


The Effect of Online Reviews on Movie Box Office Sales: An Integration of Aspect-Based Sentiment Analysis and Economic Modeling

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ABSTRACT

Due to the rapid growth of social media, potential moviegoers always depend on the online reviews to make their purchase decisions. Film companies need to know what aspects of reviews will drive sales up or down. This study proposes a framework that integrates an aspect-based sentiment analysis and econometric modeling to explore the relationships between the information features in online reviews and movie ticket sales. The empirical results indicate that whereas the rating does not matter to moviegoers and does not affect movie revenues, additional textual reviews, both positive and negative contents, do have a positive impact on moviegoers and further prompt the movie revenues. These findings have significant implications for movie producers as well as advertisers to target promotions at their audience accordingly.

KEYWORDS

Aspect-Based Sentiment Analysis, eWOM, Movie Box Office Revenues, Random Effect Model

1. INTRODUCTION

The rapid growth of diverse social media has allowed consumers to share experiences and details about products on online platforms. Research has shown that consumers consult online reviews before making purchase decisions. Grover et al. (2018) proposed a framework focusing on building the capabilities of “big data and analytics” (BDA) to assist organizations in creating strategic business value. In particular, they suggested understanding customers’ feelings through a review analysis for product innovation and service improvement. The key task is to translate original big data into valuable business information and insights via BDA. We follow the conceptual scaffold of BDA and propose a functional value module to explore the relationship between product attributes and sales. Here we use the movie industry as a case study owing to the availability of its sales data.

Due to short life cycles, there is intense competition in the movie industry. Box-office revenues may be affected by various factors, including the movie genre, director, actors, and

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plot summary, as well as the marketing strategies used to promote the movies. Previous studies indicate that most potential moviegoers read movie reviews, and electronic word-of-mouth (eWOM) impacts box-office performance (Hyunmi et al., 2017; Liu, 2006; Rui et al., 2013; Zimbra et al., 2017). For instance, Nielson reported that 70% of customers would reference eWOM before making purchase decisions, implying that eWOM has become a reliable source of information for movie consumers (Xiao et al., 2016).

Typical eWOM comprises two types of information—the numerical rating and the text of the review (Li et al., 2019). Most sentiment research has focused on simple numerical metrics such as the rating, the number of theaters in which the movie is shown, and the number of reviews (Gu et al., 2013; Li et al., 2019; Yu et al., 2012). However, movie reviews provide rich information about viewers' opinions on movies. A large number of studies applied sentiment analysis to detect the polarity of an overall text for understanding customers' thinking (Hu & Chen, 2016; Hu et al., 2018; Liu, 2012). Recently, a useful technique called Aspect-based Sentiment Analysis (ABSA) has been employed (Zhao et al., 2016). ABSA is a method that defines the terms related to the aspects and identifies the sentiment associated with each aspect. Customers could express their attitudes toward aspects which were the attributes of the product. Different aspects can produce different sentiment responses. By utilizing ABSA, there is the possibility to capture detailed information about objects of interest.

In our previous work, we suggested a tool for mining aspect -opinion pairs from eWOM sentences (Cheng & Huang, 2019). In this study, we further propose an innovative framework that integrates ABSA and economic modeling to explore the various features that influence box office revenues. First, we define five aspects that summarize movie features, such as overall impression, screenplay, special effects, director, and principal characters, and develop a novel ABSA tool to address the different aspects of eWOM in terms of positive and negative opinions. In addition, to offer a comprehensive view of the information features of reviews that may affect the box office revenues, the model considers two other main factors including movie-related variables, such as genre, and volume variables, such as number of theaters, rating, and number of reviews. Next, we apply economic modeling to investigate the relationship between these variables and the movie box office sales. In particular, this study evaluates whether taking into account the above-mentioned aspects of movie reviews improves the prediction of movie box-office performance. Our findings are particularly relevant for movie companies, which may refine marketing strategies by focusing on these particular aspects of eWOM.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Sections 3 and 4 introduce the data and research methods used in this study. Section 5 presents the empirical results and discusses their implications. The last section provides conclusions and discusses the study's limitations and avenues for future research.

2. RELATED WORK

2.1 Impact of eWOM on Sales

Recently, the media industry has realized that eWOM is a rich source of information for exploring consumer preferences (Liu & Du, 2020). Numerous studies have also found that the impact of eWOM on sales has substantially increased due to the proliferation of eWOM on social media. Specifically, eWOM has been shown to significantly affect sales for products such as books (Chevalier & Mayzlin, 2006), movies (Cheng & Huang, 2019; Dellarocas et al., 2007; Karniouchina, 2011; Liu, 2006), and mobile apps (Liang et al., 2015).

