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Authors
Kim, Ho
Hanssens, Dominique M

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Advertising and Word-of-Mouth Effects on Pre-launch Consumer Interest and Initial Sales of Experience Products

Ho Kim [a,*] & Dominique M. Hanssens [b]

[a] University of Missouri-St. Louis, College of Business Administration, 1 University Blvd, St. Louis, MO 63121, USA
[b] UCLA Anderson School of Management, 110 Westwood Plaza, Los Angeles, CA 90095-1481, USA

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Abstract

This study examines how consumers' interest in a new experience product develops as a result of advertising and word-of-mouth activities during the pre-launch period. The empirical settings are the U.S. motion picture and video game industries. The focal variables include weekly ad spend, blog volume, online search volume during pre-launch periods, opening-week sales, and product characteristics. We treat pre-launch search volume of keywords as a measure of pre-launch consumer interest in the related product. To identify probable persistent effects among the pre-launch time-series variables, we apply a vector autoregressive modeling approach. We find that blog postings have permanent, trend-setting effects on pre-launch consumer interest in a new product, while advertising has only temporary effects. In the U.S. motion picture industry, the four-week cumulative elasticity of pre-launch consumer interest is 0.187 to advertising and 0.635 to blog postings. In the U.S. video game industry, the elasticities are 0.093 and 1.306, respectively. We also find long-run co-evolution between blog and search volume, which suggests that consumers' interest in the upcoming product cannot grow without bounds for a given level of blog volume.

Keywords: Pre-launch marketing; Pre-launch consumer interest; Advertising; Blogging; Online search; New experience products; Persistence modeling; Long-term effects

Introduction

The Internet has made available a plethora of new media and tools for consumers to use in their purchase processes. Consumers routinely consult experts' blogs, online user reviews, and critic reviews. Search engines help consumers find relevant blog postings and online reviews for decision making. Online review sites provide consumers a venue to share their consumption experiences with other consumers, thereby influencing their future purchase decisions. These online tools seem especially influential for experience products such as motion pictures, music, video games, books, and television shows (Chevalier and Mayzlin 2006; Dellarocas, Zhang, and Awad 2007; Dhar and Chang 2009; Duan, Bin, and Whinston 2008a, 2008b; Godes and Mayzlin 2004; Liu 2006; Xiong and Bharadwaj 2014; Zhu and Zhang 2010).

For experience products, pre-launch marketing is crucial for financial success. First, the life cycle of experience products is relatively short because repeat purchase is rare. For example, according to The Numbers (www.the-numbers.com), even the most successful movies exit first-run theaters after three months. Second, because of the short life cycle, initial sales during the first few weeks are the most critical. One statistic shows that 41% of a movie's revenue is generated during the opening week (Liu 2006). These facts suggest the importance of maximizing pre-launch consumer interest and, thus, the importance of pre-launch marketing (Elberse and Anand 2007).

Motivated by the importance of online tools and pre-launch marketing in experience product industries, this article aims to understand how firms' marketing activities and consumers' online activities – such as blogging and online search – interact in pre-launch periods to influence the initial sales of a new experience product. We ask the following questions. First, how do advertising and blog postings affect consumers' interest in an

* Corresponding author.
E-mail addresses: kimho@umsl.edu (H. Kim), dominique.hanssens@anderson.ucla.edu (D.M. Hanssens).

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upcoming film or video game? Is advertising more effective than blog postings, or vice versa, in generating pre-launch consumer interest? Is there any persistent effect of advertising and blog postings on pre-launch consumer interest in a new experience product? Second, pre-launch search and word-of-mouth (WOM) activities help predict the initial sales of films and video games (Kulkarni, Kannan, and Moe 2012; Xiong and Bharadwaj 2014). Thus, which of the two consumer activities (i.e., search or WOM) better predicts opening-week sales?

We answer these questions by analyzing the U.S. motion picture and video game industries—two of the largest and fastest-growing experience product sectors in the U.S. economy (Motion Picture Association of America [MPAA] 2014; Siwek 2014). Our data set includes pre-launch weekly ad spend, blog volume, online search volume, opening-week sales, and product characteristics. We treat pre-launch online search volume as a measure of pre-launch consumer interest in the upcoming new product, as implied in previous studies (e.g., Du and Kamakura 2012; Du, Hu, and Damangir 2015; Hu, Du, and Damangir 2014; Kulkarni, Kannan, and Moe 2012). For the first research question, we examine the long-term effects of advertising and blog postings on search volume during the pre-launch phase of a new product. To understand the dynamic relationships among the pre-launch time-series variables and to identify possible persistent effects, we apply a vector autoregressive (VAR) modeling approach (Hanssens, Parsons, and Schultz 2008; Lütkepohl 2005). We summarize the estimation results using generalized impulse response functions (GIRFs) to show how a random shock to one of the focal variables influences the other variables over the course of pre-launch periods. For the second question, we develop a set of predictive models – a base model and three test models – in which the dependent variable is the opening-week revenue of movies.[1] We focus on the opening-week revenue because viewership in the first week is critical for the financial success of a movie but the most difficult to predict. The predictors of the base model are the opening-week advertising, number of screens, and various movie characteristics. The predictors of the test models include pre-launch blog and/or search volume, in addition to those in the base model. To test predictive performance, we compare the mean absolute percentage errors (MAPEs) of the four models in holdout samples.

