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Do online reviews matter? — An empirical investigation of panel data

Wenjing Duan [a,*], Bin Gu [b,1], Andrew B. Whinston [b,2]

[a] Funger 515, School of Business, The George Washington University, Washington, DC 20052, United States
[b] CBA 5.202, McCombs School of Business, The University of Texas at Austin, Austin, Texas 78712, United States

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ABSTRACT

This study examines the persuasive effect and awareness effect of online user reviews on movies' daily box office performance. In contrast to earlier studies that take online user reviews as an exogenous factor, we consider reviews both influencing and influenced by movie sales. The consideration of the endogenous nature of online user reviews significantly changes the analysis. Our result shows that the *rating* of online user reviews has no significant impact on movies' box office revenues after accounting for the endogeneity, indicating that online user reviews have little persuasive effect on consumer purchase decisions. Nevertheless, we find that box office sales are significantly influenced by the *volume* of online posting, suggesting the importance of awareness effect. The finding of awareness effect for online user reviews is surprising as online reviews under the analysis are posted to the same website and are not expected to increase product awareness. We attribute the effect to online user reviews as an indicator of the intensity of underlying word-of-mouth that plays a dominant role in driving box office revenues.

1. Introduction

On September 12, 2004, an anonymous consumer disclosed in his online journal that the ubiquitous, U-shaped Kryptonite lock could be easily opened with a ballpoint pen [26]. Within days, the news penetrated virtually every blog (short for "web logs," where individuals publish their personal diaries) and Internet chat room. The online word-of-mouth frenzy forced Kryptonite to announce a free exchange program on September 22 for any affected lock. The Kryptonite incident demonstrates the sheer power of online word-of-mouth today. With the help of the Internet, information is no longer only controlled by news media or large businesses. Everyone can share their thoughts with millions of Internet users and influence others' decisions through online word-of-mouth.

Word-of-mouth has been recognized as one of the most influential resources of information transmission since the beginning of society, especially for experience goods [21,22]. However, conventional interpersonal word-of-mouth communication is only effective within limited social contact boundaries, and the influence diminishes quickly over time and distance [17]. The advances of information technology have profoundly changed the way information is transmitted, and have transcended the traditional limitations of word-of-mouth. Consumers can now easily and freely access information and exchange opinions on companies, products, and services on an unprecedented scale in real time.

Online customer review systems are one of the most powerful channels to generate online word-of-mouth [11]. With the popularity of online word-of-mouth activity, an increasing number of businesses have started to offer online word-of-mouth services. Amazon.com is well-known for its extensive customer review systems. Major television networks such as ABC, CBS, and NBC sponsor Usenet newsgroups to elicit viewers to talk about their programs and shows. Similarly, almost every studio and film distributor has utilized the Web as a critical marketing venue by creating websites and discussion forums for their movies [18]. The Web has become a medium to reach audiences directly and generate buzzes with tremendous efficiency and flexibility, regardless

* Corresponding author. Tel.: +1 202 994 3217; fax: +202 994 5830.
E-mail addresses: wduan@gwu.edu (W. Duan), Bin.Gu@mccombs.utexas.edu (B. Gu), abw@uts.cc.utexas.edu (A.B. Whinston).
[1] Tel.: +1 512 471 1582; fax: +1 512 471 0587.
[2] Tel.: +1 512 471 7962; fax: +1 512 471 0587.

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of geographic boundaries. The most successful example of leveraging online word-of-mouth as the major marketing tool is the "mega hit" *The Blair Witch Project* (1999). The movie was initially seen as a teenage fright flick with a "tiny" production budget of $60,000. Thanks to the large-scale discussions generated on the Web, it eventually became a huge box office success ($248 million worldwide).

In spite of the widespread belief that the Internet may act as a huge "megaphone" in promoting product sales, few literature has provided evidence that online word-of-mouth, such as product reviews and recommendations, plays any role in influencing consumers' choices and purchase decisions. There have been a number of recent studies investigating the impact of online word-of-mouth on product sales [5–7,12,19,21,32]. However, the results are mixed. Some of the research supports the view that online user review has a significant impact on sales [7], while other research challenges such a view [6,21,32].

The challenges and confusion mainly come from three aspects. First, studies differ in their view of the influence of online user reviews. Some focus on user reviews' persuasive effect that influence a consumer's assessment of product quality [5–7,19,32], while others focus on user reviews' awareness effect that increase product awareness among consumers through dispersion [12,21]. Second, many studies treat word-of-mouth as exogenous [6,7,12,19]. Word-of-mouth, however, is not only the driving forces of consumer purchase but also the outcome of product sales. The causality between product sales and word-of-mouth works in both directions. Ignoring the dual influencer and indicator roles of word-of-mouth is one of the main causes of the confusion. Third, many researchers conduct their analyses in a cross-sectional context [5–7,32]. A cross-sectional setting, however, cannot control for the intrinsic product heterogeneity. In particular, it cannot explain whether the difference in product sales is due to the unobserved differences in product quality or the effect of word-of-mouth.

Given previous limitations and challenges, we assess both the persuasive effect and the awareness effect of online user reviews in this study using a simultaneous equation system to fully capture the dual nature of online user reviews. In addition, we examine the relationship between online word-of-mouth and product sales in a panel data setting to control for individual heterogeneities. We utilize online user reviews for motion pictures as our research context because rapid spread of word-of-mouth has been historically considered a critical factor for financial success by the entertainment industry [10,25,34,37]. A recent report by Forrester Research found that approximately 50% of young Internet surfers rely on word-of-mouth recommendations to purchase CDs, movies, videos or DVDs [21]. We construct a panel data set including daily online user reviews and daily movie box office sales. Our simultaneous equation system takes full advantage of the panel data structure and specifies causality in both directions. Using the simultaneous equation system, we seek to clarify the confusion in prior studies by providing measures of the true effect of online user reviews.

