Department of Economics

University of Warwick

1004544

EC331 Research in Applied Economics

April 2013

"Word-of-click": How do word-of-mouth information dynamics impact box-office revenues?

Research supervisor: Dr. Stefania Borla[1]

[1] The author is grateful to Dr. Stefania Borla for her supervision and comments throughout this project. Any errors remain the author's own.

Abstract

The proliferation of the internet and social media websites in the last decade has contributed to an almost instantaneous word-of-mouth effect. This is particularly relevant for experience and information goods whose quality is ex-ante uncertain such that demand is partly determined by the amount of word-of-mouth the product generates. By analysing online communication regarding films, this paper aims to explore how consumers learn information from word-of-mouth. The volume of pre-release word-of-mouth is found to have significant explanatory power for both opening weekend and aggregate box-office revenue, suggesting that consumers learn information from the quantity of online "buzz". This paper also finds that consumers are less likely to learn from the sentiment of word-of-mouth, especially in the early weeks of a film's run. Consumers are shown to be more likely to learn quality from professional critical reviews.

Word count: 5,000

Table of contents

1.	**Introduction**	**4**
2.	**Literature review**	**5**
3.	**Theory and Hypotheses**	**9**
4.	**Methodology**	**10**
5.	**Data description**	**14**
6.	**Results**	**16**
7.	**Conclusion**	**22**
8.	**Bibliography**	**25**
9.	**Appendices**	**28**
	Appendix 1: Correlation matrix between dependent variable and variables of interest	
	Appendix 2: Diagram illustrating timing of revenue and word-of-mouth variables	
	Appendix 3: Jarque-Bera (S-K) test for normality	
	Appendix 4: Variable list	
	Appendix 5: Summary statistics of key variables	
	Appendix 6: OLS regressions with the natural logarithm of weekend revenue per theatre as dependent variable	
	Appendix 7: OLS regressions omitting number of theatres	
	Appendix 8: Specification tests	

1. Introduction

The stock and insurance markets have been rigorously researched by applied economists for their inherent uncertainty and the inevitable risk they involve. However, another market that is worthy of attention for such properties is the film industry.

Films are fundamentally experience goods. Their quality is difficult to ascertain in advance due to incomplete information but is revealed with consumption, or in the case of films, with watching the film. In other words, their quality is ex-ante uncertain. This uncertainty creates a role for information dynamics in determining demand. Word-of-mouth is one such source of information.

With the invention and widespread adoption of the internet in developed countries, social media has become ubiquitous prompting consumers to share and reveal their preferences online. As of December 2012, Twitter had over 200 million active monthly users, reportedly tweeting around 500 million tweets a day[2]. These numbers represent vast amounts of information being shared online. This creates an almost instantaneous word-of-mouth effect which when applied to the film industry can manifest itself in a "buzz" for a film. There has been a recent rise in media attention to the success stories of several viral marketing campaigns adopted by film distributors that have prompted a social networking "buzz" which due to an information multiplier, has led to increasing box-office returns being observed. If firms can credibly identify their consumers and the relevant word-of-mouth online, this information could have substantial implications for their demand, supply and pricing decisions; this provides the motivation for this paper.

Word-of-mouth suggests that information cascades may exist which implies there may be a "social multiplier" effect on revenues as attracting a new customer may increase the demand

[2] Reported by *V3*

of other consumers if the consumers are subject to influence by word-of-mouth. Moretti (2011) defines the presence of a multiplier effect as if the elasticity of aggregate demand is greater than the elasticity of individual demand to movie quality.

The volume and sentiment of online conversation has also been shown to have some predictive power on box-office revenues. This offers a contradiction to the industry assumption of “nobody knows” (De Vany, 2006) that affirms that due to the ex-ante uncertainty of demand, box-office revenues cannot be predicted. This implies that exhibitors can only know ex-post, whether demand was high enough that a premium price could have been charged. De Vany (2006) suggests that to pre-empt high demand and set a higher price ex-ante would be ‘gambling with the information dynamics’.

The rest of the paper is organised as follows. Section 2 presents a review of the existing literature. Section 3 covers the theory and proposes the hypotheses. Section 4 discusses the methodology. Section 5 describes the data. Section 6 discusses the results. Finally, section 7 concludes.

2. Literature review

This paper contributes to the existing literature on three discernible topics: models explaining uncertainty of motion picture demand, the information dynamics of word-of-mouth, and social learning.

The primary empirical response to investigating the uncertainty of demand is to examine the demand for individual films by modelling box-office revenues on a set of film-specific explanatory variables. Common film covariates explored include quality, budget, advertising, stars, genre, awards and reviews.

Various proxies have been estimated to account for word-of-mouth effects. Elberse and Eliashberg (2003) model weekly box-office revenue using weekly screen average as their word-of-mouth explanatory variable. Their findings suggest that advertising expenditure has significant predictive power for opening week revenue and screens. Word-of-mouth communication becomes important for subsequent weeks.

Another approach is to model word-of-mouth through the residuals. Using a nested-logit model, Moul (2007) uses the heteroskedasticity and serial correlation in the error term as a proxy for word-of-mouth communication. His results indicate that word-of-mouth accounts for around 10% of the variation in implied consumer expectations among films which generates autocorrelation and heteroskedasticity. However, a major limitation of this approach is the caveat that he is unable to discern between word-of-mouth communication between consumers and exogenous post-release information such as published box-office announcements.

Whilst such results have provided significant and informative results, McKenzie (2009) recognises that traditional OLS techniques for modelling demand based on box-office revenues can lead to misleading results due to word-of-mouth effects that lead to extremely skewed and kurtotic revenue distributions. Previous research has indicated similar results prompting De Vany and Walls (1996, 1999, 2004) and McKenzie (2008) to develop models of box-office success that account for these distortions. Dubbed by De Vany as a 'new-new economics' approach to modelling uncertainty, such models are beyond the scope of this study but their results and the implications will be taken into account when constructing the model and discussion of results.