Several important findings emerge. First, blog postings[2] are more effective than advertising in generating consumers' interest in new motion pictures and video games during the pre-launch phase. More important, blog postings have permanent, trend-setting effects on consumers' search activities, while advertising has only temporary effects. In other words, advertising can temporarily boost pre-launch consumer interest, but it cannot start or enhance a trend in consumer interest in an upcoming motion picture or video game. By contrast, blog postings can start a trend in consumers' interest for an upcoming motion picture or video game. In terms of elasticity, the four-week cumulative elasticity of online search is 0.187 to advertising and 0.635 to blog postings in the U.S. motion picture industry. In the U.S. video game industry, the numbers are 0.093 (the four-week cumulative elasticity of online search to advertising) and 1.306 (the four-week cumulative elasticity of online search to blog postings), respectively.

Second, online search is more effective than advertising in generating bloggers' WOM activities. This suggests that consumers' interest in an upcoming new product greatly influences bloggers' WOM activity around the product and more so than advertising. In summary, we find that blog postings and online search are very responsive to each other during the pre-launch periods of a new experience product. This finding suggests that strong viral effects exist between online search and blog postings in pre-launch periods of motion pictures and video games.

Third, online search and blogging activities in pre-launch periods are individually evolving, but they are also in a dynamic equilibrium. This means that pre-launch search volume (or consumers' interest in the upcoming product) cannot grow without bounds for a given level of blog volume; that is, sustaining pre-launch consumer interest requires continued blogging activities throughout the pre-launch period. Finally, pre-launch search and blog volume improve the prediction of opening-week box office revenues of movies. Search volume is superior to blog volume in predictive performance, suggesting the importance of monitoring consumers' online search activity during pre-launch periods.

The remainder of the article proceeds as follows. We first review extant literature and summarize the contributions of the current study. Then, we introduce our data sets, discuss the modeling procedure, and present the empirical results. We conclude with a discussion of the main findings, their managerial implications, and proposed future extensions of this work.

Literature Review

The past several years have witnessed increasing interest in the effects of advertising and WOM on the sales of *existing* products and services. Villanueva, Yoo, and Hanssens (2008) examine the long-term value of customers acquired through WOM versus firm-initiated marketing and find that customers acquired through WOM have more long-term value than customers acquired through marketing for a web hosting company. Trusov, Bucklin, and Pauwels (2009) compare the effect of WOM referrals with that of traditional marketing actions and find that WOM referrals are substantially more effective in driving member growth at a social network site.

[1] We do not examine predictive performance for the video game industry because no reliable video game sales data are available. Although VGChartz (www.vgchartz.com) publishes video game sales date used by some previous studies, its method of sales estimation raises concerns about data accuracy (e.g., https://en.wikipedia.org/wiki/VG_Chartz).

[2] We relied on two sources to collect blog postings. For the motion picture data set, we used the Google blog search engine (see Appendix A for an example); for the video game data set, we acquired blog postings data from Meltwater, a media intelligence company. Our empirical findings are consistent across the two data sources. For a more detailed description, refer to the Data section.

Stephen and Galak (2012) examine how two types of earned media, traditional and social, affect sales for a micro-lending site. They find that the greater frequency of social earned media activity allows social earned media to be more effective than traditional earned media. Onishi and Manchanda (2012) use blog postings as a form of earned media and show that blog stock is more effective than ad stock in generating daily movie revenue in the Japanese market. Pauwels, Aksehirli, and Lackman (forthcoming) classify WOM into three topical categories (ad WOM, brand WOM, and purchase WOM) and combine them with marketing activities, organic search activities, and on- and off-line store traffic to quantify dynamic interactions among these activities of an apparel retailer.

Scant research examines the effectiveness of *pre-launch* advertising and WOM on release-time market outcomes. Two notable exceptions are Gopinath, Chintagunta, and Venkataraman (2013) and Burmester et al. (2015). Gopinath, Chintagunta, and Venkataraman (2013) analyze the effects of advertising and WOM on movie revenue at the designated market area level and find that release day performance is impacted by prerelease advertising and blog volume, but not by blog valence. Burmester et al. (2015) examine the effectiveness of print advertising and print publicity appearing in game magazines and find that pre-launch print publicity is more effective than pre-launch print advertising in generating the release-week sales of video games in Germany. These two studies are notable for their attempts to examine the impact of pre-launch advertising and WOM on initial sales of experience products. However, they do not examine how the two media dynamically interact with consumer interest over the course of pre-launch periods, leaving an important question unanswered: how pre-launch advertising and WOM differ in terms of long-term persistent impacts on consumer interests.

Several studies investigate the strategic implications of online search activity of consumers. Kim, Albuquerque, and Bronnenberg (2010) use aggregate product search data from Amazon.com to demonstrate that online search behavior can predict demand for new products. Kulkarni, Kannan, and Moe (2012) find that pre-launch online search volume improves the prediction of opening-week box office revenue of movies. Recently, researchers have paid attention to search index data from Google Trends to address marketing and economic problems. Du and Kamakura (2012) uncover common trends in consumers' interest in vehicle shopping by analyzing a search index of keywords related to automobiles. Hu, Du, and Damangir (2014) augment sales data with the Google search index and decompose advertising's impact into two components: generating consumer interest in pre-purchase information search and converting that interest into sales. Du, Hu, and Damangir (2015) show that the predictive performance of a market response model can be significantly improved by augmenting the standard market response model with online search trends. Choi and Varian (2012) show that search engine data from Google Trends can be used to forecast near-future market outcomes in a real-time manner. Hand and Judge (2012) show that Google Trends data can improve the accuracy of cinema admission forecasting models at the industry level. Finally, Stephen and Galak (2012) use Google Trends search index data to control for consumers' interest in the focal firm of their analysis. In summary, the findings from these studies highlight the validity of using online keyword search volume as a measure of consumers' interest in products.

