# How much is a Facebook Like or Post really Worth? The Effects of Word-of-Mouth on Box Office Revenue


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## Abstract

This study tests the positive feedback mechanism by investigating whether the word-of-mouth (WOM) posted on Facebook about movies affects the box office revenue. All foreign and domestic movies released in Taiwan from 2017 to 2018 were merged with the data relating to volume and valence WOM posted on Facebook by using text mining techniques. Employing the Two-Stage Least Squares method to address the endogeneity issue, this study found that Facebook WOM volume and valence affect box office revenue positively and significantly. The effects of Facebook WOM on box office revenue, however, did not change regardless of whether the subject of discussion on Facebook was a domestic or foreign movie.


**Keywords:** Box office revenues, cultural distance, motion picture industry, online word-of-mouth, positive feedback mechanism.

## Introduction

Word-of-Mouth (WOM) refers to all opinions of certain products, services or corporations exchanged between individuals (Rosen, 2009). There is a positive feedback mechanism between WOM and sales performance (Srinivasan et al., 2002). The more people are satisfied with a product, the more potential consumers discuss this product. There is no doubt that the discussion itself plays a vital role to improve sales performance. The successful sales performance triggers more discussions among people, thus creating more WOM and improving sales performance ceaselessly. According to the literature (e.g., Hsu and Jane, 2016; Basuroy et al., 2020), in the movie market a positive feedback mechanism exists between WOM and box office.

Today, online WOM is playing an important role which helps consumers reach their purchase decisions. There are various channels to spread online WOM for movies, such as review-aggregation websites, blogs and social media platforms. In comparison to other channels, social media has a more important role to play as online WOM is considered due to its explosive growth over the last two decades. Among all social media platforms, Facebook, has 2,912millionmonthly active users as of

April 2022, remains the biggest and arguably most powerful social network in the world (DataReportal, 2022). Facebook, a social media founded in the United States, provides many functions for users to transfer text messages, upload photos, videos and documents to their pages for sharing with their friends and other Facebook users. Users can "like," comment and share posts and tag their friends. These information sharing functions of Facebook are vital in this study, since they allow users to generate and spread massive WOM. Users' remarks on movies may have become an effective and cost-saving marketing tool to their Facebook friends. Facebook's huge reach has led it become one of the world's most important marketing and advertising platforms for businesses.

Facebook's penetration rate in Taiwan reached 98.9% in 2019, one of the highest penetration rates in the World (Taiwan Network Information Center, 2019), which shows that Facebook has a huge influence in Taiwan. Meanwhile, according to 2019 THEME Report (Motion Picture Association, 2020),the Taiwanese consumers spent about USD 0.4billion on movies in 2019, ranked 14th in the world. In addition, foreign movies accounted for extremely high level at93.1%of overall box office. These unique features, therefore, make Taiwan an ideal case study to understand the influence on box office imposed by Facebook WOM.

This study aims to explore whether the WOM posted on Facebook about movies are sufficient to affect the box office revenue. Moreover, this study divided Facebook WOM into two dimensions - WOM volume and WOM valence-in order to find out how box office revenue is affected by the public opinions posted on Facebook. This study used the data of all movies shown in Taiwan between 2017 and 2018 and employed a Facebook search and big data analytics tool, QSearch Trend, to gather the data relating to WOM posted on Facebook, such as the number of posts for each movie, number of reactions, number of comments, number of shares, number of likes and other emotion icons (emoticons) clicked by users. QSearch Trend is powerful as it automatically collects over 94% of all publicly available social media data from Facebook, Youtube, Instagram, and influential websites. As far as we know this is one of the few studies has used QSearch Trend Data for analysis.

## Literature Review

Basuroy et al. (2003) examined the influence on weekly box office in accordance with experts' opinions on 175 movies and the number of cinema screens for each movie which were publicized by Variety between the end of 1991 and the beginning of 1993. According to their findings, both positive and negative comments affected weekly box office revenue significantly. Furthermore, experts' opinions not only affected box office, but were able to predict box office revenue. Their findings also indicated that negative comments were more influential than positive comments.

Basuroy et al. (2014) randomly chose 200 movies released in the United States from December 2006 to February 2008 as samples and then gathered experts' opinions and user ratings from website Rotten Tomatoes. Their findings suggested that both volume and valence of experts' opinions affected box office more than the WOM relating to user ratings. They were believed to be the first researchers who pointed out that in the Internet era experts' opinions are more influential to consumers than the mass media.

Using 194 films that had theatrical release in the United States between January 2007 and February 2008 and user and expert reviews from website Rotten Tomatoes, Basuroy et al. (2020) compared the differential impacts of electronic WOM and expert reviews on movie revenues. Taking into account the endogeneity problem, several conclusions were obtained: (a) compared to user ratings, expert ratings had a more influential role on movie going decisions; (b) experts tended to provide more negative but consistent reviews then users; (c) experts' reviews had an impact on wide release movies whereas users ratings did not; (d) experts' reviews mattered most when their reviews and electronic WOM were in closer agreement about the film quality.

