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Reference:

Vujić Sunčica, Zhang Xiaoyu.- Does Twitter chatter matter? Online reviews and box office revenues
Applied economics - ISSN 0003-6846 - Abingdon, Routledge journals, Taylor & Francis Ltd, 50:34-35(2018), p. 3702-3717
Full text (Publisher's DOI): <https://doi.org/10.1080/00036846.2018.1436148>
To cite this reference: <https://hdl.handle.net/10067/1488020151162165141>

Does Twitter Chatter Matter?

Online Reviews and Box Office Revenues[†]

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Abstract

With a rapid rise of text-based social media and online Word-of-Mouth (WOM) activity, millions of people express their thoughts and opinions on a variety of topics. Considering that nowadays WOM is a most influential source of information when guiding consumers' choice and purchase decisions, in this paper we look at the relationship between Twitter messages (tweets) and cinema box office revenues. Using static and dynamic panel data regression approaches, we show that the frequency, sentiment and timing of tweets posted about a film are correlated to different extent with the movie's box office revenues, with negative tweets being particularly damaging to the box office revenues. From a managerial perspective, this is important to know, such that film production companies and distributors can adjust their strategy accordingly.

Keywords: Social Media (Twitter), Cinema Box-Office Sales, Panel Data Models.

JEL classification: M30, C33, C53, C55

[†] Acknowledgments: We would like to thank Felix Ming Fai Wong for sharing the data from the paper of Wong et al. (2012).

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I. Introduction

Social media, such as Facebook, Wikipedia, blogs and microblogs (e.g., Twitter), YouTube, LinkedIn, etc.² refer to the means of interactions among people in which they create, share, and exchange information and ideas in virtual communities and networks (Ahlqvist et al., 2008). Compared to the more traditional ones (based on face-to-face communication), social media and social networks are arguably less personal, but they are easily accessible at minimal cost, have a significant reach, can be amended to incorporate additional information, and are more capable of immediate responses to queries (Hennig-Thurau et al., 2004). Due to its advantages, this relatively recent phenomenon is becoming an increasingly important part of our lives. For example, Figure 1 shows the number of social network users worldwide from 2010 to 2016 with the projections until 2020 (in billions). In 2016, one third of the world population was in some sort of social networks. In 2018, it is estimated that there will be around 2.67 billion social network users around the globe, up from 1.91 billion in 2014 (Statista, 2016).

What comes with this new phenomenon is the availability of a vast amount of (personal) data. Similar information would have been extremely difficult to obtain in such large quantities prior to the creation of social media and social networks, since large public surveys are normally considered to be costly and time-consuming.³ Hence,

² Kaplan and Haenlein (2010) classified social media into six categories by characteristic: (1) Social networks (e.g., Facebook) allow people to reunite or form new communities and attract millions of users on a daily basis; (2) Collaborative projects (e.g., Wikipedia) put a twist on the traditional encyclopaedias and provide the community with easy access to knowledge; (3) Blogs and microblogs (e.g., Twitter) permit people to share their opinions with the world; (4) Content communities (e.g., YouTube) allow various kinds of video sharing for the purpose of entertainment and truth telling; (5) Virtual social worlds (e.g., Second Life) allow users to experience various aspects of face-to-face interaction in a virtual world; (6) Virtual game worlds (e.g., World of Warcraft) are similar to virtual social worlds but with less self-disclosure as user behaviour is limited by strict guidelines.

³ O'Connor et al. (2010) connect measures of public opinion measured from polls with sentiment measured from Twitter text messages and demonstrate that relevant sentiments observed from tweets correlate well

researchers and business decision-makers started to take an interest in these data as a way of helping them identify consumer trends and predict their behaviour (Maresova et al., 2015; Asur and Huberman, 2010). In viral marketing, firms have begun utilising tweets, microblogs and Word-of-Mouth (WOM) (Buttle, 1998; Ennew et al., 2000) to perform sentiment analysis and extract the crowd’s mood or a feeling towards a product, which is then subsequently used when designing marketing and advertising campaigns and the firm’s overall strategy (Jansen et al., 2009; Lee et al., 2008; Leskovec et al., 2007).

In this paper we look at the relationship between cinema box office revenues and Twitter messages (tweets), one of the fastest growing social networks on the Internet.⁴ Twitter is a micro-blogging network, which enables users to send/receive text-based online messages of up to 140 characters (so-called “tweets”), averaging 11 words per message (O’Connor et al., 2010). It can be described as a *directed social network*, where each user has a set of subscribers known as followers. Twitter updates usually consist of personal information about the users, news or links to content such as images, videos and articles. We examine both the tweet sentiment (*positive*, *negative*, and *mentioned*) and the tweet temporal context (*before*, *after*, *current*, and *don’t know*) in order to explain box office revenues for a particular movie.

We have focused on explaining cinema box office revenues for a particular movie using the chatter from Twitter for the following reasons. (i) Posting Twitter messages about the movies is characterized both by a large number of users discussing movies, as well as a substantial variance in their opinions (Asur and Huberman, 2010). A large

with polling data on consumer confidence and political opinion, and can also predict future movements in the polls.

