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경영학박사학위논문

Dynamic Effects of electronic Word-of-Mouth on Product Performance: Comparison of Online Consumer Reviews and Social Media Buzz

온라인 구전이 제품 성과에 미치는 동태적 영향

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이 지 수

Abstract

Dynamic Effects of electronic Word-of-Mouth on Product Performance: Comparison of Online Consumer Reviews and Social Media Buzz

Jisu Yi

College of Business Administration

The Graduate School

Seoul National University

This research aims to examine the dynamics of electronic word-of-mouth effects on product's financial performance considering two types of platforms (i.e., online consumer reviews and social media). Our joint model not only captures the time varying effects of each channel, but also investigates whether online consumer reviews and social media buzz assist or hinder one another in increasing product's financial performances. The panel data of 137 movies with daily revenues, audiences' reviews, and posts on Twitter and Instagram is used in the empirical analysis. The results show that both the volume and the valence of online consumer reviews have impacts on increasing movie revenues. Whereas, only the volume, not the valence, of social media buzz affects movie revenues. Interestingly, while the influence of online consumer reviews increases over time, that of social media buzz decreases over time. In addition, the results indicate that there is a synergy effect of two platforms of word-of-mouth. This research suggests implications for managing electronic word-of-mouth of various sources from an integrated point of view.

Keywords: Word-of-mouth, online consumer reviews, social media buzz, endogeneity, three-stage least squares model, marketing strategy

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1. Introduction

In the era of Web 2.0, the values of sharing, participation, and openness are highly emphasized. Individuals are enthusiastic in sharing all kinds of opinions—their expectations, satisfaction, and disappointment—on the Web. With others' opinions on product and service experiences shared widely on the Web, consumers have evolved into Web-fortified decision makers (Blackshaw and Nazzaro 2006). Not surprisingly, for companies, the task of creating and managing online word-of-mouth (WOM) has become a critical mission. Companies are allocating a portion of their marketing budgets to WOM management. In particular, the importance of social media has become more emphasized in recent years. According to *The CMO Survey*, companies spent 12 percent of their marketing budget on social media in 2018, up from 3.5 percent in 2009.

Although marketing practitioners are concentrating on managing electronic word-of-mouth across various media, such as online consumer reviews and social media, there has not been any clear conclusion as to how multiple types of WOM media and their interplay affect a product's financial outcomes. Previous literature on WOM effects mainly focus on online consumer reviews (OCR), which are posted on a variety of websites including

Yahoo! Movies, Epinion.com, and Yelp. Although several recent studies pay attention to the role of Twitter and Facebook as platforms for word-of-mouth (e.g., Asur and Huberman 2010; Rui, Liu, and Whinston 2013), to date, their interplay with online consumer reviews is rarely investigated in the literature. Lumping online word-of-mouth platforms together without taking account of their differences or viewing word-of-mouth from a single platform may result in incomplete understanding of the WOM effect. OCR and social media buzz are similar in that they play roles as information sources for a consumer's decision making but they diverge in various aspects. For instance, social media buzz is "pushed" to the uninformed reader regardless of his or her will, whereas the reader has to "pull" or voluntarily search for OCR to gather additional information on a product one already knows. In addition, whereas social media is based on a personal (at least online) relationship, OCR is written by an unidentifiable individual for the unspecified masses. Meanwhile, in terms of immediate dissemination of information and real-time communication, social media is dominant over OCR. Due to such disparities, it is expected that the individuals who are more responsive to each kind of WOM will differ. In results, at the product level, we expect that the influences of the two types of WOM may be strengthened or weakened depending on the phases in the product life cycle in which heterogeneous consumers adopt the product.

This study therefore seeks to verify the WOM effects on product performance by including not only online consumer reviews—the traditional channel of electronic word-of-mouth (eWOM)—but also buzz from social media—another important channel of WOM—in a joint model and find their respective dynamic impact on a product's financial performance over time. Specifically, we address the following research questions to examine the dynamic effects of OCR and social media buzz on product performance: How are the volume and valence of each type of WOM related to product performance? How will their impact change over the product life cycle? Finally, does the interplay between online consumer reviews and social media buzz affect product performance and, if so, how does such an interaction change over the product life cycle? In our effort to find the answers to these questions, we construct a sample that includes sales, online consumer review, and social media buzz information for the movie industry. A panel data analysis reveals that the effects of WOM significantly change over time and the time trends vary according to the type of WOM. This study serves as a bridge between research streams on online consumer reviews and social media and provides practical implications for eWOM management.

2. Theoretical Backgrounds

2.1. electronic Word-of-Mouth (eWOM)

Electronic word-of-mouth (eWOM) refers to the use of various Internet platforms such as online discussion forums, online bulletins, newsgroups, blogs, review sites, and social media to facilitate information exchanges among communicators (Goldsmith and Horowitz 2006). Consumers are often faced with a high level of product uncertainty, lacking information about the product quality or whether the product fits their needs (Maity, Dass, and Malhotra 2014; Urbany 1986). Word-of-mouth (WOM) communication can be utilized as an important information source in consumer decision making. Although eWOM is less personal than traditional WOM, it exerts greater influence due to its immediate transmission and wide coverage (Hennig-Thurau et al. 2004). eWOM provides product information that can reduce potential risks from purchase failure (Kim, Mattila, and Baloglu 2011; Sweeney, Soutar, and Mazzarol 2008). Consumers can increase the likelihood of choosing a product that most closely suits their needs and preferences by making the purchase decision after obtaining a sufficient amount of information via eWOM (Dellarocas 2003). Moreover, instead of extensively searching for comprehensive information, consumers can refer to the summarized opinions of other customers via eWOM, which reduces search and evaluation costs (Bronner and de Hoog 2010; Goldsmith and Horowitz 2006).

A substantial body of research has tried to quantify the effects of eWOM, focusing particularly on *online consumer reviews* (OCR). OCR includes reviews and ratings posted on online review forum sites such as Yelp, Yahoo! Movies, and Epinion.com. Among various metrics of OCR, *volume* and *valence* are the most frequently investigated in previous literature. The volume of OCR is the total number of review units written about a particular product. The volume of reviews indicates how many people have chosen the product (Rosario, Sotgiu, De Valck, and Bijmolt 2016). The significance of OCR volume is relevant to the bandwagon effect (Salganik and Watts 2008), the phenomenon in which people are swayed by popularity. Opinions from many people signal the popularity of the product and are hard to ignore (Weaver et al. 2007). Many studies have tested OCR volume as a factor that may increase product sales (e.g., Bae, Shim, and Kim 2010; Chevalier and Mayzlin 2006; Chintagunta, Gopinath, and Venkataraman 2010; Liu 2006). Liu (2006) suggests a model that verifies the effect of online consumer reviews of 40 movies collected from the Yahoo! Movies website. According to Liu (2006), volume significantly predicts revenue through increasing the awareness of a movie. Bae, Shim, and Kim (2010) also conclude that the sales of Korean movies increase as the volume of online reviews increases.

Valence is another key characteristic of OCR. It is often measured by the average ratings of posted reviews and indicates the level of preference and satisfaction of consumers (Kim and Gupta 2012; Liu 2006) A positive relationship between ratings and product performance has been identified in many previous studies (e.g., Chevalier and Mayzlin 2006; Li and Hitt 2008). According to Chevalier and Mayzlin (2006), valence is important because consumers refer to viewer ratings as a means to socially confirm purchase decisions they have already made. They find the positive influence of online consumer ratings on sales of a book. Meanwhile, with regard to the valence effect, the existence of a negativity bias has been suggested. Negativity bias refers to the phenomenon in which negative information is valued more greatly than its positive counterparts. Previous literature has found evidence that negative eWOM is a fatal blow to product evaluations, as its influence is greater than the impact of positive eWOM (e.g., Ba and Pavlou 2002; Berger, Sorensen, and Rasmussen 2010; Chevalier and Mayzlin 2006; Sun 2012). On the other hand, some studies suggest that only the volume of reviews matters and the valence of reviews is not influential (Bae, Shim, and Kim 2010; Duan, Gu, and Whinston 2008; Forman, Ghose, and Wiesenfeld 2008; Liu 2006).

As the eWOM effect has been studied extensively, researchers have started paying attention to its moderators. Mudambi and Schuff (2010) insist that the information value of WOM can vary depending on the speed of informers' responses and how much relevant feedback they have provided in the past. They also suggest that the higher the expertise of the informer, the higher the evaluation of the review's utility. Zhu and Zhang (2010) empirically tested the differential impact of OCR across products and found that the impact is greater for less-popular products than popular ones. Their study also finds evidence that online reviews are more influential for consumers who have greater Internet experience.