De Vany and Walls (1996) model the information dynamics as Bayesian, they suggest that box-office revenues follow a Bose-Einstein distribution leading to information cascades.

Their results indicate autocorrelation of weekly revenues and strong evidence of demand uncertainty as booking patterns and information dynamics are shown to produce ‘highly unpredictable distributional dynamics and uneven revenues’ (pp.1513).

McKenzie (2008) studies the distribution of weekly screen average revenue observing that its probability mass in the right tail increases until week six and then decreases. He attributes this to word-of-mouth effects in the early weeks of a film’s run.

A major limitation of these studies is that they fail to observe word-of-mouth directly. This may be attributed to the lack of access to social media data which has only become established over the last 5 years and only recently been sufficient to provide any significant insight. Social media prompts an almost instantaneous word-of-mouth thus can be expected to markedly influence the information dynamics. More recent empirical studies have begun to develop models that exploit this new data.

Yong Liu (2006) uses word-of-mouth data collected from *Yahoo! Movies* Message Board coded into weekly measures of word-of-mouth volume and sentiment. His results suggest that word-of-mouth has explanatory power for both opening weekend and aggregate measures of revenue. Liu finds that this is due to the informative effect of word-of-mouth volume, whilst valence is found to be insignificant. Duan, Gu and Whinston (2005) support these conclusions regarding the dominance of volume using daily *Yahoo! Movies* data. Also using data from *Yahoo! Movies*, Dellarocas, Awad and Zhang (2004) find evidence to suggest that online ratings can be considered a useful proxy to represent real-world word-of-mouth.

Yu-Hsi Liu (2012) uses weekly *Twitter* data to explore the explanation power of word-of-mouth. With an unbalanced random effects model, Liu finds that the role of sentiment is important in explaining box-office revenues, suggesting that this provides evidence for quality learning. In contrast to Liu (2006), the role of volume is found to be insignificant.

Asur and Huberman (2010) also used data collected from *Twitter*. They define a variable that measures the rate at which tweets are created and find that serves as an important pre-release predictor of box-office revenue, outperforming other industry measures such as the Hollywood Stock Exchange. Regarding sentiment, they find it only significant in predicting revenues post-release. Two limitations of their study are their lack of discussion of potential endogeneity and omission of any film-specific variables.

Godes and Mayzlin (2004) research the volume and dispersion of word-of-mouth using Usenet newsgroup conversations as word-of-mouth proxies to investigate TV show ratings. Their results imply that dispersion is important in explaining ratings whereas volume only gains significance in later weeks, providing support for Elberse and Eliashberg (2003). One limitation of their paper is the lack of consideration of pre-release word-of-mouth; this is one area where this paper aims to make a significant contribution to the literature.

These mixed results represent an ambiguity of the effects of word-of-mouth on consumer behaviour. This paper aims to provide some further insight and clarification of these effects.

Regarding social learning, Ellison and Fudenberg (1995) find social learning from interpersonal word-of-mouth to be most efficient when communication is limited. Limited word-of-mouth leads to conformity amongst individuals whereas increasing information makes diversity more likely. Banerjee (1992, 1993) find evidence for “herding” when individuals place more weight on the information observed from others than their own private information. However, these papers pre-date the proliferation of social media online which has had a huge impact on the transmission mechanisms of information thus it will be worthwhile to investigate if such conclusions still hold.

Moretti (2011) finds evidence for a social learning impact on box-office sales, estimating that it accounts for 32% of sales for films with opening weekend demand that was higher than expected.

3. Theory and Hypotheses

In a market with incomplete information, consumers will endeavour to determine their ex-ante expectation of quality by acquiring information that will help them determine their preferences. In the film industry, such information is provided via advertising, critical reviews and word-of-mouth.

If word-of-mouth is a complement to these other information sources, the volume of word-of-mouth will raise consumers awareness, contributing to higher revenues. Liu (2006) refers to this as the informative effect of volume. This leads to the first hypothesis.

Hypothesis 1: The volume of pre-release word-of-mouth will have significant explanatory power for opening weekend revenue

That is, the coefficient on the volume variable will be positive. Given significance, this would provide evidence of social learning.

The role of sentiment is to heighten or lower expectations through a ‘persuasive effect’ thus influencing whether consumers are inclined to go and see the film or not. However, the net effect of this is ambiguous as whilst negative sentiment can lower expectations, it still heightens awareness. The expectation is that the role of sentiment will gain importance post-release. Pre-release, given quality is ex-ante uncertain, consumers are less likely to trust other consumers subjective preferences thus the awareness aspect of volume should dominate, whereas post-release, consumers may have more interest in the sentiments inherent in the comments as they can be interpreted as recommendations of consumers who have seen the film.

Hypothesis 2: The sentiment of word-of-mouth will be more significant post-release. Volume should lose significance

Given a positive correlation of word-of-mouth between weeks, a corollary of hypothesis 1 is that pre-release word-of-mouth can explain aggregate revenue. This would provide evidence to the contrary of the industry notion of “nobody knows”, suggesting that the amount of online “buzz” may be able to predict total sales.

Hypothesis 3: The volume of pre-release word-of-mouth will have significant explanatory power for total domestic gross revenue

The final hypothesis concerns the relative importance of word-of-mouth in determining demand to other information sources. Both word-of-mouth sentiment and critical reviews provide information on quality to consumers which through a persuasive role should increase consumers’ expectations and prompt them to watch the film. If consumers learn quality from both critics and word-of-mouth, then neither should swamp the effect of the other.