Box office performance was affected by many other factors, not just experts' opinions and the WOM of general public. For example, Alaveras et al. (2018) gathered 38 EU member nations' annual movie-showing data in 1996 - 2014, tracked all import and export of offline movies between EU member nations and USA, and employed a two-stage Heckman model to analyze the data. Their findings indicated that the movie trade between countries is subjected to several factors such as cultural distance, success in home market and movie budgets.

Previous studies have not provided much evidence regarding the impacts of Facebook WOM volume and valence on box office.

In addition, relatively little evidence is found regarding the relationship between cultural difference and box office, and the differential impacts of Facebook WOM on box office by cultural difference. This study aims to fill a knowledge gap on these issues.

## Data

This study obtained all movies shown in Taiwan in 2017 - 2018 in total 1,381 samples. The data relating to box office revenue includes movie titles, showing date and production countries. Based on the research made by Basuroy et al. (2020), this study gathered the WOM posted within one week before the movie was shown and the WOM posted within one week after the movie was shown. For example, “Robin Hood” was shown on December 20, 2018 in Taiwan. WOM data between December 13, 2018 and December 27, 2018 were gathered. The number of posts, number of reactions, number of comments and number of shares were treated as the movie's WOM volume. The number of likes, number of haha and number of love were treated as positive WOM valence while angry was treated as negative WOM valence. Surprise and cry were not employed as WOM valence because both emoticons could not tell whether people liked or disliked the movie when they clicked surprise and cry emoticons.

The screen of an article about the movie “Robin Hood” was captured and used to describe WOM. As shown by Figure 1, this article itself was treated as a post. Move the mouse to the “Like” in the lower left corner and activate emoticons which are provided for Facebook users to click. As soon as users click one of the emoticons, they find the number of reactions to this post. Users can easily find the number corresponding to each emoticon. Use this post as an example, there are 30 reactions including 28 likes, 1 love and 1 surprise. Moreover, users can find the number of comments, number of shares and number of views in the lower right corner.

The method proposed by Hofstede (2011) was employed to calculate cultural index in order to find out cultural difference between all movie production countries and Taiwan. Types of movies, movie classifications (ratings), sequel-related data (i.e. whether movies were sequels) and release dates were gathered from Yahoo! Movies, Wikipedia and website www.douban.com.This study examined nine types of movies, namely, (a) scifi (science fiction), (b) romance and comedy, (c) horror, (d) action, (e) suspense, (f) documentary, (g) historical and biographical, (h) animation, and (i) drama. Following Basuroy et al.(2014) and Basuroy et al. (2020), the information on a film's production budget and expert reviews were collected from IMDb and Rottentomatoes.com. Definitions of the variables and summary statistics are shown in Table 1.

A shown in Table 1, the average box office revenue amounted to NTD 15.70 million (USD 0.51 million).[1]“Fast & Furious 8”, a popular action movie produced in 2017 starring Vin Diesel and Dwayne Johnson, generated the highest box office revenue NTD 651 million (USD 21.28 million). It is worth mentioning that “Fast & Furious 8” generated not only the highest box office revenue, but most reactions and likes, 536,311 reactions and 517,762 likes, respectively.

The average cultural difference index of movies (CD) was 1.98. The great majority of movies (379) out of the samples were produced in USA. The cultural difference between Taiwan and USA was 3.72, the third largest difference. The cultural difference index between Taiwan and South Korea was 0.27. 106 movies out of the samples were produced in South Korea.

## Methodology

According to Godes and Mayzlin (2004), WOM not only affected future sales, but had much to do with the sales revenue in previous periods, and thus pointed out the endogeneity problem possibly existing between WOM and box office revenue. Therefore, in this study, Durbin-Wu-Hausman Test was employed to examine if there was an endogeneity problem between the Facebook WOM and box office. If the null hypothesis $(H_0: cov(e,x) = 0)$ was rejected, then there was an endogeneity issue between the Facebook WOM and box office.

This study employed the OLS regression and Two-Stage Least Squares (2SLS) regression to examine the influence on box office imposed by online WOM volume and valence. The empirical frameworks are expressed as follows:

$$lnBoxOffice_i = \alpha_0 + \alpha_1 lnWOMvolume_i + X_i'\phi_1 + \varepsilon_{i1}, (1)$$

$$lnBoxOffice_i = \beta_0 + \beta_1 lnWOMvalence_i + X_i'\phi_2 + \varepsilon_{i2}, (2)$$

where *i* denotes the $i^{th}$ movie. Since box office has a right-skewed distribution, the natural logarithm is employed to approximately normalize the box office revenue.

$lnWOMvolume_i$ represents a set of the variables measuring Facebook WOM volume for ith movie, including the number of posts, number of reactions, number of comments and number of shares. $lnWOMvalence_i$ Similarly, represents a set of the variables measuring Facebook WOM valence for ith movie, including negative valence such as angry face as well as positive valence such as the number of likes, the number of haha and the number of love.

Similar to the box office variable, WOM variables have a right-skewed distribution as well. In an effort to control for the influence imposed by the potential outliers and to ensure to obtain an unbiased regression result, this study employed the method proposed by Liu et al. (2018). When taking natural logarithms of WOM, 1 is added to the WOM values. This transformation can mitigate the influence of outliers. Moreover, it does not change the results of regression. **X*i*** denotes a vector of explanatory variables controlling for the characteristics of ith movie. Characteristics include the type of movie, classification, movie schedule, movie produced domestically or not, sequel or not, index of cultural difference between the movie production country and Taiwan, the quadratic term of the index of cultural difference, the natural logarithm of production budget and movie ratings from the experts.