⁴ According to Statista (2016), the number of active Twitter users in 2016 at about 300 million was comparable to Instagram (400 million), Skype (300 million) and Viber (249 million), but it is lagging behind Facebook (1,590 million) and WhatsApp (1,000 million).

amount of tweets ensures the neutrality of the reviews. We cannot underestimate the power of these tweets, since in many cases they do have the ability to reflect a person's thoughts about something at a particular point of time. One or two tweets by themselves may not mean much, but when millions of them are collected, it is possible to extract crowd sentiments for a specific purpose (O'Connor et al., 2010). Finally, rapid spread of Word-of-Mouth (e.g., through Twitter) and "movie-gossip Web sites" have been an important factor of financial success of Hollywood entertainment industry (Orwall and Ramstad, 2000). However, prior research on the relationship between WOM and market performance of motion pictures is rather limited (Duan et al., 2008). (ii) The movie industry is of interest to both economists and the public because of its high profits and entertainment nature (Zhang and Skiena, 2009). For example, in 2015, the total revenue of the U.S. movie market was \$11.3 billion and it's on the growing path.⁵ Cinema box office sales measure the gross revenue generated by a particular movie and therefore is widely used as an indicator of the movie's overall success and popularity. The decision-makers in the motion picture industry care greatly about it, because of its vast impact upon various aspects, particularly the potential profitability of a given film. For example, the producers use this figure as a base of deciding whether a sequel should be made, and if so, what the budget should be. Also, for the film distributors, depending on how well the theatrical distribution was, they may alter their non-theatrical and home video distribution strategy (Marich, 2013). Finally, prices of movie tickets are fixed, typically determined by local markets, and cannot be adjusted as a response to demand shocks (Friberg and Grönqvist, 2012; Duan et al., 2008). (iii) The real-world outcomes for both cinema box-office revenues as well as Twitter chatter about a particular movie can be

⁵ Source: <http://www.the-numbers.com/market/>

easily observed. These are high frequency data (hourly, daily), enabling different empirical (econometric) analyses. The challenges in this domain are related to measuring and classification of the vast amount of WOM information available on Internet (Godes and Mayzlin, 2004).

The results of the paper can be summarized as follows. The daily box office revenues are autocorrelated – the previous day’s box office revenue is significantly correlated with the box office revenues in the current period. There is a positive relationship between the total volume of tweets and the cinema box office revenues, thus indicating the importance of product *awareness* effect (Duan et al., 2008). Negative tweets decrease cinema box office revenues, which is in line with the previous literature on the effect of negative movie reviews (Basuroy et al., 2003; James, 2006). Finally, tweets posted before watching the movie (and while in the cinema) increase cinema box office revenues, thus capturing the hype that has been built up about a movie based on its trailer and other methods of pre-release advertisement.

In relation to the existing literature from marketing and information sciences, relating large-scale social media (Twitter) content with movie box-office revenues (Liu et al., 2016; Hur et al., 2016; Barthelemy et al., 2012; Wong et al., 2012; Asur and Huberman, 2010; O’Connor et al., 2010; Duan et al., 2008), the longitudinal nature of the data, as well as static and dynamic panel data regression approaches, enable us (i) to take into account that the daily box office revenues are autocorrelated, (ii) to control for individual product (movie) heterogeneity, and (iii) to treat the online user reviews as endogenous. Only Duan et al. (2008) have previously used the panel data approach in this context, although the authors split their analysis by different weeks, not fully utilising the

longitudinal nature of the available data. Relating cinema box office revenue for a particular movie to the chatter from Twitter *has not*, to the best of our knowledge, been previously explored in the economics literature.

The remainder of the paper is organised as follows. Section 2 presents an overview of related literature. Section 3 describes the data and the empirical approach. Section 4 provides estimation results and robustness checks. Section 5 concludes the paper.

II. Related Literature

Related literature can be divided into three strands: (i) theoretical predictions from behavioural economics literature on information transmission and learning from others; (ii) literature predicting cinema box office sales relying on public opinion gathered through social media and online (expert) reviews; and (iii) literature predicting demand for other products relying on social media and expert reviews.

(i) Paper by McFadden and Train (1996) provides an early theoretical model on the implications of learning from self and others on the sales of new products. With one-shot purchases (such as movies and books), there is no value from learning from self (since the information cannot be used in future purchase decisions), and firms which know that learning from others will affect their sales will be more willing to invest in products that satisfy the tastes and needs of a majority of the population. Banerjee (1992, 1993) studies the economics of rumours (Banerjee, 1993) and the herd behaviour (Banerjee, 1992), and shows that people might rely on the decision of others rather than use their own information. Ellison and Fudenberg (1995) study WOM communication

and social learning and show that decision conformity among agents is more likely with less communication. Kirman (1993) makes a comparison between ants and economics agents and shows that “recruitment”, “contagion”, “mimicking”, or “herding” might lead to an asymmetric distribution of market share between two products with the same quality.

(ii) Despite a large popularity of social networks in general and Twitter in particular, previous literature on the use of microblogs in order to extract WOM and public opinion on products, elections, movies, etc., is rather limited.⁶ In the context of movie industry, early research uses different proxies for WOM, such as online user reviews (Chintagunta, et al., 2010; Dellarocas et al., 2007; Zhang et al., 2004), revenues per screen collected in the previous week (Elberse and Eliashberg, 2003), or cumulative viewership (Neelamegham and Chintagunta, 1999). The findings on the relationship between WOM and the cinema box office revenues are mixed, which can be explained by the imprecise measurement of WOM (Neelamegham and Chintagunta, 1999). On the other hand, there is a range of studies in (cultural) economics and marketing sciences providing evidence on a positive relationship between online expert reviews and market performance of motion pictures (Pentheny, 2015; Koschat, 2012; Gemser et al., 2007; Reinstein and Snyder, 2005; Basuroy et al., 2003; Eliashberg and Shugan, 1997).⁷

⁶ Nielsen “Trust in Advertising Report” (<http://www.nielsen.com/us/en/insights/news/2013/under-the-influence-consumer-trust-in-advertising.html>) shows that in 2013, 84% of respondents around the globe say that WOM recommendations from friends and family, often referred to as *earned advertising*, are the most influential, while 68% trust consumer opinions posted online when purchasing goods and services.