Hypothesis 4: The information from professional critics and tweet sentiment are complements and therefore both are expected to have positive and statistically significant coefficients across time

4. Methodology

The methodology is influenced by Liu (2006). However, as with Liu (2012) I will be using data collected from *Twitter* as it is more representative of real-world word-of-mouth. Online media used in previous literature such as Yahoo! Movies (Liu, 2006; Duan et al, 2005) are film-specific websites that users visit with the intention of learning film quality. *Twitter* is a micro-blogging website where users can post short messages of up to 140 characters known as ‘tweets’ which are instantly available for the public to see. As with real-world communication, consumers are more likely to be subject to random occurrences of film-specific conversation.

$$\ln\left(wkndrev_{i,t}\right) = \alpha + \beta_1 \ln(budget_i) + \beta_2 \ln(theatres_{i,t}) + \beta_3 threed + \beta_4 adaptation_i + \beta_5 prequel_i + \beta_6 horror_i + \beta_7 action_i + \beta_8 comedy_i + \beta_9 ratingpg_i + \beta_{10} ratingpg13_i + \beta_{11} critics + \beta_{12} \ln\left(tweets_{i,t}\right) + \beta_{13} \ln\left(tweets_{i,t-1}\right) + \beta_{14} posper_{i,t} + \beta_{15} posper_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable, weekend revenue, is the value of box-office sales from each Friday to Sunday of a film’s run. It is a well-reported measure in the industry. Autocorrelation is expected between weekend revenue in t and $t-1$. The correlation matrix in Appendix 1 reveals a strong positive correlation of 0.9430. Liu (2006) refers to this as a ‘dynamic carryover’ effect.

Total domestic gross revenue is the aggregate revenue from the domestic market[3]. This is a time-invariant measure. As in Liu (2006), natural logarithms are used for both revenue measures to deal with any potential non-linearity.

Production budget is the cost of producing a film. As print and advertising costs are not made available to the public, production budget serves as a good proxy. Advertising provides a source, in addition to word-of-mouth and critical reviews, for consumers to gather information about a film before consumption, in order to develop their expectation of the film’s quality. Therefore, production budget is expected to have a positive coefficient ($\beta_1 >$

[3] *The-Numbers.com* define the domestic market as the United States, Canada, Puerto Rico and Guam

0) as high levels of advertising implies the film is more likely to reach more audiences which should result in higher demand and revenue. Production budget is taken as a natural logarithm.

The number of theatres is a time-variant variable, representing the supply-side of the industry as exhibitors and distributors can choose to expand the number of theatres a film is shown at in order to meet demand. The number of theatres a film opens at is an indication of the expectation of demand. Therefore, I expect $\beta_2 > 0$. Endogeneity must be considered here as a high number of theatres may imply high revenue as there is potential for more ticket sales and the reverse holds as high revenue and demand will prompt distributors to increase the number of theatres the film is exhibited at. The theatre variable enters the model as a natural logarithm.

The next set of variables represents the film-specific control variables. Genre is divided into four dummy variables: horror and thriller, drama, action and adventure, and comedy and romantic comedy. Drama is omitted to avoid multicollinearity.

MPAA[4] rating is coded into three dummy variables: PG, PG-13 and R. Rating R is omitted.

Three dummy variables are included for whether the film is shown in 3D, whether the film is an adaptation or remake, and whether the film is a prequel/sequel.

Critical reviews are measured by the percentage of positive out of total reviews for a film. Thus I expect $\beta_{11} > 0$ as positive reviews should increase consumers' expectations and prompt them to watch the film. The significance will depend on the relative importance of critical reviews compared to other information sources such as word-of-mouth and advertising.

[4] Motion Picture Association of America

The variable of interest tweet volume is measured as the total number of tweets for a film. As discussed, given the awareness effect hypothesis, the coefficient is expected to be positive. As this value could theoretically take an unbounded positive value, its natural logarithm is taken.

Tweet sentiment, $posper$, measures the percentage of positive out of total tweets. Therefore the sentiment variable is expected to have a positive coefficient as a higher value implies a higher proportion of positive tweets which according to the theory should increase consumers' expectations leading to more audience and more revenue.

Endogeneity is expected between the independent variable, weekend revenue, and the word-of-mouth measures due to a reciprocal causality. Word-of-mouth may be a precursor as well as an outcome of consumer behaviour (Godes and Mayzlin, 2004). According to the hypotheses, a high level of word-of-mouth is expected to cause high revenue. Likewise, high revenue implies high audience numbers thus high word-of-mouth. I wish to avoid using Instrumental Variables estimation as this would involve using an indirect observation of word-of-mouth as an instrument, which is one area where this paper aims to contribute to the literature. Therefore, as in Liu (2012), I exploit the timing of the revenue and word-of-mouth variables. Tweet data is coded such that $t = 1$ refers to the pre-release week from Monday to Thursday which corresponds to opening weekend revenue for $t = 1$ from Friday, Saturday and Sunday. The same definitions apply to subsequent weeks. Appendix 2 gives a diagrammatic representation of the timing. This should serve to limit the effect of endogeneity.

Ordinary Least Squares regressions were used to distinguish between the individual weekly effects and to investigate the word-of-mouth effects with total domestic gross revenue as the dependent variable. Potential non-normality was suspected due to the skewed, kurtotic and scale-free revenue distributions that are typical of the film industry due to the dominance of extreme events (blockbusters generate the majority of the revenue in the industry). This would violate the OLS assumption that the residuals are normally distributed. Under OLS, non-normality causes unbiased but inefficient estimates. To address this, log specifications were used for any variables that could take a theoretically infinite value. Appendix 3 presents the results of a Jarque-Bera test for normality.

The Central Limit Theorem proposes that as the number of observations tends to infinity, skewness approaches 0 and kurtosis approaches 3 portraying the features of the normal distribution. Therefore, for sufficiently large samples ($n > 30$), the normal distribution can act as an approximation. Hence, OLS is appropriate for this data.