Overall, although there is controversy regarding which eWOM metric (i.e., volume vs. valence) is more significant, the importance of eWOM in product performance is undeniable. However, considering that the eWOM effect has been tested using online consumer reviews only in most previous studies, it is necessary to examine the effect using more diverse types of word-of-mouth media.

2.2. Social Media Buzz

Social media has become another important platform for eWOM. Social media refers to an open online platform that allows individuals to share their thoughts, opinions, experiences, and information. Typical examples of social media are Facebook, Twitter, Instagram, and Weibo. Individuals create or expand relationships with others on the basis of friendship in social networks. In the era of social media, each individual plays the role of “media” because they can send and share information on their own without having to rely on other media (Thevenot 2007). Through social media services, brief messages are broadcasted to people in a sender's network (Kaplan and Haenlein 2011). Social media buzz spreads product information with unprecedented speed to a large number of people connected through the network. This information may have a significant impact on the adoption of new products in various ways. For instance, consumers can learn about the release of a new product through their friends' messages on social media. The messages also help consumers infer the products' quality at a time point when no other WOM information is widely available (Hennig-Thurau, Wiertz, and Feldhaus 2015). Meanwhile, negative comments produced by consumers can also spread rapidly, which may hurt brand reputation in a short time (Thomas et al. 2012). Those who read negative comments about a product may hesitate to purchase the product or exclude it from their consideration set. For these reasons, companies allocate a portion of their budget to managing their social media buzz.

As a representative social media platform, the impact of Twitter has been tested in various contexts, such as political outcomes (Park 2013; Petrova et al. 2016), stock price (Yu, Duan, and Cao 2013), movie success (Hennig-Thurau, Wiertz, and Feldhaus 2015; Jain 2013; Rui, Liu, and Whinston 2013), and television viewership (Gong, Zhang, Zhao, and Jiang 2017; Wang 2016). Similar to OCR, the "Twitter effect" is assessed in terms of post volume and valence. For instance, Gong et al. (2017) demonstrate the effect of Twitter volume on television program viewership. They show that Twitter posts by the program's producer directly increase viewership, whereas "retweets" by influencers contribute indirectly to a rise in viewership by increasing new followers of the program. Jain (2013) utilizes a text analytics algorithm and finds that positive Tweets, rather than negative, were predictive of a movie's revenues. Rui, Liu, and Whinston (2013) and Hennig-Thurau, Wiertz, and Feldhaus (2015) also find that the volume and valence of postings on Twitter influence the demand for movies. Moving from Twitter, Goh and Heng (2013) investigate the relationship between posting on Facebook brand pages and consumer spending on fashion products. In addition, Nam and Kannan (2014) discover that information about brand familiarity and competition included in social tags can be a useful predictor of product performance and enterprise value. Despite some research, research on social media buzz is still limited to Twitter effects only and there is no clear answer as to how the social media effects vary over time.

2.3. Comparison of Online Consumer Reviews and Social Media Buzz

As mentioned earlier, studies on online consumer reviews and social media have been developed separately and the joint impact of different media is seldom examined in previous literature. Both types of media are similar in that they generate word-of-mouth effects but it is expected that their patterns will differ due to the characteristics of each media. This section compares online consumer reviews and social media buzz based on criteria suggested by Bughin, Doogan, and Vetivik (2010).

Bughin, Doogan, and Vetivik (2010) propose the concept of "word-of-mouth equity," claiming that the ability to generate WOM messages that can influence purchase is an "asset" determining a brand's competitiveness. They suggested four criteria that determine the impact of WOM messages: network, contents, senders, and message sources. First, WOM exerts greater influence when the network in which it is propagated is close and trusted. This is consistent with the long-standing academic discussion on the relationship between the tie strength of the network and the persuasiveness of its messages (Brown and Reingen 1987). In the case of social media, messages are communicated among acquaintances or those, despite the lack of an offline relationship, who become friends and interact online. Conversely, online consumer reviews are aimed at anonymous readers. Their target is unclear and extremely broad. As such, social media messages have the advantage of being propagated through a close and trusted network, whereas OCR has the distinct weakness of being spread over a large, dispersed network. A meta-analysis by Rosario et al. (2016) compared effects of WOM on product performance across platforms and discovered that WOM via homophily-medium, such as social media, exercises greater influence in selection of new or hedonic products than WOM via other media.

Second, word-of-mouth exerts greater influence when its contents are related to a relevant key buying factor. While online reviews mainly describe experiences of product consumption, social media messages often cover not only product reviews but also emotions or situational contexts of consumption. In this regard, relevance of message is higher for online reviews than social media buzz.

Third, the stronger the influence of the sender, the greater the influence of WOM message. Senders of social media buzz are identifiable and voluntarily engaged to the reader by selective subscription. Therefore message via social media can be interpreted as WOM from more influential sender than online reviews written by unidentifiable, less relevant writers.

Last but not least, WOM based on own experience has greater influence. Although both online reviews and social media posts may evaluate a certain product, the latter does not necessarily require actual purchase. For example, social media buzz may express expectancy prior to purchase or hearsay about the brand. Thus, online reviews, which are based mainly on actual consumption, are likely to be more influential.

Going a step further, Nam and Kannan (2014) classified user-generated content (UGC) into four types—online reviews, social media, social tags, and blogs—and compared each in terms of product focus, self-presentation, collaborative interaction, and social interaction richness. According to their comparison, online reviews tend to be focused on the product itself, with less self-presentation. Meanwhile, the degree of collaborative interaction and social interaction richness are higher in social media than online reviews.

Putting the aforementioned discussion together, TABLE 1 summarizes the differences between online reviews and social media buzz. Between WOM media, there exist various differences, including attributes of the message, reader-sender relationship, and the characteristics of the network. Due to such disparities, it is expected that each type of eWOM will be more effective for people of different characteristics, and in results, the pattern of influence of two types of WOM on product performance will differ.

TABLE 1. Comparison of Online Consumer Reviews and Social Media

Factor	Online Consumer Reviews	Social Media
Network	Large and dispersed	Close and trusted
Relevant key buying factors	High	Moderate
Influence of senders	Low (not identifiable)	High (identifiable)
Message source	Own experience	Own experience/ hearsay
Focus	Narrow	Broad
Functionality of information	High	Moderate
Self-presentation	Low	High
Real-time distribution	Moderate	High
Social interaction	Low	High
Summary statistics	Yes	No

3. Hypotheses

3.1. Influences of Online Consumer Reviews on Product Performance

The most important metrics that constitute online consumer reviews are volume and valence. Having a great number of online reviews is a signal that the number of people who selected the product is high and this cue plays an important role in speculating the quality of the product. In fact, information cascade, or the phenomenon in which people make purchase decisions based on the behavior of others, is more likely to occur as the number of people who have already adopted the product increase (Bikhchandani, Hirshleifer, and Welch 1992). Therefore, it can be anticipated that the higher the number of online consumer reviews, the higher the likelihood of purchase, which in turn results in higher product performance.

The valence of online consumer reviews is also an important clue to inferring product quality (Li and Hitt 2008; Lim and Chung 2011; Yi, Lee, and Kim 2017). Receiving positive appraisal from earlier adopters can enhance the appeal of the product. In this regard, we expect a positive relationship between the valence of online reviews and product sales.

In addition, we anticipate that the impact of online consumer reviews is strengthened in the later stages of the product life cycle. In diffusion theory, after a period of time post-launch, late majority adopters begin to consider product purchase. Unlike early adopters, late majority adopters tend to be highly risk-averse and mainly refer to others' opinions to minimize the risk and maximize the utility from product consumption (Ahn and Kim 2003). Therefore, it can be expected that the relevant information—that is, early audiences' reviews—from which the reader can infer the quality of the product will have a strong influence among late adopters (Bruce, Foutz, and Kolsarici 2012; Gopinath, Thomas, and Krishnamurthi 2014). In this regard, Elberse and Eliashberg (2003) find that those who come to theaters during the first week of release tend to utilize external sources, such as advertising and product features, whereas those who visit theaters later are inclined to rely on internal sources, such as reviews or referrals of others. Sonnier, McAlister, and Rutz (2011), in comparing the impact of advertisements and online reviews, confirm that the influence of online reviews increases with time, whereas that of advertisements decreases. Based on the aforementioned reasons, we suggest the following hypotheses on the effects of online consumer reviews.

H1a. The volume of online consumer reviews is positively related to product sales.

H1b. The valence of online consumer reviews is positively related to product sales. In other words, the higher the consumer ratings, the greater the product sales.