Although several studies have examined the effectiveness of advertising and online WOM in the context of existing products, scant research has explored how the two types of media generate consumers' interest in *upcoming new products over the course of pre-launch periods*. Yet these are precisely the questions that managers need answers to, because there is still time to proactively adjust their marketing strategies. For example, if marketers find that one type of communication (e.g., WOM) has a more sustainable effect on pre-launch consumer interest than another type of communication (e.g., traditional advertising), they can take advantage of this finding to maximize the effectiveness of their pre-launch marketing activities.

One reason for this paucity of research is that it is difficult to obtain sensible long time-series metrics that reflect consumers' emerging pre-launch interests. While marketers may use repeated cross-section surveys during pre-launch periods of a new product (e.g., Chintagunta and Lee 2012), such surveys can not only be time consuming and cost prohibitive but also suffer from consumer self-reports. By contrast, our study uses Google Trends search data to collect consumers' interest in upcoming experience products—a "big data" approach that can overcome the weaknesses of repeated self-report surveys.

The contributions of this study are twofold. First, by examining relationships among advertising, blog postings, and online search over 60 weeks of pre-launch periods, we shed light on how a leading indicator of sales – i.e., pre-launch online search volume – interacts with paid and earned media—i.e., advertising and blog postings. By using the long time-series data, we are able to examine any persistent effects of the two media types in generating pre-launch consumer interest. Specifically, we find that pre-launch WOM has a permanent, trend-setting effect on pre-launch search volume while advertising has only temporary effects. Second, we compare the performance of online search volume with that of online WOM volume in predicting opening-week revenue of a new movie. We find that search volume is the statistically superior metric, suggesting the importance of pre-launch keyword search volume as a leading indicator of market success of an experience product. Table 1 compares the related studies.

Conceptual Framework

In this section, we explain why advertising, blog postings, and online search may have dynamic effects on one another over the course of pre-launch periods, why blog postings can be more effective than advertising in generating online search during the periods, and why pre-launch search volume may be a better predictor of opening sales than pre-launch blog volume.

Table 1
Comparison of related studies.

Study	Activity			Period of outcome variable			WOM measure
	Marketing	WOM	Online Search	Pre-launch	Opening	Post-launch [a]	
Burmester et al. (2015)	v	v			v		Volume of print publicity
Choi and Varian (2012)			v			v	
Dhar and Chang (2009)		v				v	Volume, valence
Du and Kamakura (2012)			v			v	
Du, Hu, and Damangir (2015)	v		v			v	
Duan, Gu, and Whinston (2008a)		v				v	Volume, valence
Duan, Gu, and Whinston (2008b)		v				v	Volume, valence
Gopinath, Chintagunta, and Venkataraman (2013)	v	v			v	v	Volume, valence
Hand and Judge (2012)			v			v	
Hu, Du, and Damangir (2014)	v		v		v	v	
Karniouchina (2011)		v			v	v	Volume, valence, inconsistency
Kulkarni, Kannan, and Moe (2012)	v		v		v		Volume, valence
Liu (2006)		v			v	v	Volume, valence
Onishi and Manchanda (2012)	v	v			v	v	Volume, valence, content
Pauwels, Aksehirli, and Lackman (forthcoming)	v	v	v			v	Valence, content
Stephen and Galak (2012)		v				v	Volume
Trusov, Bucklin, and Pauwels (2009)	v	v				v	Volume
Villanueva, Yoo, and Hanssens (2008)	v	v				v	Volume
Zhu and Zhang (2010)		v				v	Volume, valence
This study	v	v	v	v	v		Volume

[a] Analysis on existing products are classified as post-launch analysis.

Dynamic Interactivity

Advertising, blog postings, and online search may influence one another over the course of pre-launch periods. As an initial disseminator of product information, advertising may trigger blogging and online search activities (advertising → blogging and online search). Consumers who become aware of a new product through advertising may want to find other sources of product information to make a better judgment about the product. They may regard blog postings as an alternative source of product information in pre-launch periods (Gopinath, Chintagunta, and Venkataraman 2013; Onishi and Manchanda 2012). To find blog postings scattered on the Internet, consumers are likely to rely on search engines (Pew Research Center 2012). Thus, as advertising triggers consumers' online search, blog postings may trigger further online search for product information (blogging → online search). Conversely, online search for a product, which represents the searcher's interest in the product (Kulkarni, Kannan, and Moe 2012), may influence bloggers' posting activities because bloggers are motivated to discuss trendy topics and popular new products for various reasons (King, Racherla, and Bush 2014). Some bloggers are even professional reviewers and industry experts, who may be responsive to general consumers' interest for economic reasons. That is, the more public interest in a topic (new movies and video games in this case), the more blogging activity is generated as a result of this popularity (online search or consumer interest → blogging). Finally, blogging and search activity may influence the advertising spending of focal firms because firms may monitor consumer behavior around their products and adjust their future advertising spending accordingly to maximize advertising effectiveness. The influence can be positive, negative, or null, depending on the firms' strategies (blogging and online search → advertising).[3] We expect that the interrelationship among the three activities may not only be contemporaneous but also persistent because of various spillover effects of the activities.

Differential Effect Sizes

While the three activities may influence one another, their effect sizes may be different. Advertising is a unidirectional communication from firms to consumers. Because advertising's main objective is to persuade consumers to act in the way advertisers want (Bagwell 2007), consumers may attribute advertising claims to a profit motive (Lord and Putrevu 1993). Such attribution can negatively affect their perceptions of the

[3] On the one hand, a large amount of buzz may induce firms to decrease their advertising spending because firms can take advantage of high interest among consumers (e.g., http://www.wsj.com/articles/star-wars-carries-its-own-marketing-weight-for-disney-1449536686) to save on their advertising spending. (The authors thank an anonymous reviewer for bringing up this point.) On the other hand, a large amount of buzz may encourage firms to increase their advertising spending because the higher the baseline demand for a product (the intercept in a sales response model), the higher the optimal advertising spend. Given that pre-launch blog/search volume is a good indicator of the success of a new experience product, it is in the studio's best interest to take advantage of this apparent consumer interest through additional advertising. This implies that a larger amount of pre-launch buzz would lead to a larger advertising spending. Finally, the amount of buzz may have no immediate effect on advertising spending because it is difficult to micro-adjust ad schedules once they are set (Elberse and Anand 2007; Sissors, Baron, and Smith 2010). Which of the three is dominant is an empirical question, which we answer in the Pre-launch Period Analysis section.