To predict movie box office sales, most previous works attempt to incorporate several different factors into models and assess their significance (Hu et al., 2018; Zimbra et al., 2017). Hu et al. (2018) categorize the research into three streams according to the eWOM factors that affect box office performance. The first stream of research uses movie-related variables such as MPAA (Motion Picture Association of America) rating and genres. The second stream employs volume, a numerical

variable related to viewers, such as the average rating, the total number of reviews, and the number of theaters in which a movie is shown. Valence, the third type of factor considered, concerns textual variables using sentiment analysis from reviews, including the overall sentiment score, review polarity, and feature-opinion pairs. They find that sentiment scores obtained from movie reviews improve the accuracy of box-office performance predictions. They also show that the number of movie reviews influences box-office performance.

Liu (2006) adopts eWOM factors such as the number of reviews and average ratings to examine weekly box office revenues. The numerical rating, which represents the reviewer's overall assessment of the product value, is a quantitative summary of the reviewer's experiences. However, the author finds that average user ratings do not exert a significant direct impact on movie sales. Duan et al. (2008) propose a ratings-based model to verify the valence effect and the relation between movie box office sales and eWOM volume. They argue that eWOM could drive customers' purchase decision and increase the outcome of product sales. Dellarocas et al. (2007)'s revenue-forecasting model integrates user ratings. Based on the product diffusion theory, they show that the inclusion of eWOM from *Yahoo! Movies* substantially increases the accuracy of the box-office revenue forecasting models.

In addition, star power, which refers to the movie's cast, is the most expensive outlay in the movie's production cost. Karniouchina (2011) shows that star power plays an essential role in enhancing box office revenues. In particular, the movie cast has the potential to enhance opening week box office receipts both directly and by contributing to the overall movie anticipation.

As for valence, users often write reviews sharing subjective emotions or objective information in online forums after watching movies. As suggested by Gu et al. (2013), the consumers' evaluation of product quality is based on online reviews. Chevalier and Mayzlin (2006) note that negative reviews usually have a greater impact on consumers' choices than positive reviews. Their result illustrates that positive online reviews improve the sales of popular products more than the sales of niche products.

Yu et al. (2012) find that sentiments in product reviews have a significant impact on the future sales performance of the product. Hur et al. (2016) propose a non-linear machine-learning algorithm that incorporates review sentiment into box-office performance forecasting. They find that after the movie's release, emotional reviews are more accurate indicators of movie success than neutral reviews.

Lee et al. (2017) propose an entropy model that integrates review ratings and review text sentiment to evaluate the impact on box-office performance. They find that consumers are more likely to trust highly rated movies. A broad range of opinions in review texts indicate that consumers trust the review platform. Thus, when taking into account the entropy of the review text sentiment, user ratings have a significant impact on movie sales.

Zimbra et al. (2017) propose a model that uses the valence, volume, and period of tweets to evaluate movie performance on different platforms. They assess the changeover time of user sentiments on Twitter regarding movies. The authors designed three periods of analysis including pre-release, release weekend, and post-release-weekend. The result illustrates that the valence of tweets on Android before a movie's release and the volume of tweets on iOS after the release significantly influence movie revenues. They also observe that consumers are interested in reviews that mention the director or script.

2.2 Sentiment Analysis and Aspect-Based Sentiment Analysis

Sentiment analysis is a subfield of natural language processing (NLP) research that consists of extracting emotions related to raw texts. It could be used in various applications to detect the opinions of audiences including probabilistic models and support vector machines (Liu & Zhang, 2012). Some methods could be integrated with machine learning techniques for sentiment classification to determine the polarity of a sentence, that is, whether a sentence expresses a positive, negative, or neutral sentiment toward the subject (Hu et al., 2018; Liang et al., 2015).

In recent years, sentiment analysis has become a popular technique for review analysis. It is an effective and efficient way to capture the emotions of review writers with respect to a particular topic.

Many online stores developed platforms for consumers to represent their after-buying experience through ratings and reviews. This rich information could assist potential customers when making purchase decisions. Several studies have investigated the relationship between various aspects of ratings and product sales. As mentioned above, volume refers to the number of online reviews, while valence is a measure of the positivity or negativity of reviews and indicates the attitude of the reviewer toward the product (Chang & Wang, 2018)

Several ABSA techniques have been proposed in the literatures (Akhtar et al., 2017; Cheng & Huang, 2019; Choi et al., 2018). ABSA is a method that breaks down text into aspects and then allocates each aspect a sentiment level (positive, negative or neutral). Instead of detecting the sentiment of an overall text, ABSA further looks into the specific sentiments with respect to different aspects of a product or service.

Rui et al. (2013) construct a naive Bayesian classifier based on a lexicon of positive and negative words and phrases. Lexicon-based methods use an existing dictionary, which is a collection of opinion-related words along with their positive or negative sentiment strength (Liu & Zhang, 2012). Sentiment analysis would be affected by the product feature extraction technique used to identify opinion orientation (Orbach & Einav, 2007). Yu et al. (2012) defines various ways to extract specific and critical features for reviews, including noun frequency and topic modeling. Data collected from different domains often contain noise, thus complicating opinion - related word and aspect extraction.