H1c. The impact of the volume of online consumer reviews on product sales increases over time.

H1d. The impact of the valence of online consumer reviews on product sales increases over time.

3.2. Influences of Social Media Buzz on Product Performance

As social media posts are in real-time and spread rapidly, they can serve as informational advertisements to publicize newly launched products in the early stages of the product life cycle (Gong et al. 2017). This has been found to reduce information asymmetry between consumers and companies (Hennig-Thurau, Wiertz, and Feldhaus 2015). Accordingly, the volume of social media buzz related to a product helps raise awareness of the product soon after launch. Asur and Huberman (2010) show that the performance of a movie can be predicted by the number of Twitter posts that appear immediately before its release.

In addition to volume, the valence of social media buzz is also expected to have a positive relationship with product performance. This is because positive reactions from potential customers can arouse interest toward a product. Rui, Liu, and Whinston (2013) also find that the more positive Twitter posts there are regarding a particular movie, the higher its performance.

However, the influence of social media buzz on product performance is expected to decrease gradually as it reaches the later stages of the product life cycle. One important motivation for social media usage is self-determination (Lambrecht, Tucker, and Wiertz 2018). Social media users often disclose their tastes by boasting their consumption. They tend to post product-related messages early on in the market or at the initial stage of a product launch (Toubia and Stephen 2013). In other words, senders of social media buzz have a greater desire to share information when they have made an early purchase because the early consumption signals they are "in the know" on the latest trends. In addition, receivers of that information are expected to have a greater desire for imitative consumption when the information in question is up-to-date. The decline in the impact of social media buzz over time is also related to the way readers access the contents of social media. Social media buzz is not voluntarily read by the reader for the purpose of gaining information but, instead, is exposed to the reader during social media activities regardless of his or her will. In such regards, social media is similar to traditional advertising that "pushes" information to receivers. Therefore, like advertisements, social media may be effective at the early phase of a product launch but if similar messages are repeated over time, consumers may lose interest and the positive effects will erode. Moreover, information substitution over time can reduce the social influence from social media (Bell and Song 2007; Chen, Wang, and Xie 2011; Choi, Hui, and Bell 2010). Considering these discussions, we developed the following hypotheses on the effect of social media buzz.

H2a. The volume of social media buzz is positively related to product sales.

H2b. The valence of social media buzz is positively related to product sales. In other words, the higher the proportion of positive opinions on social media, the greater product sales.

H2c. The impact of the volume of social media buzz on product sales decreases over time.

H2d. The impact of the valence of social media buzz on product sales decreases over time.

3.3. Interplay of Online Consumer Reviews and Social Media Buzz

Because available information is scarce at the beginning of a product release, a single piece of accessible information can affect decision making in this stage (Ratchford, Lee, and Talukdar 2007). When there is a lack of information, information signals from both online consumer reviews and social media buzz have a high level of diagnosticity. Thus, it is expected that there is a positive interaction effect between online consumer reviews and social media buzz. In other words, considering the high level of uncertainty in the early product stages, support from one source is likely to be more reliable when there is also strong support from the other source (Chen, Wang and Xie 2011). The positive interaction is also related with the view of integrative marketing communication (IMC). A central tenet of IMC is that an individual medium strengthens the contributions of other media (Naik and Raman 2003; Schultz 2002). Integration is important, as the combined effect of multiple campaigns exceeds the sum of the individual effects (Belch and Belch 1998). In our context, it is expected that there is a synergy between online consumer reviews and social media buzz because the two types of eWOM can often serve different functions for consumers' decision making. Specifically, whereas OCR is post-consumption WOM, social media buzz can be both pre- and post-consumption WOM (Rui, Liu, and Whinston 2013). Regarding new products, OCR is mainly used to confirm and reaffirm a consumer's choices (Bailey 2005), whereas social media is primarily used to get up-to-date information. Therefore, their complementary relationship is expected to cause a synergy effect. However, such positive interaction effects are expected to weaken with time. This is because, over time, as social media buzz includes more post-consumption than pre-consumption WOM, the pieces of information might become similar (Rui, Liu, and Whinston, 2013). At the same time, as information is sufficiently accumulated in each medium, consumers become more confident about the product quality even when referring to a single medium. We therefore suggest the following hypotheses on the interaction effects of the two types of eWOM.

H3a. The interaction effect between the volume of online consumer reviews and that of social media buzz on product sales is positive. In other words, the greater the volume of one medium, the stronger the volume effect of the other medium on product sales.

H3b. The interaction effect between the volume of online consumer reviews and that of social media buzz decreases over time.

4. Empirical Analysis

4.1. Research Methods

4.1.1. Data Collection

We chose movies as the research context for the following reasons. First, movies are typical experiential goods, which means the consumer finds it difficult to predict the content's quality or the level of satisfaction prior to the experience. Thus, when consumers choose a movie to watch, they tend to collect and utilize information through diverse sources. Second, movies are a popular topic of conversation not only in daily lives but also in online conversations, news articles, and web posts. For instance, the number of posts in Korean with the word “movie” on Twitter, blogs, online communities, Instagram, and newspapers reached 1.7 million during August 2018 alone. If the frequency was added across each movie title, the number of posts would be much higher. From these characteristics, we consider movies suitable for verifying the effect of eWOM. The movies in our sample were selected based on Korean domestic box office revenues from January 2015 to June 2018. Because social media has become more popular in recent years, we analyzed movies that were released within the last three years. In addition, we only considered movies whose total audiences reached 300,000 to obtain a sufficient amount of eWOM for the analysis. This resulted in a total sample size of 137 movies that satisfy the criteria.

During the data collection, multiple archival sources were used. The performance of the movies was collected from the Korean Film Council (www.kobis.or.kr). The source compiles real-time data of domestic movies and provides information such as daily revenues, attendance, seat occupancy, and number of screens.

Online consumer reviews were collected from the *Naver Movie* website (https://movie.naver.com/). As of 2018, the *Naver* portal has the largest user base in Korea and *Naver Movie* has the highest number of movie reviews on a single website. *Naver Movie* presents the sales ranking of movies, basic information provided by distributers, and reviews from audiences. A reviewer must log into his/her individual account to post a review and only one vote is allowed for each movie. It is noted that when leaving a review involves costs, the likelihood of false reviews decreases, which may increase the value of the review contents (Ott, Cardie, and Hancock 2012). Furthermore, because a rating cannot be deleted by anyone other than the reviewer, the review data in *Naver Movie* tends to be stored for a long period of time (Cha, Cheon, and Yoon 2015). The website categorizes reviews into “netizens' ratings,” which anyone, audience or not, can leave and “audiences' ratings," which only those who have viewed the movie, as confirmed by their reservation data, can leave. We have confined our subject of analysis to "audiences ratings" to minimize the involvement of manipulated fake ratings. In regard to consumer ratings data, most previous studies have utilized aggregated ratings for their analysis due to the difficulty in tracking considerably large numbers of ratings for each movie in a chronological order. However, aggregated ratings data are unable to evaluate time-periodic influences. For movies, marketing campaigns are concentrated at the beginning of the release. The extremely short life cycle of movies also causes marketers to promptly react to daily outcomes. Moreover, as movie ratings are accumulated every second, potential purchasers can check the ratings in real-time. Therefore, it is more suitable to utilize individual rating units rather than aggregated ratings. To this end, we used Web-crawling techniques to collect every rating for each movie. This type of disaggregated data enables us to investigate the time-varying effects of online consumer reviews.

Next, for social media buzz, posts on Twitter and Instagram were collected. Twitter is a representative social media platform that instantly transmits users' sentiments in real-time. More than 20% of the population in the United States are Twitter users (Yoon, Polpanumas, and Park 2017). Instagram is another important platform of social media buzz. The service started as a platform for sharing photographs and videos and was acquired by Facebook in 2012. Instagram has been one of the fastest growing social media services in recent years. It has a rapidly expanding user base of more than 700 million users worldwide and monthly activated users (MAU) numbering more than 10 million as of 2017 in Korea. The social media data were provided by Social Metrics. Social Metrics, operated by Daum Soft Co., Ltd., is the nation's largest data analysis service with over 17.6 billion Twitter posts, which covers every Twitter posting written in Korean since 2011, and over 1 billion Instagram posts created since 2014. The service provided data related to Twitter and Instagram postings that include titles of 137 movies as keywords.