In the 2SLS model, IVs are treated as explanatory variables and endogenous variables are treated as dependent variables in the first stage estimation. In Equations (3) and (4), dependent variables include WOM volume variables and WOM valence variables ***STWOMi*** are treated as explanatory variables which represent the IVs for ith movie, also represent the WOM of same type of movies shown in the same period.

$$lnWOMvolume_i = \gamma_0 + \gamma_1 STWOM_i + \varepsilon_{i3}, \quad (3)$$

$$lnWOMvalence_i = \delta_0 + \delta_1 STWOM_i + \varepsilon_{i4}, \quad (4)$$

In the second stage estimation, we substitute the WOM-fitted value (in natural logarithms) obtained by Equations (3) and (4) into Equations (1) and (2) to obtain Equations (5) and (6) as follows:

$$lnBoxOffice_i = A_0 + A_1 lnWOM\widehat{volume}_i + X_i'\phi_5 + \varepsilon_{i5}, \quad (5)$$

$$lnBoxOffice_i = B_0 + B_1 lnWOM\widehat{valence}_i + X_i'\phi_6 + \varepsilon_{i6}, \quad (6)$$

Following Chintagunta et al. (2010), we used WOM for the same type of movies shown in same period as the IVs to solve the endogeneity problem between WOM and box office. When processing the IVs, 1 was added to the value and then natural logarithm was taken. Then, the Cragg-Donald Test (Cragg and Donald, 1993) was employed to test whether the IVs were weak and to check if the WOM for the same type of movies shown in same period were valid IVs. As suggested by Staigeret al. (1997), if F-statistic is greater than 10, then our IVs are sufficiently strong.

## Results

### The effects of Facebook WOM volume, cultural distance and other factors on box office revenue

As shown in Table 2, in all OLS models, the WOM volume variables affect total box office positively and significantly. However, there is a two-way relationship between WOM and box office, causing a potential endogeneity problem (Bikhchandani et al.,1992). Based on the results of 2SLS models, the Durbin-Wu-Hausmans' endogeneity tests were significant in Models (2) and (4).According to the second-stage estimation results, all WOM volume variables affected box office positively and significantly. These findings conformed to the expectations and literature (e.g., Basuroy et al., 2014; Hsu and Jane, 2016).

For other explanatory variables, in Models (1) - (2) and (5) - (8), a significant and negative cultural difference combing with its significant and positive quadratic term implied a U-shaped relationship between cultural difference and box office where box office revenue decreases as cultural difference increases, and when cultural difference reaches a certain level, box office revenue starts to increase. This U-shaped relationship between cultural difference and box office revenue conforms to the research findings stated in Alaveras et al. (2018).

Compared to non sequels, sequels significantly increased the box office in all regression models. This result is consistent with the findings in previous studies (e.g., Basuroy and Chatterjee, 2008). For the movies released in Chinese New Year holidays performed better, resulting in higher box office revenues.A1% increase in production budget would increase box office revenue by 22 - 36%. These findings were consistent with empirical evidence of previous studies. For example, Basuroy et al. (2003) found that big budgets enhanced box office revenue. In addition, expert ratings were found to be significantly negative in Models (1) - (4), which means movies with higher (lower) expert ratings leaded to lower (higher) box office revenue. These findings are different from other research (e.g., Basuroy et al., 2020) that has found that expert opinion was positively associated with box office revenue. Our results from Taiwan's movie market, however, are not unreasonable. According to Kim et al. (2013),due to language barriers and cultural differences, when Hollywood movies are released outside the US market, positive expert reviews may not successfully reflect in higher box office revenues, and low-rating movies can be profitable if they fit into particular cultural contexts. As mentioned before, in Taiwan in 2019, foreign movies accounted for extremely high level at93.1%of overall box office and the vast majority of films imported by Taiwan were from Hollywood.

Finally, the Cragg-Donald F-statistics in all WOM volume models were greater than 10, which indicated that the WOM for the same type of movies shown in same period were valid IVs to solve the endogeneity problem between WOM volume and box office.

**The effects of Facebook WOM valence on box office revenue**

Table 3 presents how the box office revenue was affected by Facebook WOM valence in the week before and after movies were shown. When the number of angry increased by 1%, box office increased by 0.48%. This result coincided with the result of Hsu and Jane (2016) who studied in Taiwan's motion picture industry but contradicted to a general expectation. However, this finding may be explained by Festinger's (1957) cognitive dissonance theory. Moviegoers, who received angry emoticons for one movie, may prefer this movie emotionally and think that buying tickets for this movie has less harm and more benefits from cognition. Hence, it is possible for them to make the decision of buying tickets, resulting in an increase in box office. In addition, according to Sorensen and Rasmussen's (2004) viewpoint, informative comments are sufficient to promote products and services positively, regardless of whether the comments are positive or negative. The number of likes, haha and love, which is treated as positive WOM valence, exhibited a positive correlation with box office. These results conformed to expectations.