Extracting specific features from reviews that capture what consumers are most concerned about is essential. In our previous work (Cheng & Huang, 2019), we develop a ABSA framework constructing both movie reviews and movie aspect thesaurus databases. We hire experts for manually annotating features and opinions words that include both explicit and implicit features. Next, we propose a machine learning method on extracting feature-opinion pairs from review sentences and build a sentiment dictionary for movie reviews collected from IMDb. Each review sentence could be preprocessed as several aspect-opinion pairs and could be stored in the database. To perform ABSA, we define comprehensive lists of aspect thesaurus that may be used in reviews to refer to the various movie aspects.

In this study, we follow Cheng and Huang (2019) on extracting feature-opinion pairs from review sentences and propose a model based on movie-related features, volume, and valence to evaluate how the information features of movie reviews affect the prediction of box-office performance. The valence feature expresses user opinions after watching the movie. This study seeks to determine how the text of positive or negative reviews influences the box office during the week after the movie's initial release.

3. DATA AND VARIABLES

3.1 Data Sources

The weekly market dynamics and review information were used to estimate the movie box office revenues. These data were collected from two popular and complementary sources—IMDb and Box Office Mojo. IMDb has wide coverage of movie plot synopses, and Box Office Mojo, as its name suggests, provides comprehensive information on movie revenues and budgets. We used a Java web crawler during a five-week period for each movie released from 2013 to 2014 and selected only those movies that users generated more than 100 reviews to allow for a sufficient number of aspect-opinion pairs from each review. Reviews cover movie genres such as action, drama, comedy, and horror. For each movie selected, the measurements of related variables were generated over a five-week periods. By this way, we collected a panel data including 285 (57x5) observations on 57 movies during the five-weeks.¹

3.2 Variables Description

In addition to information on the movie box office revenues, this dataset reports the number of movies in theaters (*Theater*), the number of weeks since a movie was in theaters (*Week*), the number

of reviews (*Review*), the average numerical rating (*Rating*), and the genres of the movie. The average numerical rating ranges from “1” (least recommended) to “10” (most recommended). The number of reviews collected from the reviewers are varied for each movie in a week. The dataset provides 14,625 textual reviews on 57 movies in total. To further analyze the textual reviews, this study employed “aspect -opinion pairs” to determine whether a sentence expresses positive or negative opinions regarding a movie aspect. The feature and opinion extraction has been successfully applied in previous studies(Cheng & Huang, 2019; Cheng & Lin, 2019 ; Lash & Zhao, 2016). We followed their definitions and were left with five feature aspects: overall assessment (OA), screenplay (ST), special effects (SE), director (PDR), and principal characters (PAC).

Let us present an example of a movie review crawled from the IMDb website as follows; the movie title is “The Hunger Games.”

3.2.1 Example of Preprocessing Module

“The special effects are impressive. Jennifer Lawrence is an AWESOME actress though, and she did a great job. The movie is great for people who haven’t read the books as well. One of the greatest films of all time”

After NLP preprocessing, the review could be separated into four sentences. Each sentence could be processed by Stanford Parser and several “aspect-opinion pairs” are extracted among features that appear in the comments. There is an example illustrated as below.

Each textual review comprises several aspect-opinion pairs. To quantify the critical value of review texts for the purpose of sentiment analysis, this study counted the number of sentences in each review and named this weekly data series as “*Sentence*.” Moreover, the sentences in each review were divided into two groups, named “Positive Sentence (*PS*)” and “Negative Sentence (*NS*),” respectively. The percentages of positive sentences and negative sentences to sentences (*PS_S* and *NS_S*) were calculated. Next, positive sentences were decomposed into five different aspects: “overall (*OAP*),” “actors and actresses (*PACP*),” “director (*PDRP*),” “special effects (*SEP*),” and “screenplay (*STP*).” Similarly, negative sentences were decomposed into the same five aspects as *OAN*, *PACN*, *PDRN*, *SPN*, and *STN*. The percentages of each aspect to total sentences were calculated. They are *OAP_S*, *PACP_S*, *PDRP_S*, *SEP_S*, *STP_S*, *OAN_S*, *PACN_S*, *PDRN_S*, *SEN_S*, and *STN_S*, respectively. The movie box office revenues might vary across different movie genres; thus, the movies were categorized into four types: drama (*Drama*), action (*Action*), horror (*Horror*), and comedy (*Comedy*).

The movie box office revenues depend on price and quantity. In other words, price is one of the potential factors affecting movie revenues. However, according to Orbach and Einav (2007), a uniform pricing model has been applied to the movie industry in the U.S. since the early 1970s. This implies that quantity, the number of moviegoers, plays a major role in prompting revenues. The more people watch a movie, the higher the movie box office revenues. Hence, this study did not include the price factor in the regression analysis. Finally, log-linear forms were used in the analysis as this approach provides a straightforward interpretation of the empirical results as percentage changes in movie box office revenues. The detailed descriptions of the variables used in this study are reported in Table 2.