Our findings challenge conventional thinking by showing that user *ratings* do not affect movie sales after controlling for endogeneity of user reviews and product heterogeneity, suggesting little persuasive effect for online user reviews. This result is consistent with earlier findings with regard to the impact of movie critics. Eliashberg and Shugan [16] showed that movie critics' ratings are predictors of movie performance, but they do not influence movie performance. We find that, in the online user review setting, user ratings share a similar characteristic. They reflect movie quality, but they do not influence movie sales. This result indicates that consumers are fully capable of inferring the true quality of a movie from online reviews without being influenced by the ratings of the reviews *per se*. Our analyses also show that the number of postings is significantly correlated with movie sales after taking into account of the causality issue, indicating the presence of significant awareness effect. The finding is surprising as online user reviews are posted to the same website and, as a result, not expected to increase product awareness. We attribute the awareness effect to online user reviews as an indicator of the intensity of underlying word-of-mouth which plays a dominant role in driving box office revenues. Moreover, we find that the number of user reviews online is significantly driven by movie sales, confirming that user review is not only an influencer of, but also an indicator of sales. In addition, our results show that the number of postings is positively autocorrelated, demonstrating the self-driving essence of online word-of-mouth. Finally, from the data of the first two weeks, we obtained significantly different results. Such a difference captures the rapidly-changing nature of the effect of word-of-mouth on the Internet.

Our paper enriches the empirical research on the impact of online word-of-mouth. From the methodology perspective, we demonstrate the importance of controlling for the dual role of online word-of-mouth as an influencer and an indicator of product sales, and the importance of controlling for the unobserved but inherent product heterogeneity in the analysis of online word-of-mouth. From the managerial perspective, we identify both the persuasive and awareness effect of online user review. We show that consumers are rational in inferring movie quality from online user reviews without being unduly influenced by the rating, thus presenting a challenge to businesses that try to influence sales through "planting" positive product reviews. Our findings of awareness effect, also suggest that the underlying word-of-mouth process could have a significant impact on sales, suggesting that businesses should embrace and facilitate word-of-mouth activities.

The rest of the paper is organized as follows. The next section provides the literature review followed by the discussion of research objectives and hypotheses. We then describe our source of data and the empirical model. Main findings are presented and discussed next, and the paper ends with a discussion of limitations and future research.

2. Literature review

Research on the impact of interpersonal communication is common in the economics literature. The early studies of *Learning from Others* provide evidence that word-of-mouth communication may affect others' decisions in different social contexts [33]. Smallwood and Conlisk [42] showed that a product may capture the entire market regardless of its quality through some type of learning process. Banerjee [2,3] presented two models indicating that people place such a significant weight on other people's opinions that they may even ignore their own private information. Kirman [27] demonstrated a similar result that *Learning from Others* can cause a significant differentiation in market share between two products with the same quality. Ellison and Fudenberg [17] studied a simple model of word-of-mouth communication and found that social learning is often most efficient when communication between agents is limited.

A number of previous empirical studies have been conducted to examine the impact of interpersonal word-of-mouth, but results are mixed. Katz and Lazarsfeld [24] found that word-of-mouth plays the most important role in influencing the purchase of household goods and food. Coleman et al. [9] used word-of-mouth to explain adoption of tetracycline among physicians. Foster and Rosenzweig [20] attributed adoption of high-yield varieties of seeds by farmers to word-of-mouth effect. However, Van den Bulte and Lilien [45] cast doubt on the role of word-of-mouth as a sales driver. They re-examined the analysis by Coleman et al. [9] and found that marketing efforts, not word-of-mouth, plays a dominant role in physicians' adoption decision.

The utilization of the Internet as a venue for publicizing feedback and recommendations on products and businesses has gained growing popularity. However, little is known about if online word-of-mouth has any influence on consumer purchase decisions. Dellarocas [11] provides a comprehensive review of the current progress and challenge of studying online feedback systems. Chatterjee [5] used surveys to examine the impact of negative online user reviews. The results indicate that the use of online word-of-mouth information depends on a consumer's intent to purchase online. Consumers who are more familiar with a specific retailer are less likely affected by the negative reviews. Chen et al. [7] studied the underlying patterns of online consumer posting behavior through online reviews for automobiles. They found that automobile characteristics such as quality and price have a significant impact on users' inclination to post. Chen et al. [6] empirically investigated the impacts of both online user reviews and recommendation information on book sales in Amazon.com from the consumer search cost perspective. They found that recommendations are positively associated with sales, while consumer ratings are not found to be related to sales. They also found that recommendations are more important for less popular books. Li and Hitt [28] investigated the self-selection effect and information role of online product reviews. By analyzing the data of online book reviews, they found that average rating declines over time and early consumer reviews demonstrate positive bias due to the self-selection effect.

Online user reviews can influence product sales through either *awareness* effects or *persuasive* effects. Awareness effects indicate that reviews convey the existence of the product and thereby put it in the choice set of consumers. Persuasive effects, in contrast, are to shape consumers' attitudes and evaluation towards the product and ultimately influence their purchase decision. These two effects have been studied intensively in prior literature in marketing on the effect of advertising. It is found that advertising has a significant positive effect on brand awareness, but no effect on perceived quality [8]. A recent work by Godes and Mayzlin [21] focused on measuring the influence of dispersion of word-of-mouth, a concept closely related to the awareness effect. They examined word-of-mouth communication for TV shows within and across different Usenet newsgroups. They found that *dispersion* of word-of-mouth is significantly correlated with a TV show's performance early on, while *volume* exhibits significance only in later periods. As cross cross-newsgroup dispersion creates more awareness than within newsgroup dispersion, the results indicate that awareness effect of online word-of-mouth has a significant influence. Their empirical analyses took into account the dual nature of word-of-mouth communication as both an influencer and an outcome. However, the system of seemingly unrelated regressions (SUR) does not handle the endogeneity of word-of-mouth when it acts as an influencer of the sales. In this paper, our focus is to examine both the persuasive effect and awareness effect of online user reviews which is critical to understand the influence of online user feedback systems. We use a simultaneous equation system that fully characterizes the interdependent relationship between online user reviews and movie revenues. Moreover, we use movie review data that are essentially different from Usenet newsgroup conversations. In addition to measuring *volume*, we measure user *ratings* that are often considered a driving force of consumers' product choice, which is not available for Usenet newsgroup data and thus has not considered by Godes and Mayzlin [21].

