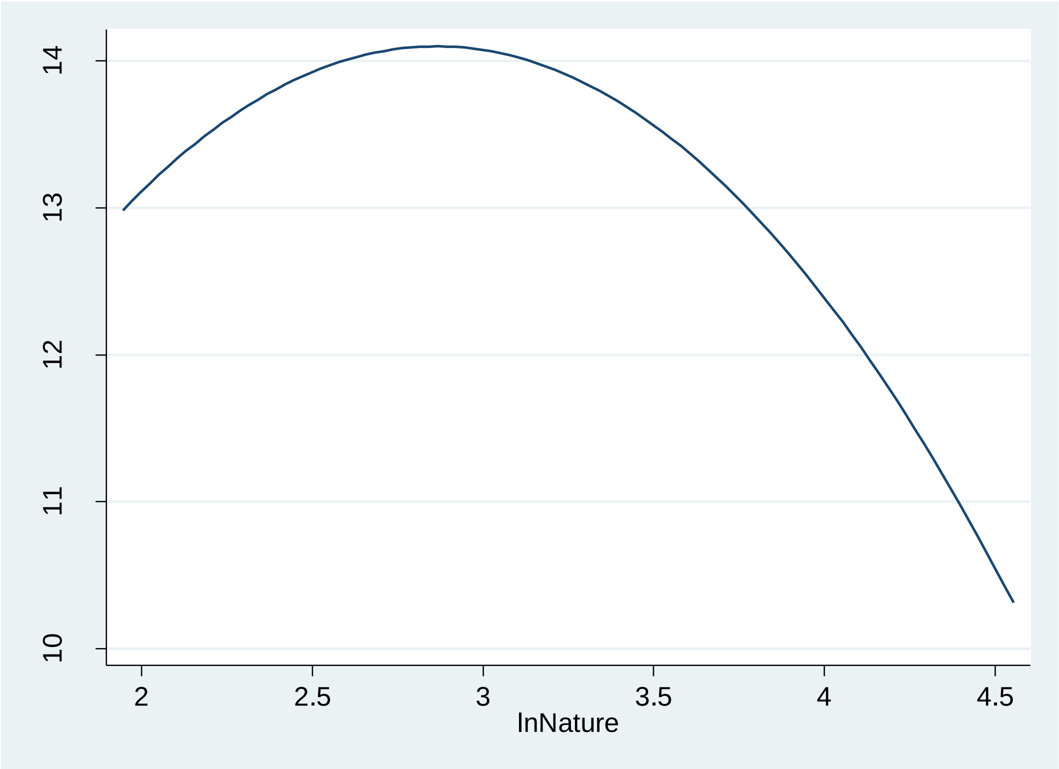

Figure 6.1 No significant correlation between **Budget** and **Nature**

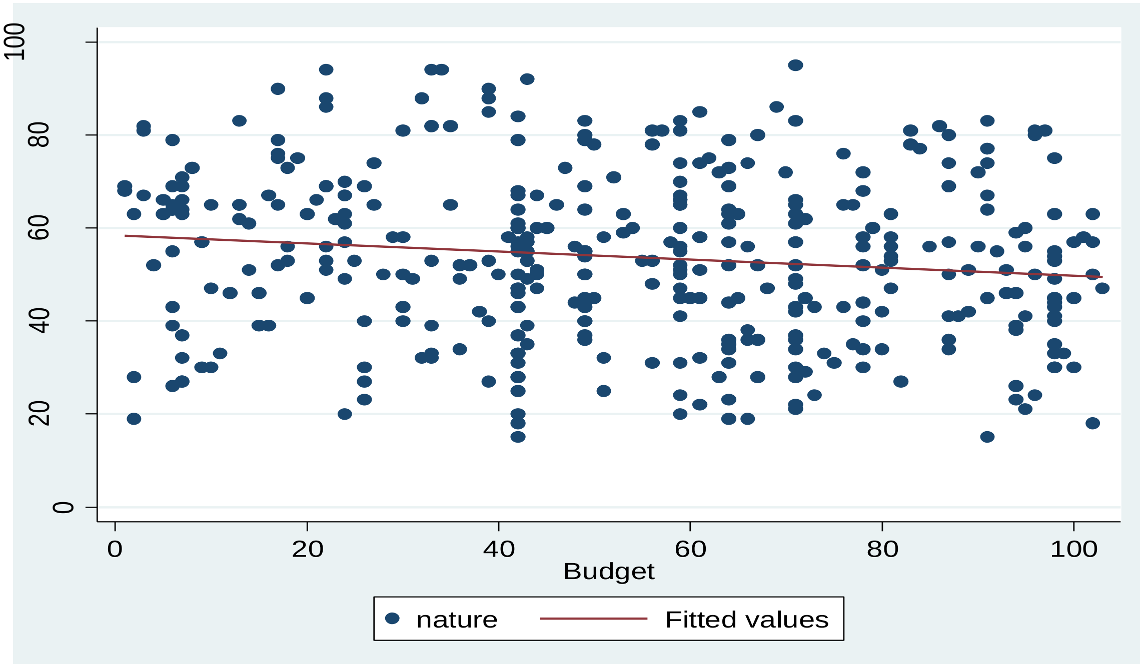

Figure 6.2 No significant correlation between **Budget** and **Number**

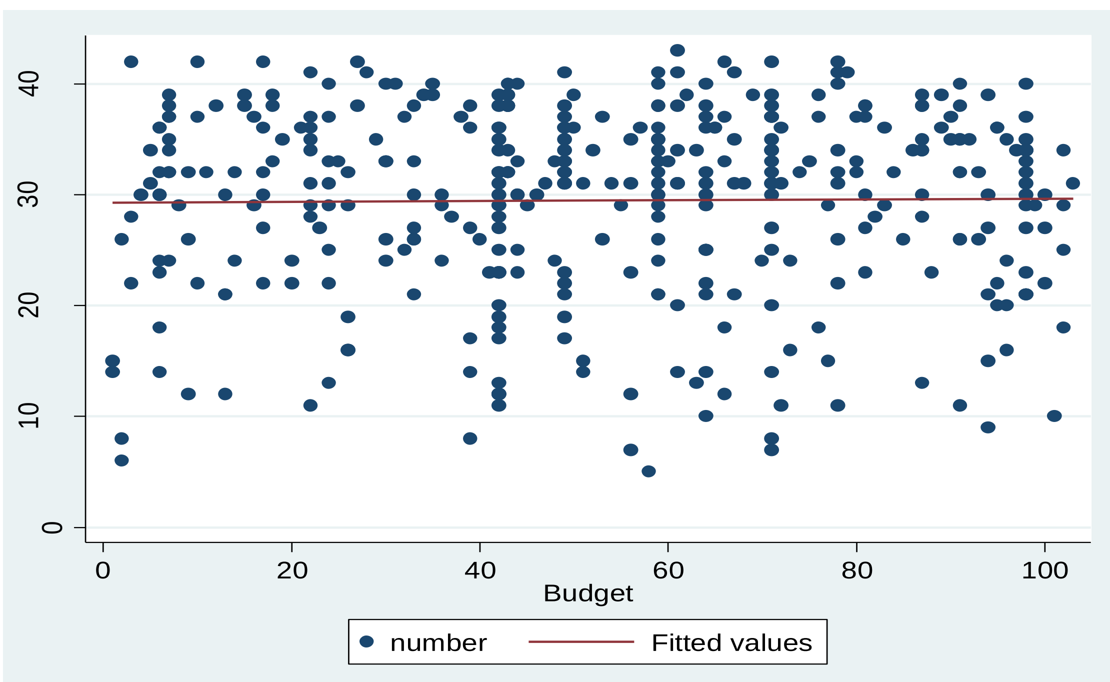

Figure 6.3 No significant correlation between **Budget** and **ln(Nature)**