Table 1. Example

Review sentences	Aspect -opinion pairs
The special effects are impressive.	(SE, positive)
Jennifer Lawrence is an AWESOME actress though, and she did a great job.	(PAC, positive)
The movie is great for people who haven’t read the books as well.	(OA, positive)
One of the greatest films of all time.	(OA, positive)

Table 2. Definition and Description of the Variables used in this Study

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Theater	The number of theaters in which a movie is shown	285	2501.323	1060.339	54	4324
Rating	The average rating of the reviews for a movie in a week	285	6.274	1.239	0	9
Review	Total number of reviews for a movie in a week	285	51.312	97.290	0	1173
Sentence	Total number of sentences for a movie in a week	285	367.554	740.406	0	9227
Positive Sentence (PS)	Total number of positive sentences for a movie in a week	285	222.211	461.120	0	5829
Negative Sentence (NS)	Total number of negative sentences for a movie in a week	285	145.344	281.597	0	3398
Positive Sentence/Sentence (PS_S)	The proportion of positive sentences to total sentences for a movie in a week	284	0.592	0.090	0.3	1
Negative Sentence/Sentence (NS_S)	The proportion of negative sentences to total sentences for a movie in a week	284	0.408	0.090	0	0.7
Positive OA/Sentence (OAP_S)	The proportion of positive OA to total sentences for a movie in a week	284	0.224	0.073	0	0.6
Positive PAC/Sentence(PACP_S)	The proportion of positive PAC to total sentences for a movie in a week	284	0.138	0.069	0	0.538
Positive PDR/Sentence(PDRP_S)	The proportion of positive PDR to total sentences for a movie in a week	284	0.026	0.025	0	0.25
Positive SE/Sentence(SEP_S)	The proportion of positive SE to total sentences for a movie in a week	284	0.032	0.028	0	0.138
Positive ST/Sentence(STP_S)	The proportion of positive ST to total sentences for a movie in a week	284	0.172	0.057	0.029	0.538
Negative OA/Sentence(OAN_S)	The proportion of negative OA to total sentences for a movie in a week	284	0.161	0.059	0	0.429
Negative PAC/Sentence(PACN_S)	The proportion of negative PAC to total sentences for a movie in a week	284	0.083	0.050	0	0.385
Negative PDR/Sentence(PDRN_S)	The proportion of negative PDR to total sentences for a movie in a week	284	0.016	0.017	0	0.143
Negative SE/Sentence(SEN_S)	The proportion of negative SE to total sentences for a movie in a week	284	0.015	0.022	0	0.182
Negative ST/Sentence(STN_S)	The proportion of negative ST to total sentences for a movie in a week	284	0.132	0.056	0	0.375
Drama	1 if the genre of movies is Drama; 0 otherwise	285	0.175	0.381	0	1
Action	1 if the genre of movies is Action; 0 otherwise	285	0.474	0.500	0	1
Horror	1 if the genre of movies is Horror; 0 otherwise	285	0.175	0.381	0	1
Comedy	1 if the genre of movies is Comedy; 0 otherwise	285	0.175	0.381	0	1
Ln Revenue (LnRev)	The natural logarithm of weekly box office revenues of a movie	285	15.851	1.530	10.524	19.174
Week	Number of weeks since the movie has been in theater	285	3	1.417	1	5

Note: Among 285 observations, there was one movie with no comments from reviewers on the 4th week, which makes the variable of total review sentences for that week become zero. By the rules of mathematics, one value derived from dividing by zero will be invalid. Therefore, the numbers of observations for proportion variables are all reduced to 284.

4. METHODOLOGY

Few studies (e.g., Cheng & Huang, 2019) explored the contextual factors influencing box-office revenue by integrating opinion mining and machine learning techniques. However, they did not investigate the casual relationship between reviews and movie sales. This study extends the conceptual framework and fills the research gap by developing a panel data econometric model to examine the causal effects of review features on the box-office revenues.

As mentioned above, a total of 285 observations were collected on 57 movies during a five-week period. To explore the relationship between box office revenues and reviewers' opinion, this study employs the following empirical model:

$$y_{it} = \alpha + \beta x_{it} + \gamma z_{it} + \varepsilon_{it}$$

where y_{it} is $\ln \text{Revenue}_{it}$ for movie i in week t . x_{it} is a vector of review variables, which is our major concern in this study, including both numerical ratings and textual variables, such as the volume of reviews, sentences, positive sentences, and negative sentences. z_{it} is a vector of control variables that affect movie revenues, including the number of movies in theaters, the genres of the movies, and a measure of movie newness such as the number of weeks a movie has been in theaters. ε_{it} is the error term.

4.1 Baseline Models

Reviewers' opinions, both numerical ratings and textual reviews, might affect prospective moviegoers' decisions and influence the box-office performance of movies. The numerical ratings represent how much consumers like the movie. By contrast, textual reviews reveal consumers' deep thoughts and detailed movie-watching experiences. The numerical rating, volume of reviews, sentences, positive sentences, and negative sentences are included simultaneously in the empirical model to examine their impacts on movie revenues.