⁷ Pentheny (2015) further differs between the source of the review – consumer or critic, and takes into account the *identity of the consumer*. Koschat (2012) also stresses that the impact of the third-party endorsements on a consumer depends on the consumer’s type and his/her media portfolio, while Chatterjee (2001) specifies that better-informed consumers are less likely affected by the negative reviews. In their paper on the relationship between expert reviews and the demand for wine, Friberg and Grönqvist (2012) argue that *identity of a reviewer* is also important.

More recently, researchers have started using different computational linguistics techniques in order to extract WOM and positive/negative sentiments from abundance of personal data available through online movie reviews sites and Twitter chatter. For example, Wong et al. (2012) investigate the predictive limitations of tweets for cinema box office sales and show that, compared to opinions from other online movie reviews sites (such as IMDb – International Movie Database, and Rotten Tomatoes), Twitter opinions are positively biased and do not necessarily translate into predictable box-office sales. Conversely, Asur and Huberman (2010) show that tweet frequency and positive/negative tweet sentiments can be used to forecast the cinema box office revenues after the movies are released, and that they outperform market-based predictors, such as the Hollywood Stock Exchange, while Zhang and Skiena (2009) use a high-speed text processing analysis of online daily newspapers along with the IMDb data in order to forecast cinema box office sales. More recently, Liu et al. (2016) and Hur et al. (2016) use linear and nonlinear regression models and show that large-scale social media (Twitter) content is correlated with movie box-office revenues. Barthelemy et al. (2012) demonstrate various techniques (count the occurrence of the title in tweets; Naïve Bayes; a bag-of-words model) for estimating tweet frequencies and attempt to use these to predict movie revenue. However, the authors point that adding other factors, such as revenue of the lead actor, budget of the movie, etc., could provide a better model for revenue prediction.⁸

⁸ In order to forecast cinema box office sales using regression or stochastic models, previous research uses information about the movies themselves, such as the movies genre, Motion Picture Association of America (MPAA) rating, running time, release date, the number of screens on which the movie debuted, and the presence of particular actors or actresses in the cast (see for example, Simonoff and Sparrow, 2000; De Vany and Walls, 1999).

Previous literature benefits from the cross-sectional or time series dimension of the data and mostly looks at correlations between WOM and box-office revenues (with the exception of Sharda and Delen (2006) who use the neural networks approach). A limited number of papers discuss the exogeneity assumption of WOM (Duan et al., 2008; Reinstein and Snyder, 2005; Elberse and Eliashberg, 2003). Further, most of the papers do not take into account idiosyncratic (both observable and unobservable) movie effects.

Most related to our methodological approach is the paper by Duan et al. (2008) who examine the persuasive and awareness effects of online user reviews on movies' daily box office performance using simultaneous equations panel data regression approach. The authors show that the *rating* of online user reviews has no significant impact on movies' box office revenues after accounting for their potential endogeneity, indicating that online user reviews have little persuasive effect on consumer purchase decisions. However, the authors find that box office sales are significantly influenced by the *volume* of online posting, suggesting the importance of product awareness effect. Although the paper takes into account both unobserved movie heterogeneity and endogeneity of online WOM, the authors split their analysis by different weeks, hence not fully utilising the longitudinal nature of the data.

(iii) Considering other products, Foster and Rosenzweig (1995) attributed adoption of new technologies in agriculture to learning from others (WOM) effect. Gruhl et al. (2005) show how online chat activity predicts book sales, while Shaman and Karspeck (2012) build a statistical model based on Google search data to predict flu outbreaks seven weeks ahead. Bollen et al. (2010) study how public mood extracted from Twitter messages can be used to predict the Dow Jones Industrial Average (DJIA) over

time. O'Connor et al. (2010) show that results from presidential job approval and consumer confidence polls can be replicated by the relevant sentiments observed from tweets. More recently, Maresova et al. (2015) analyse the use of social networks with respect to customer support in the banking sector in the Czech Republic, while Friberg and Grönqvist (2012) use expert reviews in leading print media in Sweden to examine the demand for wine.

II. Data Description and Empirical Approach

2.1 Data Description

Data analysed in this paper contain daily tweets in relation to five different movies (Chronicle, The Grey, The Iron Lady, The Woman in Black, and This Means War). The movies were released in the period between the 30th December 2011 and the 17th February 2012.⁹ The tweets about the movies were collected on an hourly basis a few weeks straight after the release of the relevant movie, when most of the box office revenue is gathered and people are very active at expressing their opinions about the movie. The sample period also coincides with the Academy Awards season (the Oscars). For every movie, the total number of tweets gathered per hour is partitioned into subsets based on the tweet relevance (*relevant* and *irrelevant*), the tweet sentiment (*positive*, *negative*, and *mentioned*) and the tweet temporal context (*before*, *after*, *current*, and *don't*

⁹ Based on the information from www.boxofficemojo.com, The Iron Lady was released on the 30th December 2011, The Grey was released on the 27th January 2012, both Chronicle and The Woman in Black were released on the 3rd February 2012, while This Means War was released on the 17th February 2012.

know). For an example of tweet classifications, see Table 1. For further information about the data collection, see the paper by Wong et al. (2012).¹⁰

Hourly tweet frequencies are aggregated to daily tweet frequencies in order to ensure comparability with the daily revenue data, collected from the Box Office Mojo website.¹¹ Only *relevant* tweets are retained and analysed in the paper. The final dataset after aggregation consists of 151 tweet-days in relation to the relevant movie, in the period between the 03rd February 2012 and the 07th March 2012. Table 2 shows the summary statistics of the final sample used in the panel regression analysis (see later).