A Balanced Random Effects regression was also run as a robustness check and to explore the across time effects of word-of-mouth on revenue. Fixed Effects regression was deemed inappropriate due to the large number of time-invariant independent variables in the model, which are absorbed by the intercept in a fixed effects model due to their perfect collinearity with the individual dummies. This is consistent with previous literature (Liu, 2012).

5. Data description

Panel data has been manually collected for 90 individuals films over 3 times periods: $t = 1$ (pre-release week and opening weekend), $t = 2$ (opening week and 2nd weekend) and $t = 3$ (second week and 3rd weekend). The dependent variables box-office weekend revenue and total domestic gross revenue are collected from online film database *The-Numbers.com*[5][6]. The independent film-specific covariates such as production budget, number of theatres,

[5] Any missing values were supplemented by data from *Boxofficemojo.com*
[6] Data courtesy Nash Information Services, LLC (www.the-numbers.com)

genre, MPAA rating, whether the film is shown in 3D, is an adaptation, is an prequel/sequel and critical reviews are also collected from *The-Numbers.com*.

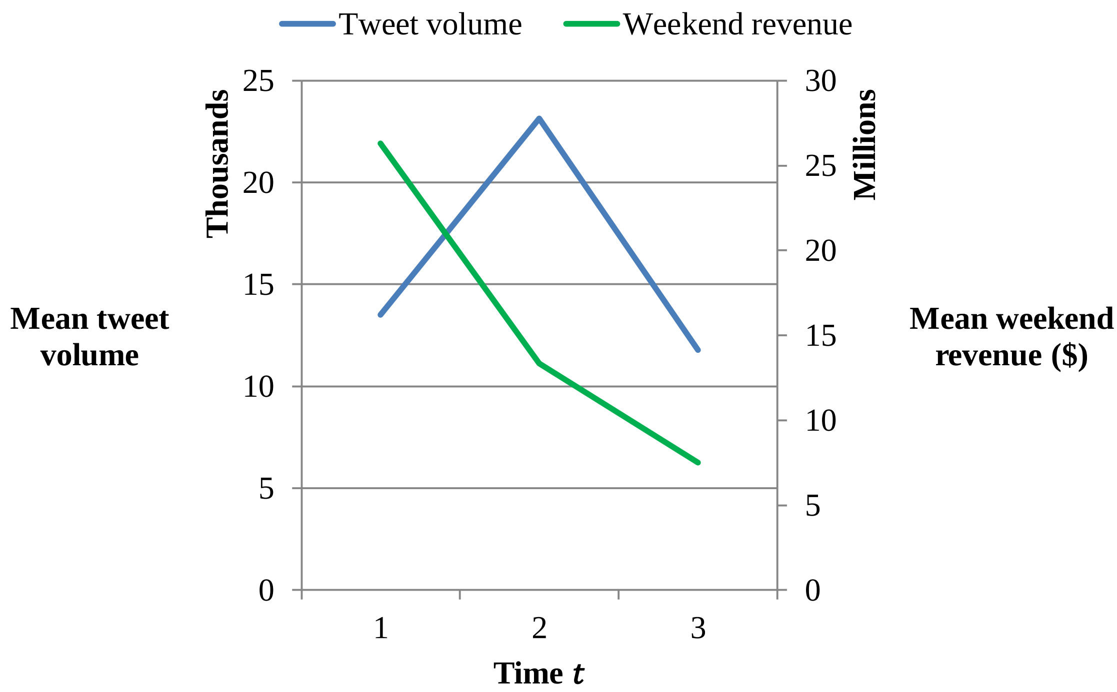
Word-of-mouth data is collected from *Boxoffice.com* who report a 'Twitter Index' which includes daily tweet counts and the positive to negative ratio[7] of tweets for theatrical films. These were coded into weekly measures of volume and sentiment, the variables of interest.

There are several caveats concerning the collection of word-of-mouth data. It is impossible to observe every instance of word-of-mouth on *Twitter*. Problems that may arise during collection include generic film names, spelling mistakes, or tweets not directly referencing the film title.

Films collected were based on the top 150 of *IMDb.com*'s list of most popular feature films released in 2010. The final sample required films to 1) be given initial wide-release at the US box-office, 2) have complete revenue, word-of-mouth, budget and theatre data. This resulted in a final sample of 90 individual films.

The revenue and word-of-mouth data are consistent with industry characteristics and previous literature. Weekend revenue peaks in the opening weekend then sharply declines. 89 of the 90 films report their highest revenue in the opening weekend. *Twitter* activity is most prevalent in the opening week. The minimum value of the percentage of positive reviews is 50%. That is, the amount of positive reviews always exceeds, or is equal to, the number of negative reviews. The decrease in the mean percentage of positive reviews may reflect the pre-release high expectations of consumers which increases the likelihood of disconfirmation of expectations leading to a decrease in positivity of word-of-mouth in subsequent weeks (Liu, 2006). Appendix 5 provides summary statistics of key variables.

[7] Neutral and objective opinions are not observed



One limitation of the data is it only covers the pre-release week and the first two weeks of a film's run. However, for this data, the first two weekend's revenue account for 59% of the total domestic gross. This is consistent with the industry trend of revenues to peak at release and follow an exponential decay over time. Previous studies have consistently discovered insignificance of word-of-mouth measures in later weeks (Liu, 2006) thus this is not a major deficiency and should not detract from my conclusions. Some other studies also concern a similar time period (Duan, Gu and Whinston, 2005). Furthermore, the data includes another dependent variable that aggregates revenue for the entire run of each film thus incorporating data from the later weeks.

6. Results

Table 1 presents the weekly OLS regressions. Regarding week 1, the coefficient on the *ltweets* is positive and significant at the 0.1% level, thus providing support for the first hypothesis. It implies a 1% increase in the volume of pre-release tweets corresponds to a 0.244% increase in opening weekend revenue. This is consistent with Liu (2006) whose sample indicates a corresponding value of 0.592%[8].