4.1.2. Definition of Variables

To measure movie performances, we employed daily box office sales during the first 8 weeks from the release of a movie ("Sales"). To capture the effect of online consumer reviews, we introduced "OCR_vol" and "OCR_val," which are the volume and valence of online consumer reviews, respectively. The volume was measured by the accumulated number of review ratings posted for a specific movie on *Naver Movies* at day *t*. The valence was measured by the mean value of star ratings posted for a specific movie on

Naver Movies at day *t*. We chose to calculate the volume and valence of online reviews based on accumulated reviews instead of daily reviews because a consumer, when viewing reviews, accesses the number and distribution of the entire ratings accumulated until that point through the summary statistics posted on the reviews' webpage. Next, to capture the effects of the volume and valence of social media buzz, "sBuzz_vol" and "sBuzz_val" were employed, respectively. The volume of social media buzz equals the daily number of Twitter and Instagram posts that include the title of the movie in question. In measuring the valence of social media buzz, we applied a sentiment analysis approach based on the natural language processing (NLP) technology. Specifically, using deep-level NLP, which searches lexical items, emotional expressions mentioned along with the movie titles are sorted by their frequency. Then, these emotional expressions are classified into positive, neutral, and negative according to the classification dictionary pre-constructed by the data source. In this process, expressions such as "box office hits" or "fun (interesting)" were categorized as positive, whereas expressions like "exhausting" and "offensive" were classified as negative. It should be noted that, in case of genres such as drama or horror, expressions such as "sad" or "scary" frequently appear. These vocabularies are classified as negative expressions in a general sentiment analysis but in our analysis, these words are not negative expressions in that they are emotional reactions induced by the characteristics of the genre and the intention of the movie producers. Thus, we examined the entire lexical classification considering the movie genre and excluded any inadequately matched expressions. Through this process, we finalized the frequencies of positive, negative, and neutral expressions in Twitter and Instagram postings for each movie and used the ratio of positive expressions among positive and negative words as the valence of social media buzz. TABLE 2 describes the example of a selected movie, 'Along with the gods'.

TABLE 2. Classification Results for a Selected Movie

(*'Along with the Gods'*)

Positive	Count	Negative	Count	Neutral	Count
Hits (흥행)	14,943	Swear (욕하다)	10,679	Different (다르다)	5,302
Pleased (기쁘다)	14,334	Bother (거슬리다)	7,631	Necessary(필요하다)	4,097
Good (좋다)	12,237	Illegal (불법)	5,485	Revive (부활하다)	3,773
Love (사랑하다)	11,680	Despair (절망)	5,261	Understand (이해하다)	3,765
Best (최고이다)	7,040	Hate (싫어하다)	5,167	Far (멀다)	3,293
Like (좋아하다)	5,229	Monsters (괴물)	4,197	Narrow (좁다)	2,806
Interesting (재미있다)	5,032	Scary (무서운)	4,047	Less (적다)	2,786
Proud (자랑스럽다)	4,025	Late (늦다)	3,177	Disseminate (소문내다)	2,261
Expect (기대)	3,831	Painful (힘들다)	2,783	Leave (떠나다)	2,165

For control variables, we took into account time-varying factors that may affect the performance of movies besides word-of-mouth. Specifically, as a proxy for active public relations and marketing activities, the number of daily news articles from *Naver News* about a specific movie was measured ("News"). Screening is also an important variable that determines movie sales (Dellarocas, Zhng, and Awad 2007; Jedidi, Krider, and Weinberg 1998). The number of screens during the opening week can be regarded as an indicator of the expected profitability of a movie, as a movie with high market potential tends to be screened at a large number of cinemas. In this respect, screening can signal the quality as well as accessibility of a movie. Thus, we included "Screens," which is the daily number of screenings of a movie, as a control variable. "Search" refers to the number of online searches of a movie by keyword on the *Naver* portal during a certain period. This variable was used to estimate the level of interest in the market, which could affect the amount of word-of-mouth. Lastly, because theaters attract more audiences on Friday and weekends, we included "Weekend," which is a dummy variable indicating Friday, Saturday, and Sunday. TABLE 3 describes the definitions of variables.

TABLE 3. Definition of the Variables

Variable	Measurement	Source
$\boldsymbol{Sales_{it}}$	Daily Box Office sales of movie *i* at day *t. (units: million KRW)*	Kobis
$\boldsymbol{OCR\_vol_{it}}$	The cumulative number of review ratings posted for movie *i* at day *t* (units: 1000).	Naver Movies
$\boldsymbol{OCR\_val_{it}}$	The mean value of star ratings displayed for movie *i* at day *t* (accounting for all ratings to the time point).	Naver Movies
$\boldsymbol{sBuzz\_vol_{it}}$	The number of social media postings for movie *i* at day *t* (units: 1000).	Twitter / Instagram
$\boldsymbol{sBuzz\_val_{it}}$	The ratio of the number of positive expressions to the sum of positive and negative expressions for movie *i* at day *t*.	Twitter / Instagram
$\boldsymbol{News_{it}}$	The number of news for movie *i* at day *t*.	Naver News
$\boldsymbol{Screens_{it}}$	The number of screens for movie *i* at day *t*	Kobis
$\boldsymbol{Search_{it}}$	The search volume index for movie *i* at day *t*.	Naver Trends
$\boldsymbol{Weekend_{it}}$	A dummy variable indicating if day *t* is a weekend (coded as 1 if day is Fri., Sat., or Sun., and 0 otherwise)	-
$\boldsymbol{Age_{it}}$	The elapsed days from the release date of movie *i*	-

4.1.3. Empirical Model Specification

There are several issues to be considered in formulating a model for verifying the hypotheses presented in this study. First, movie-specific features, such as production budget, directors, castings, and genre can affect the market performance and formulation of word-of-mouth. To control for the idiosyncratic factors, we applied a fixed-effects approach by introducing movie-specific dummy variables. Such a fixed-effect approach can control for unobserved factors by capturing time-invariant features across movies. It also provides more robust estimates in case an error term is correlated with other explanatory variables (Duan, Gu, and Whinston 2008).

Second, because the amount of eWOM could be an outcome as well as a driver of movie sales, there is an endogeneity issue. A Durbin-Wu-Hausman test on our sample confirms the existence of such endogeneity (χ^2 = 83.206, $p < .01$). A single equation approach with ordinary least squares (OLS), which has been applied in most previous studies on WOM effects in the movie industry (e.g., Basuroy et al. 2003; Eliashberg and Shugan 1997; Liu 2006), does not consider the mutual causality issue. As an alternative, this study formulates a system of equations that sets multiple dependent variables: the movie performance and the eWOM volume. Specifically, the model allows for the correlation between the error terms of respective equations, thereby taking into account endogeneity. Taking these issues into consideration, we constructed the following system of equations for movie sales, the volume of online consumer reviews, and the volume of social media buzz.

$$\begin{aligned}Sales_{it} = {} & \beta_0 + \beta_1 Sales_{it-1} + \beta_2 OCR\_vol_{it} + \beta_3 OCR\_val_{it} + \beta_4 sBuzz\_vol_{it} + \\ & \beta_5 sBuzz\_val_{it} + \beta_6 OCR\_vol_{it} * sBuzz_{vol_{it}} + \beta_7 OCR_{vol_{it}} * t + \\ & \beta_8 OCR_{val_{it}} * t + \beta_9 sBuzz_{vol_{it}} * \mathrm{t} + \beta_{10} sBuzz_{val_{it}} * \mathrm{t} + \\ & \beta_{11} OCR_{vol_{it}} * sBuzz_{vol_{it}} * \mathrm{t} + \beta_{12} News_{it} + \beta_{13} \mathrm{Screen}_{it} + \\ & \beta_{14} Weekend_{it} + \beta_{15} \mathrm{Age}_{it} + \omega_i + \varepsilon_{it}. \qquad (1)\end{aligned}$$

$$\begin{aligned}OCR\_vol_{it} = {} & \gamma_0 + \gamma_1 Sales_{it} + \gamma_2 News_{it} + \gamma_3 Search_{it} + \gamma_4 Weekend_{it} + \\ & \gamma_5 Age_{it} + \varphi_i + u_{it}, \qquad (2)\end{aligned}$$

$$\begin{aligned}sBuzz\_vol_{it} = {} & \lambda_0 + \lambda_1 Sales_{it} + \lambda_2 News_{it} + \lambda_3 Search_{it} + \lambda_4 Weekend_{it} + \\ & \lambda_5 Age_{it} + \pi_i + \upsilon_{it}. \qquad (3)\end{aligned}$$

Equation (1) explains the sales of movie *i* at period *t* by linear combination of the volume and valence of online consumer reviews and social media buzz. The βs indicate the influence of explanatory variables that determine the performance of a movie. A one-day lagged variable for sales was included considering the self-reflexive nature of sales. To investigate the joint effect, the interaction between online consumer reviews and social media buzz was included. Time interaction terms were included to capture the time trend of the eWOM effects. Equation (2) expresses the volume of online reviews of movie *i* at period *t* by linear combination of sales and time-varying control variables. The γs indicate the influence of explanatory variables that determine the volume of online reviews. Equation (3) explains the volume of social media buzz of movie *i* at period *t* by linear combination of sales and time-varying control variables. The λs indicate the influence of explanatory variables that determine the volume of social media buzz. In addition, ω_i, φ_i, and π_i from each equation are variables that indicate the fixed effects of movies, which control the time-invariant idiosyncratic factors of each movie.