However, as presented in Table 3, the variable "Review," which reflects the volume of reviews, and the variable of "Sentence," which indicates the number of sentences in each review text, are highly correlated. In addition, the variable "Sentence" is composed of "PS" and "NS", therefore the correlation coefficients among these three variables are also expected to be high. To avoid the problem of multicollinearity and capture the eWOM effects of both numerical ratings and textual reviews on the movie box office revenues, besides the variable "Rating," this study employs the variables "Reviews," "PS," and "NS" separately as the independent variable in different regression equations. Multiple regression models are constructed as follows:

$$\ln \text{Revenue}_{it} = \alpha + \beta_1 (\text{Rating})_{it} + \beta_2 (\text{Review})_{it} + \gamma_1 (\text{Theater})_{it} + \gamma_2 (\text{Drama})_i + \gamma_3 (\text{Comedy})_i + \gamma_4 (\text{Horror})_i + \gamma_5 (\text{Week})_t + \varepsilon_{it} \quad (1)$$

$$\ln \text{Revenue}_{it} = \alpha + \beta_1 (\text{Rating})_{it} + \beta_2 (\text{PS})_{it} + \gamma_1 (\text{Theater})_{it} + \gamma_2 (\text{Drama})_i + \gamma_3 (\text{Comedy})_i + \gamma_4 (\text{Horror})_i + \gamma_5 (\text{Week})_t + \varepsilon_{it} \quad (2)$$

$$\ln \text{Revenue}_{it} = \alpha + \beta_1 (\text{Rating})_{it} + \beta_2 (\text{NS})_{it} + \gamma_1 (\text{Theater})_{it} + \gamma_2 (\text{Drama})_i + \gamma_3 (\text{Comedy})_i + \gamma_4 (\text{Horror})_i + \gamma_5 (\text{Week})_t + \varepsilon_{it} \quad (3)$$

Table 3. Correlation Matrix

	Theater	Rating	Review	Sentence	PS	NS	PS_S	NS_S	OAP_S	PACP_S	PDBF_S	SEP_S	STP_S	OAX_S	PACN_S	PBRN_S	SEN_S	STN_S	Drama	Action	Horror	Comedy	LaRev	Week
Theater	1																							
Rating	0.18	1																						
Review	0.37	0.04	1																					
Sentence	0.37	0.06	0.99	1																				
PS	0.36	0.08	0.99	0.998	1																			
NS	0.37	0.02	0.99	0.99	0.99	1																		
PS_S	0.19	0.56	0.06	0.07	0.10	0.03	1																	
NS_S	-0.19	-0.56	-0.06	-0.07	-0.10	-0.03	-1	1																
OAP_S	0.15	0.27	0.03	0.02	0.03	0.00	0.63	-0.63	1															
PACP_S	-0.01	0.26	0.02	0.03	0.04	0.02	0.29	-0.29	-0.20	1														
PDBF_S	-0.01	0.10	0.03	0.02	0.03	0.02	0.14	-0.14	0.00	-0.07	1													
SEP_S	0.23	0.02	0.17	0.18	0.18	0.17	0.14	-0.14	-0.05	-0.19	-0.01	1												
STP_S	0.01	0.16	-0.05	-0.05	-0.04	-0.06	0.29	-0.29	-0.03	-0.37	-0.13	0.01	1											
OAX_S	-0.03	-0.39	-0.04	-0.06	-0.07	-0.04	-0.65	0.65	-0.28	-0.23	-0.09	-0.21	-0.25	1										
PACN_S	-0.11	-0.18	0.00	0.01	0.00	0.03	-0.38	0.38	-0.37	0.23	-0.08	-0.05	-0.35	0.06	1									
PBRN_S	-0.15	-0.20	-0.01	-0.01	-0.01	0.00	-0.14	0.14	-0.10	0.02	-0.03	-0.03	-0.08	-0.07	-0.01	1								
SEN_S	-0.09	-0.22	0.04	0.04	0.04	0.05	-0.21	0.21	-0.15	-0.17	-0.12	0.25	0.00	-0.14	0.02	0.01	1							
STN_S	-0.10	-0.18	-0.08	-0.08	-0.09	-0.06	-0.46	0.46	-0.30	-0.37	0.01	-0.04	0.12	0.00	-0.34	0.01	0.07	1						
Drama	-0.04	0.00	0.03	0.02	0.02	0.01	0.17	-0.17	0.03	0.33	0.07	-0.09	-0.15	-0.02	0.04	0.00	-0.02	-0.28	1					
Action	0.12	0.01	0.05	0.08	0.08	0.07	-0.04	0.04	-0.13	-0.10	-0.09	0.33	0.10	-0.18	0.19	0.04	0.17	0.00	-0.44	1				
Horror	-0.09	0.00	-0.02	-0.03	-0.03	-0.02	-0.04	0.04	0.15	-0.25	0.09	-0.08	0.05	0.12	-0.20	-0.04	0.00	0.13	-0.21	-0.44	1			
Comedy	-0.03	-0.01	-0.08	-0.09	-0.09	-0.08	-0.08	0.08	0.00	0.05	-0.05	-0.27	-0.03	0.14	-0.09	-0.01	-0.20	0.15	-0.21	-0.44	-0.21	1		
La Rev	0.91	0.20	0.49	0.47	0.47	0.48	0.21	-0.21	0.17	0.01	0.00	0.22	0.00	-0.05	-0.11	-0.13	-0.07	-0.13	-0.04	0.04	-0.07	0.05	1	
Week	-0.62	0.00	-0.49	-0.45	-0.44	-0.47	-0.04	0.04	-0.05	0.01	0.02	-0.07	0.01	-0.04	0.01	0.07	-0.01	0.09	0.00	0.00	0.00	0.00	-0.68	1