As hypothesised, pre-release sentiment is insignificant in explaining opening weekend revenue. Regarding hypothesis 2, the sentiment of tweets remains insignificant for all weeks although it has notably increased in significance by the weekend of week 2. One limitation of the data is the lack of data past week 2. It may be that sentiment becomes significant in subsequent weeks as in Liu (2012) but the data provides inconclusive support for this hypothesis. However, it does show that by the second weekend, the volume measure of word-of-mouth has lost significance, suggesting that consumers learn from the informative effect in the early weeks of a film's run but in the later weeks rely on information from alternative sources such as advertising and critical reviews. This is reinforced by the increasing significance of both the budget and critics variables. Critical reviews become significant at the 0.1% level in week 3.

This conclusion is further supported by analysis of the coefficient and significance of the lagged volume of tweets variable. Insignificance in week 2 suggests that it is only the word-of-mouth in the directly preceding week that determines revenue that weekend. A positive and significant coefficient for week 3 suggests that for later weeks, it is the volume of tweets in the earlier weeks that are most important.

The one week lag of tweet sentiment is significant at the 5% level in week 3; however, it does not have the expected sign. One explanation may be that due to the specification of the percentage of positive reviews, a value closer to 0.5 implies opinion is more divided. This might make consumers more likely to watch the film to form their own opinion. We might

[8] The slight difference may be attributed to Liu (2006) using weekly revenue in his specification, instead of weekend revenue as employed in this paper

expect the sign to turn positive in subsequent weeks as consumers' trust in the sentiment of the word-of-mouth increases as more people have watched the film leading to a more substantial consensus on its quality being determined.

Table 1

Week (t)	1	2	3
lbudget	**0.088**	**0.090**	**0.118***
	(0.069)	**(0.070)**	**(0.053)**
ltheatres	**2.079*****	**2.191*****	**1.533*****
	(0.330)	**(0.346)**	**(0.090)**
threed	**0.044**	**0.131**	**0.201**
	(0.153)	**(0.151)**	**(0.118)**
adaptation	**-0.002**	**-0.005**	**-0.110**
	(0.099)	**(0.098)**	**(0.079)**
prequel	**0.048**	**-0.016**	**-0.055**
	(0.133)	**(0.130)**	**(0.099)**
horror	**0.106**	**-0.044**	**-0.092**
	(0.177)	**(0.195)**	**(0.152)**
action	**0.067**	**0.006**	**0.072**
	(0.160)	**(0.160)**	**(0.124)**
comedy	**-0.005**	**-0.030**	**0.103**
	(0.152)	**(0.153)**	**(0.116)**
ratingpg	**-0.136**	**0.109**	**0.194**
	(0.165)	**(0.168)**	**(0.128)**
ratingpg13	**-0.100**	**0.135**	**0.167**
	(0.121)	**(0.127)**	**(0.095)**
critics	**0.004**	**0.006***	**0.007*****
	(0.002)	**(0.002)**	**(0.002)**
ltweets	**0.244*****	**0.265****	**0.002**
	(0.047)	**(0.081)**	**(0.090)**
lagltweets	**-**	**-0.088**	**0.168**
		(0.091)	**(0.085)**
posper	**0.003**	**-0.002**	**0.012**
	(0.006)	**(0.006)**	**(0.009)**
lagposper	**-**	**0.232**	**-0.018***
		(0.713)	**(0.009)**
const	**-16.578*****	**-17.627*****	**-12.403*****
	(2.477)	**(2.591)**	**(0.627)**
R^2	0.7542	0.7914	0.9191

Dependent variable: LWKNDREV
z-values are in parentheses
* p<0.05; ** p<0.01; *** p<0.001

The insignificance of the film-specific control variables is consistent with the literature (Liu, 2006; Liu, 2012) and are not reported henceforth but are included to correct for the degrees of freedom.

Table 2 presents the results of an OLS regression with the natural logarithm of total domestic gross revenue as the dependent variable. This provides support for hypothesis 3 and serves as a robustness check for hypothesis 1. The volume of pre-release tweets is significant in explaining aggregate revenue as a 1% increase in the number of tweets prompts a 0.19% increase in total revenue.

Table 2

Variable	Coefficient
lbudget	**0.199**** **(0.074)**
ltheatres	**2.302***** **(0.353)**
critics	**0.006*** **(0.002)**
ltweets	**0.191***** **(0.050)**
posper	**0.007** **(0.006)**
const	**-17.666***** **(2.646)**
R^2	0.7760

Dependent variable: LDOMGROSS

To determine the across time effects of word-of-mouth, a balanced Random Effects regression was run. The results, as presented in Table 3, are consistent with the findings from the weekly regressions. The average effect of volume of tweets across time is significant with a coefficient of 0.209. This is lower than the regression for week 1 which is representative of the higher tweet activity in the first two weeks. Tweet sentiment is still insignificant across time.

Table 3

Variable	Coefficient
lbudget	**0.087**
	(0.053)
ltheatres	**1.920*****
	(0.129)
critics	**0.005****
	(0.002)
ltweets	**0.209*****
	(0.033)
posper	**-0.000**
	(0.004)
const	**-15.431*****
	(0.927)
R^2 within	0.3977
R^2 between	0.8697
R^2 overall	0.7087

Dependent variable: LWKNDREV

Regarding hypothesis 4, Table 1 illustrates that critical reviews are significant in weeks 2 and 3, whilst tweet sentiment remains insignificant throughout. The Random Effects regression consolidates these effects. As both these variables represent quality judgements, consumers may consider professional critical reviews as a substitute to quality learning from tweets. Hence, the critical reviews variable may be swamping the effects from tweet sentiment. To further investigate this, the Random Effects regression is re-run, omitting critical reviews. The results are reported below. The percentage of positive reviews has notably increased in significance from a p-value of 0.986 to a p-value of 0.232. However, it remains insignificant. This provides evidence against hypothesis 4 and suggests that critical reviews and tweet sentiment may be substitutes.