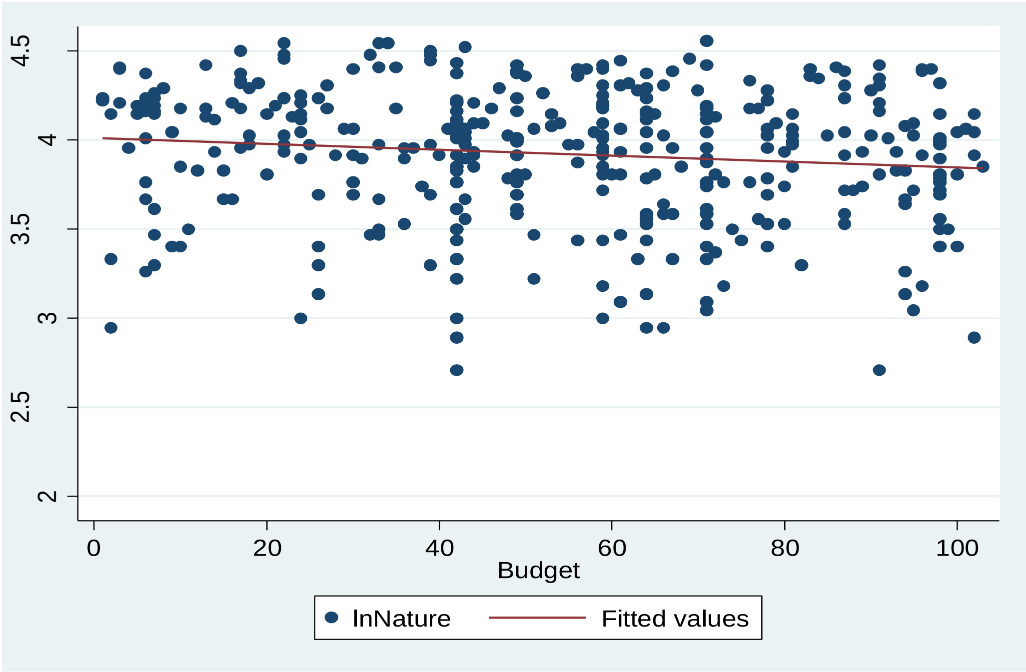

Figure 6.4 No significant correlation between **Budget** and **ln(Number)**

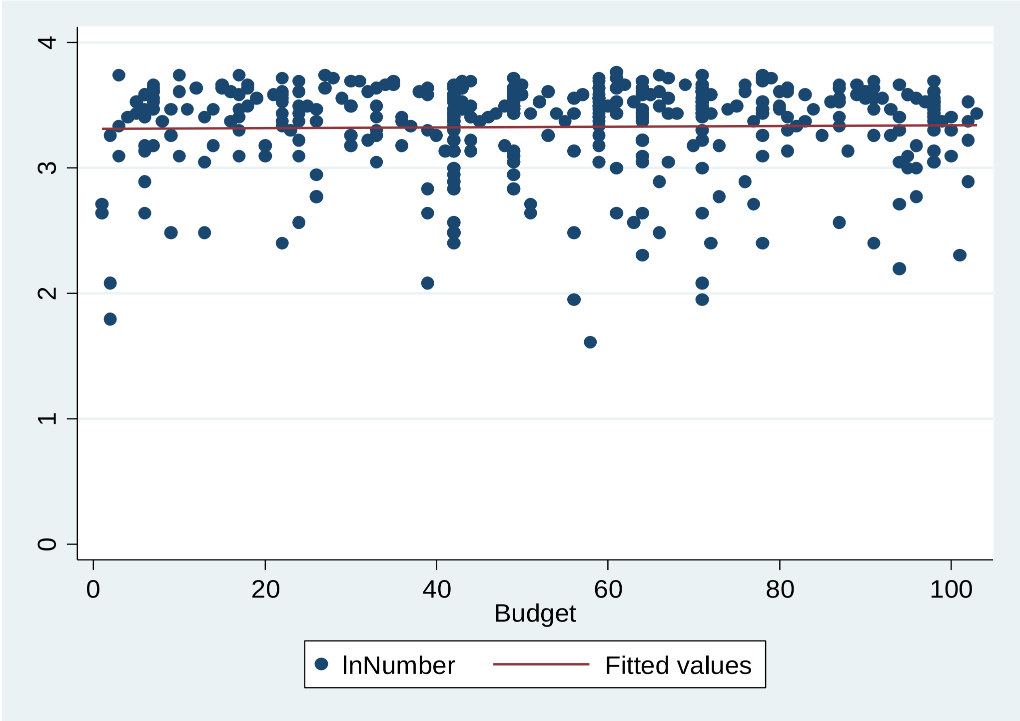

Table 7

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	Coefficient	t-statistic	p-value
ln(Nature)	-1.58013	-5.05	0.000***
ln(Number)	2.739158	6.80	0.000***
Foreign×ln(Nature)	2.939125	3.67	0.000***
Foreign×ln(Number)	-.792288	-1.04	0.298
Foreign	-12.32641	-4.37	0.000***
Screen	-0.0003444	-0.43	0.666
Distributor	1.481185	8.09	0.000***
Director	.2224725	0.85	0.395
Star-First-Tier	-.0005365	-0.00	0.998
Star-Second-Tier	.9973426	4.61	0.000***