Table 2
Differences among advertising, blog postings, and online search and implications.

Activity	Subjects of activity	Motivations	Other important points	Implications
Advertising	Firms	Persuasion of consumers, profit motive	Profit motive may negatively affect credibility of advertising.	Blog postings may be more effective than advertising in generating pre-launch consumer interest in a new product.
Blog postings (user-created)	Consumers	Self-enhancement, opinion leadership, altruism	Most-prevalent form of WOM in pre-launch period. Consumers may perceive blog postings as more credible than advertising. Blog postings do not easily disappear from the Internet.	Blog postings may have a longer-lasting effect than advertising in generating pre-launch consumer interest. Search volume may be a superior predictor to blog volume for predicting opening-week sales of a new product.
Online search	Consumers	Consumption interest in the product, finding credible product-related information created by other users	More common than blogging activity. Blog postings need to be viewed to influence consumers.	

credibility of advertising (Burmester et al. 2015), which in turn may have a negative impact on the effectiveness of the advertising claim. Furthermore, because consumers do not have sufficient knowledge to discern high- versus low-quality experience goods, manufacturers have an incentive to engage in heavy pre-launch advertising, even for low-quality products (Song, Jang, and Cai 2015), resulting in a low return to pre-launch advertising for experience goods (Elberse and Anand 2007).

Blog postings differ from advertising in that they are created by bloggers who are also enthusiasts and/or experts independent of the advertiser. Bloggers' WOM engagement is motivated by self-enhancement (Angelis et al. 2012; Fiske 2002; Wojnicki and Godes 2008), opinion leadership (Sun et al. 2006), and concerns about others (Dellarocas and Narayan 2007). As such, consumers may attribute product information in blog postings to the provision of neutral product-related information that can help their purchase decisions, actively search for blog postings, and be more receptive to blog postings than advertising claims. Blogs are also the most prevalent form of WOM in the pre-launch periods of an experience product (Gopinath, Chintagunta, and Venkataraman 2013; Onishi and Manchanda 2012), reflecting experts' (opinion leaders') interests, excitement, and expectations (Xiong and Bharadwaj 2014). Furthermore, unlike most advertising (especially advertising on traditional media), online postings do not easily disappear from the medium—the Internet. Consumers can find blog postings that were created a long time ago with a search engine. These features suggest that, compared with advertising in traditional media, blog postings may have a greater and longer-lasting effect in generating consumers' interest in an upcoming experience product.

Differential Predictive Performance of Search and Blog Postings

Online search activity differs from blogging in that it reflects consumers' interest in the searched product (Du and Kamakura 2012; Du, Hu, and Damangir 2015; Hu, Du, and Damangir 2014; Kulkarni, Kannan, and Moe 2012). Online search may also lead to media consumption activity because consumers use search engines to find other people's opinions. As blog postings need to be viewed to influence sales (Onishi and Manchanda 2012), search volume of a product – as a measure of consumers' media consumption activity and interests – may have a direct impact on the sales of the related products. Finally, search activity is more common among Internet users than blogging activity. Of U.S. adult Internet users, 91% use a search engine, while only 32% post a comment on the Internet (Pew Research Center 2012). These differences between search and blogging activity suggest that search volume may be a better predictor of new product sales than blog volume. Table 2 summarizes the

Table 3
Variables and data sources of the movie data.

Category	Variable	Source of data
Focal variables	Weekly ad spend	Nielsen
	Weekly blog postings	Google blog search engine
	Weekly search volume	Google Trends
	Number of screens in the opening week	The Numbers
	Opening-week revenue	The Numbers
Movie characteristics	Genre, MPAA rating, production budget, sequel, director power variables	IMDb
	Average critic rating	Metacritic
	Monthly seasonality: January–April; May–August; September–October, November–December	Einav (2007)
Other variables	National holiday	

Table 4
Descriptive statistics of the movie data (N = 137).

	Mean	Median	Std. Dev.	Min	Max
Ad spend ($000)	17,608	19,152	11,004	0.19	39,418
No. of blog postings	608	191	1,435	9	10,682
Google search volume (index)[a]	28,408	7,937	78,652	155	621,220
No. of opening-week screens	7,629	8,646	4,897	9	21,625
Opening week box office revenue ($000)	24,931	17,012	30,397	78	200,077
Critic rating (Metascore, [0–100])	57.7	58.3	15.2	23.8	92.7
Production budget ($000)	59,041.1	40,000	54,694.9	11	250,000.0
Past movie box office revenue of the focal director ($ M)	$942	$ 516	$ 1,097	$ 0.013	$ 6,518
Average director rating from the past	6.72	6.77	0.63	5.22	8.71
Genre (%)	Action: 22.6, Comedy: 27.7, Drama: 19.0, Others: 30.7				
MPAA (%)	G: 2.2, PG: 21.9, PG13: 41.6, R: 34.3				
Sequel	15 movies (10.9%) are sequels.				
Release month (%)	Jan–Apr: 20.4, May–Aug.: 29.9, Sep.–Oct.: 18.2; Nov.–Dec.: 31.4				

[a] Google search volume is an index. The computation is explained in Appendix B.

differences among advertising, blog postings, and online search and their implications.

