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**The Dynamics of Online Word-of-Mouth and Product Sales –
An Empirical Investigation of the Movie Industry¹**

Wenjing Duan²

Funger 515, School of Business

The George Washington University, Washington, DC 20052

Phone: (202) 994-3217 Fax: (202) 994-5830

wduan@gwu.edu

Bin Gu

CBA 5.202, McCombs School of Business

The University of Texas at Austin, Austin, Texas 78712

Phone: (512) 471-1582 Fax: (512) 471-0587

Bin.Gu@mcombs.utexas.edu

Andrew B. Whinston

CBA 5.202, McCombs School of Business

The University of Texas at Austin, Austin, Texas 78712

Phone: (512) 471-7962 Fax: (512) 471-0587

abw@uts.cc.utexas.edu

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² Corresponding author

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ABSTRACT

There are growing interests in understanding how word-of-mouth (WOM) on the Internet is generated and how it influences consumers' purchase decisions at retail outlets. A unique aspect of the WOM effect is the presence of a positive feedback mechanism between WOM and retail sales. We characterize the process through a dynamic simultaneous equation system, in which we separate the effect of online WOM as both a *precursor* to and an *outcome* of retail sales. We apply our approach to the movie industry, showing that both a movie's box office revenue and WOM valence significantly influence WOM volume. WOM volume in turn leads to higher box office performance. This positive feedback mechanism highlights the importance of WOM in generating and sustaining retail revenue.

Keywords: Online user reviews; Word-of-mouth; e-Commerce; Motion picture; Simultaneous equations.

INTRODUCTION

Word-of-mouth (WOM) has been recognized as one of the most influential resources of information transmission since the beginning of human society (Godes and Mayzlin 2004; Maxham and Netemeyer 2002; Reynolds and Beatty 1999). However, conventional interpersonal WOM communication is only effective within limited social contact boundaries, and the influence diminishes quickly over time and distance (Ellison and Fudenberg 1995; Bhatnagar and Ghose 2004). The advances of information technology and the emergence of online social network sites have profoundly changed the way information is transmitted and have transcended the traditional limitations of WOM (Laroche et al. 2005). The otherwise fleeting WOM targeted to one or a few friends has been transformed into enduring messages visible to the entire world. As a result, online WOM plays an increasingly significant role in consumer purchase decisions.

Online WOM presents both challenges and opportunities to retailers. On the one hand, WOM provides an alternative source of information to consumers, thus reducing retailers' ability to influence these consumers through traditional marketing and advertising channels. Prior studies show that a variety of aspects of WOM influence retail sales. Some found that WOM dispersion (Godes and Mayzlin 2004) and valence (Chevalier and Mayzlin 2006; Forman et al. 2007) have significant effects on product sales, while others found that WOM volume serves as the key driver of product sales (Chen et al. 2004; Liu 2006). On the other hand, online WOM provides a new venue for retailers to reach consumers and to strategically influence consumer opinions. Anecdotal evidence has surfaced in recent years suggesting that online WOM could be successfully leveraged as a new marketing tool (Dellarocas 2003).

A unique aspect of the WOM effect that distinguishes it from more traditional marketing effects is the positive feedback mechanism between WOM and product sales. That is, WOM leads to more product sales, which in turn generate more WOM and then more product sales. The positive feedback mechanism indicates that WOM is not only a driving force in consumer purchase but also an outcome of retail sales (Godes and Mayzlin 2004; Srinivasan et al. 2002). Prior studies on WOM have not fully recognized this unique nature of WOM effect and often treat WOM as exogenous, like traditional marketing effects (Chen et al. 2004; Liu 2006). Ignoring WOM's dual roles of precursor and outcome may misplace causality and lead to erroneous results. The objectives of this study, therefore, are to explicitly model the positive feedback mechanism between WOM and retail sales and identify their dynamic interrelationship. We propose a simultaneous equation system to fully capture the dual nature of online WOM and its dynamic evolution in a panel data setting.

We have chosen the movie industry as our research context because industry experts agree that WOM is a critical factor underlying a movie's staying power, which leads to its ultimate financial success (Elberse and Eliashberg 2003). In addition, the movie industry has by far received the most attention in marketing literature on WOM, which allows in-depth comparison of our results with those of previous studies. We, however, note that movies are a unique type of experience goods and the results from the industry do not necessarily generalize to other retailing sectors. Rather, our goal is to use the movie industry as a context to highlight the importance of considering the dynamics of and the interrelationship between retail sales and online WOM and to demonstrate the validity of the simultaneous equation approach in this setting. We found that both a movie's box office revenue and WOM valence significantly influence WOM volume. WOM volume in turn leads to higher box office performance. Our

results clarify conflicting results reported in earlier studies with regard the influence of user ratings on box office revenue. We show that user ratings do not directly influence box office revenue. However, they affect box-office revenue indirectly through WOM volume. Our results also confirm that online WOM is not only a *precursor* to, but also an *outcome* of, product sales. We show that ignoring the dual nature of WOM leads to erroneous results.

Online WOM in the movie industry takes many forms, including online reviews, discussion boards, chat rooms, blogs, wikis, and others. In this study, we focus on online user reviews because statistics suggest that user reviews are more prevalent than other forms of WOM communication in the movie industry. Beyond volume, another subtle but important difference between online user reviews and other types of WOM is that user reviews usually reflect user experience and consumer satisfaction, which are mainly viewed as a source of product information (Chen and Xie 2004; Li and Hitt 2007). Meanwhile, other types of WOM, such as discussions in online community sites, reflect more about consumer expectation, which could be heavily influenced by social structure (Gopal 2006; Liu 2006).

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

LITERATURE REVIEW

Researchers and practitioners have long recognized the importance of person-to-person WOM (e.g., Katz and Lazarsfeld 1955; Coleman et. al. 1966; Foster and Rosenzweig 1995). The use of the Internet for publicizing feedback and recommendations on products and businesses

has broadened the reach of WOM and sparked an interest in re-examining the effect of WOM in the digital age (Chen and Xie 2004; Dellarocas 2003; Senecal and Nantel 2004; Zufryden 2000). Two dimensions of WOM activities have been considered in these studies: WOM volume (i.e., the amount of WOM disseminated) and WOM valence (i.e., the preference carried in the WOM information), often measured as positive, negative, or with user ratings. Studies suggest that the volume of digital WOM is positively associated with product sales, but the relationship between WOM valence and sales is often mixed (Liu 2006). Chevalier and Mayzlin (2006) found that improvement in volume and valence of a book's review leads to an increase in sales. However, with a similar data set from Amazon.com, Chen et al. (2003) found that WOM valence is not related to sales. By separating WOM dispersion across different online communities from dispersion within communities, Godes and Mayzlin (2004) noted that dispersion across communities is the main factor that influences sales performance.