The coefficient on “*Rating*” in regressions (1)–(3) captures the eWOM effects of numerical ratings on the box office revenues, while the coefficients on “*Review*,” “*PS*,” and “*NS*” of regressions (1), (2) and (3), respectively, identify the eWOM effects of textual reviews. Furthermore, the coefficient on “*Theater*” in regressions (1)–(3) indicates whether the number of movies played by theaters influences the movie revenues. The coefficients on “*Drama*,” “*Comedy*,” and “*Horror*” indicate whether the movie revenues are affected by the genres of the movies. The reference category is “*Action*.” Finally, the coefficient on “*Week*” in regressions (1)–(3) shows the relationship between the newness of a movie and box office revenues.

4.2 Extended Models

Sentiment analysis contends that the number of sentences, including positive and negative sentences, might affect movie viewers’ behavior. However, the proportions of positive and negative sentences to total sentences may also play an important role in consumers’ movie-watching choices. To evidence this aspect and avoid multicollinearity, this study adds the proportions of positive and negative sentences to total sentences, respectively, into regression (1). Specifically, the regression models are as follows:

$$\ln Revenue_{it} = \alpha + \beta_1(Rating)_{it} + \beta_2(Review)_{it} + \beta_3(PS_S)_{it} + \gamma_1(Theater)_{it} + \gamma_2(Drama)_i + \gamma_3(Comedy)_i + \gamma_4(Horror)_i + \gamma_5(Week)_t + \varepsilon_{it} \quad (4)$$

$$\ln Revenue_{it} = \alpha + \beta_1(Rating)_{it} + \beta_2(Review)_{it} + \beta_3(NS_S)_{it} + \gamma_1(Theater)_{it} + \gamma_2(Drama)_i + \gamma_3(Comedy)_i + \gamma_4(Horror)_i + \gamma_5(Week)_t + \varepsilon_{it} \quad (5)$$

where *PS_S* and *NS_S* represent the ratios of positive and negative sentences to total sentences, respectively. The sum of these two variables is equal to 1.

To further investigate how different aspects of textual reviews influence the box office revenues, this study uses the relative proportions of aspects as predictors in the regression analyses. To avoid multicollinearity, the empirical model is specified as follows:

$$\ln Revenue_{it} = \alpha + \beta_1(Rating)_{it} + \beta_2(Review)_{it} + \beta_3(OAP_S)_{it} + \beta_4(PACP_S)_{it} + \beta_5(PDRP_S)_{it} + \beta_6(SEP_S)_{it} + \beta_7(STP_S)_{it} + \beta_8(OAN_S)_{it} + \beta_9(PACN_S)_{it} + \beta_{10}(PDRN_S)_{it} + \beta_{11}(SEN_S)_{it} + \gamma_1(Theater)_{it} + \gamma_2(Drama)_i + \gamma_3(Comedy)_i + \gamma_4(Horror)_i + \gamma_5(Week)_t + \varepsilon_{it} \quad (6)$$

Finally, in the presence of different inherent features of individual movies, the Hausman test is usually conducted to determine whether a fixed or random effect model should be employed in estimation. However, since a fixed effect model does not account for time-invariant variables such as the genres of movies (Choi et al., 2018), random effect models are adopted in this study. In addition, the panel dataset is likely to violate the ordinary least squares assumptions, such as the lack of heteroscedasticity and serial correlation. This study employs random effect models with Huber/White standard error correction, and thus, the results are robust to heteroscedasticity and autocorrelation (Huber, 1967; White, 1980; Wooldridge, 2010).

5. RESULTS AND IMPLICATION

5.1 Empirical Results

The analytical results of the random effect estimation with Huber/White standard error correction are summarized in Table 4.