Data

The Movie Data Set

Our movie data set consists of 137 movies, most of which were released in 2009. For each of the 137 movies, we collect weekly ad spend, blog volume (the number of blog postings), and online search volume. These weekly variables are collected from 60 weeks before release until the release week. In the opening week, we also collect the number of screens and theatrical revenue. Finally, we collect various movie characteristics. Table 3 summarizes the variables and their sources, and Table 4 shows descriptive statistics of the main variables.

Advertising, Screens, and Box Office Revenue

The advertising data cover major media outlets such as television, print, radio, and outdoor expenditure as collected by Nielsen. The median ad spend of the 137 movies during the analysis period is $19 million. The number of opening-week screens and box office revenue come from The Numbers. The median opening-week screens and opening-week revenue of our sample movies are 8,646 and $17 million, respectively.

Blog Postings and Search Volume

Weekly blog postings for the movies come from the Google blog search engine, which was used in previous studies (Gopinath, Chintagunta, and Venkataraman 2013; Stephen and Galak 2012). As a preliminary analysis, we conducted a series of experiments with different search conditions and compared the search results. The experiments showed that the best search condition is (1) searching for blogs whose titles contain the word “movie,” “film,” or “flick,” and (2) within those blogs, searching for postings whose titles contain the focal movie’s title. For example, to find blog postings of the movie *12 Rounds*, we use the following search condition in the Google blog search engine: *inblogtitle:movie OR film OR flick inposttitle: “12 rounds”*. For each week of each movie, we repeated the search trials five times and used the mode of the number of blog postings so gathered.[4,5] Fig. A.1 in Appendix A exhibits a weekly search result for blog postings about the movie *Avatar*. As Fig. A.1 shows, blogger identities are diverse, including lay consumers, amateur and professional critics and contributors to industry magazines (e.g., *The Hollywood Reporter*) and entertainment websites (e.g., www.mediastinger.com). Examining samples of blog postings reveals that lay consumers merely spread the news of upcoming movies without in-depth evaluation, while critics, magazines and entertainment websites provide in-depth analysis.[6]

To obtain weekly online search volume of a movie, we use Google Trends (www.google.com/trends), a site that reports the weekly search index of keywords entered into the Google search engine. To improve the accuracy of search volume, we use relevant search terms suggested by Google Trends. To further improve data accuracy, we focus on search instances that occur only in the U.S. motion picture category using English as the search language. Because Google normalizes the Google Trends search index, we develop a method to transform the keyword search index into a measure that is comparable across both

[4] In most cases, the five search results agree with one another. That is, the Google blog search engine gives the same number of blog postings for the same search condition in the five trials. In rare cases, the five search trials disagree—usually with one outlier and four same numbers. When they disagree, we use the mode of the search results because the outliers occur once.

[5] We do not include valence of blog postings in our analysis. Due to our data collection approach, determining valence of individual blog postings – which requires analyzing sentiments of each blog posting by text mining – was infeasible.

[6] Due to the limitation of the data gathering process, we could not calculate the proportions of different blogger identities.

movies and weeks. Appendix B describes the technical details of the method. The first column of Appendix C shows an example of weekly ad spend, blog volume and search volume in the movie data set.

Movie Characteristics

We collect genre, MPAA rating, production budget, whether the movie is sequel or not, director power variables, average critic rating, monthly seasonality (Einav 2007), and whether a week contains national holidays. For director power, we collect two variables: total revenue of past movies in which the director was involved as a director, writer, or producer and the average user rating of those movies.

The Video Game Data Set

Our video game data set consists of 66 video games released in 2013 and 2014. For each of the 66 video games, we collect weekly ad spend, blog volume, and online search volume. These weekly variables are collected from 60 weeks before release until the release week. Table 5 summarizes the variables and their sources. Table 6 shows descriptive statistics of the variables.

Advertising

The advertising data come from Kantar Media and cover major media outlets. The median ad spend of the 66 video games during the analysis period is $1.4 million.

Blog Postings and Search Volume

We purchased weekly blog postings for the video games from Meltwater. Meltwater scans major blog sites and reports the weekly number of related blog postings. The weekly online search volume is obtained from Google Trends. To improve the accuracy of search volume, we follow a similar procedure described for the movie data set. That is, we use relevant search terms suggested by Google Trends and focus on search instances that occur only in the U.S. video game category using English as the search language. Then, we use the method explained in Appendix B to create a search volume measure that is comparable across video games and weeks. The second column of Appendix C shows an example of weekly ad spend, blog volume and search volume in the video game data set.

Table 5
Variables and data sources of the video game data.

Category	Variable	Source of Data
Focal variables	Weekly ad spend	Kantar Media
	Weekly blog postings	Meltwater
	Weekly search volume	Google Trends

Table 6
Descriptive statistics of the video game data (N = 66).

	Mean	Median	Std. Dev.	Min	Max
Ad spend ($000)	2,925	1,401	4,703	0.3	29,993
No. of blog postings	1,029	631	1,419	15	8,257
Google search volume (index) [a]	9,919	2,799	19,794	85	101,719

[a] Google search volume is an index. The computation is explained in detail in Appendix B.

Pre-launch Period Analysis

Model Development

The purpose of the pre-launch analysis is to examine how the focal variables (i.e., advertising, blog postings, and online search) dynamically interact over the course of pre-launch periods. The dynamic system in our conceptual framework and the purpose of the pre-launch analysis suggest that persistence modeling (Dekimpe and Hanssens 1999) is appropriate. As such, we develop a multivariate time-series model using the VAR framework. Our modeling approach consists of two steps. First, we test for endogeneity and the possibility of permanent effects of the focal variables. From the test results, we specify an appropriate VAR model that can account for endogeneity and dynamic interactions among the variables. Second, we estimate the model and calculate short- and long-term responses of the variables in the form of elasticities. Throughout this procedure, we use appropriate methods to deals with the panel structure of our data. Table 7 displays these analysis steps.