Figure 2 and Figure 3 show the tweet composition with respect to the tweet sentiment and the tweet temporal context, respectively. The majority of tweet sentiments seem to be positive or neutral (*mentioned*), indicating that most tweets are helpful in publicizing the movie through WOM. In terms of timing, tweets posted before and after watching a film are the majority of all tweets posted for each movie.

Figure 4 shows the *polarity* ratio (Asur and Huberman, 2010), defined as a ratio of positive to negative tweets, by movie, by week. The number of positive tweets exceeds the number of negative tweets by a large margin for all the movies (weeks) in the sample. Positive sentiments following the release of a movie can be considered as recommendations by people who have seen the movie, and are likely to influence others who are going to watch the same movie (Asur and Huberman, 2010). Further, such a

¹⁰ Tweets used for this paper are part of the final dataset by Wong et al. (2012), collected in the period from 0:00 hour on the 3rd February 2012 to 0:00 hour on the 8th March 2012. They used the Twitter Streaming API (<https://dev.twitter.com/streaming/overview> – a Twitter tool that enables real time extraction of tweets) to gather a total of 12 million worldwide tweets by tracking keywords in the titles of their 34 selected movies. The posting language was limited to English due to the high level of difficulty to filter for keywords in other languages. After filtering out the spurious tweets with keywords in the wrong order, and accounting for variation in spacing and punctuation, they obtained their final dataset of 1.77 million tweets. Out of these 1.77 million tweets, 51% were classified as irrelevant, and the authors focus their analysis on the remainder of 49% of relevant tweets.

¹¹ www.boxofficemojo.com

large positive bias might be due to the psychology of cultivating optimistic and helpful image among their followers, which can have implications for developing marketing and advertising campaigns, i.e., focusing on enhancing positive reviews, rather than reducing negative reviews from a few dissatisfied customers (Wang et al., 2012). The jump in week 8 for *The Iron Lady* picks well the positive buzz created by the two Oscar nominations for this film.¹² In comparison to other online movie reviews sites (such as IMDb and Rotten Tomatoes), Twitter users are more positive in their reviews, except for Oscar-nominated films (Wang et al., 2012).

Figure 5 shows the *subjectivity* ratio (Asur and Huberman, 2010), defined as a ratio of positive and negative tweets to neutral (objective) tweets, by movie, by week. Except for *The Iron Lady*, subjectivity decreases the further away we are from the release date of the film.

Figure 6 plots the log-transformed time series of total tweets against the daily gross revenues by a relevant movie. Both series of Twitter messages and daily gross revenues show a declining trend after the release of the movie. Further, the trends of the two series seem to coincide, exhibiting peaks and troughs over roughly the same periods. The tweets series is smoother than the daily gross revenues series, while the peak in the tweets series for *The Iron Lady* coincides with the two Oscar nominations for this film. Figure 7 and Figure 8 show similar patterns with respect to the log-transformed time series of tweet sentiments (Figure 7) and tweet timing (Figure 8) against the daily gross revenues by a relevant movie.

¹² Meryl Streep won the Oscar for the Best Performance by an Actress in a Leading Role, while Mark Coulier and J. Roy Helland won the Oscar for the Best Achievement in Makeup for this movie.

2.2 Empirical Approach

In order to examine the effect of the volume of tweet posting on box office revenues, we utilise the panel regression approach. We begin the empirical analysis by validating the relationship between daily gross revenue and daily tweet posting rate. Following Verbeek (2012), the empirical specification is:

$$Daily\ gross_{it} = \alpha_i + \beta_1 Total\ tweet_{it} + \varepsilon_{it} \quad (1)$$

where *Daily gross* is a daily gross revenue for movie *i* in day *t* (in US dollars), and *Total tweet* refers to a total number of tweets per movie per day. We next expand the analysis by examining the effect of the tweet sentiments (*positive*, *negative*, and *mentioned*) on film revenues:

$$Daily\ gross_{it} = \alpha_i + \gamma_1 Positive_{it} + \gamma_2 Negative_{it} + \gamma_3 Mentioned_{it} + \varepsilon_{it} \quad (2)$$

Finally, we explore how the impact of tweets differs with respect to the tweet temporal context (*before*, *after*, *current*, and *don't know*):

$$Daily\ gross_{it} = \alpha_i + \delta_1 Before_{it} + \delta_2 After_{it} + \delta_3 Current_{it} + \delta_4 Don't\ know_{it} + \varepsilon_{it} \quad (3)$$

In all model specifications (1) to (3), the variables are log-transformed in order to stabilize the level and the variance of a series. The α_i captures the movie fixed effects, which are constant over time. This should pick up the idiosyncratic characteristics associated with each movie, such as movie genre, salary of the lead actor, Oscar nomination(s), movie budget, marketing costs, the company distributing the movie, etc. The movie fixed effects further capture all time-invariant unobserved movie-specific effects, which are potentially correlated with the observed regressors, thus making the estimation more flexible and robust (Duan et al., 2008). All model specifications have

further been estimated without and with inclusion of the time (weekend and month) fixed effects. The ε_{it} is assumed to be independent and identically distributed over individual movies and time, with mean zero and variance σ_ε^2 . To account for possible remaining correlation in the error term, over time and across different movies, we clustered standard errors at the movie level. Hence, the models (1) to (3) are estimated as the standard *fixed effects models*, with robust standard errors.¹³