**The differential impacts of Facebook WOM volume and valence on box office revenue by cultural distance**

In addition to exploring the effect of Facebook WOM on box office revenue, we went one step further to examine if Facebook WOM volume and valence affected box office revenue differently when the level of CD was different. To do so, several interaction terms between WOM and CD were included in the estimate models. The results are presented in Table 4.

It is interesting to observe the negative coefficients of the interaction terms, which means, on average, the effects of Facebook WOM volume and valence on box office revenue decreased as CD increased. However, the effects of the interaction terms were not significant anymore after controlling for the endogeneity, which suggests that the effects of Facebook WOM on box office revenue did not change regardless of whether the subject of discussion on Facebook was a domestic or foreign movie.

## Conclusions and Discussions

This study employed QSearchTrend, a powerful Facebook search and big data analytics tool, to acquire the online Facebook WOM posted by general public and then discussed how Facebook WOM affected box office performance. Dealing with the endogeneity problem and controlling for numerous explanatory variables, this study found that WOM volume and both positive and negative WOM valence affect box office revenue positively and significantly. This study also found that when cultural difference increases, box office revenue decreases at a decreasing rate. This finding has pointed out the viewers' cultural identity and a U-shaped relationship between cultural difference and box office revenue.

The great majority of literature focused on the influence on box office in the United States imposed by WOM and concluded that WOM volume and valence were influential factors; also found that negative valence was more influential on box office than positive valence. When we compared our results with those from literature, we found that the marginal effects of this Taiwan's study are smaller than those of western countries' papers. Dealing with the endogeneity issue when estimating the influence on box office imposed by WOM may be one possible explanation. The findings of this research are similar to the marginal effects of Hsu and Jane (2016), and coincide with the viewpoints of Festinger (1957) and Sorensen and Rasmussen (2004) regarding the positive promotion effect created by the negative WOM.

With its positive influence on box office performance, Facebook WOM plays an important role, which supports the positive feedback mechanism. This study helps movie publishers evaluate their current and future marketing strategies, allowing movie publishers to use WOM information to segment markets based on public discussions, choose appropriate market based on the initial discussions of movies, administer online WOM, pay attention to the negative comments about the movies, appoint online writers to comment on the movies, and assess the benefit to the schedule and session of movies.

## Limitations and Future Research

Due to data limitation, this study was unlikely to gather all Facebook WOM information relating to movies, and there was no way to find out whether all comments were positive or negative, either. This study employed the method proposed by Basuroy et al. (2020) and gathered the Facebook WOM posted within one week before movies were shown and within one week after movies were shown, and treated the opinions as a variable to measure WOM volume, but was unable to analyze the content of opinions. In the Internet era, many platforms have been created for the general public to discuss movies such as Yahoo! Movies, YouTube and cell phone apps in addition to Facebook. Future researchers may try to find a method so they can evaluate WOM data comprehensively and use other suitable IVs to solve the endogeneity issues arising from WOM.

## References


- Alaveras, G., Gomez-Herrera, E., & Martens, B. (2018). Cross-border circulation of films and cultural diversity in the EU. *Journal of Cultural Economics*, 42(4), 645-676.
- Basuroy, S., & Chatterjee, S. (2008). Fast and frequent: Investigating box office revenues of motion picture sequels. *Journal of Business Research*, 61(7), 798-803.
- Basuroy, S., Chatterjee, S., &Ravid, S. A. (2003). How critical are critical reviews? The box office effects of film critics, star power, and budgets. *Journal of Marketing*, 67(4), 103-117.
- Basuroy, S., Ravid, S. A., & Hall, B. (2014). How relevant are experts in the internet age? Evidence from the motion pictures industry. Working Paper, University of Oklahoma.
- Basuroy, S., Ravid, S. A., Gretz, R. T., & Allen, B. J. (2020). Is everybody an expert? An investigation into the impact of professional versus user reviews on movie revenues. *Journal of Cultural Economics*, *44*(1), 57-96.
- Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5), 992-1026.
- Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, 29(5), 944-957.
- Cragg, J. G., & Donald, S. G. (1993). Testing identifiability and specification in instrumental variable models. *Econometric Theory*, 9(2), 222-240.
- DataReportal. (2022). Global Social Media