Table 4. Empirical Results

Variable	Baseline Models			Extended Models		
	Regression	Regression	Regression	Regression	Regression	Regression
	(1)	(2)	(3)	(4)	(5)	(6)
Theater	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***
Drama	0.0041	0.008	0.0094	-0.0206	-0.0206	0.033
Comedy	0.3173**	0.3204**	0.3184**	0.3233**	0.3233**	0.4073**
Horror	-0.0211	-0.0186	-0.0208	-0.0193	-0.0193	0.0099
Week	-0.3194***	-0.3322***	-0.3280***	-0.3101***	-0.3101***	-0.3229***
Rating	0.032	0.0295	0.0318	0.0001	0.0001	0.0169
Review	0.0013**			0.0014**	0.0014**	0.0013**
PS		0.0002**				
NS			0.0004**			
PS_S				0.6118**		
NS_S					-0.6118**	
OAP_S						0.9693
PACP_S						0.3743
PDRP_S						0.5572
SEP_S						3.9499***
STP_S						0.5541
OAN_S						0.3275
PACN_S						0.5266
PDRN_S						0.7265
SEN_S						0.2981
Constant	14.4609***	14.5482***	14.5221***	14.2501***	14.8619***	13.9846***
Adjusted	0.859	0.8557	0.8555	0.8616	0.8616	0.862
N	285	285	285	284	284	284

Note: 1. ** p<0.05; *** p<0.01

2. See the note indicated in Table 2.

3. *PS_S* and *NS_S* are correlated as one of them is equal to 1 minus the other. To avoid multicollinearity, can only one variable be used as a reference group at a time in the regression. In other words, either one of them can be introduced as an intercept dummy. The coefficient estimate on each variable is the same but the sign of the effect is reversed. However, the intercept value is different depending on the reference (default) category selected.

The coefficients on “*Theater*” in all regressions are 0.0008, and all are statistically significant. This result indicates that the more theaters are showing the movie, the greater the box office revenues, in line with our expectations. The coefficients on “*Week*” in all regressions are negative, and all are statistically significant. This result implies that movie revenues decrease over time. The movie is most attractive upon release, and potential moviegoers are most likely to see it. With time, movie revenues begin to decrease, possibly due to the emergence of illegal copies or lower consumer interest.

In comparison to action movies, comedies generate greater movie revenues. The coefficients on “*Comedy*” in all regressions range from 0.3173 to 0.4073 and are statistically significant. In contrast, “*Horror*” and “*Drama*” genres have no impact on movie revenues. This may indicate that moviegoers in our dataset are more interested in comedies than action movies.

Concerning the eWOM effects, our primary interest in this study, the “*Rating*” coefficients in the regressions (1)–(6) vary from 0.0001 to 0.032 but are not statistically significant (at the 10% significance level), while the “*Review*” coefficients in regressions (1), (4), (5), and (6) are close to 0.001 and are significant at the 5% level. These results imply that the rating has no significant impact on moviegoers and does not affect movie revenues. However, one additional review text has a positive impact on moviegoers and further increases movie revenues by 0.1%. The “*PS*” coefficient in regression (2) is equal to 0.0002 and is significant at the 5% level, and the “*NS*” coefficient in regression (3) is 0.0004 and is statistically significant at the 5% level, thus suggesting that both positive and negative textual contents increase movie revenues. This finding is in contrast with the effects of the volume of reviews, that is, more reviews lead to higher revenues. Notably, these results demonstrate that even the negative textual comments from reviewers have stronger positive effect on movie revenues than their positive counterparts. This suggests that the increases of absolute number of reviews would improve movie revenues, no matter whether they are positive or negative sentences.

In order to differentiate the effects between positive and negative sentences, we need to employ the proportional measures, instead of absolute sentences, as suitable independent variables. The findings of the three regressions (1)–(3) in the baseline models show the effect of the number of sentences on box office revenues. The empirical results of regressions (4) and (5) in Table 4 reflect how the proportion of positive and negative sentences to total sentences influences movie revenues. The “*PS_S*” and “*NS_S*” coefficients are 0.6118 and -0.6118, respectively, and both are statistically significant. This indicates that both a greater proportion of positive sentences and a smaller proportion of negative sentences lead to higher revenues. This finding is intuitive: as review readers read text comments with a larger proportion of positive sentences, they are impressed by the encouraging information indicating public recognition of and support for the movie. They may, thus, reduce the risk of watching a lousy movie. This belief enhances the motivation to watch the movie and further increases box office sales. As, by definition, the proportions of positive and negative sentences sum to 1, “*PS_S*” and “*NS_S*” are always perfectly correlated such that the coefficients are the same in magnitude but with opposite signs. In this study, to avoid multicollinearity, we discuss one proportion at a time. In order to manifest the conflicting results of positive vs. negative comments, we decided to follow (Li et al., 2019) to run the positive and negative proportions as independent variables separately in two regressions.

Finally, to explore the effects of different aspects on movie revenues, we further decompose the proportions of positive and negative sentences. The results are shown in the last column of Table 4. Most variables related to aspects are insignificant, except for the “*SEP_S*” coefficient. This result indicates that higher proportions of positive sentences that describe the special effects of a movie increase box office performance, thus suggesting that people go to the movies to enjoy top-class theater equipment.²

Overall, the study’s results show that the numerical rating does not affect a movie’s box office revenues, while the text of the review does, especially the number of reviews and the positive and negative sentences in the reviews. Moreover, both positive and negative review texts generate growth in box office revenues. This finding somewhat echoes that voice of share leads to catch people’s eyes and further generates high profits. Most importantly, larger proportions of positive sentences, especially related to the movie’s special effects, increase movie box office revenues.