Previous research (De Vany and Walls, 1999; Elberse and Eliashberg, 2003; Reinstein and Snyder, 2005; Duan et al., 2008) argues that box office revenues are autocorrelated – the box office revenues in the current period are likely to be highly correlated with the box office revenues in the previous period. Further, it can be argued that the daily tweets are endogenous, due to the reverse causality. In order to account for the assumption that the (daily) box office revenues are autocorrelated and that the daily tweets are endogenous, we also estimate the dynamic version of equations (1) to (3):

$$\begin{aligned} \text{Daily gross}_{it} = & \alpha_i + \beta_0 \text{Daily gross}_{it-1} \\ & + \beta_1 \text{Total tweet}_{it} + \varepsilon_{it} \end{aligned} \quad (1a)$$

$$\begin{aligned} \text{Daily gross}_{it} = & \alpha_i + \gamma_0 \text{Daily gross}_{it-1} \\ & + \gamma_1 \text{Positive}_{it} + \gamma_2 \text{Negative}_{it} + \gamma_3 \text{Mentioned}_{it} + \varepsilon_{it} \end{aligned} \quad (2a)$$

$$\begin{aligned} \text{Daily gross}_{it} = & \alpha_i + \delta_0 \text{Daily gross}_{it-1} \\ & + \delta_1 \text{Before}_{it} + \delta_2 \text{After}_{it} + \delta_3 \text{Current}_{it} \\ & + \delta_4 \text{Don't know}_{it} + \varepsilon_{it} \end{aligned} \quad (3a)$$

¹³ Random effects estimator, although (asymptotically) most efficient estimator, often suffers from the problem of endogenous regressors. Hence, we have opted for the fixed effects estimator here, since we explicitly deal with the potential endogeneity of regressors when estimating the dynamic panel regression results.

where $Daily\ gross_{it-1}$ is a daily gross revenue for movie i in day $t - 1$ (in US dollars). The models (1a) to (3a) are estimated using the Arellano-Bond (1991) difference GMM estimator. There are several advantages of this approach. (i) The model enables treating the daily tweets as endogenous, since the causality may run in both directions – from the volume of tweets to the box office revenues and vice versa, hence making the tweets potentially correlated with the error term. The difference GMM estimator uses the lagged levels of the endogenous regressors (daily volume of tweets) as their instruments. This makes the endogenous variables pre-determined and, therefore, not correlated with the error term. (ii) In the presence of the lagged dependent variable $Daily\ gross_{it-1}$ and autocorrelation in the error term, the assumption of regressor exogeneity is violated (Verbeek, 2012). The first-differenced lagged dependent variable is then instrumented with its lagged levels. (iii) The difference GMM uses first-differences in order to eliminate time-invariant unobserved movie-specific heterogeneity.

III. Estimation Results

3.1 Static Panel

Table 3 reports estimation results of the effect of tweet posting on cinema box office sales. The structure of the table is as follows. Columns (1) and (2) report the effect of total daily tweets on film revenues, without (column (1)) and with (column (2)) time (weekend and month) fixed effects. This is equivalent to model specification (1). Columns (3) and (4) report the effect of the tweet sentiments (*positive*, *negative*, and *mentioned*) on film revenues, without (column (3)) and with (column (4)) time (weekend and month) fixed effects. This is equivalent to model specification (2). Columns (5) and

(6) report the effect of the tweet temporal context (*before*, *after*, *current*, and *don't know*) on film revenues, without (column (5)) and with (column (6)) time (weekend and month) fixed effects. This is equivalent to model specification (3). All specifications are estimated as the standard fixed effects models, with robust standard errors in brackets.

The estimation results in columns (1) and (2) in Table 3 confirm a positive relationship between the total tweets and cinema box office sales. When testing the effects of the tweet sentiments (*positive*, *negative*, and *mentioned*) on film revenues, the estimation results in columns (3) and (4) in Table 3 confirm positive effects of the positive tweets and negative effects of the negative tweets, although only the effect of positive tweets remains significant after the inclusion of time (weekend and month) fixed effects in column (4). The effect of *mentioned* is not significant, which is not surprising, since a simple mention of a film does not distinctively encourage or discourage others from viewing it.

When testing the effects of the tweet temporal context (*before*, *after*, *current*, and *don't know*) on film revenues, the estimation results in columns (5) and (6) in Table 3 show that tweets posted before the movie have significant positive effects, even after controlling for the time (weekend and month) fixed effects. This is to be expected, since tweets posted before watching a movie capture the hype that has been built up about a movie based on its trailer and other methods of pre-release advertisement. This further means that the general effect of any kind of tweet wears off as time passes by. Tweets with an unknown posting date have significant negative effects on cinema box office sales, even after controlling for the time (month and day) fixed effects.

3.2 Dynamic Panel

The estimation results presented in Table 3 are potentially inconsistent because it can be argued that the daily tweets are endogenous, since the causality may run in both directions – from the volume of tweets to the box office revenues and vice versa, hence making the tweets correlated with the error term. Further, the box office revenues in the current period are likely to be highly correlated with the box office revenues in the previous period, which is not accounted for by the estimation results presented in Table 3.