Table 7
Analysis steps.

Steps	Literature
1. Model development	
a. Endogeneity test	Granger (1969)
b. Panel unit-root test	Im, Pesaran, and Shin (2003); Maddala and Wu (1999)
c. Panel cointegration test	Kao (1999); Pedroni (1999, 2004)
d. Model specification based on test results (VAR, VAR in differences, VECM)	Dekimpe and Hanssens (1999)
2. Model estimation and policy simulation	
a. Estimation	Engle and Granger (1987); Phillips and Moon (1999)
a.1 Fully modified OLS to estimate the long-run equilibrium	
a.2 Pooled OLS	
b. GIRF	Kireyev, Pauwels, and Gupta (forthcoming); Pauwels, Aksehirli, and Lackman (forthcoming); Pesaran and Shin (1998)

Table 8
Estimation results of the movie data.

	Coefficient	Std. Err.	t-Stat	p-Value
(a) Long-run equilibrium relationship among advertising, blog postings and search during pre-launch period				
Long-run relationship between advertising and search (β_1)	0.1623	0.0108	15.0485	0.0000
Long-run relationship between blog postings on search (β_2)	1.2216	0.0482	25.3601	0.0000
(b) Adjustment of firm and consumer activities to deviation from long-run equilibrium during pre-launch period				
Adjustment of advertising to deviation (α_A)	0.0219	0.0165	1.3225	0.1860
Adjustment of blog postings to deviation (α_B)	0.0146	0.0055	2.6436	0.0000
Adjustment of search volume to deviation (α_S)	−0.0666	0.0059	−11.2157	0.0000
Model fit	ΔAd_{it}	$\Delta \mathrm{Blog}_{it}$	$\Delta Search_{it}$	
R^2	0.293	0.312	0.148	
Adj. R^2	0.289	0.308	0.143	

In the first step, we conduct a series of tests that help determine our model specification. To determine whether we need to model a system of equations among advertising, blog posting, and online search, we conduct Granger causality tests (Granger 1969). If Granger causality tests show that one variable is temporally caused by another variable, the former should be treated as an endogenous variable, meaning that it should be modeled as a function of the latter. If more than one variable is temporally caused, we need to develop a system of multiple equations.

Next, we need to determine whether each variable should be included in levels or in differences in the model. To address this question, we conduct a series of panel unit-root tests (Im, Pesaran, and Shin 2003; Maddala and Wu 1999) and panel cointegration tests (Kao 1999; Pedroni 1999, 2004). If panel unit-root tests indicate that an activity is evolving, we need to difference to avoid spurious regression problems (Granger and Newbold 1974), unless the variables are in a long-run equilibrium. We test the long-run equilibrium with panel cointegration tests (Kao 1999; Pedroni 1999, 2004). If the panel cointegration tests find evidence of long-run equilibrium among the non-stationary variables, we estimate an appropriate vector error correction model (VECM); otherwise, we estimate a VAR model with appropriately differenced variables. A model developed through this procedure captures both immediate as well as lagged effects and direct as well as indirect interactions among the endogenous variables (e.g., Kireyev, Pauwels, and Gupta forthcoming; Pauwels, Aksehirli, and Lackman forthcoming).

In the second step, we estimate the specified model and compute GIRFs. We use the pooled ordinary least squares to estimate the model (Enders 2004; Engle and Granger 1987). In case of VECM, the long-run equilibrium is estimated by the fully modified ordinary least squares (OLS), an appropriate method for a panel data set (Phillips and Moon 1999). On the basis of the estimation results, we derive GIRFs of the endogenous variables. GIRFs can be considered the outcome of a *conceptual experiment* in which the time profile of the effect of hypothetical shocks on endogenous variables at a time point is compared with a baseline profile (i.e., the expected values of endogenous variables in the absence of the shocks; Dekimpe and Hanssens 1999; Pesaran and Shin 1998; Trusov, Bucklin, and Pauwels 2009). As such, GIRFs can identify persistent, long-term relationships, if any, among the time-series variables in the system.

Empirical Analysis of the Movie Data

We follow the steps in Table 7 to find the most appropriate model for the pre-launch period analysis of the movie data. Appendix D provides the results of panel unit-root and cointegration tests. The panel unit-root tests indicate that the three variables should be differenced, and the cointegration tests reveal that the three variables are in a long-run equilibrium. This means that the three activities – advertising, blog postings, and online search – follow a common long-run path during the pre-launch periods and that if one variable deviates from the common path at a certain time point, it will ultimately return back to the equilibrium in the following periods. Eq. (1) represents this feature of the three activities:

$$\begin{bmatrix} \Delta Ad_{it} \\ \Delta \mathrm{Blog}_{it} \\ \Delta Search_{it} \end{bmatrix} = \begin{bmatrix} \alpha_A \cdot e_{i,t-1} \\ \alpha_B \cdot e_{i,t-1} \\ \alpha_S \cdot e_{i,t-1} \end{bmatrix} + \sum_{l=1}^{P} \begin{bmatrix} \pi_{11}^l & \pi_{12}^l & \pi_{13}^l \\ \pi_{21}^l & \pi_{22}^l & \pi_{23}^l \\ \pi_{31}^l & \pi_{32}^l & \pi_{33}^l \end{bmatrix} \begin{bmatrix} \Delta Ad_{i,t-l} \\ \Delta \mathrm{Blog}_{i,t-l} \\ \Delta Search_{i,t-l} \end{bmatrix} + \boldsymbol{\Gamma}(\Delta \mathbf{x}_{it}) + \begin{bmatrix} u_{it}^A \\ u_{it}^B \\ u_{it}^S \end{bmatrix}, \tag{1}$$