In our model specification, the error terms in the three equations might be correlated because the explanatory variables in Equation (1) are the dependent variables in Equations (2) and (3) and vice versa. In this case, the OLS estimation causes inconsistent results. Thus, we concluded that 3SLS (Zellner, Arnold, and Theil 1962) is appropriate from the simultaneous causality of our focal variables. 3SLS is an estimation method combining seemingly unrelated regressions (SUR) and the two-stage least square (2SLS) estimation. It employs the inter-correlated structure in error terms across the equations using generalized least squares (GLS) (Davidson and MacKinnon 1993; Greene 2012). We simultaneously estimated the parameters in the three equations using the three-stage least square (3SLS) approach.

4.2. Analysis

4.2.1. Data Description

The summary of the variables is presented in TABLE 4. FIGURE 1A and FIGURE 1B demonstrate the time plots of the selected movies: '*Along with the Gods'* and '*The Battleship Island'*, respectively. Basically, time series plots of two movies show common patterns in several aspects. For instance, daily sales of both movies peaked in the early phase of release and declined over time and both movies gained greater turnover on Friday, Saturday, and Sunday compared to other days of the week. The volume of online reviews was also concentrated in the early phase and the rating of audiences—the valence indicator of online reviews—was highest immediately after release and gradually decreased over time. The declining pattern of audience ratings is consistent with the previous literature (Godes and Silva 2012; Li and Hitt 2008; Wu and Huberman 2008). It is notable that both movies were Korean blockbusters that cost 35 billion KRW and 26.7 billion KRW, respectively. Both movies received significant attention prior to their release and were regarded as having high market potential. Both movies were also shown on a high number of screens on the opening day—1,538 for '*Along with the Gods'* and 2,027 for '*The Battleship Island'*, which was far above the average (i.e., 515 screens) in the sample. However, the market performance of two movies greatly differed. Whereas '*Along with the Gods'* had an audience of more than 14 million, '*The Battleship Island'* had only 6.5 million. From the two panels of plots, we infer that the difference between eWOM played a major role in determining the performance of the two movies in the market. The main difference between the two movies, as shown in FIGURE 1A and 1B, is that the number of online reviews and accumulated viewer ratings of '*Along with the Gods'* exceeded that of '*The Battleship Island'* throughout the entire period. It is also worth noting that, although the volume and valence of social media buzz regarding '*Along with the Gods'* rebounded after its release, those of '*The Battleship Island'* monotonically decreased and approached zero early. The more precise investigation of eWOM effects are suggested based on our empirical estimation in the following section.

TABLE 4. Summary Statistics of the Variables

Variable	Mean	Std. Dev.	Min.	Max.
Sales (in KRW 10 mil.)	810.949	1213.357	.83	12,000
OCR_vol (thousands)	7.273	18.187	.41	278.88
OCR_val	8.507	.609	5.24	9.78
sBuzz_vol (thousands)	2.851	6.144	0	90.254
sBuzz_val	0.711	.195	0	1
News	31.462	40.950	0	398
Screens	515.211	376.184	2	2,553
Search	28.389	26.545	0	100
Weekend	-	-	0	1
Age	22.050	13.779	1	56

FIGURE 1A. Time Series Plots of '*Along with the Gods*'

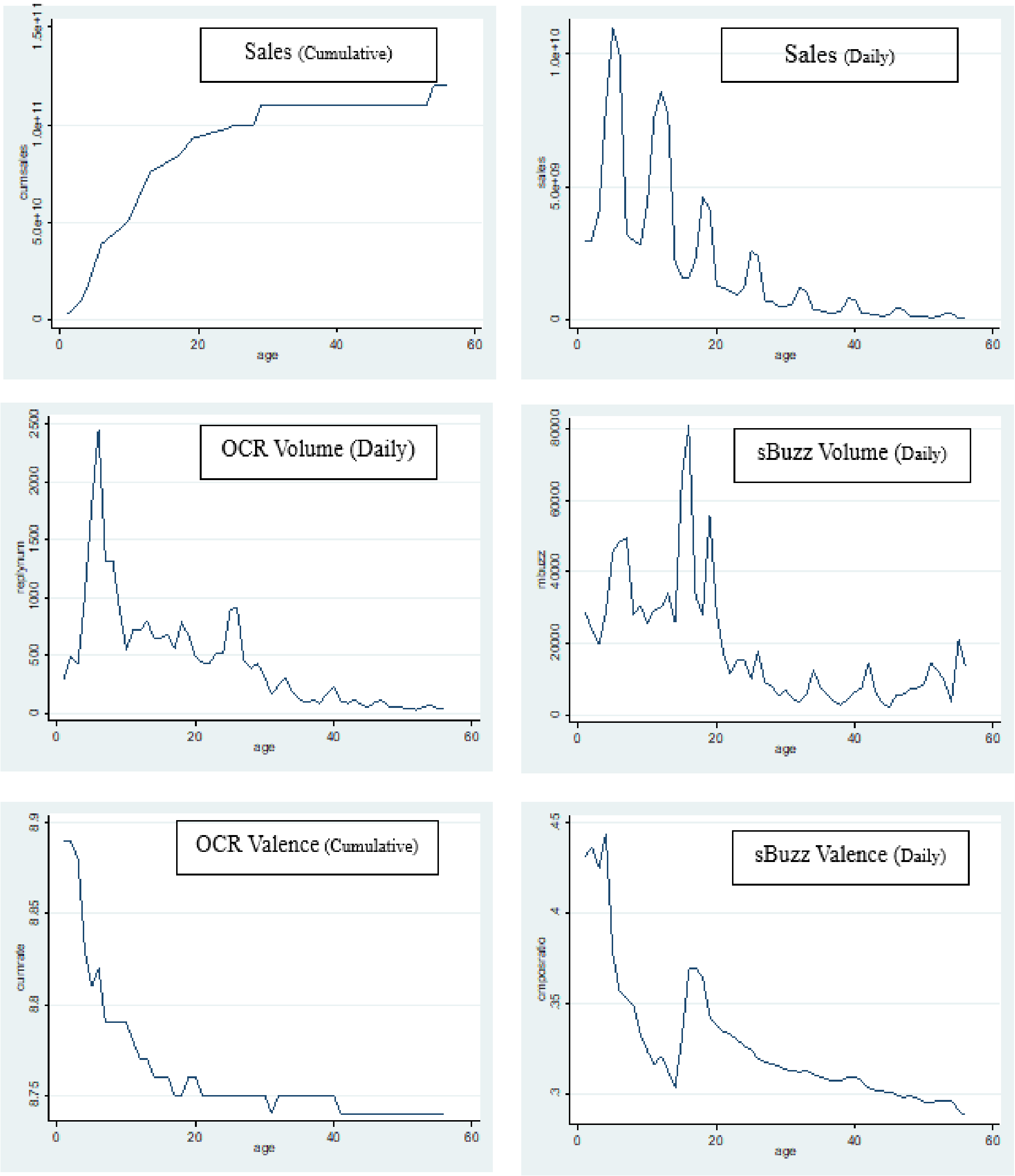
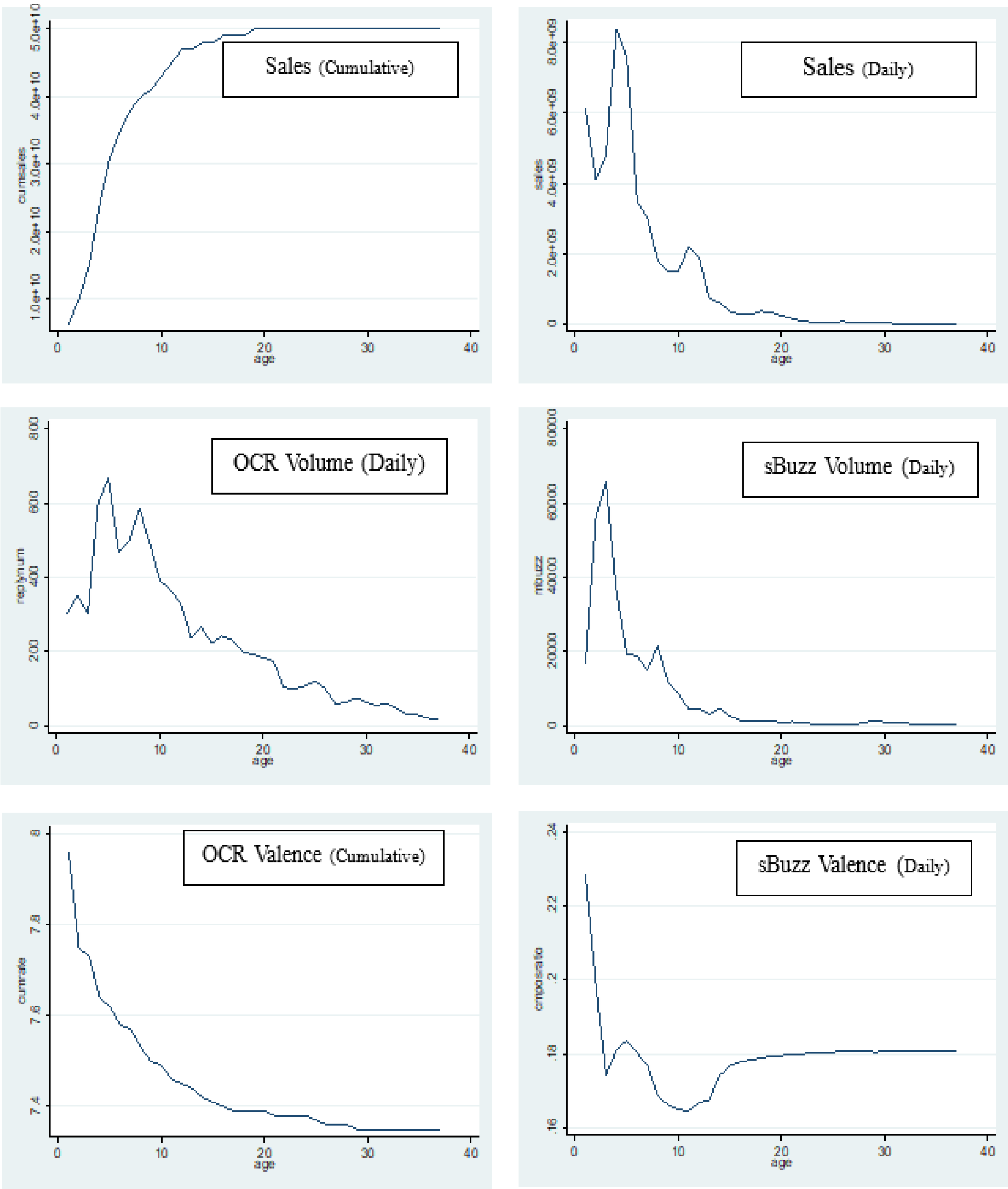