The estimation results in Table 4 correct for this by inclusion of lagged daily gross revenues and treating the daily volume of tweets as endogenous. The models are estimated using the Arellano-Bond (1991) difference GMM estimator, implemented in Stata using `xtabond2` command (Roodman, 2009). The structure of Table 4 is similar to the structure of Table 3. Columns (1) and (2) report the effect of total daily tweets on film revenues, without (column (1)) and with (column (2)) time (weekend and month) fixed effects. This is equivalent to model specification (1a). Columns (3) and (4) report the effect of the tweet sentiments (*positive*, *negative*, and *mentioned*) on film revenues, without (column (3)) and with (column (4)) time (weekend and month) fixed effects. This is equivalent to model specification (2a). Columns (5) and (6) report the effect of the tweet temporal context (*before*, *after*, *current*, and *don't know*) on film revenues, without (column (5)) and with (column (6)) time (weekend and month) fixed effects. This is equivalent to model specification (3a).

Due to the small number of movies in the sample, only the second lag of endogenous variables is used as instrument. The second lag is required, because it is not

correlated with the error term in the current period, while the first lag is.¹⁴ Exogenous regressors (weekend and month effects) are used as their own instruments. The standard errors are consistent with panel-specific autocorrelation and heteroskedasticity in one-step estimation. The small sample adjustment is also applied. The tests for the absence of first-order (AR(1)) and second-order (AR(2)) serial correlation in the first-differenced residuals are reported, as well as the *Hansen-J* statistic testing the hypothesis of the over-identifying restrictions, asymptotically distributed as χ^2 under the null of valid instruments, with degrees of freedom reported in parentheses. The test for AR(1) process in first differences rejects the null hypothesis (which is to be expected). The test for AR(2) in first differences does not reject the null hypothesis of no autocorrelation in levels. The *Hansen-J* statistic does not reject the null hypothesis of the validity of surplus instruments.¹⁵

The estimation results in Table 4 show that the previous day’s box office revenue is significantly correlated with the box office revenues in the current period – this effect is robust in all specifications, from (1) to (6). The estimation results in columns (1) and (2) confirm a positive relationship between the total volume of tweets and cinema box office sales, thus indicating the importance of product *awareness* effect – underlying WOM could have significant effect on sales, suggesting that movie distributors should “embrace and facilitate” WOM (Duan et al., 2008).

¹⁴ Generally, one can experiment with a second or deeper lags to find a good instrument, but using longer lags reduces sample size. If the number of movies is large enough, one may use all available lags (second and further lags), as well as variables in levels (system GMM) as instruments.

¹⁵ Due to the small number of movies in the sample, a large number of instruments generated by the difference GMM estimator causes the Sargan test of overidentifying restrictions to be weak, hence it is not reported.

When testing the effects of the tweet sentiments (*positive*, *negative*, and *mentioned*) on film revenues, the estimation results in columns (3) and (4) confirm positive effects of the positive tweets and negative effects of the negative tweets, although only the effect of negative tweets remains significant after the inclusion of time (weekend and month) fixed effects in column (4). This is in line with previous literature showing that negative movie reviews decrease box office receipts (Basuroy et al., 2003), and that it is “almost impossible to recover from bad buzz” (James, 2006). The effect of *mentioned* is only marginally significant, after the inclusion of time (weekend and month) fixed effects in column (4).

When testing the effects of the tweet temporal context (*before*, *after*, *current*, and *don't know*) on film revenues, the conclusions are similar to the static panel results.

3.3 Time Effects

Throughout all of the three model specifications, in both static and dynamic panel regressions, the time (weekend and month) fixed effects remain robust. In particular, there is a significant negative effect of the second month after the movie release, because daily gross revenue obviously tends to be larger after the initial release of the movie and gradually decrease over time. When it comes to the weekend effect, Friday, Saturday and Sunday bring more revenues in relation to other days of the week. The latter is to be expected, since there are potential differences of consumers' movie-going behaviour between the weekend and weekdays – Friday, Saturday and Sunday are the peak days when general public goes to the cinema.¹⁶

¹⁶ To test the robustness of the estimated time effects, we have re-specified the models, including a linear time trend or week dummies instead of a month dummy. We have further tried specification with the

IV. Conclusions

The movie industry is a very risky business; it is the aim of every producer that all films achieve great popularity, but many fail to do so along the way. In this paper we hypothesized that the volume of Word-of-Mouth (WOM) such as tweets may be an important determinant of the box office revenues. From a managerial perspective, it is important to know how a vast amount of WOM affects box office revenues, such that film production companies and distributors can adjust their strategy accordingly.

The results of the paper can be summarized as follows. The daily box office revenues are autocorrelated – the previous day’s box office revenue is significantly correlated with the box office revenues in the current period. There is a positive relationship between the total volume of tweets and cinema box office sales, thus indicating the importance of product *awareness* effect (Duan et al., 2008) – underlying WOM could have significant effect on sales, suggesting that movie distributors should facilitate the dispersion of WOM. Negative tweets decrease cinema box office revenues, which is in line with the previous literature on the effect of negative movie reviews (Basuroy et al., 2003; James, 2006). Such finding implies that if firms were to manage the tweet sentiments, they should focus more on trying to prevent the occurrence of negative tweets. Tweets posted before watching the movie (and while in the cinema) increase cinema box office revenues, thus capturing the hype that has been built up about a movie based on its trailer and other methods of pre-release advertisement. This further means that the general effect of any kind of tweet wears off as time passes by.

inclusion of separate day-of-the-week dummies instead of a weekend dummy. The results for these models led to the same empirical conclusions as the ones presented and are available upon request. We have opted for the reported specifications because they are parsimonious.

