# How Does Online Word-of-Mouth Influence Revenue? Evidence from Twitter

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## Abstract

This paper measures how online word-of-mouth communication influences box-office revenue. Theoretical models interpret word-of-mouth as a process of quality learning. However, it is often argued that in online word-of-mouth, consumers do not care about quality learning, but just the fads. Positive online opinions increase interest in a movie, but negative opinions raise people's awareness, which may also increase interest. This paper attempts to distinguish between these potential impacts. Using Twitter data collected from May 2011 to Aug 2011, after controlling for the movie-specific variables, this paper finds that valence of online word-of-mouth has a significant impact on box-office revenue, but volume does not. Consumers do learn product quality from online word-of-mouth, and they value the information on product quality much more than the information volume. These results provide the evidence on consumers' learning patterns on social networking websites, suggesting that quality learning may occur in online word-of-mouth communication.

# 1. **Introduction**

This paper measures how online word-of-mouth communication influences box-office movie revenue. Word-of-mouth communication is defined as all kinds of communications among consumers about their product experiences. Theoretical models interpret word-of-mouth communication as a process of learning,[1] but what consumers learn from word-of-mouth is still an empirical question.

This paper fills this gap by documenting the empirical evidence on learning content, using evidence from the movie industry. A movie is a typical experience good, whose product quality is ascertained by consumers only after a purchase. For such experience products in cultural industries, we often observe a mixed impact of online word-of-mouth, which raises a question about consumers' learning mechanism. Two different behaviors, quality discovery and herding, can co-exist in word-of-mouth. For example, positive online opinions increase interest in a movie, but negative opinions raise people's awareness, which may also increase interest. Distinguishing between these potential impacts is the primary contribution of this paper.

My results have important implications for a central assumption of learning theory. Defining valence as whether online comments are positive on a movie, I find that that valence of online word-of-mouth communication has a significant impact on box-office revenue, but volume does not. Moreover, professional critics and online comments are both important to consumers, so professional critics do not substitute or overwhelm the learning effect of tweets. These results provide evidence on consumers' learning patterns on social networking websites, suggesting that quality learning occurs in online word-of-mouth communication.

Some literature has applied learning theory to movie consumption. De Vany and Walls (1996) build a theoretical model to show that learning from information cascades leads to Bose-Einstein

[1] Ellison, Fudenberg (1995) and Gale (1996) were the first to introduce Bayesian learning into the model of word-of-mouth. Assuming that consumers learn product quality from online word-of-mouth, consumers update their *ex ante* expectation on goods. It is a dynamic process that shapes demand continuously. In a repeated game, each agent's learning leads to either herding or diversity choice at an aggregate level.

distributional dynamics for box-office revenue. They take the autocorrelation of movie revenue as the evidence of learning. Moretti (2011) finds empirical evidence consistent with the social learning model by observing the dynamic divergence of box-office revenue between “good movies” and “bad movies.” He finds that other factors orthogonal to movie quality, such as weather shocks, have no impact on consumers’ decisions. Moul (2007) takes the autocorrelation of weekly box-office revenue, the seasonally correlated residuals, and the series autocorrelation of movie attendance as the evidence of social learning. Elberse and Eliashberg (2003) use “revenues per screen in the previous week” as a proxy for word-of-mouth and find it a key factor to a movie’s success.

Moretti, Moul, Elberse and Eliashberg all take the dynamics of revenue as evidence of social learning. But a common limitation of their studies is that they do not observe word-of-mouth directly. Since word-of-mouth contains information valuable to consumers as they update their priors, it is an *ex ante* variable. In contrast, revenue is an *ex post* variable. To fully analyze the effect of word-of-mouth, we need to measure word-of-mouth directly with an *ex ante* variable.

Some empirical studies do measure online word-of-mouth communication directly. Liu (2006) finds that the Yahoo! Movies message volume is significantly correlated with weekly movie revenue, but the valence is not. Duan, Gu and Whinston (2008) find that the ratings of online reviews on Yahoo! Movies do not have a significant impact on box-office revenues, but the volume of reviews does. In contrast, Chevalier and Mayzlin (2006) use data from Amazon.com and find that improvements in larger volume and better valence of books’ reviews both increase book sales. The conflict between these findings raises questions about what consumers actually learn from online word-of-mouth, and this paper will go in depth to explore these questions.