Table 4

Variable	Coefficient
lbudget	**0.074**
	(0.055)
ltheatres	**1.910*** **
	(0.131)
ltweets	**0.225*** **
	(0.034)
posper	**0.005**
	(0.004)
const	**-15.672*** **
	(0.942)
R^2 within	0.4011
R^2 between	0.8547
R^2 overall	0.6996

Dependent variable: LWKNDREV

As a robustness check, the OLS regressions were re-run with weekend revenue per theatre as dependent variable, as shown in Appendix 6. The results are consistent with my conclusions. Notably, as hypothesised, the sentiment of tweets becomes significant in week 3. Another point of interest is that by accounting for the number of theatres in the dependent variable, budget becomes significant. This could suggest that the number of theatres reflects some of the information consumers learn from advertising as the decision to open on a large number of theatres is likely to be supported by a large advertising campaign to attract audiences to meet the supply of theatre seats.

Considering the potential endogeneity of the number of theatres, the data was unable to provide a suitable instrument in order to conduct IV estimation. However, the regressions were re-run removing the theatre variable (Appendix 7). The conclusions do not change hence endogeneity is not considered a serious problem for this sample.

Specification tests[9] were run to check that the estimates were unbiased. The model is found to exhibit no heteroskedasticity or omitted relevant variables and indicates acceptable Variance Inflation Factors with a mean VIF of 2 suggesting that multicollinearity is not an issue.

7. Conclusion

This paper investigates the word-of-mouth information dynamics for films and aims to explain its impact on the uncertainty of demand and the existence of social learning. The main finding is that the informative effect of word-of-mouth tends to dominate, particularly in the early weeks, via increasing awareness. This is consistent with much of the existing literature on word-of-mouth effects (Liu, 2006; Duan, Gu and Whinston, 2005; Asur and Huberman, 2010). It supports Ellison and Fudenberg (1995) as herding behaviour is observed in the first two weeks, then as information has accumulated and spread in later weeks, consumers are less likely to conform by merely being influenced by volume, and more likely to exhibit diversity. In contrast to Liu (2012), the results suggest that consumers are less concerned with quality learning via word-of-mouth and are more likely to be influenced on product quality from professional critical reviews. The R^2 is higher than some observed in previous literature excluding word-of-mouth effects, thus suggesting that word-of-mouth measures are an important measure to account for in explaining box-office revenue.

Implications

The findings represent the importance of word-of-mouth as a source of information, particularly for experience and information goods. This has important implications and extensions to other industries. If word-of-mouth volume can be detected and accurately measured by firms and shown to reveal consumer preferences, it could have substantial

[9] Appendix 8

implications for their demand, supply and pricing decisions. For example, in the film industry, variable admission prices could be charged depending on the amount of "buzz" films have accumulated online[10]. Given a low price-elasticity of demand for a film, if exhibitors observed high levels of word-of-mouth, implying high audience, they could charge premium prices to maximise revenue. The welfare implications are ambiguous. Observing online word-of-mouth may lead to asymmetric information as firms are provided with information on demand and consequently may be able to price discriminate hence extracting more producer surplus and reducing consumer surplus. However, increased communication between consumers and producers may lead to innovation if firms are able to detect unmet needs of consumers through online discussion which could lead to increased social welfare.

Limitations

Some data limitations have already been mentioned such as the lack of time periods, the imperfect measurement of word-of-mouth and the potential endogeneity of number of theatres.

The autocorrelation of revenue implicitly provides evidence of learning. This paper does not directly address this autocorrelation as including a lagged revenue variable in the regression is likely to swamp the effects of the variables of interest. Autocorrelation does not bias the OLS coefficients. However, it can result in underestimation of standard errors which could cause insignificant variables to appear significant. Any future work that could account for the autocorrelation would be beneficial to substantiate such conclusions.

[10] This is pure conjecture. The film industry has complex pricing contracts between distributors and exhibitors based on several metrics.

Future research

One valuable extension would be an investigation into the extent to which online word-of-mouth serves as a suitable proxy for real-world conversations, which are harder to measure than online communication.

Furthermore, this paper only considers the volume and sentiment of word-of-mouth. An enlightening area for future research would be to explore the effects of other measures such as dispersion, duration and intensity.

8. Bibliography

Asur, S., Huberman, B. A. (2010), 'Predicting the Future With Social Media', Social Computing Lab, HP Labs, Palo Alto, California

Banerjee, A. (1992), 'A simple model of herd behavior', *Quarterly Journal of Economics*, vol. 110, pp. 797-817

Banerjee, A. (1993), 'The economics of rumours', *Review of Economic Studies*, vol. 60, pp. 309-327

Bennett, M. 'Twitter looks to introduce Facebook-style 'Like' option', *V3*, Available at: http://www.v3.co.uk/v3-uk/news/2220029/twitter-looks-to-introduce-facebookstyle-like-option, Last accessed: 21/04/2013

Box Office Mojo [online], Available at: http://boxofficemojo.com, Last accessed: 24/01/2013

Contrino, P., Edghill, A. (2010), *The Business of Movies – Boxoffice.com* [online], Available at: http://www.boxoffice.com, Last accessed: 24/01/2013

Dellarocas, C., Awad, N. F., Zhang, X. (2004), 'Exploring the Value of Online Reviews to Organizations: Implications for Revenue Forecasting and Planning', MIT Working Paper

De Vany, A. (2006), 'Ch. 19: The Movies', *Handbook of the Economics of Art and Culture,* vol.1, (Ginsburgh and Throsby, eds, 2006), pp. 615-666, Handbooks in Economics 25, North-Holland

De Vany, A., Walls, W. D. (1996), 'Bose-Einstein Dynamics and Adaptive Contracting in the Motion Picture Industry', *The Economic Journal*, vol. 106