Statistics.Retrieved fromhttps://datareportal.com/social-media-users

- Festinger, L. (1957). *A theory of cognitive dissonance* (Vol. 2). Stanford University Press.
- Godes, D., &Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4), 545-560.
- Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. Online readings in psychology and culture, 2(1), 2307-0911.
- Hsu, Y. L., & Jane, W. J. (2016). Bidirectional causality for word of mouth and the movie box office: An empirical investigation of panel data. *Journal of Media Economics*, 29(3), 139-152.
- Kim, S. H., Park, N., & Park, S. H. (2013). Exploring the effects of online word of mouth and expert reviews on theatrical movies' box office success. *Journal of Media Economics*, *26*(2), 98-114.
- Liu, Q., Zhang, X., Zhang, L., & Zhao, Y. (2018). The interaction effects of information cascades, word of mouth and recommendation systems on online reading behavior: An empirical investigation. *Electronic Commerce Research*, 1-27.
- Motion Picture Association. (2020). 2019 THEME Report. Retrieved fromhttps://www.motionpictures.org/wp-content/uploads/2020/03/MPA-THEME-2019.pdf
- Rosen, E. (2009). The anatomy of buzz revisited: Real-life lessons in word-of-mouth marketing. New York, NY: Broadway Business.
- Sorensen, A. T., & Rasmussen, S. J. (2004). Is any publicity good publicity? A note on the impact of book reviews. NBER Working paper, Stanford University.
- Srinivasan, S. S., Anderson, R., &Ponnavolu, K. (2002). Customer loyalty in e-commerce: an exploration of its antecedents and consequences. *Journal of Retailing*, 78(1), 41-50.
- Staiger, D., Stock, J. H., & Watson, M. W. (1997). The NAIRU, unemployment and monetary policy. *Journal of Economic Perspectives*, 11(1), 33-49.
- Taiwan Network Information Center.(2019). Taiwan Internet Report 2019. Retrieved fromhttps://report.twnic.tw/2019/assets/download/TWNIC_TaiwanInternetReport_2019_EN.pdf


**Table 1:Definitions and summary statistics of the selected variables (n = 1,381)**

| Variable | | Mean | S. D. | Min | Max | Data Source |
|---|---|---|---|---|---|---|
| BoxOffice[a] | Total box office revenue generated by $i^{th}$ movie in Taiwan | 15,700,000 | 56,800,000 | 100 | 651,000,000 | www.atmovies.com.tw |
| Post | The number of posts on Facebook within one week before and one week after $i^{th}$ movie was released | 117.42 | 205.93 | 0 | 2,794 | QSearch Trend |
| Reaction | Same as above, number of reactions | 16,807.76 | 48,225.76 | 0 | 536,311 | |
| Comment | Same as above, number of comments | 1,147.52 | 3,321.48 | 0 | 85,748 | |
| Share | Same as above, number of sharing posts | 1,041.70 | 2,580.30 | 0 | 39,052 | |
| Angry | The number of angry on Facebook within one week before and one week after $i^{th}$ movie was released | 79.38 | 1,054.71 | 0 | 26,401 | |
| Like | Same as above, number of likes | 15,505.97 | 44,023.32 | 0 | 517,762 | |
| Haha | Same as above, number of haha | 334.05 | 1,551.28 | 0 | 28,895 | |
| Love | Same as above, number of love | 392.12 | 1,124.23 | 0 | 15,846 | |

| Variable | | Mean | S. D. | Min | Max | Data Source |
|---|---|---|---|---|---|---|
| CD | Index of cultural difference between $i^{th}$ movie production country and Taiwan | 1.98 | 1.27 | 0 | 3.97 | Taiwan Film Institute<br>Ministry of Culture<br>www.atmovies.com.tw |
| Scifi | $Scifi_i$ = 1 if $i^{th}$ movie is a science fiction movie; = 0 otherwise | 0.05 | 0.21 | 0 | 1 | Yahoo! Movies<br>Wikipedia<br>www.douban.com |
| Comedy | $Comedy_i$ = 1 if $i^{th}$ movie is a romance or comedy movie; = 0 otherwise | 0.22 | 0.41 | 0 | 1 | |
| Horror | $Horror_i$ = 1 if $i^{th}$ movie is a horror movie; = 0 otherwise | 0.14 | 0.35 | 0 | 1 | |
| Action | $Action_i$ = 1 if $i^{th}$ movie is an action movie; = 0 otherwise | 0.11 | 0.31 | 0 | 1 | |
| Suspense | $Suspense_i$ = 1 if $i^{th}$ movie is a suspense movie; = 0 otherwise | 0.09 | 0.28 | 0 | 1 | |
| Documentary | $Documentary_i$ = 1 if $i^{th}$ movie is a documentary movie; = 0 otherwise | 0.06 | 0.24 | 0 | 1 | |
| History | $History_i$ = 1 if $i^{th}$ movie is a historical or biographical movie; = 0 otherwise | 0.05 | 0.22 | 0 | 1 | |
| Animation | $Animation_i$ = 1 if $i^{th}$ movie is an animation movie; = 0 otherwise | 0.07 | 0.26 | 0 | 1 | |
| Drama | $Drama_i$ = 1 if $i^{th}$ movie is an drama movie; = 0 otherwise | 0.21 | 0.41 | 0 | 1 | |
| Taiwan | $Taiwan_i$ = 1 if $i^{th}$ movie is produced in Taiwan; = 0 otherwise | 0.08 | 0.27 | 0 | 1 | Taiwan Film Institute<br>Ministry of Culture<br>www.atmovies.com.tw |
| G [b] | $G_i$ = 1 if $i^{th}$ movie is rated G (General Audiences); =0 otherwise | 0.23 | 0.42 | 0 | 1 | Yahoo! Movies<br>Wikipedia<br>www.douban.com |
| PG | $PG_i$ = 1 if $i^{th}$ movie is rated PG (Parental Guidance Suggested); = 0 otherwise | 0.23 | 0.42 | 0 | 1 | |
| NC12 | $NC12_i$ = 1 if $i^{th}$ movie is rated NC12 (No one 12 and Under admitted); = 0 otherwise | 0.42 | 0.49 | 0 | 1 | |
| NC17 | $NC17_i$ = 1 if $i^{th}$ movie is rated NC17 (No one 17 and Under admitted); = 0 otherwise | 0.12 | 0.33 | 0 | 1 | |
| Sequel | $Sequel_i$ = 1 if $i^{th}$ movie is sequel; = 0 otherwise | 0.09 | 0.29 | 0 | 1 | |
| CNY | $CNY_i$ = 1 if $i^{th}$ movie is released in Chinese New Year holidays; = 0 otherwise | 0.01 | 0.12 | 0 | 1 | Taiwan Film Institute<br>Ministry of Culture<br>www.atmovies.com.tw |
| Summer | $Summer_i$ = 1 if $i^{th}$ movie is a summer vacation movie; = 0 otherwise | 0.13 | 0.34 | 0 | 1 | |