Studies on WOM effects in the movie industry show a similar set of mixed results. Neelamegham and Chintagunta (1999) empirically assessed the relationship between WOM and weekly revenue but failed to obtain any significant results. Elberse and Eliashberg (2003) used average revenue per screen in the previous week as a proxy of WOM in their analysis of demand and supply of motion pictures. They found such a measurement of WOM to be a key predictor of box office revenue. Liu (2006) studied the temporal relationship between user WOM and box office revenue on a weekly basis by extending the earlier models proposed by Eliashberg and Shugan (1997) and Basuroy et al. (2003). The results suggest that the volume of WOM accounts for most explanatory power of aggregate and weekly revenue, but WOM valence is not significantly correlated with movie revenue. Dellarocas et al. (2007) used a modified Bass Diffusion model to study the effect of online user reviews in forecasting movie revenue. Their

results indicated that the average valence of user ratings is a better predictor than other variables of future movie revenue.

There are several important differences between this paper and previous studies. First, most prior studies consider WOM as an exogenous factor that influences product sales but overlook the fact that WOM is influenced by product sales and therefore is endogenous. One notable exception is Godes and Mayzlin (2004). However, their system of seemingly unrelated regressions (SUR) does not account for the endogeneity of WOM when it acts as an influencer of the sales. This study, unlike others, adopts a simultaneous equation system that more fully characterizes the interdependent relationship between online WOM and movie revenue, which allows full control of the endogeneity of the WOM effect as well. Second, our model takes a dynamic approach, not only considering the concurrent relationship between WOM and retail sales, but also studying how WOM and retail sales affect each other over a longer term.

Third, one unique feature of online WOM is its unprecedented speed of transmission through the Internet. Rather than being influenced by weekly newspaper entertainment inserts or magazines, consumers today are more likely to visit online user review sites, which prominently feature the most recent reviews—ones often posted minutes or hours ago. Given this speed, we differ from prior studies by considering WOM effects on a daily rather than weekly basis, which allows us to consider the main and lagging effects of WOM over a relatively short period of time.

Fourth, prior studies of the movie industry focus on cross-sectional data. The cross-sectional approach is necessary when variables of interests are time-invariant such as the critics' ratings. However, the cross-sectional approach does not account for unobserved individual effects. This is of particular concern for the study of WOM effects. WOM volume and valence vary both over time and across movies; the cross-sectional variation, however, mainly captures

differences in consumer taste rather more than WOM effects. To separate WOM effects from unobserved consumer taste for movies, we control for individual effects and explore the time-series variations in WOM measures to identify the true influence of WOM.

Fifth, our model considers the interplay between WOM valence and WOM volume. In particular, we consider how WOM valence affects consumers' incentive to distribute WOM, which in turn influences retail sales. Finally, in measuring WOM valence, we consider both cumulative and daily WOM valence. WOM cumulative valence³ is the most popular format of displaying aggregate user feedback information on most social network websites, while daily WOM valence captures the underlying changes in WOM valence. By including both measures, our approach allows us to identify whether consumers are influenced by the aggregate information provided by the website, or by the underlying WOM process.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Figure 1 depicts our conceptual framework, which integrates the interrelationship between WOM and box office revenue into the extant representation of the movie market (Elberse and Eliashberg 2003; Liu 2006). As shown in Figure 1, WOM influences current and future box office revenue, which in turn affects the generation of current and future WOM. To capture the dynamic interdependent process between WOM and movie box office revenue, we propose two sets of hypotheses. The first set considers the influence of WOM on movie box office revenue while the second set considers the influence of movie box office revenue on WOM.

WOM influences movie sales in two ways (Liu 2006). First, the distribution of WOM increases consumer awareness. Second, WOM valence influences consumer evaluation of the

³ Cumulative valence is the average WOM valence of all WOM received since a product's release. Daily valence is the average WOM valence of WOM received on a particular date.

products and their ultimate purchase decisions. Marketing researchers have long recognized that consumer awareness is the first step in the consumer decision making process and plays a major role in marketing strategies (Bettman 1979; Lilien et al. 1992). Other marketing activities, including WOM's influence on consumer evaluation, hinge on consumer awareness. WOM's awareness effect also takes the central stage in the positive feedback mechanism. It is through WOM dissemination that a popular movie generates buzz, which in turn leads to even higher box office sales. WOM's influence on product evaluation, on the other hand, does not lead to the positive feedback mechanism, as increases in WOM valence could lead to higher sales but higher sales are not likely to lead to even higher WOM valence. As such, we consider WOM's awareness effect as the primary effect in the positive feedback mechanism and focus our hypothesis on the dynamic interrelationship between WOM volume and movies sales.

While the awareness effect of WOM has been considered in the literature, we note that prior studies have treated WOM as an exogenous factor. Our objective is to re-evaluate the influence of WOM in a model that considers the endogenous nature of WOM. Moreover, we note that prior studies consider the WOM effect in a static setting with a focus on the concurrent relationship between WOM and retail sales. However, unlike person-to-person WOM, online WOM is stored by review sites, and its influence could go beyond the concurrent term. WOM is also known for its fleeting nature. Buzzes generated for a movie can quickly wear out if there is no follow-up. Our results therefore differ from prior studies by measuring both the concurrent and lagging effects of WOM over retail sales. We thus propose the first set of hypotheses:

H1: The influence of WOM volume on concurrent movie sales is positive.

H2: The influence of WOM volume on movie sales beyond the concurrent term is positive.

However the influence diminishes quickly.