Movie industry experts appear to agree that word-of-mouth is a critical factor underlying a movie's staying power which leads to its ultimate financial success. However, prior research on the relationship between word-of-mouth and market performance of motion pictures is surprisingly limited. Neelamegham and Chintagunta [35] empirically assessed the relationship between word-of-mouth and weekly revenues, but failed to obtain any significant results. They attributed the failure to the inadequacy of the measurement of word-of-mouth, which may also explain the lack of significant results of the word-of-mouth effect in the previous literature. Elberse and Eliashberg [15] used revenues per screen in the previous week as a proxy of word-of-mouth in their analysis of demand and supply of motion pictures. They found such a measurement of word-of-mouth to be a key predictor of box office revenues. Dellarocas et al. [12] employed a modified Bass Diffusion model to study the effects of online user reviews in forecasting movie revenues. Their results showed that the early online user review information can help generate accurate future forecasts of movie revenues. Reinstein and Snyder [40] apply a difference-in-difference approach to uncover the impact of movie critics on sales. They have identified marginal positive influence of movie critics on the demand. Extending earlier models [4,16], Liu [32] examined the relationship between online user feedback and movie sales based on weekly data regressions. The results suggest that word-of-mouth valence is not correlated with movie sales, but online message volume is significantly correlated with the weekly movie sales. In contrast to the cross-sectional and single-equation OLS setting used in Liu [32], we propose a simultaneous equation panel data analysis in this study to capture the dual nature of word-of-mouth and its interaction with sales. In addition, we use daily data as opposed to the weekly data to capture the unprecedented speed of information transmission on the Internet.

On the other hand, a range of studies have provided evidence for a positive relationship between critical reviews and theatrical success [29,30,31,38,39,41,43,46]. Eliashberg and Shugan [16] tried to distinguish critics' role as "influencers", whose opinions influence their audience and thus the box office, from their roles as "predictors", as merely a leading indicator of their respective audience with no significant influence on actual box office revenues. The authors found that critical reviews correlate with late and cumulative box office revenues but do not have a significant correlation with early box office performance. This finding implies that a critical review is more likely to be a "predictor" than an "influencer". A recent study by Sorensen and Rasmussen [44] evaluated the impact of New York Times book reviews on sales. Their results suggest that "any publicity is good publicity:" even negative reviews lead to increases in sales.

3. Hypotheses

In this study, we aim to investigate the impact of online word-of-mouth on product sales. As a context for our inquiry, we choose online user reviews for motion pictures. There are several reasons for choosing such a research context. First, given that price may play an important role in consumers' purchasing decisions and product satisfaction, choosing the movie industry to study online word-of-mouth has its unique advantage. Movie ticket prices are typically determined in the local markets. Therefore, we can rule out the possibility that price is mediating consumers' purchasing decisions. Second, word-of-mouth has traditionally been considered a critical factor in influencing box office performance, but there is no consistent documented support. We would address such a shortcoming by exploring the impact of online word-of-mouth on movie sales. Third, compared with other products such as books and music CDs, which usually have only sales rank data, motion picture box office sales data is publicly available, thus significantly reducing measurement error. Finally, both online user reviews and movie sales are high-frequency data that can be collected on a daily basis. This provides sufficient observations for empirical analysis.

Online user reviews have two effects on consumer purchase decisions. First, most review sites allow a user to provide both an overall rating (often denoted by a letter or star grade) and a detailed review. The rating and review could influence other consumers' perception of product quality. The effect is equivalent to the persuasive effect studied in the advertising literature. Duan et al. [14] report that about 22% of users of CNET sort products by user ratings. In addition, prior research also suggests that review ratings have a positive impact on movie sales [40,41]. To measure the persuasive effect of online user reviews, we consider *rating* as part of the measurement of word-of-mouth. Besides influencing a user's perception of product quality, online user reviews also increase product awareness among consumers. The awareness effect is most significant when user reviews is dispersed to online communities that are previously unaware of the product. For online user reviews posted on retail website, we expect no direct awareness effect since consumers who visit the product page are aware of the product in the first place. However, we expect *volume* of online user reviews to be an indicator of the intensity of the underlying word-of-mouth effect. Previous theoretical and empirical research provides support for the positive relationship between *volume* of word-of-mouth and product sales [21,32,33]. We thus derive the following hypotheses:

H1. Number of user postings has a positive impact on box office revenues.

H2. User review ratings have a positive impact on box office revenues.

We measure *user review ratings* from two different perspectives, i.e. *cumulative rating* and *daily rating*. *Cumulative rating* is the arithmetic average of all the previous user review ratings, while *daily rating* is the arithmetic average of user review ratings posted in a single day. *Cumulative rating* represents the summary score posted by the user review website. *Daily rating* reflects the most recent word-of-mouth information disseminated by users who have just watched the movie. Considering that some of the users may only browse the overall rating while others tend to read the most recent posts more carefully, we separate H2 into two parts.

H2a. Cumulative user review rating has a positive impact on box office revenues.

H2b. Daily user review ratings have a positive impact on box office revenues.

De Vany and Walls [13] explored the demand and supply dynamics and the path of the distribution of film revenues. Their results indicate that weekly revenues are autocorrelated: more recent revenue increase is more likely to experience additional revenue growth. Recent research by Elberse and Eliashberg [15] verify that previous week per screen revenues are positively correlated with current week sales. Such a positive autocorrelation of movie sales results from the nature of the consumer demand of motion pictures [13]. While the previous studies constrain autocorrelation to weekly data, we extend it to daily data in this study.

H3. Daily box office revenues are autocorrelated: a movie which experienced increasing revenues in the previous day is more likely to experience additional growth than a movie which experienced growth in the distant past.

Word-of-mouth not only leads to future sales, it is also an outcome of previous sales. For example, Chen et al. [7] found that the number of online postings is positively related to past automobile sales controlling for price and quality. Godes and Mayzlin [21] illustrated that the number of Usenet postings is positively correlated with a TV show's performance. Hence, we hypothesize:

H4. Box office revenues have a positive impact on the volume of word-of-mouth.

Previous research of word-of-mouth indicates that volume of word-of-mouth communication peaks in a short period of time [21]. Such a buzz effect indicates that word-of-mouth often leads to more word-of-mouth, suggesting a positive autocorrelation. Thus, we have the following hypothesis:

H5. Daily number of user reviews is autocorrelated: a recent increase in the number of postings for a movie is more likely to elicit more user reviews in the following day.