5.2 Managerial Implication

Our empirical results show that potential moviegoers are not entirely satisfied with the numerical rating but are willing to read the text of the review to decide on a movie. This scenario is in line with the social phenomenon: moviegoers make a decision based on detailed opinions instead of an aggregate numerical rating. Moreover, this study demonstrates that negative sentences are as important as positive sentences to review readers. Positive opinions usually increase box office sales (e.g., Chevalier & Mayzlin, 2006), but negative opinions can also cause growth in movie revenues.

People sometimes watch movies out of curiosity. On the one hand, they might want to experience how unpleasant the movie is; on the other hand, they might come out with a different perspective, as opinions are subjective. Furthermore, moviegoers might want to experience the special effects with the movie theater's professional equipment. In contrast to other aspects, such as cast and screenplay, it is relatively difficult to experience the special effects of a movie at home.

Peng et al. (2020) indicated that the achievement of information technology (IT) maturity represented business' management capabilities. From this point of view, BDA could help companies make better decisions and have a positive impact on profit. (Iftikhar & Khan, 2020). In accordance with this, our empirical findings are especially valuable to film companies as they reveal the primary factors that determine consumer decisions in seeing movies. As long as reviewers record their opinions in words, no matter how good or bad, they help accelerate box office sales, which are prompted by the movie trend in online reviews. To initiate movie trending, film companies can sprinkle the movie trailer through major social media platforms before the movie is released. In addition, film companies may invite opinion leaders, Internet celebrities, and movie reviewers to the movie premiere and ask them to reciprocate by recording their comments and even criticisms online, sharing them with their fans and friends to generate social media exposure and further increase the volume of discussion. Film companies can also release behind-the-scenes or/and focus group interviews for the movie to maintain the momentum as the movie is in theaters. Besides these strategies to promote the effect of eWOM, film producers should also endeavor to make advertise, distribute best quality movies, which are lauded and favored by consumers. A good movie, which receives more word of praise among comments significantly attracts more people to watch and thus improves box office sales more.

These publicity and advertising activities are expensive. To ensure the wise use of budget funds, comprehensive knowledge of what movie characteristics are valued by consumers is essential. In this regard, our empirical results show that the higher the ratio of positive reviews on special effects, the higher the movie revenues. This finding suggests that film companies should publicize the movie's special effects to increase the movie attractiveness. For example, as data management platforms (DMPs) collect audience deep insights about consumers, film companies can work with DMPs to direct advertising at moviegoers who highly value special effects. Given sufficient knowledge of the factors that affect box office revenues, along with smart marketing strategies, a significant increase in box office movie revenues could be expected.

6. CONCLUSION AND LIMITATIONS

This study employed random effect models, using data from IMDb and Box Office Mojo, to examine the critical features of online reviews that influence movie box office revenues. The primary contribution of this study to the movie revenue and eWOM literature is the extraction of movie features and opinions from textual reviews and the adoption of an econometric model to assess their impact on box office performance. The empirical results indicate that whereas the rating does not affect movie revenues, the textual reviews, both positive and negative, generate growth in the revenues of movie companies. Moreover, the larger proportions of positive sentences regarding the movie's special effects increase movie revenues. Film companies need to acknowledge what aspects of reviews are the most informative and what aspects of the movie drive sales up or down. Hence, our empirical results have significant implications for movie producers as well as advertisers to target promotions at their audience.

Our study has a few limitations that deserve mention. First, since this study collected information from IMDb for the period 2013–2014, the data primarily consist of movies released in the USA. Therefore, the study's results are limited and may only be valid for movies released in the USA. Our analysis does not take into account other areas or countries that have similar platforms providing user comments and movie information. Future studies could adopt our approach to investigate the factors affecting movie revenues in other areas and determine whether the region or culture is a

critical factor for movie box office performance. Second, our analysis provided evidence that both positive and negative textual comments prompt movie revenues. One possible reason is that a movie is an experiential product, and the movie ticket is not too expensive for consumers to take the risk of watching an unpleasant movie. However, this result may not hold if the ticket is too expensive. Therefore, future studies could examine this aspect by extending our approach to expensive products, such as houses.

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ENDNOTES

- ¹ Among these observations, there was one movie which received no opinions from reviewers on the 4th week. This indicates that the measures of variables representing the numbers of review comments could be zeroes.
- ² We took one referee's insightful suggestion to further explore the interactive effects between movie types and review aspects on box office sales. The signs of coefficients of most independent variables remain similar to the ones estimated in the original regression. The results show that the estimated coefficients of interaction terms are all statistically insignificant except for the one denoted *PACP_S*Horror*, the value of which is -4.19 at 5% significant level. This indicates that, as compared to the reference movie genre (*Action*), the revenue effect of the proportion of positive sentences on horror pictures would be reduced largely.

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