Through the analysis of tweets, this study has demonstrated the function and power of social media that is far beyond what many of us perceive it to be. On the surface, it certainly represents a new era of communication method, but beneath this simplistic facade, it is also an information goldmine with a vast amount of hidden knowledge about the users of social media. Having access to this rich database would enable researchers to explore many new territories, which would have otherwise been extremely arduous to investigate. The importance of this source of information will only continue to increase as more and more people around the world become part of the social media network.¹⁷ This is because the social media information will be an even better representation of the general consent, which provides researchers and firms with greater incentives to extract commercial as well as social values from it.

Further research should investigate the power of tweets by gathering more micro data on the Twitter users, such as gender, age, education level, etc., thus inferring further information about the *identity of the consumer* (Pentheny, 2015). In their paper on the relationship between expert reviews and the demand for wine, Friberg and Grönqvist (2012) argue that the *identity of a reviewer* is also important. In the case of WOM, a consumer and a reviewer are embodied in the same person. Further work could also take into account information from other sources of online movie reviews (e.g., IMDb, Rotten Tomatoes; Yahoo! Movies), as well as considering movie ratings gathered from these website. It would also be possible to analyse the time series properties of tweet rates.

¹⁷ For example, Marta Kagan's work on social media shows that the Millennials have already outnumbered the Baby Boomers, and that 96% of them have already joined the social networks. They further care more what they friends think, that they trust commercial advertising. For further information, see: <http://www.slideshare.net/mzkagan/what-the-fk-social-media>

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Appendix.

Figure 1. Number of Social Network Users Worldwide From 2010 to 2020 (in Billions)

Notes: This statistic shows the number of social network users worldwide from 2010 to 2016, with projections until 2020. In 2018, it is estimated that there will be around 2.67 billion social network users around the globe, up from 1.91 billion in 2014. Source: Statista (2016).

Figure 2. Tweet Sentiment Composition

Figure 3. Tweet Timing Composition

Figure 4. Polarity Tweet Ratio, By Movie, By Week

Figure 5. Subjectivity Tweet Ratio, By Movie, By Week

Figure 6. Time Series of Total Tweets Plotted Against the Daily Gross Revenue, By Movie, Log-Transformed Data

Figure 7. Time Series of Tweets By Sentiment Plotted Against the Daily Gross Revenue, By Movie, Log-Transformed Data

Figure 8. Time Series of Tweets By Posting Time Plotted Against the Daily Gross Revenue, By Movie, Log-Transformed Data

Table 1. Definition of Tweet Classes

Class	Definition	Example
Relevance		
Irrelevant	Non-English (possibly relevant), or irrelevant from the context	“thanks for the help”
Relevant	Otherwise	“watched The Help”
Sentiment		
Negative	Contains only negative comment	“liked the movie, but don’t like how it ended”
Positive	<i>Unanimously</i> and <i>unambiguously</i> positive	“the movie was awesome!”
Mention	Otherwise	“the movie was about the wolves”
Temporal Context		
After	After watching as inferred from context	“had a good time watching the movie”
Before	Before watching movie	“can’t wait to see the movie”
Current	Tweeted when person was already inside the cinema	“at cinema about to watch the movie”
Don’t know	Otherwise	“have you seen the movie?”

Source: Wong et al. (2012)

Table 2. Panel Summary Statistics after Log Transformation

Variable			Mean	Std. Dev.	Min	Max	Obs.
<i>Daily gross</i>	Domestic daily gross revenue of the film	<i>overall</i>	13.213	1.324	10.060	16.132	<i>N</i> = 151
		<i>between</i>		0.823	12.116	14.145	<i>n</i> = 5
		<i>within</i>		1.122	10.539	15.870	<i>T</i> = 30.2
<i>Total tweet</i>	Total number of relevant tweets per movie (per day)	<i>overall</i>	6.720	1.512	3.434	9.878	<i>N</i> = 151
		<i>between</i>		1.511	4.475	8.064	<i>n</i> = 5
		<i>within</i>		0.650	4.955	9.484	<i>T</i> = 30.2
<i>Positive</i>	Tweets include unambiguously positive sentiment (per day)	<i>overall</i>	5.557	1.621	2.079	9.138	<i>N</i> = 151
		<i>between</i>		1.595	3.147	6.797	<i>n</i> = 5
		<i>within</i>		0.787	3.149	8.783	<i>T</i> = 30.2
<i>Negative</i>	Tweets contain any negative sentiment (per day)	<i>overall</i>	3.878	1.637	0.000	7.192	<i>N</i> = 150
		<i>between</i>		1.591	1.438	5.285	<i>n</i> = 5
		<i>within</i>		0.788	1.851	7.502	<i>T</i> = 30
<i>Mentioned</i>	Tweets that simply mentioned the film (per day)	<i>overall</i>	6.205	1.469	2.944	9.096	<i>N</i> = 151
		<i>between</i>		1.479	4.073	7.704	<i>n</i> = 5
		<i>within</i>		0.585	4.619	8.607	<i>T</i> = 30.2
<i>Before</i>	Tweets posted prior to watching movie (per day)	<i>overall</i>	5.277	1.891	1.386	9.168	<i>N</i> = 151
		<i>between</i>		1.873	2.393	6.959	<i>n</i> = 5
		<i>within</i>		0.849	2.819	8.121	<i>T</i> = 30.2
<i>After</i>	Tweets posted after watching movie (per day)	<i>overall</i>	5.658	1.563	1.609	8.778	<i>N</i> = 151
		<i>between</i>		1.537	3.257	6.991	<i>n</i> = 5
		<i>within</i>		0.710	3.730	8.795	<i>T</i> = 30.2
<i>Current</i>	Tweets posted while watching movie (per day)	<i>overall</i>	4.379	1.435	0.693	7.279	<i>N</i> = 151
		<i>between</i>		1.429	2.053	5.477	<i>n</i> = 5
		<i>within</i>		0.654	2.569	6.322	<i>T</i> = 30.2
<i>Don't know</i>	Tweets posted with uncertainty about the timing (per day)	<i>overall</i>	5.334	1.326	2.773	7.760	<i>N</i> = 151