Online user reviews are considered public goods since providing reviews on the Internet costs reviewers' effort, but benefits all the users. Public goods theory suggests that an individual contributes less when there are substantial sources of contribution [12,23]. Li and Hitt [28] evaluate the self-selection effect in online book reviews. They found that users who are most likely to contribute post their reviews early, leaving those who are less likely to contribute. Both the public goods theory and the self-selection effect lead to the following hypothesis:

H6. Daily number of user reviews is negatively correlated with the cumulative number of reviews.

4. Research methodology

4.1. Description of the data

The data for this study was collected from three sources, Yahoo! Movies (YM: http://www.movies.yahoo.com), Variety.com (Variety: http://www.variety.com), and BoxOfficeMojo.com (Mojo: http://www.boxofficemojo.com). We matched the list of movies, based on the Variety's year 2003–2004 box office rank in the US market, with that on YM and Mojo for user reviews and daily box office information. By the time we collected the data, movies still playing in the theater were not included in the sample. Our sample includes the movies that have a complete history of user reviews from their release dates and have the complete corresponding daily box office revenue data as well.[3] The final data set includes 71 movies released between July 2003 and May 2004.

For each movie, we collected the following information from YM: each user review's yahooID, post date, overall grade, grade for story, acting, direction, and visual, and length of the full review. We also collected the *Average User Grade* and *Average Critic Grade* posted on YM by the date we collected the data.[4] The letter grade of each individual user review was converted into a numerical value by assigning 13 to A+, 12 to A… and 3 to D. This set of data was aggregated, for each movie, by adding up grades and taking the arithmetic average for each day.[5] Similarly, we calculated the cumulative average grade for each movie. We thus constructed our measurement of *cumulative rating* and *daily rating.* We also summed up the daily and cumulative number of posts for each movie.

Having matched each movie by title and release date, we collected the following information from Mojo: daily gross revenues, daily rank, number of theaters engaged, average revenue per theater, and daily gross-to-date revenues. Summary data were also collected for each movie including estimated marketing costs, production budget, MPAA rating, producer, domestic gross revenues, and oversea gross revenues. Users start posting reviews usually right on the opening day of the movie on YM, and reviews keep emerging long after the movie's theater lifetime.[6] The specific post date information provided by YM for each review can be matched with daily box office revenues. Table 1 presents the summary statistics for our sample. Table 2 provides the description and measurement of the key variables used in the empirical analysis.

Table 1
Summary statistics

Variable	*N*	Mean	Std. Dev.	Min.	Max.
Budget (*M*)	64	46.06	32.17	4.00	150.00
Est. marketing costs (*M*)	57	24.00	7.13	10.00	50.00
US gross (*M*)	71	66.16	51.21	10.39	377.03
Total user posts	71	1350.24	882.80	342.00	4562.00
Avg. User Grade	71	8.89	1.02	6.00	11.00
Avg. Critic Grade	71	7.46	1.75	3.00	11.00

YM posts an assessment of *Average User Grade* which is calculated based on all the user ratings. However, only those with detailed reviews will be posted on the website, which means we were not able to collect all user ratings.[7] To test if such a sample is a representative of all the postings in terms of the review grade, we kept track of 12 new-release movies for two weeks from their opening date. We collected all the reviews posted and the updated *Average User Grade* provided by YM at 2–6 min intervals. At each interval, the average review grade calculated based on the posts with full reviews was compared with the *Average User Grade* posted on YM. We observed almost perfect correlation for all the movies, suggesting that the portion of user reviews shown on YM sites is a good proxy of all the user ratings (this part of data and analysis will not be reported here).

Similar to the pattern of box office life cycle of motion pictures, we observed that, for most movies, the number of user reviews skyrockets immediately after the opening and drops significantly afterwards. Most movies are shown in theaters for eight to ten weeks. Typically, the box office receipts peak at the time of initial film release, followed by an exponential decay over time. Since word-of-mouth effect decreases over time very quickly, it is essential to capture the dynamics in the early periods. We therefore constructed a balanced panel data set of the 71 movies for the first two weeks in this study. The descriptive statistics for some key variables of the first two weeks is presented in Tables 3 and 4. The tables show that the average number of postings drops significantly from week 1 to week 2 (the mean value of DAILYPOST changes from 88.54 to 36.95 and the maximum number decreases from 633 to 231). Such a difference implies that most buzz is created in the early period and the intensity keeps changing over time, thus making the importance of using daily data even more evident. Tables 5 and 6 present the pooled data correlation matrix of the key variables for week 1 and 2. DAILYREVENUE_{it} and DAILYPOST_{it} in general have a strong positive correlation (0.65 for the first week and 0.56 for the

[3] All the movies in our sample were nation-wide releases from their opening days.

[4] The average critic grade was calculated based on 13–15 critics reviews invited by YM and posted on the YM website.

[5] We contacted Yahoo! Movies to verify such a numerical transformation of the original letter grade. We were notified that the average user grade posted on the Yahoo! Movies website is calculated in the same way.

[6] Reviews that were posted later e.g., after 2–3 months of movie's release date were probably based on experience other than in the theater, such as from TV, DVD, or other venues. Although we collected all the reviews, we only used those that were posted during the movie's theatre running time.

[7] A lot of users only provide a letter grade instead of a full review, which will not be shown on YM, but will be aggregated into the *Average User Grade* on YM website.

Table 2
Variables, descriptions, and measures

Variable	Description and measure
$\mathrm{DAILYREVENUE}_{it}$	Daily revenue for movie *i* in day *t* (in thousands, US dollars)
$\mathrm{DAILYREVENUE}_{i,t-1}$	Daily revenue for movie *i* in day *t*−1 (in thousands, US dollars)
$\mathrm{CUMUPOST}_{it}$	Cumulative number of reviews posted for movie *i* until day *t*
$\mathrm{DAILYPOST}_{it}$	Number of user reviews posted for movie *i* in day *t*
$\mathrm{DAILYPOST}_{i,t-1}$	Number of user reviews posted for movie *i* in day *t*−1
$\mathrm{CUMURATING}_{i,t-1}$	Cumulative *Average User Grade* for movie *i* until day *t*−1
$\mathrm{DAILYRATING}_{i,t-1}$	Daily *Average User Grade* for movie *i* until day *t*−1
$\mathrm{WEEKEND}_{it}$	A dummy variable indicating if day *t* is a weekend (coded as 1 if day is Friday, Saturday, and Sunday, 0 otherwise)