FIGURE 1B. Time Series Plots of '*The Battleship Island*'



4.2.2. Estimation Results

TABLE 5 summarizes the estimated results of the proposed Equation (1) using the 3SLS model. For comparison, we also estimated the partial models by varying the explanatory variables. Model 1 does not reflect any eWOM effects and Models 2 and 3 only take into account the effect of OCR and social media, respectively. Model 4 includes OCR and social media but does not consider mutual interactions between the two platforms. The last column in TABLE 5 summarizes the estimated results of the proposed model. The proposed model showed the highest model suitability ($R^2 = .702$) among the alternative models. This demonstrates that a model that involves both types of online word-of-mouth channels and considers their interactions has more explanatory power in predicting movie sales. According to the proposed model, movie sales are higher when sales from the previous period were high ($\beta_1 = .343$, $p < .001$). As we have hypothesized in H1a and H1b, the volume and valence of online consumer reviews are positively related to movie sales ($\beta_2 = 10.040$, $p < .10$; $\beta_3 = 298.4$, $p < .001$). Moreover, both the volume and valence of online reviews are found to have more influence over time ($\beta_7 = .233$, $p < .001$; $\beta_8 = 3.890$, $p < .05$). These findings confirm both H1c and H1d.

The volume of social media buzz shows the positive effect on movie sales. In other words, the more social media buzz regarding a movie, the higher the sales of that movie (β_4 = 137.624, $p < .001$). However, its influence decreases over time (β_9 = -.267, $p < .001$). Unlike volume, the valence of social media buzz does not have a significant impact on movie sales (β_5 = 9.719, n.s.; β_{10} = 3.210, n.s.). Thus, only H2a and H2c are supported among the hypotheses related to social media buzz.

Lastly, the interaction term between online consumer reviews and social media buzz has a significant positive impact on movie sales (β_6= .324, $p < .05$). It is interpreted that eWOM from two platforms might create a synergy effect in boosting sales. It is also found that this synergy is greatest in the early phase and mitigated over time (β_{11}= -.002, $p < .05$). Thus, H3a and H3b are supported by the results.

The estimation results of Equations (2) and (3) are summarized in TABLE 6. Although we did not develop hypotheses surrounding the incidences of two types of eWOM, several interesting results were found. First, as anticipated, the volume of online reviews and social media buzz are positively related to the sales of a movie (γ_1 = .0001, $p < .001$; λ_1 = .002, $p < .001$). These results indicate the existence of the reciprocal relationship between product performance and amount of eWOM. Moreover, the volume of the both types eWOM tend to increase with the number of news articles (γ_2

$= .001$, $p < .001$; $\lambda_2 = .025$, $p < .001$). The search volume, a proxy for level of interest, is a significant predictor of social media buzz ($\lambda_3 = .034$, $p < .001$) only. Social media posts are more frequently generated on the weekend, whereas online consumer reviews are less frequently written on the weekend ($\gamma_4 = -.033$, $p < .001$; $\lambda_4 = .905$, $p < .001$). Considering that more audiences watch movies on the weekend, these results are caused by the real-time nature of social media. Lastly, it is found that the generation of word-of-mouth in both platforms becomes less active as time passes after the release of a movie ($\gamma_5 = -.002$, $p < .001$; $\lambda_1 = -.018$, $p < .01$).

TABLE 5. 3SLS Estimation Results: Sales Equation

	Model 1	Model 2	Model 3	Model 4	Proposed Model Equation (1)
VARIABLES	$Sales_{it}$	$Sales_{it}$	$Sales_{it}$	$Sales_{it}$	$Sales_{it}$
$Sales_{it-1}$	.554(.010)***	.552(.010)***	.371(.019)***	.364(.020)***	.343(.018)***
OCR_vol_{it}		6.937(.919)***		8.520(1.335)***	10.040(6.079)+
OCR_val_{it}		297.0(80.69)***		238.4(109.2)**	298.4(71.3)***
$sBuzz\_vol_{it}$			205.0(13.83)***	211.7(14.50)***	137.624(23.418)***
$sBuzz\_val_{it}$			53.855(66.46)	63.811(67.58)	9.719(87.66)
$OCR\_vol_{it} * sBuzz\_vol_{it}$					.324(.182)*
$OCR\_vol_{it} * t$					.233(.010)***
$OCR\_val_{it} * t$					3.890(2.130)*
$sBuzz\_vol_{it} * t$					-.267(.027)***
$sBuzz\_val_{it} * t$					3.210(5.312)
$OCR\_vol_{it} * sBuzz\_vol_{it} * t$					-.002(.001)*
$News_{it}$	4.667(.295)***	5.022(.297)***	8.283(.478)***	8.323(.472)***	7.182(.491)***
$Screen_{it}$	1.002(.045)***	1.048(.046)***	.456(.069)***	.448(.075)***	.707(.099)***
$Weekend_{it}$	424.4(15.52)***	417.1(15.46)***	350.1(24.29)***	350.2(24.51)***	399.6(26.10)***
Age_{it}	-5.919(1.034)***	-2.84(1.10)***	-3.315(1.563)**	-3.105(1.581)**	-33.77(16.04)**
Constant	392.9(98.92)***	-2,17(708.9)***	-1,74(244.1)***	254.1(910.5)	-4,381(1,500)***
Observations	5,383	5,383	4,752	4,752	4,752
Adj. R-squared	.607	.609	.681	.631	.702

Note: ***p<.001, p<.01, *p<.05, +p<.10.; Standard errors are in parentheses; Fixed effects for each movie used in estimating the model are not reported.