| Variable | | Mean | S. D. | Min | Max | Data Source |
|---|---|---|---|---|---|---|
| Budget (420)[c] | $i^{th}$ movie'sproduction budget | 40,700,000 | 56,200,000 | 1,500 | 317,000,000 | IMDb.com Rottentomatoes.com |
| Rating (736) | $i^{th}$ movie'sexpert rating | 6.33 | 1.32 | 2.00 | 9.24 | |
| **IVs** | | | | | | |
| STPost | Total number of posts on Facebook for same type of movie released in the same week | 327.28 | 346.47 | 0 | 3,003 | QSearch Trend |
| STReaction | Same as above, number of reactions | 43,984.86 | 76,966.38 | 0 | 536,311 | |
| STComment | Same as above, number of comments | 3,059.48 | 4,559.53 | 0 | 85,748 | |
| STShare | Same as above, number of sharing posts | 2,847.74 | 4,028.87 | 0 | 39,052 | |
| STAngry | Same as above, number of angry | 159.09 | 1,467.93 | 0 | 26,401 | |
| STLike | Same as above, number of likes | 40,736.06 | 70,766.66 | 0 | 517,762 | |
| STHaha | Same as above, number of haha | 783.70 | 2,100.51 | 0 | 28,895 | |
| STLove | Same as above, number of love | 1,064.69 | 1,849.41 | 0 | 16,540 | |

[a]In the period of 2017 - 2018, the average exchange rate: USD 1 = NTD 30.59.

[b]G rated movies are intended for general audiences, with all ages admitted. A PG movie rating stands for Parental Guidance, as some material may not be suitable for children. Movies with an NC-17 rating mean that no one under 18 can be admitted.

[c]Number of observations isin parenthesis.