Insert Figure 1 here

The second set of hypotheses considers the influence of movie sales on WOM generation. A number of extrinsic factors have been found to influence WOM generation, including genres, star power, and critics' ratings (Liu 2006). Studies also show that movies at the extreme end of the quality spectrum are more likely to attract WOM (Liu 2006). These factors are static for each movie and have been considered in prior studies. However, the most important factors in WOM generation are dynamic and intrinsic. We consider two main factors. First, the larger the pool of consumers who have experienced a movie, the more WOM will be generated. This is consistent with studies of product diffusion, which indicate that internal influence is mainly determined by the number of consumers who have experienced the products (Mahajan et al. 2000). We also note that not all consumers who have experienced a movie have the same incentive to spread WOM. Those who have experienced a movie most recently have more vivid memories and are more likely to spread WOM. This indicates that movie sales at a given time have the most impact on WOM generation in the concurrent term. Its influence on future WOM generation diminishes quickly. Second, changes in WOM valence influence the amount of WOM generated. Prior studies show consumers distribute positive WOM out of altruism and self-enhancement and negative WOM out of anxiety reduction and vengeance (Sundaram et al. 1998). For a given movie, when WOM valence increases, consumers dissatisfied with the movie have a stronger incentive to distribute negative WOM, motivated by vengeance to bring down the rating. At the same time, a consumer satisfied with the movie also has a greater incentive to post positive WOM due to self-enhancement. This is because higher valence indicates more of the community members agree with the consumer's assessment of the movie, which encourages him or her to distribute WOM to enhance self-esteem (Sundaram et al. 1998; Wangenheim et al. 2003). Based on these discussions, we have the following hypotheses:

H3: The influence of movie sales on concurrent WOM volume is positive.

H4: The influence of movie sales on WOM volume beyond the concurrent term is positive.

However the influence diminishes quickly.

H5: The influence of WOM valence on WOM volume is positive.

A number of other factors, such as movie genre, critics' ratings, star power, MPAA rating, and others, influence WOM and movie sales as well. Most of the factors are time invariant, and we control for these factors with individual fixed effects. Previous studies also found that the number of screens allocated to a movie strongly influences box office revenue (Elberse and Eliashberg 2003). The number of allocated screens is determined by movie exhibitors and changes weekly. We control for the number of screens in our model as shown in Figure 1.⁴

RESEARCH METHODOLOGY

Description of the Data and Measures

The sample for this study was collected from three publicly available sources: Variety.com (Variety: <http://www.variety.com>), Yahoo!Movies (YM: <http://www.movies.yahoo.com>), and BoxOfficeMojo.com (Mojo: <http://www.boxofficemojo.com>). Movies were chosen based on Variety's 2003-2004 box office rank in the U.S. market. We then matched the list of movies with that on YM and Mojo for user reviews and daily box office information. Our final data set included 71 movies with the release time in theaters between July 2003 and May 2004. All the movies in our sample were nationwide releases from their opening day.

⁴ In this paper, we use number of screens as a control variable for the revenues in each week. Number of screens is also endogenous, is a strategic decision made by the theater owners based on the movie's previous week's performance (Elberse and Eliashberg 2003). We have formulated a three-equation system, with the number of screens as the dependent variable in one equation, and obtained qualitatively similar results.

From YM, we collected the following information for each movie: each review's yahooID, post date, and review grade. From these data, we constructed WOM valence and WOM volume for each movie on a daily basis. We assigned a numerical value to the letter grade of each individual user review, so that A+ equals 13, A equals 12... and D equals 3.⁵ The numerical values were aggregated, for each movie, by adding up the values and taking the arithmetic average for each day. The calculation quantifies *daily rating* for each movie, representing its WOM valence. For WOM volume, we totaled the daily number of posts for each movie. We note that YM also posts an assessment of *Average User Grade* for each movie on its website. Different from the WOM valence calculated above, YM's average user grade is based on cumulative user ratings since a movie's release. To control for the influence of YM's average user grade, we construct a similar measure by taking the arithmetic average over all user grades since a movie's release and name it *cumulative rating* to avoid confusion.

We collected other movie information from Mojo. These variables include daily rank, daily gross revenue, theaters engaged, average revenue per theater, and daily gross-to-date revenue. We also collected summary data for each movie: production budget, estimated marketing costs, MPAA rating, producer, and domestic and oversea gross revenue.⁶ The lifetime of movies in theaters varies notably; most movies are shown for six to ten weeks (Elberse and Eliashberg 2003). For our movie sample, we constructed a panel data set of the 71 movies for 6 weeks (42 days). Table 1 presents the summary statistics for our movie sample. Table 2 provides the description and measurement of the key variables used in the empirical analysis.

⁵ We contacted Yahoo! Movies regarding its numerical transformation for calculation of average user ratings. We were notified that the average user grade posted on the Yahoo! Movies website is calculated in this way.

⁶ Since all the movie level factors are controlled by the fixed-effects, we do not provide a summary for the movie level variables information in the paper.

Tables 3 and 4 show the summary statistics and correlation matrix for the six-week daily data sample we use for the empirical estimation.

Insert Tables 1, 2, 3, and 4 here

We observed that, for most movies, the number of user reviews soars in the first few days after the opening and drops significantly afterward. Such a pattern is very similar to the box office life-cycle of motion pictures, indicating that the WOM process takes place almost instantly after the movie viewing experience. For the purpose of illustration, Figure 2 plots how box office revenue, review volume, and rating change over time on a *daily* basis. Figure 2a and Figure 2b demonstrate the dynamics of daily revenue and daily volume of reviews. These two plots display remarkably similar patterns on the day-to-day basis, even for temporal increases and drops. The plots suggest that WOM volume and box office revenue are highly interdependent, which highlights the importance of investigating sales and WOM volume simultaneously to uncover the real effect of online WOM. The highly interdependent nature of revenue and volume of reviews also makes the importance of using daily data more evident. Figure 2c plots the daily average user ratings across all movies and Figure 2d plots the daily user ratings of a randomly picked movie - “Barbershop 2”. The figures show that variations in daily user ratings persist overtime,⁷ indicating that WOM valence can change frequently and could have significant influence on movie box office revenue and WOM volume.