In addition to online communication, professional critics are another learning source different from online communication. Holbrook and Addis (2008) emphasize the difference between “evaluative judgments” (ratings or critics) and “population buzz” (volume of online attention). They suggest that the two factors are essentially separable as independent paths of movie success. Their findings have the important implication that professional critics and online comments should be analyzed separately.

Using a unique data set collected from Twitter, I analyze how online word-of-mouth communication influences the North-American weekend box-office revenues. The social networking website "twitter" has been popular since 2006, and it has become an important source of online word-of-mouth. Consumers interpret valence and volume of tweets differently. Valence is determined by whether a tweet is positive or negative about the movie, while volume counts the total number of tweets. If consumers care only about fads and societal trend, but not product quality, then it is volume, not valence, that will influence revenue.

This paper offers several contributions. First, the paper is among the first empirical papers using Twitter data to measure the impact of online word-of-mouth communication[2]. Second, I consider the differential impacts of various forms of word-of-mouth. The different impacts between professional critics and tweets are analyzed, as well as the difference between valence and volume. Third, by examining the different impacts of valence and volume, I document empirical evidence of learning patterns on social networking websites.

This paper is organized as follows: in the second section, I present the data collection process and the description. Then I present the methodology and describe the hypotheses that explore the distinguishing features of the valence and volume. Next, I provide my results. The final section is the conclusion, with implications for future research issues.

## 2. Data Description

The social networking website "twitter" serves as a platform for users to post instant comments and subscribe to others' posts, which are called "tweets". Due to tremendous world-wide growth, as of

[2] Asur and Hubertman (2010) find that the rate at which movie tweets are generated can predict movie box-office revenue by a simple linear regression, but their methodology has limitations. One of their interesting findings is that tweets have the predictive power after the movies are released, not before the release. This is indirect evidence of learning in twitter. However, Asur and Hubertman do not provide any economic rationale for their methodology. They do not control for movie-specific or time-specific variables. Further, they do not take account for potential endogeneity and auto-correlation.

2011, Twitter has 100 million active users logging in at least once a month and generates over 200 million tweets per day.

Previous studies have focused on online comments for various product review websites such as Yahoo!.com and Amazon.com. However, Twitter is different from these product review websites. Consumers search for movie comments on movie review websites with a clear intention of learning. In contrast, consumers encounter information about movies randomly and unintentionally with Twitter. Communication in Twitter is closer to the real-world word-of-mouth communication that is presented in the learning models.

The data in this paper comes from the daily counts of tweets on individual movies from May 16 2011 to Aug 19 2011. Counting the total number of English-written tweets, I link Twitter data with weekend North-American box-office revenue. Although 60% of Twitter users reside outside the United States, it is still appropriate to project English tweets to the North American movie market since overseas users are mainly tweeting in Japanese, Portuguese and Spanish, not in English.

The Twitter data on movies is collected daily by *twittercritics.com*. The variables include the daily number of total tweets (by movie), the daily number of positive tweets (by movie), and the daily number of negative tweets (by movie). Data was collected at 6am and 12pm EST every day. Volume and valence measures are included. Valence is defined as the ratio of positive tweets to total tweets, while volume counts total number of tweets.

I assume that the valence and volume of tweets have different implications to consumers. Whether a tweet is positive or negative is judged by computer programs from twittercritics.com. Due to the technological limitations, measurement error may exist in computerized content analysis. But a previous study shows that human-coded and computerized content analysis may be equally effective (Morris, 1994).

Table 1 summarizes the tweet data. I collected the tweets for 125 movies from twittercritics.com, but only 57 out of 125 were in theaters. On average, each movie had daily tweet data for 77.22 days, which is longer than the average time (about seven weeks) a movie is in theaters. This implies that on average, the duration of my tweet data is long enough to catch the fade-out pattern of online movie discussions.

Table 2 shows the descriptive statistics for the daily running total of tweets (labeled as "stock") and the daily increments of tweets (labeled as "increment") for individual movies. Although the data set has ruled out the observations of extreme small box-office revenue, some movies still have zero tweets at some points. This does not imply that these films have no tweets from May 16 through Aug 19; it just implies that on some particular days, no tweet is observed for that movie. Table 3 presents the daily dynamics of tweets within one week. On Thursday at 6am I find the fewest movie-related tweets, while the peak of movie tweets comes on Friday night so that it is observed at Saturday at 6am.