Table 3
Week 1 descriptive statistics

Variable	*N*	Mean	Std. Dev.	Min.	Max.
DAILYREVENUE (*M*)	497	3.69	4.00	0.15	34.45
CUMURATING	497	9.69	1.32	5.85	12.20
DAILYRATING	497	9.58	1.50	3.33	12.86
CUMUPOST	497	435.98	392.73	3.00	1,958.00
DAILYPOST	497	88.54	94.46	3.00	633.00

Table 4
Week 2 descriptive statistics

Variable	*N*	Mean	Std. Dev.	Min.	Max.
DAILYREVENUE (*M*)	497	2.15	2.34	0.089	19.15
CUMURATING	497	9.59	1.35	6.37	11.78
DAILYRATING	497	9.42	1.73	1.33	12.71
CUMUPOST	497	794.41	564.22	77.00	2,575.00
DAILYPOST	497	36.95	31.53	2.00	231.00

second week). However, such a correlation does not indicate any direction of causality or any timing sequence in priori. We have to fully characterize their interdependent relationships in the empirical analysis to uncover the true impact of user reviews.

Table 7 provides pairwise correlations for some characteristic variables in our sample. Similar to the observations of the first two weeks' data, the total number of user posts has a relatively high positive correlation with US gross revenues (0.68). This indicates the intrinsic connection between the number of posts and box office performance, but does not designate any causal relationship. In addition, we observed that *Average User Grade* and *Average Critic Grade* do not have a very high correlation (0.56), suggesting that online user reviews may carry different information from that of the professional critical reviews.

4.2. Empirical model specification

As we are interested in the interdependence between movies' box office revenues and online word-of-mouth information, we developed the following two-equation system: one equation with daily revenues as the dependent variable (the revenue equation) and one with daily number of posts as the dependent variable (the post equation). Such a system captures the interaction between the two dependent variables over time, and the equation of daily number of posts also characterizes the dynamics of the volume of online word-of-mouth.

$$\begin{aligned}\mathrm{DAILYREVENUE}_{it} = \theta_t &+ \alpha_1\mathrm{DAILYPOST}_{it} \\ &+ \alpha_2\mathrm{CUMURATING}_{i,t-1} \\ &+ \alpha_3\mathrm{DAILYREVENUE}_{i,t-1} \\ &+ \alpha_4\mathrm{WEEKEND}_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned}\mathrm{DAILYPOST}_{it} = \eta_t &+ \beta_1\mathrm{DAILYREVENUE}_{it} \\ &+ \beta_2\mathrm{DAILYPOST}_{i,t-1} \\ &+ \beta_3\mathrm{CUMUPOST}_{i,t-1} + \beta_4\mathrm{WEEKEND}_{it} \\ &+ \rho_i + \sigma_{it}. \end{aligned} \tag{2}$$

Let $i = 1,\ldots N$ index the movies. For the revenue equation, $\mathrm{DAILYREVENUE}_{it}$ denotes the daily gross revenues of movie *i* at day *t*, and its one-day lagged variable is defined as $\mathrm{DAILYREVENUE}_{i,t-1}$. Since the adaptation of supply (allocation of number of theaters and screens) to demand usually takes place in the later period of a movie's life cycle, there are unique advantages of investigating early box office data without worrying about the adjustment of the supply from movie distributors. In addition, number of movies showing in theaters usually does not change in a given week, thus the competition and substitution effects of various movies showing on the same day can be controlled through our *daily* panel data setting. H1 suggests that the number of postings is positively correlated with box office revenue. Thus, we expect $\alpha_1 > 0$. H3 acknowledges that daily box office revenues are positively autocorrelated and thus we expect $\alpha_3 > 0$. We define $\mathrm{DAILYPOST}_{it}$ as the total number of user reviews posted for movie *i* at day *t* and $\mathrm{DAILYPOST}_{i,t-1}$ as the total number of user reviews posted for movie *i* at day *t* − 1.

$\mathrm{CUMURATING}_{i,t-1}$ represents the cumulative average user review grade of movie *i* up to day *t* − 1. Since YM provides

Table 5
Week 1 correlation matrix

Variable	DAILYREVENUE	$\mathrm{CUMURATING}_{i,t-1}$	$\mathrm{DAILYRATING}_{i,t-1}$	$\mathrm{CUMUPOST}_{i,t-1}$	DAILYPOST
DAILYREVENUE	1.00	0.19	0.18	0.05	0.65
$\mathrm{CUMURATING}_{i,t-1}$	0.19	1.00	0.69	0.19	0.17
$\mathrm{DAILYRATING}_{i,t-1}$	0.18	0.69	1.00	0.13	0.18
$\mathrm{CUMUPOST}_{i,t-1}$	0.05	0.19	0.13	1.00	0.17
DAILYPOST	0.65	0.17	0.18	0.17	1.00

Table 6
Week 2 correlation matrix

Variable	DAILYREVENUE	$\text{CUMURATING}_{i,t-1}$	$\text{DAILYRATING}_{i,t-1}$	$\text{CUMUPOST}_{i,t-1}$	DAILYPOST
DAILYREVENUE	1.00	0.20	0.13	0.28	0.56
$\text{CUMURATING}_{i,t-1}$	0.20	1.00	0.61	0.26	0.21
$\text{DAILYRATING}_{i,t-1}$	0.13	0.61	1.00	0.19	0.17
$\text{CUMUPOST}_{i,t-1}$	0.28	0.26	0.19	1.00	0.57
DAILYPOST	0.56	0.21	0.17	0.57	1.00

Average User Grade on the top of each movie's page, it is the most noticeable information on the website. H2a indicates that the cumulative user review rating has a positive impact on movie revenues. We then expect $\alpha_2 > 0$. To test H2b, we used $\text{DAILYRATING}_{i,t-1}$ to substitute $\text{CUMURATING}_{i,t-1}$ in the revenue equation, which is formulated in Eq. (3) and estimated with Eq. (2).

$$\begin{aligned}\text{DAILYREVENUE}_{it} = {} & \delta_t + \gamma_1\text{DAILYPOST}_{it} \\ & + \gamma_2\text{DAILYRATING}_{i,t-1} \\ & + \gamma_3\text{DAILYREVENUE}_{i,t-1} \\ & + \gamma_4\text{WEEKEND}_{it} + \varphi_i + \zeta_{it}\end{aligned} \quad (3)$$

Following the discussion above, we anticipate $\gamma_1 > 0$, $\gamma_2 > 0$, and $\gamma_3 > 0$.