De Vany, A., Walls, W. D. (1999), 'Uncertainty in the movie industry: does star power reduce the terror of the box office?', *Journal of Cultural Economics,* vol. 23, pp. 285–318

De Vany, A., Walls, W. D. (2004), 'Motion picture profit, the stable Paretian hypothesis and the curse of the superstar', *Journal of Economic Dynamics and* Control, vol. 28, issue 6, pp. 1035–1057

Duan, W., Gu, B., Whinston, A. B. (2005), 'Do Online Reviews Matter? An Empirical Investigation of Panel Data', Department of Management Science and Information Systems, McCombs School of Business, The University of Texas at Austin

Elberse, A., Eliashberg, J. (2003), 'Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures', *Marketing Science,* vol. 22, no. 3, pp. 329-354

Ellison, G., Fudenberg, D. (1995), 'Word-of-Mouth Communication and Social Learning', *Quarterly Journal of Economics*, vol. 110, pp. 93-125

Godes, D., Mayzlin, D. (2004), 'Using Online Conversations to Study Word-of-Mouth Communication', *Marketing Science*, vol. 23, no. 4, pp. 545-560

The Internet Movie Database [online], Available at: http://www.imdb.com, Last accessed: 30/11/2012

Liu, Y. (2006), 'Word-of-Mouth for Movies: Its Dynamics and Impact on Box Office Revenue', *Journal of Marketing,* vol. 70, no. 3, pp. 74-89

Liu, Y. H. (2012), 'How Does Online Word-of-Mouth Influence Revenue? Evidence from Twitter', Department of Economics, Suffolk University

McKenzie, J. (2008), 'Bayesian information transmission and stable distributions: motion picture revenues at the Australian box office', *Economic Record,* vol. 84, no. 266, pp. 338–353

McKenzie, J. (2009), ‘Revealed word-of-mouth demand and adaptive supply: survival of motion pictures at the Australian box office’, Journal of Cultural Economics, vol. 33, pp. 279-99

Moretti, E. (2011), ‘Social Learning and Peer Effects in Consumption: Evidence from Movie Sales’, *Review of Economic Studies*, vol. 78, pp. 356-393

Moul, C. C. (2007), ‘Measuring Word of Mouth’s Impact on Theatrical Movie Admissions’, *Journal of Economics & Management Strategy*, vol. 16, no. 4, pp. 859-892

The Numbers [online], Available at: http://www.the-numbers.com, Last accessed: 21/04/2013

Twitter [online], Available at: https://twitter.com/twitter/status/281051652235087872, Last accessed: 21/04/2013

9. Appendices

Appendix 1: Correlation matrix between dependent variable and variables of interest

	lwkndrev	laglwkndrev	ltweets	lagltweets	posper	lagposper
lwkndrev	**1.0000**					
laglwkndrev	**0.9430**	**1.0000**				
ltweets	**0.5926**	**0.6998**	**1.0000**			
lagltweets	**0.4421**	**0.5420**	**0.8569**	**1.0000**		
posper	**0.3426**	**0.2451**	**0.1842**	**0.1321**	**1.0000**	
lagposper	**0.3172**	**0.2568**	**0.2001**	**0.1148**	**0.8219**	**1.0000**

Appendix 2: Diagram illustrating timing of revenue and word-of-mouth variables

<table>
<tr><td colspan="7">$t = 1$</td><td colspan="7">$t = 2$</td><td colspan="7">$t = 3$</td></tr>
<tr><td>M</td><td>T</td><td>W</td><td>T</td><td>F</td><td>S</td><td>S</td><td>M</td><td>T</td><td>W</td><td>T</td><td>F</td><td>S</td><td>S</td><td>M</td><td>T</td><td>W</td><td>T</td><td>F</td><td>S</td><td>S</td></tr>
<tr><td colspan="4">Pre-release week</td><td colspan="3">Opening weekend</td><td colspan="4">Opening week</td><td colspan="3">2nd weekend</td><td colspan="4">Second week</td><td colspan="3">3rd weekend</td></tr>
<tr><td colspan="4">Word-of-mouth</td><td colspan="3">Revenue</td><td colspan="4">Word-of-mouth</td><td colspan="3">Revenue</td><td colspan="4">Word-of-mouth</td><td colspan="3">Revenue</td></tr>
</table>

Appendix 3: Jarque-Bera (S-K) test for normality

Variable	**Observations**	**Pr(Skewness)**	**Pr(Kurtosis)**	**Prob>chi2**
residuals	267	0.118	0.0466	0.0426

Appendix 4: Variable list

Variable	Variable name	Description
Weekend box-office revenue (in natural log)	$lwkndrev$	(The natural logarithm of) the total value of sales each weekend
Total domestic gross revenue (in natural log)	$ldomgross$	(The natural logarithm of) the total value of sales in the domestic country for the film's full theatrical run
Production budget (in natural log)	$lbudget$	(The natural logarithm of) the total cost for the production of the film (pre-production, film, post-production)
Number of theatres (in natural log)	$ltheatres$	(The natural logarithm of) the number of theatres the film is exhibited at each weekend
3D	$threed$	Dummy variable equal to 1 if the film is shown in 3D
Adaptation/remake	$adaptation$	Dummy variable equal to 1 if the film is an adaptation or remake of a previous book/film/play/song
Prequel/sequel	$prequel$	Dummy variable equal to 1 if the film is a prequel or sequel to a previous film
Horror	$horror$	Dummy variable equal to 1 if the genre of the film is horror or thriller
Action	$action$	Dummy variable equal to 1 if the genre of the film is action or adventure
Comedy	$comedy$	Dummy variable equal to 1 if the genre of the film is comedy or romantic comedy
Drama	$drama$	Dummy variable equal to 1 if the genre of the film is drama
Rating PG	$ratingpg$	Dummy variable equal to 1 if the film certificate was rated PG or G by the MPAA
Rating PG-13	$ratingpg13$	Dummy variable equal to 1 if the film certificate was rated PG-13 by the MPAA
Rating R	$ratingr$	Dummy variable equal to 1 if the film certificate was rated R or NC-17 by the MPAA
Critical reviews	$critics$	The percentage of positive critical reviews
Tweet volume (in natural log)	$ltweets$	(The natural logarithm of) the total number of tweets
Tweet sentiment	$posper$	The percentage of positive tweets