**Table 2:Estimation results of the OLS and 2SLS models (WOM volume)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** |
| | **Dependent variable: lnBoxOffice** | | | | | | | |
| **Explanatory variable** | | | | | | | | |
| lnPost | 1.39*** | 1.16*** | | | | | | |
| | (0.06) | (0.11) | | | | | | |
| lnReaction | | | 0.95*** | 0.80*** | | | | |
| | | | (0.04) | (0.08) | | | | |
| lnComment | | | | | 0.84*** | 0.76*** | | |
| | | | | | (0.04) | (0.08) | | |
| lnShare | | | | | | | 0.83*** | 0.77*** |
| | | | | | | | (0.04) | (0.08) |
| Scifi[a] | 0.30 | 0.23 | 0.46 | 0.37 | 0.39 | 0.34 | 0.63* | 0.58* |
| | (0.32) | (0.31) | (0.31) | (0.31) | (0.33) | (0.32) | (0.34) | (0.33) |
| Comedy | -0.09 | -0.11 | -0.12 | -0.13 | -0.16 | -0.16 | -0.02 | -0.03 |
| | (0.27) | (0.27) | (0.26) | (0.26) | (0.28) | (0.28) | (0.29) | (0.28) |
| Horror | 0.37 | 0.40 | 0.29 | 0.33 | 0.04 | 0.09 | 0.30 | 0.32 |
| | (0.28) | (0.28) | (0.28) | (0.27) | (0.30) | (0.29) | (0.30) | (0.30) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Action | 0.23 | 0.22 | 0.37 | 0.34 | 0.26 | 0.25 | 0.44 | 0.42 |
| | (0.28) | (0.27) | (0.27) | (0.27) | (0.29) | (0.28) | (0.30) | (0.29) |
| Suspense | 0.54* | 0.60* | 0.55* | 0.61** | 0.40 | 0.45 | 0.68** | 0.70** |
| | (0.31) | (0.31) | (0.31) | (0.30) | (0.33) | (0.32) | (0.33) | (0.33) |
| Documentary | -1.01* | -1.19** | -0.61 | -0.84 | -0.36 | -0.51 | -0.32 | -0.43 |
| | (0.61) | (0.60) | (0.59) | (0.60) | (0.64) | (0.63) | (0.65) | (0.65) |
| History | 0.12 | 0.09 | 0.33 | 0.27 | 0.32 | 0.28 | 0.42 | 0.39 |
| | (0.32) | (0.32) | (0.31) | (0.31) | (0.34) | (0.33) | (0.34) | (0.34) |
| Animation | 0.46 | 0.28 | 0.60 | 0.41 | 0.21 | 0.14 | 0.66 | 0.58 |
| | (0.39) | (0.39) | (0.38) | (0.38) | (0.40) | (0.40) | (0.41) | (0.41) |
| CD | -1.00* | -1.37** | -0.46 | -0.89 | -0.98* | -1.18** | -1.14** | -1.28** |
| | (0.53) | (0.54) | (0.52) | (0.55) | (0.55) | (0.56) | (0.56) | (0.57) |
| CD2 | 0.27** | 0.36*** | 0.17 | 0.26** | 0.28** | 0.32*** | 0.32*** | 0.35*** |
| | (0.11) | (0.11) | (0.11) | (0.11) | (0.11) | (0.12) | (0.12) | (0.12) |
| Taiwan | -0.40 | -0.09 | -0.29 | -0.02 | 0.40 | 0.49 | 0.26 | 0.33 |
| | (0.88) | (0.88) | (0.86) | (0.85) | (0.91) | (0.89) | (0.94) | (0.91) |
| PG [b] | 0.31 | 0.27 | 0.46* | 0.39 | 0.42 | 0.39 | 0.50* | 0.47* |
| | (0.26) | (0.25) | (0.25) | (0.25) | (0.27) | (0.26) | (0.27) | (0.27) |
| NC12 | -0.17 | -0.25 | 0.01 | -0.10 | -0.13 | -0.18 | -0.003 | -0.05 |
| | (0.25) | (0.25) | (0.24) | (0.25) | (0.26) | (0.26) | (0.27) | (0.27) |
| NC17 | -0.17 | -0.39 | -0.010 | -0.31 | -0.03 | -0.16 | 0.01 | -0.08 |
| | (0.32) | (0.33) | (0.31) | (0.32) | (0.33) | (0.34) | (0.34) | (0.35) |
| Sequel | 1.54*** | 1.48*** | 1.26*** | 1.25*** | 1.17*** | 1.17*** | 1.27*** | 1.27*** |
| | (0.20) | (0.20) | (0.20) | (0.20) | (0.21) | (0.21) | (0.22) | (0.21) |
| CNY | 1.09** | 1.20** | 0.69 | 0.85* | 1.21** | 1.26** | 1.10** | 1.14** |
| | (0.48) | (0.48) | (0.47) | (0.47) | (0.50) | (0.49) | (0.51) | (0.50) |
| Summer | 0.18 | 0.23 | 0.22 | 0.26 | 0.31 | 0.32 | 0.43* | 0.43** |
| | (0.21) | (0.21) | (0.20) | (0.20) | (0.22) | (0.21) | (0.22) | (0.22) |
| lnBudget | 0.28*** | 0.36*** | 0.22*** | 0.31*** | 0.31*** | 0.35*** | 0.31*** | 0.34*** |
| | (0.06) | (0.07) | (0.06) | (0.07) | (0.06) | (0.07) | (0.06) | (0.07) |
| Rating | -0.16*** | -0.12** | -0.13*** | -0.10* | 0.02 | 0.03 | -0.05 | -0.04 |
| | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) | (0.05) |
| Constant | 5.29*** | 4.99*** | 3.39*** | 3.42*** | 4.65*** | 4.55*** | 5.12*** | 5.01*** |
| | (1.13) | (1.13) | (1.10) | (1.09) | (1.18) | (1.15) | (1.21) | (1.18) |
| **First stage** | | | | | | | | |
| lnSTWOM | | 0.58*** | | 0.56*** | | 0.60*** | | 0.60*** |
| | | (0.05) | | (0.05) | | (0.05) | | (0.05) |
| Observations | 347 | 347 | 347 | 347 | 347 | 347 | 347 | 347 |
| R-squared | 0.81 | 0.80 | 0.82 | 0.81 | 0.79 | 0.79 | 0.78 | 0.78 |
| Durbin-Wu-Hausman $\chi^2$ test | | 6.30** | | 5.22** | | 1.44 | | 0.65 |
| Cragg-Donald Wald F-statistic | | 139.11*** | | 121.82*** | | 126.40*** | | 125.55*** |

Notes: a The reference group is "Drama."
bThe reference group is "G."
cStandard errors are in the parentheses.
d***, **, and * indicate the significance at the 1%, 5%, and 10 % levels, respectively.

**Table 3:Estimation results of the OLS and 2SLS models (WOM valence)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** |
| | **Dependent variable: lnBoxOffice** | | | | | | | |
| **Explanatory variable** | | | | | | | | |
| lnAngry | 0.67*** | 0.48*** | | | | | | |
| | (0.07) | (0.11) | | | | | | |
| lnLike | | | 0.96*** | 0.81*** | | | | |
| | | | (0.04) | (0.08) | | | | |
| lnHaha | | | | | 0.67*** | 0.55*** | | |
| | | | | | (0.04) | (0.07) | | |
| lnLove | | | | | | | 0.87*** | 0.74*** |
| | | | | | | | (0.05) | (0.09) |
| **First stage** | | | | | | | | |
| lnSTWOM | | 0.51*** | | 0.56*** | | 0.63*** | | 0.54*** |
| | | (0.04) | | (0.05) | | (0.05) | | (0.05) |
| Observations | 347 | 347 | 347 | 347 | 347 | 347 | 347 | 347 |
| R-squared | 0.64 | 0.63 | 0.82 | 0.81 | 0.75 | 0.74 | 0.78 | 0.77 |
| Durbin-Wu-Hausman $\chi^2$ test | | 5.37** | | 5.19** | | 4.81** | | 3.13* |
| Cragg-Donald Wald F-statistic | | 202.69*** | | 121.13*** | | 175.28*** | | 111.60*** |