TABLE 6. 3SLS Estimation Results: WOM Equations

	Equation (2)	Equation (3)
VARIABLES	OCR_vol_{it}	$sBuzz\_vol_{it}$
$Sales_{it}$	.0001(7.11e-06)***	.002(.0001)***
$News_{it}$	.001(.0001)***	.025(.002)***
$Search_{it}$	.0004(.0003)	.034(.005)***
$Weekend_{it}$	-.033(.009)***	.905(.137)***
Age_{it}	-.002(.001)***	-.018(.008)**
Constant	.173(.045)***	12.50(.709)***
Observations	4,752	4,752
Adj. R-squared	.831	.610

Note: ***p<.001, p<.01, *p<.05, +p<.10.; Standard errors are in parentheses; Fixed effects for each movie used in estimating the model are not reported.

4.2.3. Sensitivity Analysis

In developing the empirical model, we posited that both types of WOM would have a concurrent impact on product sales. However, it is also possible that it is not WOM until the day but rather WOM until the previous day that is crucial in consumer decisions. TABLE 7 summarizes the estimated results of the alternative model with the lagged WOM variables. The results show the same pattern as the original model. Specifically, the influences of OCR volume and valence from the previous day are predictive of movie sales and these influences increase as time passes after the release. The influence of the previous day's social media buzz is limited to its volume (not valence) and decreases as time passes after the release. The interaction of OCR and social media buzz from the previous day was also positive and significant and the joint impact decreases over time. Overall, the model that reflects WOM from the previous day also confirms the relationships that were accepted in the original model.

TABLE 7. Estimation Results of the Alternative Model

VARIABLES	(1) $Sales_{it}$	(2) OCR_vol_{it}	(3) $sBuzz\_vol_{it}$
$Sales_{it-1}$	.543(.011)***	.881(.463)***	.001(.000)***
OCR_vol_{it-1}	16.84(3.028)***		
OCR_val_{it-1}	539.1(67.55)***		
$sBuzz\_vol_{it-1}$	11.66(2.161)***		
$sBuzz\_val_{it-1}$	7.377(54.93)		
$OCR\_vol_{it-1} * sBuzz\_vol_{it-1}$	.252(.044)***		
$OCR\_vol_{it-1} * t$	.213(.051)***		
$OCR\_val_{it-1} * t$	9.781(1.262)***		
$sBuzz\_vol_{it-1} *$ t	-.469(.268)+		
$sBuzz\_val_{it-1} *$ t	.326(1.680)		
$OCR\_vol_{it-1} * sBuzz\_vol_{it-1} *$ t	-.090(.012)***		
$News_{it-1}$	2.192(.313)***	.0001(.0001)	.016(.002)***
Screen$_{it}$	1.069(.052)***		
$Weekend_{it}$	500.7(16.71)***	.024(.008)***	-.257(.124)**
Age$_{it}$	-87.78(11.29)***	-.004(.0004)***	-.060(.007)***
$Search_{it}$		.001(.0004)***	.056(.004)***
Constant	-4,866(595.1)***	.340(.044)***	15.30(.676)***
Observations	4,740	4,740	4,740
Adj. R-squared	.804	.827	.622

Note: ***p<.001, p<.01, *p<.05, +p<.10.; Standard errors are in parentheses;
Fixed effects for each movie used in estimating the model are not reported.

4.2.4. Subsample Analysis

The results in the previous sections show how the influences of OCR, social media buzz, and their interaction on product sales evolve over time. However, will all movies in the sample follow a similar pattern? In this section, we conduct a subsample analysis. Based on total production budget, we extracted the top 30 movies and bottom 30 movies. Total production budget has been found to be a significant factor of a movie's success in previous literature (e.g., Basuroy, Chatterjee, and Ravid 2003; Dellarocas, Zhang, and Awad 2007; Kim, Yoon, and Choi 2018). The scale of the movie budget can determine the eWOM activities during the pre-release phase, which in turn affects the final records (Kim, Yoon, and Choi 2018). We expect that the pattern of WOM affecting sales will be dependent on the scale of the production budget. The summary statistics of the production budgets of movies in the entire sample, the high budget group, and the low budget group are summarized in TABLE 8. The production budget varies greatly across movies and ranges from 300 million KRW to 449 billion KRW. We estimated Equations (1), (2), and (3) with movies in the high budget group and those in the low budget group separately. The results are shown in TABLE 9 and 10. The main effects of volume and valence of each WOM are significant regardless of budget levels. However, their interactions and time trends differ in the two groups. Whereas the influence of OCR volume increases over time for high budget movies, it decreases over time for low budget movies. The interaction between OCR and social media buzz is significant only for high budget movies. In other words, only high budget movies benefit from the synergy between the two types of eWOM. In addition, more eWOM messages were posted when sales were high in both groups. Interestingly, in the high budget group, newly written reviews decreased as time passed, whereas in the low budget group, more reviews were generated in the later phase.

TABLE 8. Production Budget of the Movies

Movies	Average	Median	Std. Dev.	Min.	Max.	N
Whole Sample	768.348	140	945.890	3	4,496	139
High Budget	2,259.933	2,043	578.343	1,686	4,496	30
Low Budget	40.1	46.5	14.921	3	57	30

(units: 100 million KRW)

TABLE 9. Estimation Results of High Budget Movies

VARIABLES	(1) $Sales_{it}$	(2) OCR_vol_{it}	(3) $sBuzz\_vol_{it}$
$Sales_{it-1}$	.40(.02)***		
OCR_vol_{it}	406.34(32.38)***		
OCR_val_{it}	696.14(401.40)*		
$sBuzz\_vol_{it}$	40.29(6.89)***		
$sBuzz\_val_{it}$	210.52(259.80)		
$OCR\_vol_{it} * sBuzz\_vol_{it}$	11.72(2.54)***		
$OCR\_vol_{it} * t$	2.43(.56)***		
$OCR\_val_{it} * t$	16.25(3.69)***		
$sBuzz\_vol_{it} *$ t	1.67(1.79)		
$sBuzz\_val_{it-} *$ t	-12.55(8.47)		
$OCR\_vol_{it} * sBuzz\_vol_{it} *$ t	-.38(.16)**		
$News_{it}$	12.47(1.29)***	.003(.0002)*	.03(.01)***
Screen$_{it}$	1.04(.12)***		
$Weekend_{it}$	497.30(39.98)***	-.003(.006)	-.74(.27)***
Age$_{it}$	-114.22(30.76)***	-.003(.000)***	-.07(.02)***
$Sales_{it}$		.00005(.000)***	.001(.000)***
$Search_{it}$		.001(.000)***	.07(.01)***
Constant	8,67(3,78)**	.12(.02)***	-.41(.95)
Observations	1,057	1,057	1,057
Adj. R-squared	.795	.707	.767

Note: ***p<.001, p<.01, *p<.05, +p<.10.; Standard errors are in parentheses;
Fixed effects for each movie used in estimating the model are not reported.

TABLE 10. Estimation Results of Low Budget Movies

VARIABLES	(1) $Sales_{it}$	(2) OCR_vol_{it}	(3) $sBuzz\_vol_{it}$
$Sales_{it-1}$	.44(.03)***		
OCR_vol_{it}	140.1(21.53)***		
OCR_val_{it}	950.2(170.0)***		
$sBuzz\_vol_{it}$	14.99(4.75)***		
$sBuzz\_val_{it}$	135.4(141.0)		
$OCR\_vol_{it} * sBuzz\_vol_{it}$	2.59(2.08)		
$OCR\_vol_{it} * t$	-.83(.37)**		
$OCR\_val_{it} * t$	7.53(2.32)***		
$sBuzz\_vol_{it}$ * t	.52(1.26)		
$sBuzz\_val_{it-}$ * t	-5.76(4.90)		
$OCR\_vol_{it} * sBuzz\_vol_{it}$ * t	-.04(.11)		
$News_{it}$	5.190(.526)***	.0004(.000)***	-.0003(.006)
Screen$_{it}$	.918(.123)***		
$Weekend_{it}$	284.2(26.38)***	-.03(.01)***	-.11(.32)
Age$_{it}$	-48.30(19.40)**	.002(.001)***	-.14(.04)***
$Sales_{it}$		.0002(.000)***	.001(.000)**
$Search_{it}$		.001(.000)**	.12(.01)***
Constant	-7,97(1,47)***	-.065(.021)***	4.28 (1.08)***
Observations	848	848	848
Adj. R-squared	.825	.683	.600

Note: ***p<.001, p<.01, *p<.05, +p<.10.; Standard errors are in parentheses;
Fixed effects for each movie used in estimating the model are not reported.