Insert Figure 2 (a, b, c, and d) here

Empirical Model Specification

The development of our empirical model is guided by the following considerations. First, as we are interested in the drivers of both box office revenue and WOM, we construct a system

⁷ Due to averaging across 71 movies, the variation in Figure 2c is about 8 times smaller than the actual variations in daily user ratings in individual movies.

of two *interdependent* equations: one equation with daily revenue as the dependent variable (the revenue equation) and the other with WOM volume as the dependent variable (the WOM equation). We assume that in each time period (i.e., day), the errors in the two equations may be correlated, which implies that factors not included in our model could simultaneously influence both movie revenue and WOM.

Second, recognizing that interactions between consumers' movie-going behavior and WOM can go beyond the concurrent term (Elberse and Eliashberg 2003), we develop a system of *dynamic* equations. That is, in the revenue equation, we include not only the contemporaneous term of daily WOM volume, but also multi-lag terms. Likewise, in the WOM equation, multi-lag revenue terms are also incorporated. Such a specification also helps identify both equations for the simultaneous equation system since the lagged terms are exogenous variables in either equation. In addition, following extant research, we use a log-linear formulation (e.g., Elberse and Eliashberg 2003; Liu 2006) in our model. The log-linear formulation is consistent with theoretical models of a multistage consumer decision making process, where sales of a movie can be viewed as a series of conditional probabilities applied to the consumer base.⁸ A log transformation converts the relationship into a linear form for empirical estimation. Moreover, log transformation smoothes the distribution of variables in the linear regression, and the estimated coefficients of the log-linear form directly reflect the elasticity of independent and dependent variables.

Third, to control for any movie idiosyncratic factors that could influence revenue and/or WOM, such as budget, marketing, star, and others (Basuroy et al. 2003; Elberse and Eliashberg 2003; Liu 2006), we include fixed effects in the model by adding movie-specific dummy

⁸ For example, a simple two-stage consumer decision model implies the following: movie sales = consumer base * percentage of consumers aware of the movie * percentage of consumers choosing the movie given their awareness.

variables. Fixed effects capture any non-time varying factors, including intrinsic movie characteristics, critic reviews, and other exogenous determinants. In addition, fixed effects estimation also allows the error term to be arbitrarily correlated with other explanatory variables, thus making the estimation results more robust.

The system of equations is specified as follows:

Revenue Equation

$$\begin{aligned} \log(DAILYGROSS)_{it} = & \alpha_0 \log(DAILYPOST)_{it} + \sum_{j=1}^J \alpha_j \log(DAILYPOST)_{i,t-j} \\ & + \beta_1 \log(CUMURATING)_{it} + \beta_2 \log(DAILYRATING)_{it} \\ & + \gamma_1 \log(SCREEN)_{it} + \gamma_2 \log(AGE)_{it} + \gamma_3 WEEKEND_t + \mu_i + \varepsilon_{it} \end{aligned} \quad (1)$$

WOM Equation

$$\begin{aligned} \log(DAILYPOST)_{it} = & \delta_0 \log(DAILYGROSS)_{it} + \sum_{k=1}^K \delta_k \log(DAILYGROSS)_{i,t-k} \\ & + \phi_1 \log(CUMURATING)_{it} + \phi_2 \log(DAILYRATING)_{it} \\ & + \varphi_1 \log(AGE)_{it} + \varphi_2 WEEKEND_t + \rho_i + \sigma_{it} \end{aligned} \quad (2)$$

Equation (1) reflects the daily revenue and Equation (2) displays the WOM volume. Let $i = 1, \dots, N$ index the movies. $DAILYGROSS_{it}$ denotes the daily gross revenue of movie i at day t . $DAILYPOST_{it}$ denotes the total number of user reviews posted for movie i at day t .

$\sum_{j=1}^J \alpha_j \log(DAILYPOST)_{i,t-j}$ expresses the linear addition of multi-lag terms of $DAILYPOST_{it}$.

Following a similar structure, in equation (2), we include both the contemporaneous and multi-lag terms of $\log(DAILYGROSS)_{it}$. $CUMURATING_{it}$ represents the cumulative average user review grade of movie i by day t . Since YM provides *Average User Grade* on the top of each movie's page, it is the most noticeable information on the website. $DAILYRATING_{it}$ denotes the average user review grade of movie i on day t . While $CUMURATING_{it}$ measures the overall evaluation of the movie quality from the users, $DAILYRATING_{it}$ reflects the most recent and concurrent valence of WOM.

Drawing on previous literature (e.g., Basuroy et al. 2003; Elberse and Eliashberg 2003; Liu 2006), we include three control variables that vary over the movie's life cycle in equation (1). The three variables are the number of screens ($\log(SCREEN)_{it}$), number of days released ($\log(AGE)_{it}$), and a dummy variable indicating whether day t is during a weekend ($WEEKEND_t$). $\log(AGE)_{it}$ and $WEEKEND_t$ are also included in equation (2). μ_i , and ρ_i , denotes the movie-specific fixed effects that capture the idiosyncratic characteristics associated with each movie, such as its budget, marketing costs, genre, and distributor, as well as its intrinsic quality. The fixed effects capture all non-time varying, unobserved heterogeneity of each movie; thus, we are able to control for unobserved differences across movies.

FINDINGS AND DISCUSSIONS

The Three-Stage Least-Square (3SLS) procedure was used to simultaneously estimate the system of two equations. Since previous movie literature often estimates only a single equation using Ordinary Least Square (OLS) (e.g., Eliashberg and Shugan 1997; Basuroy et al. 2003; Liu 2006), we also estimate each equation individually using OLS to investigate how the results would differ if endogeneity and simultaneity of revenue and posts are not taken into account. OLS estimation is known to be inconsistent because the regressors of both equations include endogenous variables.⁹ The 3SLS Estimation results are reported in Table 5.

Insert Table 5 here

For the revenue equation (3SLS estimation), $DAILYPOST_{it}$ is a significant predictor for $DAILYGROSS_{it}$, entailing strong support for H1. The coefficient is 0.63, which is significant at the 0.01 level. The coefficients of the two lagged terms $DAILYPOST_{i,t-1}$ and $DAILYPOST_{i,t-2}$ are

⁹ The 3SLS estimation procedure may also be of concern for our specification since we include lagged endogenous variables in the equation, and a fixed-effects model may suffer from a finite sample bias (Nickell 1981). We then estimate a model suggested by Arellano and Bond (1991), using a General Method of Moments (GMM)-based method, and find qualitatively equivalent results to 3SLS.