<i>between</i>	1.373	3.694	6.485	$n = 5$
<i>within</i>	0.487	4.325	8.015	$T = 30.2$

Table 3. Panel: Estimation Results of the Effect of Tweet Posting on Box Office Sales

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
<i>Total tweet</i>	1.284** (0.303)	0.751** (0.225)				
<i>March</i>		-0.852** (0.216)		-0.747** (0.244)		-0.776** (0.217)
<i>Weekend</i>		0.843*** (0.053)		0.847*** (0.060)		0.909*** (0.067)
<i>Positive</i>			1.459** (0.362)	1.183** (0.379)		
<i>Negative</i>			-0.121 (0.279)	-0.011 (0.280)		
<i>Mentioned</i>			-0.349 (0.521)	-0.683 (0.603)		
<i>Before</i>					0.929** (0.269)	0.975*** (0.149)
<i>After</i>					0.695* (0.286)	0.110 (0.238)
<i>Current</i>					0.059 (0.425)	-0.036 (0.351)
<i>Don't know</i>					-0.994** (0.256)	-0.824*** (0.153)
<i>Constant</i>	4.583* (2.036)	7.996*** (1.485)	7.732*** (0.658)	10.726*** (1.021)	9.417*** (1.293)	11.778*** (0.950)
<i>Observations</i>	151	151	150	150	151	151
<i>R-squared</i>	0.554	0.703	0.613	0.748	0.671	0.815

Notes: Dependent variable is a log-transformed domestic daily gross revenue of the film. All tweet postings are log transformed. *March* is a dummy variable for the month of March, while month of February is a baseline category. *Weekend* is a dummy variable for a weekend (Friday, Saturday or Sunday), while Monday to Thursday are in a baseline category. Each regression is estimated using data on 5 movies (movie fixed effects are not reported). Standard errors, asymptotically robust to heteroskedasticity, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4. Dynamic Panel: Estimation Results of the Effect of Tweet Posting on Box Office Sales

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
<i>LDGR_{t-1}</i>	0.305** (0.088)	0.298** (0.087)	0.411*** (0.052)	0.326*** (0.081)	0.516*** (0.110)	0.374*** (0.090)
<i>Total tweet</i>	1.476*** (0.124)	1.286*** (0.227)				
<i>March</i>		0.087 (0.258)		-0.104 (0.119)		-0.386** (0.106)
<i>Weekend</i>		0.335 (0.202)		0.543*** (0.132)		0.586*** (0.084)
<i>Positive</i>			0.390 (0.267)	0.597 (0.415)		
<i>Negative</i>			-0.457*** (0.103)	-0.378** (0.135)		
<i>Mentioned</i>			1.165*** (0.190)	0.602* (0.297)		
<i>Before</i>					0.395 (0.204)	0.552** (0.164)
<i>After</i>					0.217 (0.232)	0.063 (0.176)
<i>Current</i>					0.567*** (0.117)	0.333* (0.144)
<i>Don't know</i>					-0.485** (0.174)	-0.577*** (0.070)
AR(1)	-1.70 (0.09)	-1.73 (0.08)	-1.73 (0.08)	-1.90 (0.06)	-1.73 (0.08)	-1.84 (0.07)
<i>p-value</i>						
AR(2)	-1.03 (0.30)	-0.44 (0.66)	-1.43 (0.15)	-0.45 (0.65)	-1.43 (0.15)	0.68 (0.50)
<i>p-value</i>						
<i>Hansen-J</i>	4.90 (30)	3.17 (30)	2.15 (92)	0.00 (92)	0.00 (118)	0.00 (118)
<i>df</i>						
<i>p-value</i>	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)
<i>Observations</i>	141	141	139	139	141	141

Notes: (1) Dependent variable is a first-difference of log-transformed domestic daily gross revenue (*DGR*) of the film. All tweet postings are log transformed. *March* is a dummy variable for the month of March, while month of February is a baseline category. *Weekend* is a dummy variable for a weekend (Friday, Saturday or Sunday), while Monday to Thursday are in a baseline category. All models are estimated using the difference GMM estimator, which eliminates unobserved film-specific effects. Each regression is estimated using data on 5 movies. (2) Standard errors, asymptotically robust to heteroskedasticity, are reported in parentheses. The small sample adjustment is also applied. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (3) The second lag of endogenous variables is used as instrument. Exogenous regressors are used themselves as their own instruments. (4) AR(1) and AR(2) are tests for the absence of first-order and second-order serial correlation in the first-differenced residuals, asymptotically distributed as $N(0,1)$ under the null of no serial correlation (p -value reported in parentheses). (5) *Hansen-J* statistic tests the hypothesis of the over-identifying restrictions, asymptotically distributed as χ^2 under the null of valid instruments, with degrees of freedom reported in parentheses. The p -value shows the probability of generating the reported statistic under the null of valid instruments.