For the post equation, the addition of variable DAILYREVENUE_{it} indicates that the number of postings is influenced by the number of people who have watched the movie. Therefore, H4 predicts that $\beta_1 > 0$. $\text{DAILYPOST}_{i,t-1}$ is the one-day lagged variable of daily number of postings and $\beta_2 > 0$ is suggested to be positive by H5. $\text{CUMUPOST}_{i,t-1}$ denotes the cumulative number of user reviews posted until day $t-1$. H6 suggests that users have less incentive to post reviews given a sufficient number of existing reviews. Therefore, we expected that $\beta_3 < 0$.

A dummy variable, WEEKEND_{it}, is included in all equations to identify the potential difference of consumers' movie-going behavior between the weekend and weekdays. θ_t, η_t, and δ_t represent intercepts that denote the aggregate time effect for each movie. For each equation, we also incorporate the fixed effects, μ_i, ρ_i, and φ_i, to capture the idiosyncratic characteristics associated with each movie, such as its budget, marketing costs, genre, distributor, as well as its intrinsic quality. The fixed effects capture all non-time-varying unobserved heterogeneity of each movie, thus we were able to control for unobserved differences across movies. In addition, fixed-effects estimation allows the error term to arbitrarily correlate with other explanatory variables, making the estimation more flexible and robust.

Table 7
Correlation matrix of movie summary variables

	Budget	Est. marketing costs	US gross	Total user review	Avg. User Grade	Avg. Critic Grade
Budget	1.00	0.68	0.44	0.37	0.19	0.15
Est. marketing costs	0.68	1.00	0.69	0.57	0.17	−0.008
US gross	0.44	0.69	1.00	0.68	0.41	0.36
Total user posts	0.37	0.57	0.68	1.00	0.43	0.16
Avg. User Grade	0.19	0.17	0.41	0.43	1.00	0.56
Avg. Critic Grade	0.15	−0.008	0.36	0.16	0.56	1.00

5. Results and discussions

5.1. Estimation results for the first week

A three-stage least-square (3SLS) procedure was employed to simultaneously estimate the system of two equations (either (1.) and (2.) or (3.) and (2.)). OLS results are presented for comparison. OLS estimation is inconsistent because the regressors of all the equations include endogenous and lagged variables. We are also concerned about the consistency of 3SLS estimation procedure since we include lagged endogenous variables in the equation, and a fixed-effects model may suffer from finite sample bias [36]. In addition, the lagged variables contribute to the identification of the system of equations. We then estimate a model suggested by Arellano and Bond [1] using a GMM-based method and find qualitatively equivalent results to 3SLS. Estimation results for the first week are presented in Tables 8 and 9. Table 8 shows the results for estimating Eqs. (1) and (2) (*cumulative user review rating*), and Table 9 presents the results for analyzing Eqs. (3) and (2) (*daily user review rating*).

In Table 8, for the revenue equation (3SLS estimation), DAILYPOST_{it} are significant predictors for DAILYREVENUE_{it}, supporting H1. The positive relationship between DAILYPOST_{it}

Table 8
First (opening) week estimation: OLS and 3SLS (cumulative rating)

Variable	OLS (fixed-effects estimation)	3SLS (simultaneous fixed-effects estimation)
	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Equation1: Revenue equation with DAILYREVENUE as dependent variable		
$\text{DAILYREVENUE}_{i,t-1}$	0.28 (0.04)***	0.21 (0.05)***
$\text{CUMURATING}_{i,t-1}$	0.56 (0.27)**	0.18 (0.18)
DAILYPOST_{it}	0.01 (0.002)***	0.02 (0.002)***
WEEKEND_{it}	3.08 (0.32)***	2.96 (0.29)***
	$N=426$, $R^2=0.87$	$N=426$, $R^2=0.89$
Equation2: Post equation with DAILYPOST as dependent variable		
DAILYREVENUE_{it}	5.35 (1.42)***	19.19 (3.21)***
$\text{CUMUPOST}_{i,t-1}$	−0.26 (0.03)***	−0.27 (0.04)***
$\text{DAILYPOST}_{i,t-1}$	0.24 (0.04)***	0.11 (0.03)**
WEEKEND_{it}	11.63 (9.98)	−40.85 (14.31)***
	$N=426$, $R^2=0.84$	$N=426$, $R^2=0.82$

***$p<0.01$, **$p<0.05$, *$p<0.10$.
Note: Time dummies (for each day) and movie dummies (fixed effect for each movie) used in estimating the model are not reported.

Table 9
First (opening) week estimation: OLS and 3SLS (daily rating)

Variable	OLS (fixed-effects estimation)	3SLS (simultaneous fixed-effects estimation)
	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Equation1: Revenue equation with DAILYREVENUE as dependent variable		
$DAILYREVENUE_{i,t-1}$	0.28 (0.04)***	0.20 (0.05)***
$DAILYRATING_{i,t-1}$	0.56 (0.27)**	0.07 (0.07)
$DAILYPOST_{it}$	0.01 (0.002)***	0.02 (0.002)***
$WEEKEND_{it}$	3.08 (0.32)***	2.96 (0.29)***
	$N=426$, $R^2=0.87$	$N=426$, $R^2=0.89$
Equation2: Post equation with DAILYPOST as dependent variable		
$DAILYREVENUE_{it}$	5.35 (1.42)***	19.19 (3.21)***
$CUMUPOST_{i,t-1}$	−0.26 (0.03)***	−0.20 (0.04)***
$DAILYPOST_{i,t-1}$	0.24 (0.04)***	0.11 (0.02)***
$WEEKEND_{it}$	11.63 (9.98)	−40.85 (14.31)***
	$N=426$, $R^2=0.84$	$N=426$, $R^2=0.82$

***$p<0.01$, **$p<0.05$, *$p<0.10$.
Note: Time dummies (for each day) and movie dummies (fixed effect for each movie) used in estimating the model are not reported.

and $DAILYREVENUE_{it}$ implies that higher *volume* of word-of-mouth generated on the web is correlated with higher offline box office revenues. The result indicates that number of online user reviews could be a good indicator of the intensity of underlying word-of-mouth effect and increase awareness among potential moviegoers. However, $CUMURATING_{i,t-1}$ does not have a significant impact on $DAILYREVENUE_{it}$ after we control for the endogeneity of user reviews, rejecting H2a. The result contrasts sharply with the results from the OLS regression, indicating the importance of controlling for the interdependence between product sales and online user reviews. We also find that the previous day's box office revenue is predictive of today's box office revenue, supporting H3. The significance of the coefficient of variable $WEEKEND_{it}$ also verifies our assumption that theaters enjoy significantly higher revenues on weekends.