The North American weekend box-office data was collected from Boxofficemojo.com from May 13, 2011 through Aug 21, 2011. There were 286 movies in both local and national chain theaters. However, given the algorithm for content analysis, only 57 out of the 286 movies have tweets data. Movies that are very unpopular or whose names are difficult to enter into the search engine will be ruled out of the tweet counting process.

Table 4 compares the two data sets. The set of 57 movies is a subset of the 286 movies in theater. Selection bias is suspected since the 57 movies have higher average box-office revenue, larger production budget and less missing data. However, this is not necessarily a limitation of my data set. Out of 286 movies, about 50 movies are only at local theaters. Since the aggregate Twitter data reflect the movie market as a whole, mass-marketed movies reflect aggregate Twitter opinions better than local movies. In this sense, my data selection is appropriate because it rules out the local movies with lower box-office revenue.

The data shows consistency with the movie industry characteristics and trends. Weekly box-office revenue declines exponentially over time, and total box-office revenue follows an exponential decay across movies. The number of theaters each week also declines over time in most of the cases.

The data exhibits a strong positive auto-correlation in box-office revenue for each movie. This serial auto-correlation of weekend box-office revenue is consistent with the previous literature, showing that consumers may learn from previous box-office performance. The correlation between movie tweets and box-office office revenue is strong, too. Not controlling for the other movie-specific variables, both the valence and volume of tweets are highly correlated with the box-office revenue with a correlation coefficient greater than 0.4. This strong correlation is a starting point for me to explore the relationship between box-office revenue and Twitter word-of-mouth.

## 3. Methodology

The theory of social learning is based on the assumption that consumers learn the true quality of products through their social networks. To see whether this assumption applies, I have the following hypotheses:

1. If consumers learn product quality from Twitter, then valence of tweets will affect weekend box-office revenue and the coefficient of valence will be positive.
2. In an extreme case in which consumers care only about fads and societal trend but not product quality at all, then it is volume, not valence, that will influence revenue.
3. If professional opinions and online word-of-mouth work through different channels and they all provide information to consumers, professional critics and reviews would not swamp the significance of tweet valence. The coefficients of both are expected to be positive.

Using panel data, with an unbalanced random-effects model, I estimated a regression equation relating weekend revenue at week *t* to daily tweets at week *t-1*. The dependent variable is the log of aggregate weekend box-office revenue which captures the weekly dynamics of the movie demand. The independent variables are the volume and valence indicators, whose coefficients measure the impact of online word-of-mouth across movies. After controlling for the movie-specific variables, the coefficients of tweets would be significantly different from zero, if consumers do learn from Twitter word-of-mouth communication. If no learning occurs, then the coefficients would be zero.

The endogeneity between revenue and tweets needs to be addressed. More tweets may bring higher box-office revenue, but higher revenue also implies more audience and hence more tweets. In contrast to earlier studies that address endogeneity with instrumental variables, I exploit the timing of tweets and box-office realizations. According to the learning theory, tweets should be a leading factor of revenue. The dependent variable, box-office revenue, is at weekend *t*, and the independent variable of tweets should be at week *t-1,* that is the tweets on Sunday, Monday, Tuesday, Wednesday and Thursday prior to weekend *t*.

The model is as follows:

$$lnRevenue_{jt} = \beta_0 + \beta_1\, Valence_{jt-1} + \beta_2\, lnVolume_{jt-1} + \beta_3\, lnProduction\ Budget_j + \beta_4\, Metascore_j + \beta_5\, Genre_j + \beta_6\, Age\ Factors_j + \beta_7\, Number\ of\ Week_{jt} + \beta_8\, Number\ of\ Theater_{jt} + \beta_9\, Holiday_{jt} + u_{jt}$$

For each week starting at the second week (t = 1, 2, 3…), where j indexes the movies (j = 1, 2, …) , the dependent variable, North-American weekend box-office revenue, is related to the Twitter word-of-mouth measures ($Valence_{jt-1}$ and $Volume_{jt-1}$) , movie-specific control variables (*Number of week*, *Production Budget*, *Theater*, *Age factors)* and the long-weekend control variable ($Holiday_t$). The independent variables are described as follows:

**Valence and Volume:** The Twitter word-of-mouth variables include volume and valence indicators. Volume is the weekly incremental number of total tweets for movie *j* from Sunday to Thursday prior to weekend *t*, while valence is defined as the average ratio of positive tweets to total tweets from Sunday to Thursday before weekend *t*. Saturday tweets are not included because they are simultaneous with the weekend box-office revenue, not prior to revenue. No interaction term between the valence and volume is considered in the model.

**Metascores:** Metascore is a movie-variant, time-invariant variable collected from Metacritic.com, a website that summarizes reviews of movies from publications and public media. It ranges from 0 to 100, and it is a weighted average in that the website assigns different weights to critics. In contrast to tweets, Metascore is much more oriented to professional, authoritative critics which are not delivered within specified social networks. The indicators of tweets directly measure online word-of-mouth, but Metascore does not reflect the dynamics of learning among users. Metascore and tweets are different in essence; they both influence weekend box-office revenue but work through different channels.

**Age factors:** Age factors are movie-variant, time-invariant variables coming from MPAA ratings of movie *j*. "Age factors include two binary dummy variables: "less than 12" and "above 25." G and PG are categorized as "less than 12; R and NC17 are categorized as "above 25."

MPAA ratings control for movie goers' age, and it is also related with Twitter user demographics. According to the Nielsen NetView report (2009), the largest age groups in Twitter range from 25 to 49, which account for 61.3% of the total users. Those movies targeting the age groups below 25 or above 49 may have fewer tweets than other movies targeting age 25 to 49. The impact of Twitter word-of-mouth on box-office revenue could be influenced by the age factors coming from MPAA ratings. Hence, it is necessary to control for the age factors coming from MPAA ratings, using age 12 and 25 as the cut-off points.

**Production Budget:** Production budget is a movie-variant, time-invariant variable collected from *boxofficemojo.com*. Production budget is highly correlated with firms' advertisement spending which influences consumers' *ex ante* expectation and box-office revenue at opening weekend. Since firms' advertisement spending data is not available, production budget is a good proxy of advertisement budget.

**Number of theaters**: Number of theaters is a movie-variant, time-variant variable which is declining over time in most of the cases. Each week, distributors and theaters make decisions on the number of theaters for next week. The number of theaters reflects distributors' and theaters' expectations on revenue. Furthermore, more theaters for movie *j* also implies lower transportation cost of seeing movie *j*. Number of theaters is directly correlated with box-office revenue and hence an important control variable.

**Genre:** Genre is a movie-variant, time-invariant variable for movie *j*. To avoid the problem of low degree of freedom, movies are categorized into only three types: action, drama and comedy. With one omitted and subsumed in the constant, the two dummy variables are "action or not" and "comedy or not."

**Number of weeks**: Number of weeks is a movie-variant, time-variant variable which shows how long movie *j* has been in theater. Since consumers seldom go to the same movie more than once, box-office revenue is usually negatively correlated with number of weeks.

**Holiday**: Holiday variable controls the effect of long weekend. There are two long weekends during May to August: Memorial Day and Independence Day. These long weekends may increase box-office revenue for all movies, but each movie was at different week *t*, depending upon when they were released. Therefore, "holiday" is a movie-variant, time-variant variable

## 4. Results

To test the three hypotheses on online learning, several random-effect models, including the above explanatory variables of box-office weekend revenue were run. The results of various regression models and robustness follow.

**Baseline with a Random-Effects Model**: Using an unbalanced panel data of box-office revenue, the results of a random-effects model shows that valence of online word-of-mouth communication has a significant impact on box-office revenue, but volume does not.

"Valence of tweets" is measured by the weekly average ratio of positive tweets to total tweets. After controlling for movie-specific variables such as age factors, production budget, Metascores, holiday and the number of theaters, valence has a significant impact on revenue. In contrast, volume of tweets is not significant. Although volume of tweets at week *t-1* is highly correlated with box-office revenue at time *t*, controlling for these movie-specific variables reduces the significance of volume.