*** significant at 1% level   * significant at 10% level

Table 8

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	Coefficient	t-statistic	p-value
ln(Nature)	-1.576222	-4.92	0.000***
Foreign×ln(Nature)	2.295634	3.68	0.000***
Art_domestic× ln(Nature)	.3982471	0.24	0.809
ln(Number)	2.719606	6.49	0.000***
Foreign×ln(Number)	-.768185	-1.00	0.319
Art_domestic×ln(Number)	-1.371782	-5.26	0.000***
Foreign	-12.44474	-1.66	0.000***
Art_domestic	-3.812902	0.00	0.997
Screen	-.0003468	-0.43	0.668
Distributor	1.483726	8.07	0.000***
Director	.2227635	0.85	0.395
Star-First-Tier	.0010004	0.00	0.997
Star-Second-Tier	.9937532	4.59	0.000***

*** significant at 1% level

Regression 3

$$\begin{aligned}\ln(Openrev\_adj) = {} & \alpha + \beta_1 \times Budget + \beta_2 \times \ln(Nature) + \beta_3 \times \ln(Number) + \beta_4 \times Foreign \times \ln(Nature) \\ & + \beta_5 \times Foreign \times \ln(Number) + \beta_6 \times Foreign + \beta_7 \times Screen + \beta_8 \times Distributor \\ & + \beta_9 \times Director + \beta_{10} \times Star-First-Tier + \beta_{11} \times Star-Second-Tier \\ & + \sum_{g=1}^{22} \omega_g \times Genre + \sum_{mp=1}^{5} \gamma_{mp} \times MPAArating + \sum_{m=1}^{12} \theta_m \times Month + \sum_{y=1}^{4} \tau_y \times year + u\end{aligned}$$

Regression 4

$$\begin{aligned}\ln(Openrev\_adj) = {} & \alpha + \beta_1 \times Budget + \beta_2 \times \ln(Nature) + \beta_3 \times \ln(Number) + \beta_4 \times Foreign \times \ln(Nature) \\ & + \beta_5 \times Foreign \times \ln(Number) + \beta_6 \times Foreign + \beta_7 \times art\_domestic \times \ln(Nature) \\ & + \beta_8 \times art\_domestic \times \ln(Number) + \beta_9 \times art\_domestic + \beta_{10} \times Screen \\ & + \beta_{11} \times Distributor + \beta_{12} \times Director + \beta_{13} \times Star-First-Tier \\ & + \beta_{14} \times Star-Second-Tier + \sum_{g=1}^{22} \omega_g \times Genre + \sum_{mp=1}^{5} \gamma_{mp} \times MPAArating \\ & + \sum_{m=1}^{12} \theta_m \times Month + \sum_{y=1}^{4} \tau_y \times year + u\end{aligned}$$

Table 9

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	Coefficient	t-statistic	p-value
Budget	-.0002947	-0.10	0.921
ln(Nature)	-1.583103	-5.11	0.000***
ln(Number)	2.741154	6.83	0.000***
Foreign×ln(Nature)	2.925681	3.58	0.000***
Foreign×ln(Number)	-.7851061	-1.03	0.305
Foreign	-12.29248	-4.31	0.000*
Screen	-.0003419	5.79	0.000***
Distributor	1.482175	8.06	0.000***
Director	.2207889	0.85	0.398
Star-First-Tier	-.0024847	-0.01	0.993
Star-Second-Tier	.9986404	4.59	0.000***

*** significant at 1% level   * significant at 10% level

Table 10

Regression Result: ln(Openrev_adj) as Dependent Variable

Variable	Coefficient	t-statistic	p-value
Budget	-.00022	-0.07	0.941
ln(Nature)	-1.578454	-4.98	0.000***
Foreign×ln(Nature)	2.935552	3.59	0.000***
Art_domestic×ln(Nature)	.3949468	0.24	0.811
ln(Number)	2.721217	6.51	0.000***
Foreign×ln(Number)	-.7629742	-0.99	0.325
Art_domestic×ln(Number)	.6790064	0.60	0.550
Foreign	-12.41864	-4.26	0.000***
Art_domestic	-3.782862	-0.45	0.656
Screen	-.0003449	-0.43	0.670
Distributor	2.064418	11.96	0.000***
Director	.221503	0.85	0.397
Star-First-Tier	-.0004628	-0.00	0.999
Star-Second-Tier	.9947475	4.56	0.000***

*** significant at 1% level

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