0.17 and 0.10 respectively, which are also positive and statistically significant, although the magnitude of their influences has significantly diminished. Thus, the results support H2. Given the log-linear formation, the coefficients suggest that every 10% increase in the volume of user reviews increases same-day box office revenue by 6.3%, next-day box office revenue by 1.7%, and third-day box office revenue by 1%. The difference in coefficients between the concurrent term and the first lag of WOM volume is 0.46, corresponding to a t-statistic of 2.61 ($p < 0.01$). It shows the decline of influence is statistically significant. Similarly, the difference in coefficients between the first and second lag of WOM volume is 0.07 ($t = 3.56, p < 0.01$).¹⁰

The fact that neither $\log(DAILYRATING)_{it}$ nor $\log(CUMURATING)_{it}$ has a significant relationship with box office revenue indicates that a review rating itself may not play an essential role in influencing consumers' movie-going behavior, after controlling for the inherent movie heterogeneity.¹¹ To put it differently, movies' box office sales are not directly influenced by time-series changes in WOM valence. The finding suggests that consumers do not blindly follow the ratings posted by other users and they are not easily manipulated by extreme online reviews that aim to change WOM valence. The finding however does not mean that online reviews are of no value to consumers. Most of user rating valence is mixed with positive and negative ratings, which may create confusion among users. As a result, users potentially pay more attention to the content rather than rating itself. This is especially true for movies and other horizontally differentiated products. For these products, a reviewer could have a very different

¹⁰ More lagged terms have been considered as well. The similar diminishing pattern sustains, and the coefficients are not statistically significant. Thus, they are not incorporated into the final model.

¹¹ Prior studies used percentage of positive, negative and mixed reviews as measures of WOM valence (Eliashberg and Shugan 1997; Basuroy et al. 2003; Liu 2006). We also try such measures of WOM valence by coding user ratings as positive when they are greater 9, negative when they are less than 5, or mixed otherwise. Consistent with the literature, we find that the percentage of positive and negative reviews are highly correlated, thus they can't be included in the same equation. We use them separately and do not find qualitatively different results compared to our current model. To more accurately reflect the information consumers can observe on YM, we keep the structure of our current model.

taste and give a rating different or even opposite of what a reader would have given. The reader of an online reviewer therefore needs to calibrate the review based on his assessment of the “agreement” between his and reviewer’s taste and make an independent judgment about the true quality of the movie.¹² Other factors of the movie business may also contribute to the insignificance of WOM valence. For example, due to the nature of the movie business, consumers often make impulse decision without paying much attention to WOM content (Liu 2006). In addition, the anonymity of the authors of the reviews may also discount their credibility for users.

For the WOM equation (3SLS estimation), the coefficient of $\log(DAILYGROSS)_{it}$ (0.42) is statistically significant at the 0.01 level, indicating that WOM volume is strongly affected by sales. Thus, H3 is supported. The influence of $\log(DAILYGROSS)_{i,t-1}$ falls to 0.16. The difference between the concurrent term and the first lag is 0.26, and the difference is statistically significant ($t = 4.95, p < 0.01$). The coefficient of $\log(DAILYGROSS)_{i,t-2}$ becomes negative (-0.02). Though it is statistically significant, the magnitude of the impact is negligible.¹³ H4, therefore, is also supported. The results overall suggest that the effect of movie box office revenue on WOM volume lasts for two days, which is slightly shorter than the effect of WOM volume on box office revenue. A 10% increase in box office revenue increases same-day WOM volume by 4.2% and next-day WOM volume by 1.6%. Integrated with the results of the revenue equation, our findings confirm the importance of considering the positive feedback mechanism of the WOM effect. That is, higher box office revenue leads to more online WOM, which in turn increases box office revenue and leads to even more online WOM.

¹² We thank an anonymous reviewer for suggesting this explanation.

¹³ The negative coefficient on the second lag implies that WOM volume generated at time t is slightly negatively correlated with box office sales at $t-2$. One possible explanation is that there is a substitution effect between WOM volume between t and $t-2$ which are positive correlation with box office sales at $t-2$.

$\log(CUMURATING)_{it}$ is not a significant predictor for volume of user reviews. However, $\log(DAILYRATING)_{it}$ is found to be significantly correlated with WOM volume in the WOM equation, which renders support for H5. This finding calls our attention to the mechanism of how WOM valence influences box office revenue. Although we do not find that WOM valence has any direct influence in driving movie-going behavior, it increases movie revenue indirectly by generating greater buzz. The more positive the valence of WOM for a given movie, the more incentive movie-goers have to spread the information and generate WOM, which eventually leads to more sales. To our knowledge, this dynamic relationship between WOM valence and WOM volume has not been reported in any previous research.

We also note a number of interesting phenomena from the coefficients on control variables. Table 5 shows that box office sales increase by 88% during weekends, but consumers are 14% less likely to distribute WOM online during weekends. The decrease in WOM volume is relative given the control of box office revenue. In absolute terms, it suggests that despite an observation of 88% more movie-goers during weekends, we only observe a 62%¹⁴ increase in WOM volume. This effect is consistent with Figure 2, which shows more fluctuation in weekend box office revenue than in weekend WOM volume.

There are some major changes in the significance of variables if we compare the results of 3SLS with those of OLS. In particular, $\log(CUMURATING)_{it}$ is a significant predictor for revenue in OLS estimation. This might explain why some of the previous research found that the overall rating is a significant influence for product sales (Basuroy et al. 2003; Chevalier and Mayzlin 2006). However, simple OLS regression does not correctly characterize the effect of online user ratings, given the correlation between the error term and the endogenous variable. In

¹⁴ Weekends have two effects on WOM volume. They increase WOM volume because consumers are more likely to go to movie theatres during the weekend. They also decrease WOM volume because consumers are less likely to post WOM online over the weekend. The net percentage change can be calculated as $(1+88%)*(1-14%) - 100%$.

our specific setting, the effect of $\log(CUMURATING)_{it}$ is overestimated in OLS given the endogeneity of $\log(DAILYPOST)_{it}$. We also find that the coefficients of $\log(DAILYPOST)_{it}$ and its two lagged terms are significantly lower in OLS, compared to those in 3SLS. This finding implies that not considering the endogeneity of $DAILYPOST_{it}$ leads to noteworthy underestimation of its effect on revenue. In addition, $\log(CUMURATING)_{it}$ is also found to be a significant influencer in the WOM equation, while it is not significant in the 3SLS estimation. The influence of overall user ratings is clearly overestimated in the OLS regression in both equations. 3SLS estimation also finds significant negative correlation between the noise terms of the two equations. The negative correlation is caused by potential measurement errors in box office revenue and WOM volume, which contribute to noise terms in the two equations in opposite directions. The negative correlation further indicates the value of using 3SLS.