Table 5 shows the results of the "valence" and "volume" models. I regress weekend box-office revenue for individual movie *j* across time *t* on "valence" and "volume" variables. The ratio of positive tweets is viewed as the valence indicator of tweets, and the volume indicator is measured by the number of the total tweets.

Valence of tweets is significant at the 0.01 significance level. Also consistent with the hypothesis of learning, the coefficient of valence is positive. The models in Table 5 includes budget, number of theaters, week that the movie has been in theater, holiday and long weekend, Genre, Metascore, and the age factors from MPAA ratings as the independent variables. Budget, theater, and number of weeks are all significant to box office revenue. Adding these movie-specific control variables even increases the significance of valence. This findings show that consumers do care about the information on product quality in online communication, even when they have access to other information sources of movie quality.

In contrast to valence, volume has an insignificant coefficient. Controlling for these movie-specific variables makes volume of tweets insignificant. It is "the number of theaters" that varies each week and swamps the volume effect. "Number of theaters" reflect the audience base every week. This finding suggests that the volume of tweets may only reflect the change of audience base, which is highly correlated with the number of theaters, but might not be a learning source in itself.

These results provide evidence on consumers' learning patterns on social network websites. Consumers may learn from the valence of tweets information, but the volume of tweets information appears to be less important to them. The result does not support the conventional thinking in cultural industries that negative comments raise consumers' awareness, which in turn can also increase consumers' interest in a product. This empirical evidence shows that in the learning process of online word-of-mouth communication, consumers may care more about others' judgments on product quality than the information volume. Even if consumers receive a limited amount of information online, the proportion of positive comments still dominates the volume effect in their learning process.

**The Role of Professional Critics:** As stated above, different from tweets, Metascore is an indicator of professional critics. It is noteworthy that Metascore and valence are both significant. Consistent with the hypothesis of learning, both their coefficients are positive. Adding Metascore as another independent variable does not swamp the significance of valence. This finding implies that professional critics and tweets opinions are both important to consumers, and professional critics do not substitute or overwhelm the learning effect of tweets. Consumers may learn from professional publications, but they may also learn from online communication via social networks as well.

**Auto-correlation of Box-office Revenue with an AR(1) Model:** As mentioned above, in addition to the professional critics and online information, consumers also learn the product quality from the last weekend box-office revenue. The high correlation between revenue at t and t-1 also suggests that this learning behavior exists. Since the last weekend box-office revenue is also a result of social learning on Twitter, simply adding the lag box-office revenue as one of the independent variables may cause under-estimation of the coefficients of tweets. Therefore, to consider the serial auto-correlation in weekend box-office revenue, an AR(1) random-effect model was run. The results are presented in Table 6 (which tests valence and volume jointly) and Table 7 (which tests valence and volume separately.)

Table 6 shows that with an AR(1) model, valence still matters but with a lower significance level at 0.1. In contrast, the coefficient of volume is still insignificant. Table 7 shows similar results that valence is significant, but volume is not. Consumers still care about valence, not volume of tweets.

**“Revenue per Theater” as Dependent Variable**: Thus far, I use “weekend box-office revenue” as the dependent variable, not revenue per theater. The reason is that “number of theaters” carries important information. The number of theaters is determined by distributors and theaters every week, and it reflects distributors and theaters’ expectations on revenue. The number of theaters also affects consumers' incentives to see a movie, since exhibitions at more theaters means lower transportation cost of going to a movie. Dropping the number of theaters from the independent variables ignores the fact that number of theaters affects revenue in various, non-linear ways.

However, for a robustness check, I estimate the random-effect regression with "box-office revenue per theater" as the dependent variable. Volume is not significant (with a P-value=0.459), and valence is still significant (with a P-value = 0.000) .

**Endogeneity of "Number of Theaters":** As noted above, "number of theaters" is an important independent variable and it swamps the significance of tweet volume. There are two possible explanations for this result: first, volume of tweets only reflects number of theaters and does not have an impact on box-office revenue. Second, "number of theater" is an endogenous variable which may reduces the significance of volume. Before we take the first one as the only explanation to "theater effect", we have to examine the second assumption of endogeneity.