For the post equation (3SLS estimation), the coefficient of $DAILYREVENUE_{it}$ is positive and significant, indicating that *volume* of word-of-mouth is also strongly affected by sales. This result supports H4 and verifies that word-of-mouth information is not only an influencer to, but also an indicator of revenues. The positive and significant coefficient of $DAILYPOST_{i,t-1}$ supports H5, signifying the self-driving progression of online word-of-mouth in the opening week. Such a finding implies that early buzz generated for a product on the web is a significant driver for later word-of-mouth interests, especially for new-released movies. $CUMUPOST_{i,t-1}$, as expected in H6, is negatively correlated with the dependent variable ($DAILYPOST_{it}$). Users have less incentive to spend time to post reviews if previous reviews already provide enough information. An alternative interpretation is due to the self-selection effect. Users who are most likely to post will contribute their reviews immediately after they watch the movie, while later users may just tend to browse the reviews with much less incentive to post. We also find $WEEKEND_{it}$ is a significant negative predictor implying that, on average, the number of reviews posted on weekdays is more than that posted on weekends.

Table 9 presents results of estimating Eqs. (3) and (2). The significance of the coefficients remains the same compared with those in Table 8. The fact that neither $DAILYRATING_{i,t-1}$ nor $CUMURATING_{i,t-1}$ has a significant relationship with box office revenues indicates that online user reviews have little persuasive effect and may not play an essential role in influencing consumers' movie-going behavior. People often believe that bad review grades would drive down sales and good reviews would increase sales. However, our results indicate that online review ratings do not significantly influence box office revenues after controlling for the inherent movie heterogeneity. To put it differently, movies box office sales are not influenced by time-series variation in user ratings, which suggests that consumers do not blindly follow the ratings posted by other users. Instead, they are more likely to read the review and make an independent judgment about the true quality of the movie. However, we find that the number of reviews plays an important role in influencing sales. There are two plausible explanations for this finding. First, increases in the number of reviews provide more information about the movie, thus attracting more users to the theatre. This *information effect*, however, shall diminish quickly with the number of reviews posted. Given that YM has more than 1000 online reviews for most movies, we believe the average *information effect* shall be quite small. Second, posting reviews online ultimately reflects a user's incentive to discuss the movie with other users. As such, the number of online reviews reflects the awareness effect of underlying word-of-mouth interests. The online user reviews collected in our data represent a snapshot of the overall word-of-mouth spread around. The strong relationship between the number of online user reviews and box office sales suggests that movie sales are significantly driven by the *awareness effect*.

There are some major changes in the significance of variables if we compare 3SLS with OLS. In particular, $CUMURATING_{i,t-1}$ is a significant predictor in OLS estimation (Table 8). This might explain why some of the previous research found that online rating is a significant influencer for product sales. Simple OLS regression does not correctly characterize the impact of online user ratings given the correlation between the error term and the endogenous variable. In our specific setting, the effect of $CUMURATING_{i,t-1}$ is overestimated in OLS given the endogeneity of $DAILYPOST_{it}$. We also noticed that the coefficient of $DAILYPOST_{it}$ increases from 0.01 in OLS to 0.02 in 3SLS, which is a noteworthy difference. This implies that not considering the endogeneity of $DAILYPOST_{it}$ leads to under-estimation of its impact on revenues. Other significant differences of coefficient include $DAILYREVENUE_{it}$ (5.35 in OLS to 19.19 in 3SLS), $DAILYPOST_{i,t-1}$ (0.24 in OLS to 0.11 in 3SLS), and $DAILYPOST_{it}$ (11.63 in OLS to −40.85 in 3SLS). In Table 9, we observed differences similar to that in Table 8. The differences of the results between 3SLS and OLS substantiate our discussion of the inconsistency of OLS estimation.

5.2. Estimation results for the second week

In order to capture the rapidly-changing nature of word-of-mouth communication, particularly on the Internet, we also estimated the two-equation system using the second week's data. OLS results still showed a major divergence from 3SLS for the data of the second week, which we will not discuss in detail. Instead, our discussion will focus on the 3SLS estimation. The results are shown in Tables 10 and 11.

For the revenue equation, the coefficients of the variables of the second week are similar to those of the first week, but the impact of the *volume* of word-of-mouth is stronger. From the first to second week, the coefficient of DAILYPOST_{it} changes from around 0.02 to 0.05 in both Eqs. (1) and (3). This change can be attributed to the differences of consumer preference in the early period of a movie's theoretical life cycle. The very early consumers (in the opening week) are those with particular interest in the movie (e.g., fan of a particular subject, star, director, and etc.). Such a self-selected portion of early consumers does not have much word-of-mouth to refer to and other people's opinion does not have a very strong impact on them either. However, the later followers are almost entirely driven by the word-of-mouth generated. Li and Hitt [28] analyzed and verified the existence of the self-selection effect in the early period of products' life cycles. Our results also indicate that such dynamics took place in a very short time frame with the help of the Internet, suggesting that using shorter time period data (e.g., daily data in this research) is more appropriate for investigating online word-of-mouth.

For the post equation, $\text{DAILYPOST}_{i,t-1}$ is no longer significant (in both Tables 10 and 11), which implies that the self-driving effect of word-of-mouth has dropped drastically in the second week. This is also consistent with the prediction of H6 implying that earlier users are more enthusiastic and easily driven by other consumers' posts. Such a finding also demonstrates the very volatile nature of online word-of-mouth. It is also observed that the coefficient of DAILYREVENUE_{it} has dropped significantly (from 19.19 in the first week to 3.92 in the second week for the $\text{CUMURATING}_{i,t-1}$ equation, and from 19.19 to 5.97 for the $\text{DAILYRATING}_{i,t-1}$ equation), though it still does remain significant. This result is consistent with our discussion of the public good nature of online user review. An increasingly small proportion of people who have watched the movie have the incentive to write reviews on the Internet given the existing number of postings.