Appendix 5: Summary statistics of key variables

Variable	Min.	Max.	Mean	Median	Standard Deviation
Weekend revenue, t=1	$3,048,665	$128,122,500	$25,316,900	$17,972,580	25,149,160
Weekend revenue, t=2	$975,541	$62,714,080	$13,333,240	$9,294,705	$12,579,960
Weekend revenue, t=3	$84,571	$34,189,970	$7,504,345	$5,169,062	$7,001,925
Total domestic gross	$6,000,000	$415,000,000	$85,044,440	$54,500,000	$82,240,460
Production budget	$3,000,000	$260,000,000	$67,876,400	$42,000,000	$57,676,480
Number of theatres, t=1	1622	4468	3036	3056	585.5242
Number of theatres, t=2	1622	4468	3047	3078	583.2841
Number of theatres, t=3	177	4386	2679	2781	842,4633
Critical reviews	4	99	47.31	47.5	24.8572
Tweet volume, t=1	758	101,328	13,512	5,742	20,332.88
Tweet volume, t=2	422	414,290	23,152	7,962	49,513.23
Tweet volume, t=3	335	218,652	11,785	4,166	25,447.32
Tweet sentiment, t=1	50%	96.78%	89.95%	85.6%	0.0915
Tweet sentiment, t=2	50%	96.63%	81.39%	84.55%	0.1230
Tweet sentiment, t=3	50%	97.96%	82.57%	85.97%	0.1171

Appendix 6: OLS regressions with the natural logarithm of weekend revenue per theatre as dependent variable

Week (t)	1	2	3
lbudget	**0.180****	**0.179***	**0.209****
	(0.067)	**(0.069)**	**(0.062)**
threed	**-0.012**	**0.085**	**0.153**
	(0.161)	**(0.161)**	**(0.142)**
adaptation	**0.008**	**0.020**	**-0.116**
	(0.106)	**(0.105)**	**(0.095)**
prequel	**0.173**	**0.114**	**0.035**
	(0.135)	**(0.133)**	**(0.118)**
horror	**0.194**	**0.090**	**0.085**
	(0.185)	**(0.204)**	**(0.180)**
action	**0.147**	**0.109**	**0.090**
	(0.168)	**(0.168)**	**(0.150)**
comedy	**0.105**	**0.112**	**0.162**
	(0.158)	**(0.158)**	**(0.140)**
ratingpg	**0.017**	**0.295**	**0.342***
	(0.168)	**(0.171)**	**(0.151)**
ratingpg13	**-0.028**	**0.223**	**0.247***
	(0.126)	**(0.133)**	**(0.114)**
critics	**0.005***	**0.006***	**0.007*****
	(0.002)	**(0.002)**	**(0.002)**
ltweets	**0.283*****	**0.321*****	**-0.039**
	(0.048)	**(0.085)**	**(0.108)**
lagltweets	**-**	**-0.100**	**0.226***
		(0.097)	**(0.102)**
posper	**0.002**	**0.001**	**0.025***
	(0.006)	**(0.007)**	**(0.011)**
lagposper	**-**	**-0.002**	**-0.023***
		(0.008)	**(0.010)**
const	**-8.750*****	**-8.984*****	**-9.574*****
	(0.658)	**(0.690)**	**(0.492)**
R^2	0.5871	0.6403	0.6718

Dependent variable: LREVPERTHEATRE

Appendix 7: OLS regressions omitting number of theatres

Week (t)	1	2	3
lbudget	**0.265****	**0.254****	**0.379****
	(0.078)	**(0.080)**	**(0.113)**
threed	**-0.064**	**0.047**	**0.062**
	(0.186)	**(0.186)**	**(0.261)**
adaptation	**0.018**	**0.041**	**-0.129**
	(0.122)	**(0.121)**	**(0.174)**
prequel	**0.289**	**0.223**	**0.205**
	(0.156)	**(0.154)**	**(0.216)**
horror	**0.276**	**0.203**	**0.419**
	(0.214)	**(0.236)**	**(0.330)**
action	**0.221**	**0.196**	**0.124**
	(0.195)	**(0.194)**	**(0.275)**
comedy	**0.208**	**0.232**	**0.273**
	(0.182)	**(0.183)**	**(0.257)**
ratingpg	**0.159**	**0.451***	**0.621***
	(0.195)	**(0.197)**	**(0.278)**
ratingpg13	**0.038**	**0.297**	**0.396**
	(0.146)	**(0.154)**	**(0.209)**
critics	**0.005***	**0.006***	**0.008***
	(0.003)	**(0.003)**	**(0.004)**
ltweets	**0.320*****	**0.369*****	**-0.117**
	(0.055)	**(0.098)**	**(0.198)**
lagltweets	**-**	**-0.109**	**0.334**
		(0.112)	**(0.188)**
posper	**0.001**	**0.004**	**0.048***
	(0.007)	**(0.008)**	**(0.019)**
lagposper	**-**	**-0.006**	**-0.031**
		(0.009)	**(0.019)**
const	**-1.493**	**-1.730***	**-4.262*****
	(0.761)	**(0.796)**	**(0.902)**
R^2	0.6245	0.6768	0.5967

Dependent variable: LWKNDREV

Appendix 8: Specification tests

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity:

chi2(1)	**1.69**
Prob > chi2	**0.1935**

Ramsey RESET test:

F(15,60)	**0.98**
Prob > F	**0.4862**