"Number of theaters" is an endogenous variable because it and "box-office revenue" influence each other simultaneously. There is a reciprocal causation between the two variables. To control for this endogenous effect, I use a dummy variable that "whether box-office revenue is higher than the last week" as the instrumental variable for the number of theaters. This dummy variable is correlated with "number of theaters," but not directly correlated with weekend box-office revenue.

After controlling for the endogeneity of the number of theaters, the significance of volume of tweets improves, but it is still not significant (with a P-value 0.076). In contrast, valence is highly significant to box-office revenue (with a P-value 0.000). The basic conclusion of valence and volume has not changed.

## 5. Conclusion

This paper measures how word-of-mouth communication on social networking websites influences box-office revenue and explains its implications for social learning theory. In the theoretical literature on social learning, word-of-mouth communication is interpreted as a process of learning product quality. However, it is often argued that in online word-of-mouth, consumers do not care about quality learning, but just the fads. In an extreme case in which consumers only care about fads and societal trends, but not product quality, it is volume of information, not valence, that will influence revenue. This paper documents the empirical evidence to see whether quality learning applies in online word-of-mouth.

Using unique, first-hand data collected from Twitter, this paper finds that valence of online word-of-mouth communication has a significant impact on box-office revenue, but volume does not. Valence meansures whether tweets are positive or negative on a movie, while volume counts the total number of tweets. The results suggest that consumers may learn from the valence of tweets information, but volume of tweets information is less important to them. The result does not support the conventional thinking in cultural industries that negative comments raise consumers' awareness, which in turn can also increase consumers' interest in a product.

This empirical evidence does not reject the assumptions of learning theory. Consumers do learn product quality from online word-of-mouth, and they value the information of product quality much more than the information volume. Rather than online fads, they care more about quality learning. The results also suggest that although professional critics and the previous box-office revenue are the additional sources of learning, the online information of product quality is still important to consumers. Professional critics and the previous box-office revenue could be the other sources of learning, but neither of them diminishes the significance of valence.

This paper still has some limitations. Although I exploit the timing of tweets and box-office realizations to distinguish the cause, there might be other factors which impact both box-office revenue and online word-of-mouth communication simultaneously. The regression alone may not be sufficient for the causal identification. Moreover, the dynamics of the declining rate in box-office revenue is also a result of social learning. Some movies with lower opening weekend performance stay longer in theater because they receive higher rating in online discussions. Exploring the question of why some movies have a lower decreasing rate in revenue and in tweets may complete the research.

With these limitations, this paper still documents empirical findings on quality learning. A positive, chronicle correlation between revenue realization and online comments exists, and quality learning may happen on social networking websites. A fruitful area of future research could be how consumers learn product quality over time. In the movie industry, we often observe that a small amount of blockbuster movies generates a large proportion of the industry's total revenues, but we do not know whether it is a result of quality learning or herding. Studying how consumers learn to distinguish good movies and bad movies will help us to see whether online learning leads to an efficient equilibrium at the aggregate level.

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Table 1: The Basic Information of Tweets

| The number of movies which have tweets data | The number of movies which have both tweets and revenue data | Maximum data duration for a movie | Minimum data duration for a movie | Average of data duration | Average tweets per movie (stock) | Average tweets per movie (daily increment) |
|---|---|---|---|---|---|---|
| 125 | 57 | 94 | 3 | 77.22 | 7438.87 | 110.47 |

Table 2: The Descriptive Statistics of Tweet Stock and Increment

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| tweets - stock | 3623 | 7438.87 | 10247.58 | 0 | 55708 |
| tweets - increment | 3623 | 110.47 | 884.66 | 0 | 31946 |

Table 3: The Daily Dynamics of Tweet within a Week

| | Monday | Tuesday | Wednesday | Thursday | Friday | Saturday | Sunday |
|---|---|---|---|---|---|---|---|
| Average daily increment of tweets | 52.57 | 47.5 | 40.46 | 36.42 | 59.11 | 79.26 | 72.02 |