IMPLICATIONS, LIMITATIONS, AND FUTURE RESEARCH

This paper develops a dynamic simultaneous equation system to capture the interrelationship between online WOM and product sales in the context of motion pictures. . . Our model specifies the dual causal relationship and reveals the positive feedback mechanism between online WOM and product sales. Our findings strongly support the value of considering the endogeneity of WOM and its interdependence with consumers' consumption behavior. The notably different results obtained from 3SLS (the statistically more robust method) and OLS suggest that extant research using simple regression techniques may have drawn biased conclusions about the direction and magnitude of the effect of WOM. Our results validate our assertion that the volume of online user reviews has an intertwining relationship with retail sales.

Our findings also bring important extensions to previous research (Liu 2006; Eliashberg and Shugan 1997; Basuroy 2003) on the relationship among WOM volume, WOM valence, and box office sales. Previous research has been focusing on the direct impact of WOM volume and

valence on box office revenues and find that most of the explanatory power comes from WOM volume not WOM valence (Liu 2006). Our study extends this approach by considering the interaction between WOM valence and WOM volume. We find that while WOM valence does not directly affect revenue, higher WOM valence indirectly increases box office revenue by generating higher volume of WOM.

The contributions of this research to retail literature on WOM are multifaceted. From the methodology perspective, we bring to light the importance of separating the effect of WOM as both a precursor and an outcome of sales. Our results also highlight the importance of using a dynamic system and high-frequency data in studying the effect of WOM in the digital environment. From the managerial perspective, we show that WOM valence and WOM volume play different roles in influencing product sales. We also show that time-series changes in WOM valence influences WOM volume which leads to higher product sales. Our findings support the idea that the online WOM process has a significant impact on sales, suggesting that businesses should embrace and facilitate WOM activities.

There are a number of opportunities to extend the current research. One important and interesting extension of our research will be to investigate the consumer decision process under the influence of WOM information, especially in the digital environment. In addition, not all WOM 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 how to establish the mechanisms that help consumers to find trusted information sources will be of particular interest for future research.

Online user reviews are only one type of consumer-generated media. The recent explosive growth of popular online social communities (e.g., YouTube.com, Flickr.com, and

Digg.com) has generated a renewed interest in the Internet as a new medium for content generation and distribution. Different from online review sites we explored here, online social communities encourage interaction between users, which potentially changes the dynamics of WOM distribution. The modeling approach used in this research therefore may not be sufficient to these contexts. Further study to characterize and identify the effect of online WOM in the new medium would be beneficial to our understanding of the effect of online consumer-generated media on marketing and retailing strategies.

Our analysis is, by necessity, restricted to online users who choose to post reviews and to post them on Yahoo!Movie. Thus, our estimates are conditioned on such a user population. While such a restriction does not necessarily bias the panel data estimation results, they should be interpreted as applying to a self-selected set of online users. In addition, this paper studies only the relationship between the *post-release* WOM and sales. However, WOM or buzz certainly has existed before a movie's release, and movie studios have made various pre-release marketing efforts to stimulate the buzz and promote the WOM (Liu 2006). A careful survey of Yahoo!Movie indicates an important and interesting difference between pre-release WOM and post-release WOM. We note that pre-release WOM activity centers in Yahoo!Movie discussion boards, and the postings mainly reflect consumer expectations; meanwhile, post-release WOM activities center in Yahoo!Movie's user review sites, where postings mainly reflect consumer satisfaction and product experience. This difference indicates that there exist potentially different mechanisms for pre-release WOM versus post-release WOM. Thus, an important extension to the current research would be to study the dynamic relationship between pre-release and post-release online WOM and to differentiate their influences.