where Ad_{it} is log-transformed weekly ad spend of movie i in week t, Blog_{it} is log-transformed blog volume, $Search_{it}$ is log-transformed search volume, and $\boldsymbol{x}_{it}$ is weekly dummy variable. The notation Δ denotes first difference (e.g., $\Delta Ad_{it}=Ad_{it}-Ad_{it-1}$), $e_{i,t-1}$ (specified in Eq. (2) below) is the deviation from the long-run path or equilibrium observed in the previous time week ($t-1$), and the parameters (α_A, α_B, α_S) denote the speed of reverting to the equilibrium. Eq. (2) represents a long-run equilibrium among the three endogenous activities:

$$e_{i,t-1} = Search_{i,t-1} - \beta_{i0} - \beta_1 Ad_{i,t-1} - \beta_2 \text{Blog}_{i,t-1}. \tag{2}$$

We estimate the long-run equilibrium relationship by the fully modified ordinary least squares estimation (Phillips and Moon 1999).[7] Then, we substitute the residuals of Eq. (2), $\hat{e}_{i,t-1}$, for $e_{i,t-1}$ in Eq. (1) to estimate the VECM by the pooled ordinary least squares method (Enders 2004; Engle and Granger 1987). We examine various lag lengths and find that the residual time series of Eq. (1) – $\hat{u}^A_{it}, \hat{u}^B_{it}, \hat{u}^C_{it}$ – become white noise at lag length P = 8. Table 8 shows the estimation results for the long-run relationship parameters (β_1 and β_2) and the short-term adjustment parameters (α_A, α_B and α_S). We omit the other parameter estimates from the table to avoid clutter.

Relationship Among Advertising, Blog Postings and Online Search

The significant, positive estimates for β_1 and β_2 indicate a positive long-run relationship among weekly ad spend, blog volume, and search volume. That is, greater online search volume is associated with higher ad spend and greater blog volume and vice versa.

The weekly adjustment parameters $\hat{\alpha}_B$ and $\hat{\alpha}_S$ are significantly different from zero. As such, weekly blog and search volume respond to the previous week's deviation from the long-run equilibrium. This relationship is shown in Eqs. (3-1) and (3-2) by substituting the parameter estimates into the corresponding equations in Eq. (1):

$$\Delta\text{Blog}_{it} = 0.0146\left(\text{Search}_{i,t-1} - \hat{\beta}_{i0} - 0.1623 Ad_{i,t-1} - 1.2216\text{Blog}_{i,t-1}\right) + \cdots + \hat{u}^B_{it}. \tag{3-1}$$

$$\Delta\text{Search}_{it} = -0.0666\left(Search_{i,t-1} - \hat{\beta}_{i0} - 0.1623 Ad_{i,t-1} - 1.2216\text{Blog}_{i,t-1}\right) + \cdots + \hat{u}^S_{it}. \tag{3-2}$$

These equations reveal that if the previous week's search volume is greater than the expected equilibrium level (i.e., if consumers search more than the amount predicted by its equilibrium relationship with blog postings and advertising level), this week's search volume will decrease from the previous week's level to return to the equilibrium level. Likewise, if the previous week's search volume is less than its equilibrium level, this week's search volume will increase. Importantly, this means that consumers' interest in a new movie (as measured by the movie's search volume) does not develop autonomously as the opening week approaches. Rather, movie studios should support advertising and blogging activities steadily throughout the pre-launch period, to maintain consumers' interest in the movies at a certain level.

The non-significant $\hat{\alpha}_A$ – the weekly adjustment parameter – suggests that advertisers (movie studios in this case) do not respond immediately to weekly blogging and search activities of consumers. This finding is consistent with the ad-space buying practice in the motion picture industry in which the majority of the advertising budget for a new movie is spent on television advertising time. Because television advertising needs to be purchased early enough to secure sufficient airtime (Elberse and Anand 2007; Sissors, Baron, and Smith 2010), movie studios have little room to adjust their ad schedule according to the weekly development in blog postings and online search.

A cointegration finding establishes, but does not reveal, specific causes for co-evolution. Many external reasons could exist for, say, an increase in both searching and blogging activity, including movie advertising. As a striking example, the highly publicized Three Mile Island nuclear accident in 1979 occurred about three weeks before the launch of the motion picture *The China Syndrome*, which had a nuclear meltdown theme. This event provided an unanticipated boost of interest in the subject matter, resulting in the movie's unusually high success at the box office (Christensen and Haas 2005). Overall, the evolving nature of these metrics shows that the pre-launch environment is inherently unpredictable, much like the evolving nature of stock prices.

Effectiveness of Advertising and Blog Postings on Pre-launch Consumer Interest

In the previous analysis, we found that continuous blogging and advertising activities are required to sustain pre-launch consumer interest in a new movie. Then, an important managerial question is, between advertising and blogging, which is more influential in raising consumers' interest in upcoming movies before launch?

We answer this question by examining the GIRFs of ad spend, blog volume, and search volume. Fig. 1 shows the GIRFs and the 95% confidence bands. Fig. 2 summarizes the four-week cumulative elasticities of the focal activities.

We find that both advertising and blog postings influence consumers' interest in upcoming movies, as measured by search volume. More important, blog postings are more effective than advertising in generating consumers' interest in upcoming movies. Fig. 2 summarizes that a 1% increase in ad spend in a pre-launch week produces a 0.187% increase in online search for the first four weeks after the shock (four-week cumulative elasticity: 0.187), while a 1% increase in blog volume in a pre-launch week leads to a 0.635% increase in online search for the first four weeks after the shock (four-week cumulative elasticity: 0.635). Therefore, we find that blog postings are more effective in generating consumer's pre-launch interest in a new movie. Indeed, Fig. 1 shows that the effect of blog postings on search is permanent while the effect of advertising on search is only transient.