Table 4: The Comparison of the Movies from the Two Data Sets

| | | Average | Max | Min |
|---|---|---|---|---|
| 57 Movies in the Twitter Dataset | Total Box Office Revenue | $90,813,260 | $366,007,900 | $1,183,354 |
| | Production Cost | $73,890,385 | $260,000,000 | $1,500,000 |
| | * 6 movies out of 57 have their production cost data missing. | | | |

| | | Average | Max | Min |
|---|---|---|---|---|
| 286 Movies on theater in the same period | Total Box Office Revenue | $22,043,286 | $366,007,900 | $11 |
| | Production Cost | $49,917,031 | $260,000,000 | $135,000 |
| | * 189 movies out of 286 have their production cost data missing. | | | |

Table 5: Results of Tweets Valence and Volume Impact

Unbalanced Random Effect Model (z-value beneath)

| Variables | Coefficients |
|---|---|
| The Number of Total Tweets *it* | .0000121<br>(0.61) |
| The Ratio of Total Tweets *it* | 4.073204**<br>(4.39) |
| The Number of Theaters *it* | .0006752**<br>(16.32) |
| Week *it* | -.2313724**<br>(-17.98) |
| Budget *i* | .010203**<br>(6.92) |
| Age factor *i* : less than 12 | -.1982936<br>(-0.89) |
| Age factor *i* : greater than 25 | .5226492*<br>(1.73) |
| Metascore | .0184549**<br>(2.63) |
| Action Dummy | -.6086928*<br>(-1.89) |
| Drama Dummy | -.3960927<br>(-1.36) |
| Holiday *it* | .0321914<br>(0.47) |
| Constant | 10.10972**<br>14.88 |
| $R^2$ within: 0.9238<br>$R^2$ between: 0.9016<br>$R^2$ overall: 0.9016 | |

**: significant at 0.05 level. *: significant at 0.1 level.

Table 6: Result of Tweets Valence and Volume Impact with AR(1) Assumption

Unbalanced Random Effect Model (z-value beneath)

| Variables | Coefficients |
|---|---|
| The Number of Total Tweets *it* | .0000346<br>(1.29) |
| The Ratio of Total Tweets *it* | 2.008503*<br>(1.92) |
| The Number of Theaters *it* | .0012265**<br>(22.27) |
| Budget *i* | .005802**<br>(3.51) |
| Metascore | .0137173*<br>(1.78) |
| Age factor: less than 12 | -.2861528<br>(-1.17) |
| Action Dummy | -1.151824**<br>(-3.64) |
| Drama Dummy | -.7543349**<br>(-2.49) |
| Holiday *it* | .01669919<br>(0.29) |
| Constant | 10.06696**<br>14.53 |

$R^2$ within: 0.7937

$R^2$ between: 0.8994

$R^2$ overall: 0.8489

**: significant at 0.05 level. *: significant at 0.1 level.

Table 7: Separated Results of Tweets Valence and Volume Impact with the AR(1) Assumption

Unbalanced Random Effect Model (z-value beneath)

| Variables | Volume Model | Variables | Valence Model |
|---|---|---|---|
| The Number of Total Tweets *it* | .0000373 | The Ratio of Positive Tweets *it* | 2.064834** |
| | (1.39) | | (1.98) |
| The Number of Theater *it* | .0012303** | The Number of Theater *it* | . 0012399** |
| | (22.13) | | (23.26) |
| Budget *i* | .0049272** | Budget *i* | .0059314** |
| | (3.04) | | (3.60) |
| Age factor *i* : less than 12 | -.2376559 | Age factor *i* : less than 12 | -.3052063 |
| | (-0.95) | | (-1.25) |
| Action Dummy | -1.024155** | Action Dummy | -1.21088** |
| | (3.25) | | (-3.87) |
| Drama Dummy | -.5614148* | Drama Dummy | -.8048779** |
| | (-1.93) | | (-2.68) |
| Metascore | .0197454** | Metascore | .0135648* |
| | (2.74) | | (1.77) |
| Holiday *it* | .0141181 | Holiday *it* | .022338 |
| | (0.25) | | (0.39) |
| Constant | 11.03485** | Constant | 10.087 ** |
| | 22.62 | | 14.59 |
| $R^2$ within: 0.7891 | | $R^2$ within: 0.7927 | |
| $R^2$ between: 0.8999 | | $R^2$ between: 0.8971 | |
| $R^2$ overall: 0.8415 | | $R^2$ overall: 0.8458 | |

**: significant at 0.05 level. *: significant at 0.1 level.