Table 10
Second week estimation: OLS and 3SLS (cumulative rating)

Variable	OLS (fixed-effects estimation)	3SLS (simultaneous fixed-effects estimation)
	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Equation1: Revenue equation with DAILYREVENUE as dependent variable		
$\text{DAILYREVENUE}_{i,t-1}$	0.31 (0.04)***	0.22 (0.05)***
$\text{CUMURATING}_{i,t-1}$	2.04 (0.76)***	0.83 (0.56)
DAILYPOST_{it}	0.01 (0.003)***	0.05 (0.01)***
WEEKEND_{it}	1.58 (0.22)***	1.44 (0.24)***
	$N=426$, $R^2=0.86$	$N=426$, $R^2=0.83$
Equation2: Post equation with DAILYPOST as dependent variable		
DAILYREVENUE_{it}	−0.02 (0.80)	3.92 (2.16)*
$\text{CUMUPOST}_{i,t-1}$	−0.21 (0.03)***	−0.16 (0.03)***
$\text{DAILYPOST}_{i,t-1}$	0.05 (0.05)	0.05 (0.03)
WEEKEND_{it}	6.30 (3.58)*	−2.32 (5.48)
	$N=426$, $R^2=0.79$	$N=426$, $R^2=0.82$

***$p<0.01$, **$p<0.05$, *$p<0.10$.
Note: Time dummies (for each day) and movie dummies (fixed effect for each movie) used in estimating the model are not reported.

Table 11
Second week estimation: OLS and 3SLS (daily rating)

Variable	OLS (fixed-effects estimation)	3SLS (simultaneous fixed-effects estimation)
	Coefficient (Std. Err.)	Coefficient (Std. Err.)
Equation1: Revenue equation with DAILYREVENUE as dependent variable		
$\text{DAILYREVENUE}_{i,t-1}$	0.31 (0.04)***	0.19 (0.05)***
$\text{DAILYRATING}_{i,t-1}$	0.08 (0.05)*	0.04 (0.03)
DAILYPOST_{it}	0.009 (0.003)***	0.05 (0.01)***
WEEKEND_{it}	1.57 (0.22)***	1.50 (0.25)***
	$N=426$, $R^2=0.86$	$N=426$, $R^2=0.83$
Equation2: Post equation with DAILYPOST as dependent variable		
DAILYREVENUE_{it}	−0.02 (0.80)	5.97 (2.32)**
$\text{CUMUPOST}_{i,t-1}$	−0.21 (0.03)***	−0.13 (0.03)***
$\text{DAILYPOST}_{i,t-1}$	0.05 (0.05)	0.04 (0.02)
WEEKEND_{it}	6.30 (3.58)*	−6.79 (5.84)
	$N=426$, $R^2=0.79$	$N=426$, $R^2=0.80$

***$p<0.01$, **$p<0.05$, *$p<0.10$.
Note: Time dummies (for each day) and movie dummies (fixed effect for each movie) used in estimating the model are not reported.

6. Conclusions

The objective of this research is to investigate the impact and characteristics of online word-of-mouth. Our results yield interesting and important insights for both academic researchers and practitioners.

We developed a simultaneous equation system to capture the interdependent relationship between online word-of-mouth and movie sales. Our model fully specifies the dual causal relationship and reveals the true effect of word-of-mouth on movie sales. In contrast to earlier online word-of-mouth studies, we found that higher ratings do not lead to higher sales, but the number of posts is significantly associated with movie sales. These results suggest that consumers are not influenced by the persuasive effect of online word-of-mouth, although they are affected by awareness effect generated by the underlying process of word-of-mouth. Businesses shall therefore focus more on the mechanisms that facilitate dispersion of underlying word-of-mouth exchange rather than try to influence online ratings.

Our empirical analysis conducted in different time periods captured the fast-changing nature of online word-of-mouth communication. We found that word-of-mouth has a greater impact on movie sales in the later period but at the same time the buzz effect of word-of-mouth starts to diminish. The significant differences between the time periods suggest the importance of employing a dynamic system in studying the effect of word-of-mouth in the digital environment. As online word-of-mouth starts to establish an enlarging presence in people's routine life, it is critical for firms and organizations to understand the effects of online word-of-mouth on their managerial decisions.

Our research has established a relationship between online word-of-mouth information and offline movie sales. However, we did not directly observe how word-of-mouth information would affect consumers' choices and purchasing decisions. One important and interesting extension of our research will be to investigate the consumer's decision under the influence of word-of-mouth information, especially in the digital environment. In addition, not all word-of-mouth is equal. Consumers need to distinguish the "true" and "honest" opinions from all kinds of feedback and recommendations on the web. Under such circumstances, how consumers choose their information source and the mechanisms that help consumers to find trusted information sources will be of particular interest for future research. Moreover, further study to characterize and identify the impact of the online word-of-mouth information from different resources and formats would also be beneficial to our understanding and design of online feedback and information systems.

The present study has several other limitations. Our analysis is, by necessity, restricted to online users who choose to post reviews and post them on YM. Thus, our estimates are conditioned on such a user population. While such a restriction does not bias the panel estimation results, they should be interpreted as applying to a self-selected set of online users. All the movies in our sample are nation-wide releases. It would be interesting in future research to compare the *wide* and *limited* release movies. Furthermore, we have focused on only one entertainment product in this study. While we believe our results are relatively generalizable, it certainly would be important to replicate and extend such a study to other industries.

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Wenjing Duan is an Assistant Professor in Information Systems and Technology Management at The George Washington University.

Bin Gu is an Assistant Professor in Information Systems at The University of Texas at Austin.

Andrew B. Whinston is the Hugh Roy Cullen Centennial Chair in Business Administration, Professor of Information Systems, Computer Science and Economics, Jon Newton Centennial IC2 Fellow, and Director of the Center for Research in E-Commerce at The University of Texas at Austin.