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TABLES AND FIGURES

Figure 1. Conceptual Framework: WOM and Box Office Revenue

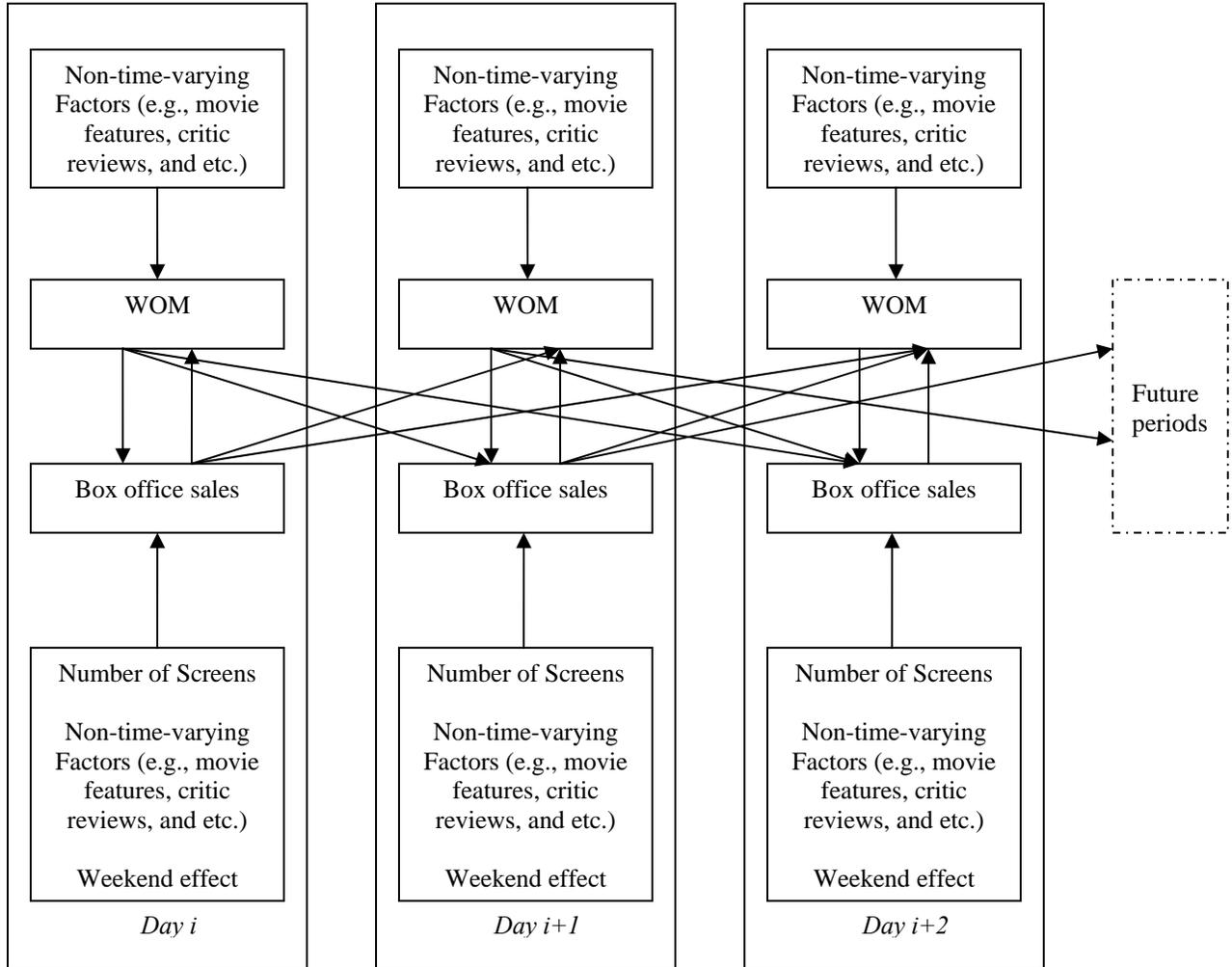


Table 1. Summary Statistics of the Movie Sample

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
<i>Budget (million \$)</i>	64	46.06	35.00	32.17	4.00	150.00
<i>Est. Marketing Costs (million \$)</i>	57	24.00	25.00	7.13	10.00	50.00
<i>US Gross (million \$)</i>	71	66.16	57.94	51.21	10.39	377.03
<i>Total User Posts</i>	71	1350.24	1294.00	882.80	342.00	4562.00
<i>Avg. User Rating</i>	71	8.89	9.00	1.02	6.00	11.00
<i>Avg. Critic Rating</i>	71	7.46	7.00	1.75	3.00	11.00

Table 2. Key Variables, Descriptions, and Measures

Variable	Description and Measure
$SCREENS_{it}$	Daily number of screens for movie i in day t
$DAILYGROSS_{it}$	Daily revenue for movie i in day
$DAILYPOST_{it}$	Number of user reviews posted for movie i in day t
$CUMURATING_{it}$	Cumulative average user grade for movie i until day t
$DAILYRATING_{it}$	Daily average user grade for movie i until day t
AGE_{it}	Number of days movie i has been released at day t
$WEEKEND_t$	A dummy variable indicating if day t is a weekend (coded as 1 if day is Friday, Saturday, or Sunday, and 0 otherwise)

Table 3. Summary Statistics of the Daily Data

Variable	N	Mean	Median	Std. Dev.	Min.	Max.
$SCREENS$	2866	2076.56	2288.00	932.20	18.00	3703.00
$DAILYGROSS$ (million \$)	2866	1.51	0.65	2.40	0.0004	34.45
$DAILYPOST$	2834	30.94	15.00	51.47	1.00	633.00
$CUMURATING$	2834	9.60	9.89	1.33	5.85	12.20
$DAILYRATING$	2834	9.46	9.77	2.01	1.00	13.00
AGE	2899	21.16	21.00	12.08	1.00	42.00

Table 4. Correlation Matrix of Key Daily Variables

Variable	1	2	3	4	5	6	7
1 $\log(DAILYGROSS)_{it}$	1						
2 $\log(DAILYPOST)_{it}$	0.79***	1					
3 $\log(SCREENS)_{it}$	0.68***	0.59***	1				
4 $\log(CUMURATING)_{it}$	-0.04	0.07	0.13**	1			
5 $\log(DAILYRATING)_{it}$	0.14***	0.15**	0.16**	0.10**	1		
6 $\log(AGE)_{it}$	-0.58**	-0.67***	-0.42***	0.51***	-0.05	1	
7 $WEEKEND_t$	0.42***	0.20**	-0.06	-0.02	-0.006	-0.02	1