5. Discussion

5.1. Summary of the Results

This study examines the dynamic influence of eWOM via different platforms on product performance. According to the analysis results, both the volume and valence of online consumer reviews play significant roles in raising the sales of new products and their influence strengthens over time. This finding that the impact of online consumer reviews tends to increase over the latter part of the product life cycle concurs with previous studies (e.g., Sonnier, McAlister, and Rutz 2011). On the other hand, the influence of social media buzz is less salient than that of online consumer reviews. Unlike our expectation, only the volume of social media buzz has a positive impact on sales, whereas valence does not. We infer that the following factors may have affected the results. First, unlike online review ratings, there is no numeric index to measure positivity in social media buzz. Therefore, the valence of social media buzz is often vague. Second, the absence of summary statistics on the aggregate level may lower the influence of social media valence (Hennig-Thurau, Wiertz, and Feldhaus 2015). Finally, even negative publicity may help raise product awareness (Berger, Sorensen, and Rasmussen 2010). We cannot rule out the possibility of such indirect positive influences offsetting the direct negative influence of negative social media buzz.

As we anticipated, the interaction between online consumer reviews and social media buzz has a positive impact on movie sales. In other words, if the volume of one medium is great, it will strengthen the volume effect of the other medium on product sales. It was also found that the synergy effect reaches its peak during the opening period and then decreases over time.

5.2. Implications

Previous literature on Word-of-Mouth effects mostly investigates a single type of WOM platform, namely, online consumer reviews. This research suggests a deeper understanding of eWOM effect considering two representative platforms of eWOM, which are online consumer reviews and social media. It is the first trial that simultaneously examines the dynamic influences of two types of eWOM on product performances.

This research also provides important implications for marketing managers on how to allocate WOM-related budgets over time after a product is launched. Based on our analysis, the impact of social media buzz reaches its maximum at the release phase and then decreases over time. During the early phases of a product launch, thus, it is better to focus on increasing the volume of social media buzz, thereby raising awareness of the product among consumers. Some theaters and opera houses in the United States are now testing “Tweet seats,” in which audiences are allowed to use mobile phones to broadcast the performance via Twitter. According to our findings, it is advisable to adopt these methods as early as possible. After some time, however, managers need to pay more attention to increasing the volume of OCR over that of social media. This is because the volume of OCR plays a decisive role in the purchase decision among late adopters, who are risk-averse. It is therefore useful to provide incentives that motivate moviegoers to leave online reviews as the product approaches the mature stage. In addition, the findings that the impact of OCR valence on sales increases with time remind us that reputation management in review forums is crucial for the long-term success of the product. For movies, although the product quality cannot be refined after launch, the ongoing monitoring of fake negative reviews can help maintain a good reputation in online review forums. Other experiential goods, such as video games and mobile applications, can improve quality and induce positive reactions by resolving inconvenience issues, an example of which is fixing bugs by referring to customer feedback on review websites. We expect these findings to provide practical guides for today’s companies significantly investing in online word-of-mouth management.

Finally, yet importantly, the positive interactions between OCR and social media buzz highlight the importance of integrative management of eWOM channels. According to our analysis, if there is a sufficient amount of buzz on social media, for example, the impact of OCR on sales may be strengthened and vice versa. In addition, it is important to increase buzz on both platforms simultaneously from the early stage because synergy is mitigated as the later stages of the product life cycle approach.

5.3. Limitations and Future Research

This study investigated the word-of-mouth effects on product performance across different eWOM types (i.e., online consumer reviews and social media buzz). However, several potential shortcomings need to be considered. First, this study did not reflect the size of the network surrounding the sender in social media. The network size is an important factor that determines the influence of word-of-mouth messages (Bughin, Doogan, and Vetivik 2010). As posts of social network users with a large number of followers have far-reaching influence, giving greater weight to these posts can improve the practicability of the analysis. Second, in our dataset, it was impossible to distinguish social media posts written by consumers from those written by companies. Many companies run their own branded accounts on Facebook, Twitter, or Instagram and use the owned media as advertising platforms. Company-driven marketing messages usually target early adopters who are sensitive to trends. According to a recent study by Lambrecht, Tucker, and Wiertz (2018), however, early trend propagators are less responsive to company-driven Tweets than late trend propagators. Their findings suggest that the impact of company-driven buzz may change over time after the product launch. In this regard, further studies investigating the influences of owned media and earned media and their dynamic changes over time can contribute to a deeper understanding of social media buzz. Lastly, IMC literature has consistently emphasized the use of synergy between media. In the context of our research, cross-media synergy can also be generated between traditional advertising and eWOM. For instance, the influence of eWOM might be strengthened with an increase in television commercials or, conversely, when there are few television commercials and the pattern might change across eWOM channels. Future studies that address the interplay of traditional advertising and different types of eWOM may provide meaningful insights on eWOM management from an integrated view.

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국문초록

본 연구는 온라인 구매자 리뷰와 소셜 미디어간의 비교를 중심으로 온라인 구전이 제품 성과에 미치는 동태적 영향을 밝히고 있다. 온라인 구매자 리뷰와 소셜 미디어는 구매자의 채택에 영향을 미치는 정보원의 역할을 한다는 점에서는 유사하지만, 교환되는 정보의 성격과 정보가 전파되는 방식 등에 있어서는 상당한 차이를 보인다. 본 연구는 구전 매체로서의 온라인 구매자 리뷰와 소셜 미디어를 개념적으로 대비할 뿐 아니라, 두 매체의 구전 효과가 시간의 흐름에 따라 다르게 나타남을 입증하고 있다. 또한, 온라인 구매자 리뷰와 소셜 미디어 상 구전의 합작 효과(joint effect)를 모형에 반영함으로써 각 매체가 서로 다른 매체의 효과를 조절하는 지 여부를 검증하였다. 137편 영화의 판매 성과, 온라인 구매자 리뷰, 소셜 미디어 상의 게시물 데이터를 활용한 실증 분석에서는 제품 성과와 온라인 구전간의 내생성을 고려한 연구 모형을 수립하고, 이를 3SLS 방식으로 추정하였다. 실증 분석을 통해 발견한 주요 결과는 다음과 같다.

첫째, 온라인 구매자 리뷰의 경우, 리뷰의 규모(volume)와 방향성(valence)이 모두 제품 성과를 높이는 데에 기여하며, 그 영향력은 제품 출시 후 시간이 지날수록 증가하는 것으로 나타났다. 둘째, 소셜

미디어 구전의 경우, 구전의 규모(volume)만이 제품 성과를 높이는 데에 유의한 영향을 미쳤으며, 방향성(valence)의 효과는 유의하지 않았다. 온라인 구매자 리뷰와 달리, 소셜 미디어 구전의 영향력은 제품 출시 직후에 가장 높으며 시간이 지날수록 감소하는 것이 확인되었다. 셋째, 온라인 구매자 리뷰와 소셜 미디어 구전 간에는 양의 상호작용 효과가 발견됨으로써 한 매체의 구전 규모가 클수록 다른 매체의 구전 효과가 증대된다는 것이 확인되었다. 한편, 이들간의 시너지 효과는 제품 출시 직후에 가장 높으며 시간이 지날수록 점차 감소하는 것으로 나타났다.

본 연구는 다음과 같은 시사점을 지닌다. 첫째, 온라인 구전과 관련한 기존 연구에서는 주로 온라인 구매자 리뷰를 중심으로 그 효과를 검증해왔기에 상대적으로 소셜 미디어 구전의 효과에 대한 이해가 매우 부족했다. 이에 본 연구에서는 충분한 수의 패널을 활용해 소셜 미디어 상의 구전의 효과를 실증적으로 검증했을 뿐 아니라, 온라인 구매자 리뷰와의 합작 효과를 검증함으로써 온라인 구전에 대한 이해를 확장하는 데에 기여하고 있다. 둘째, 이 연구의 결과는 실무적으로도 중요한 시사점을 제시한다. 즉, 온라인 구매자 리뷰와 소셜 미디어 상의 구전이 제품 성과에 미치는 영향이 시간에 따라 변화한다는 결과는 온라인 구전 관리에 있어 각 매체 간 시너지를 고려한 통합적인 관점의 접근이 필요하며, 제품 출시 이후 시간의 경과에 따라 각 매체에

차별적인 중요도를 부여해야 함을 시사하고 있다.

주요어: 온라인 구전, 온라인 구매자 리뷰, 소셜 미디어 구전, 내생성, 3SLS 추정, 마케팅 전략

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