Notes: a Standard errors are in the parentheses.

b***, **, and * indicate the significance at the 1%, 5%, and 10 % levels, respectively.

cAll regressions included controls for movies genres dummies, index of cultural difference, the quadratic term of the index of cultural difference, Taiwan,movies classification dummies,Sequel, CNY, Summer,lnBudget, Rating, and a constant.

**Table 4:Estimation results of the OLS and 2SLS modelswith interactionterms of WOM and CD**

| **Panel A** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** |
| | **Dependent variable: lnBoxOffice** | | | | | | | |
| **Explanatory variable** | | | | | | | | |
| lnPost | 1.50*** | 1.11*** | | | | | | |
| | (0.08) | (0.19) | | | | | | |
| lnPost*CD | -0.00028** | 0.000084 | | | | | | |
| | (0.00012) | (0.00021) | | | | | | |
| lnReaction | | | 1.00*** | 0.83*** | | | | |
| | | | (0.046) | (0.11) | | | | |
| lnReaction* CD | | | -0.0000009** | -0.000003 | | | | |
| | | | (0.0000003) | (0.000005) | | | | |

| Panel A | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** |
| lnComment | | | | | 0.85*** | 0.73*** | | |
| | | | | | (0.048) | (0.11) | | |
| lnComment*CD | | | | | -0.000003 | 0.000009 | | |
| | | | | | (0.00001) | (0.000014) | | |
| lnShare | | | | | | | 0.84*** | 0.77*** |
| | | | | | | | (0.048) | (0.11) |
| lnShare*CD | | | | | | | -0.000007 | -0.0000002 |
| | | | | | | | (0.000009) | (0.000013) |
| CD | -0.85 | -1.43** | -0.36 | -0.83 | -0.96* | -1.25** | -1.11** | -1.27** |
| | (0.53) | (0.59) | (0.52) | (0.57) | (0.55) | (0.59) | (0.56) | (0.59) |
| CD2 | 0.25** | 0.37*** | 0.15 | 0.25** | 0.27** | 0.33*** | 0.31*** | 0.35*** |
| | (0.11) | (0.12) | (0.11) | (0.12) | (0.11) | (0.12) | (0.12) | (0.12) |
| **Panel B** | **(9)** | **(10)** | **(11)** | **(12)** | **(13)** | **(14)** | **(15)** | **(16)** |
| | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** | **OLS** | **2SLS** |
| | **Dependent variable: lnBoxOffice** | | | | | | | |
| **Explanatory variable** | | | | | | | | |
| lnAngry | 0.75*** | 0.54*** | | | | | | |
| | (0.074) | (0.13) | | | | | | |
| lnAngry*CD | -0.00018*** | -0.00011 | | | | | | |
| | (0.00006) | (0.00007) | | | | | | |
| lnLike | | | 1.01*** | 0.83*** | | | | |
| | | | (0.046) | (0.11) | | | | |
| lnLike*CD | | | -0.0000009** | -0.0000003 | | | | |
| | | | (0.0000004) | (0.0000005) | | | | |
| lnHaha | | | | | 0.74*** | 0.61*** | | |
| | | | | | (0.044) | (0.085) | | |
| lnHaha*CD | | | | | -0.000041*** | -0.000025 | | |
| | | | | | (0.000012) | (0.000015) | | |
| lnLove | | | | | | | 0.93*** | 0.77*** |
| | | | | | | | (0.051) | (0.13) |
| lnLove*CD | | | | | | | -0.000047** | -0.000015 |
| | | | | | | | (0.000021) | (0.000031) |
| CD | -1.68** | -2.11*** | -0.33 | -0.80 | -1.57*** | -1.85*** | -1.11** | -1.46** |
| | (0.72) | (0.74) | (0.51) | (0.57) | (0.59) | (0.60) | (0.56) | (0.61) |
| CD2 | 0.45*** | 0.54*** | 0.14 | 0.24** | 0.38*** | 0.45*** | 0.31*** | 0.38*** |
| | (0.15) | (0.15) | (0.11) | (0.12) | (0.12) | (0.13) | (0.12) | (0.13) |

Notes: a Standard errors are in the parentheses.

b***, **, and * indicate the significance at the 1%, 5%, and 10 % levels, respectively.

cAll regressions included controls for movies genres dummies, Taiwan, movies classification dummies,Sequel, CNY, Summer,lnBudget, Rating, and a constant. 2SLS regressions also includedlnSTWOM in the first stage.

**ENDNOTES:** [1] In the period of 2017 - 2018, the average exchange rate: USD 1 = NTD 30.59.

**Figure 1:**An illustration of Facebook WOM, using "Robin Hood" as an example

**Source:** https://www.facebook.com/ETtodayMOVIE/ videos/ 1833476880069705/