*** p<.01, ** p<.05

Figure 2. Dynamics of WOM and Box Office Revenue for the Movie Sample

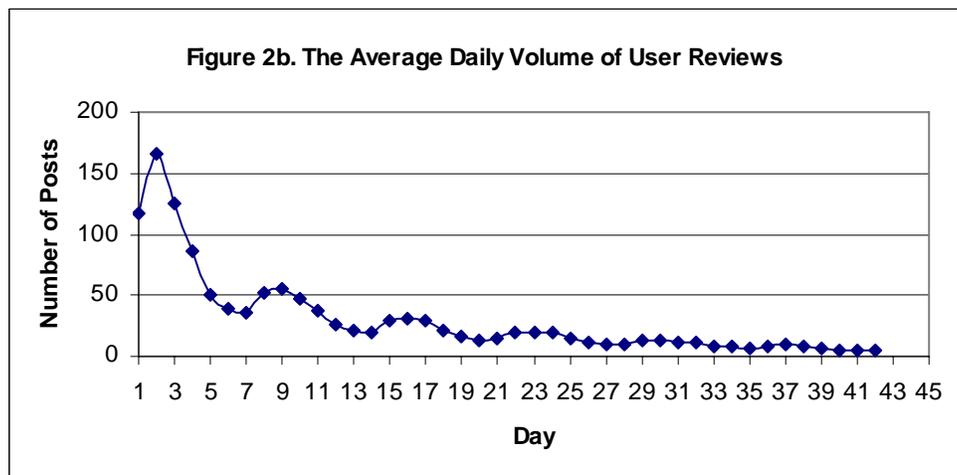
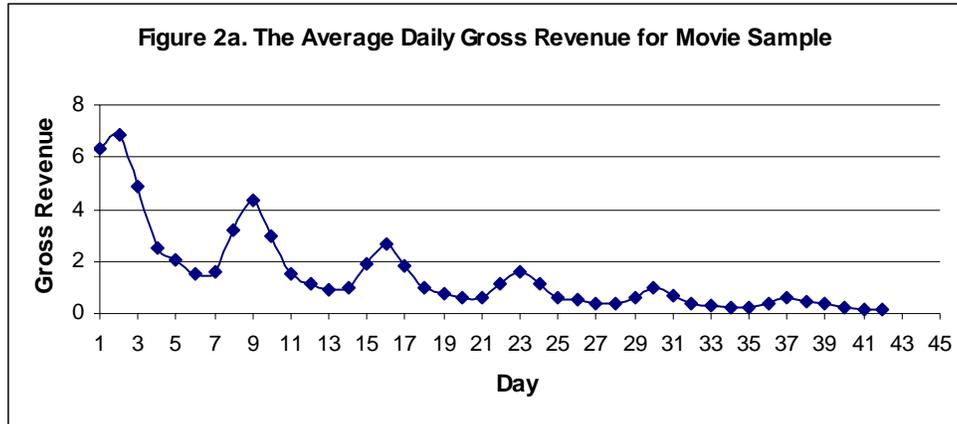


Figure 2c. The Average Daily User Ratings

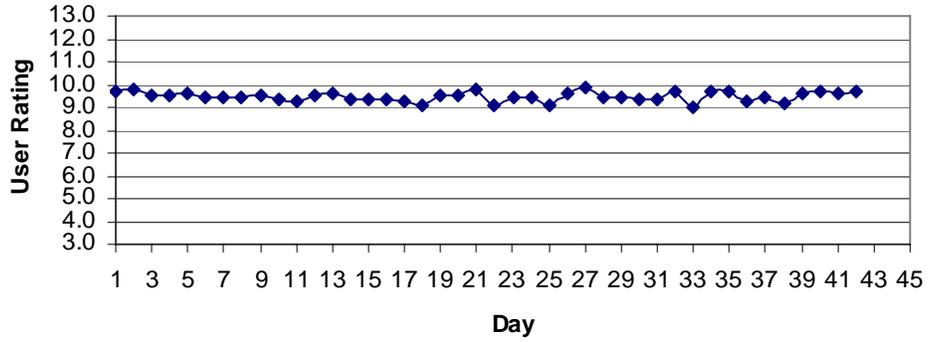


Figure 2d. The Average Daily User Ratings for Movie "Barbershop 2"

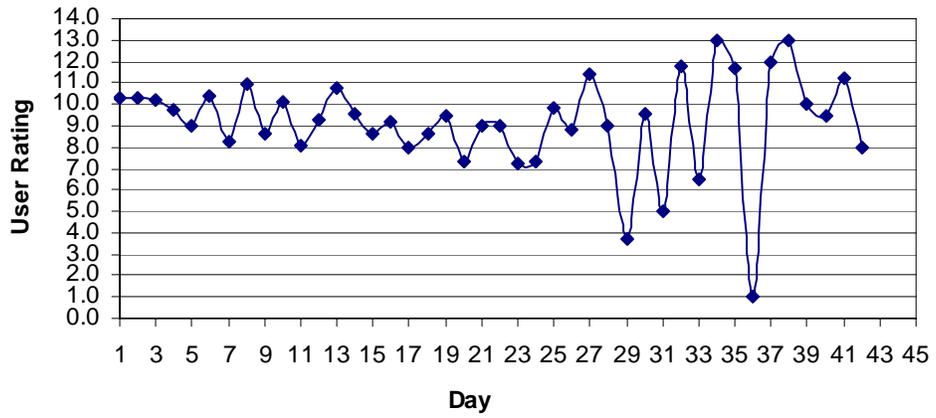


Table 5. OLS and 3SLS Estimation Results

	OLS	3SLS
Variable	Coefficient (Std. Err.)	Coefficient (Std. Err.)
<i>Equation1: Revenue equation with log(DAILYGROSS)_{it} as Dependent Variable</i>		
log(DAILYPOST) _{it}	0.33 (0.02)***	0.63 (0.15)***
log(DAILYPOST) _{i,t-1}	0.15 (0.02)***	0.17 (0.03)***
log(DAILYPOST) _{i,t-2}	-0.04 (0.02)**	0.10 (0.02)***
log(CUMURATING) _{it}	0.43 (0.09)***	-0.15 (1.18)
log(DAILYRATING) _{it}	-0.10 (0.04)**	-0.11 (0.07)
log(SCREENS) _{it}	0.90 (0.02)***	0.50 (0.07)***
log(AGE) _{it}	-0.29 (0.02)***	0.04 (0.10)
WEEKEND _t	1.01 (0.03)***	0.88 (0.08)***
CONSTANT	5.07 (0.23)	6.14 (2.82)
	$R^2 = 0.83$	$R^2 = 0.89$
<i>Equation2: WOM equation with log(DAILYPOST)_{it} as Dependent Variable</i>		
log(DAILYGROSS) _{it}	0.33 (0.02)***	0.42 (0.03)***
log(DAILYGROSS) _{i,t-1}	0.09 (0.03)***	0.16 (0.02)***
log(DAILYGROSS) _{i,t-2}	0.14 (0.03)***	-0.02 (0.01)**
log(CUMURATING) _{it}	0.31 (0.10)***	-0.07 (0.70)
log(DAILYRATING) _{it}	0.21 (0.05)***	0.19 (0.04)***
log(AGE) _{it}	-0.44 (0.02)***	-0.45 (0.03)***
WEEKEND _t	0.04 (0.03)	-0.14 (0.03)***
CONSTANT	-4.66 (0.25)	-2.79 (1.71)
	$R^2 = 0.72$	$R^2 = 0.85$
Cross Model Correlation		-0.91

*** p<.01, ** p<.05

Note: Movie dummies (fixed effect for each movie) used in estimating the 3SLS model are not reported