Another important finding is the strong effect of consumers' search activities on movie bloggers' blogging activities. According

[7] We do not use the full-information maximum likelihood method (Johansen 1991), because we find that the residuals do not follow a normal distribution.

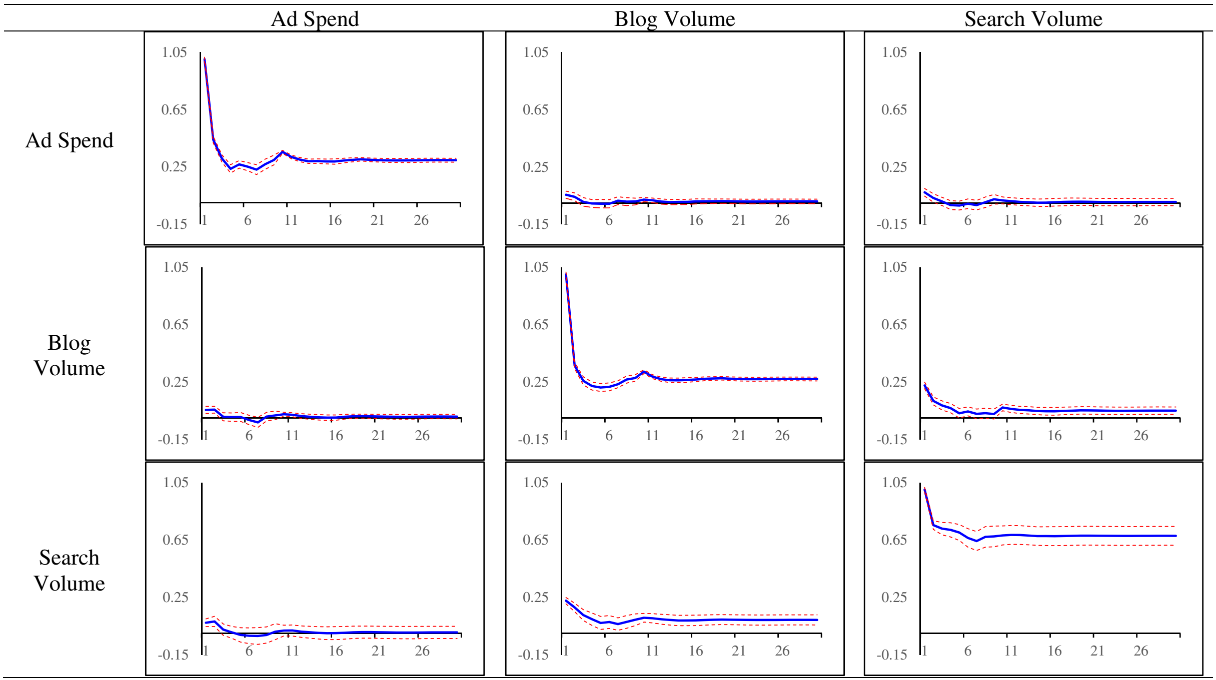


Fig. 1. Weekly elasticities of the row variable to the column variable: the movie data set. (The horizontal axis represents the weeks of and after the shock. 1 represents the week when the shock occurs.)

to Fig. 2, a 1% increase in online search volume in a pre-launch week produces a 0.504% increase in blog postings for the first four weeks after the shock (four-week cumulative elasticity: 0.504), while a 1% increase in ad spend in a pre-launch week leads to a 0.130% increase in blog postings for the first four weeks after the shock (four-week cumulative elasticity: 0.130). In other words, consumers' interest and movie buffs' blogging activities are mutually highly responsive, and more so than their reactions to advertising. These findings lend support to our expectations derived in the Conceptual Framework section.

Previous research offers support to our finding that blog postings are more effective than advertising in building pre-launch consumer interest. First, as Table 2 shows, consumers' differential perceptions of credibility of advertising and blog postings may result in a differential impact of the two media. Second, online postings do not easily disappear from the Internet. Consumers can find online WOM that was created a long time ago, thus granting online buzz a strong viral effect over time (Onishi and Manchanda 2012; Xiong and Bharadwaj 2014). Finally, the quality of experience goods is not fully known until they are consumed. If pre-launch advertising is not a reliable quality indicator (Song, Jang, and Cai 2015) and the pre-launch WOM has a greater uncertainty-reducing potential than advertising (Burmester et al. 2015), consumers may respond more actively to WOM than advertising in pre-launch periods.

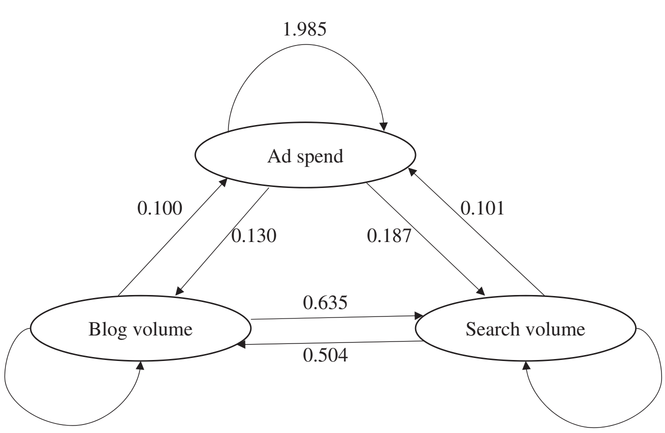


Fig. 2. Four-week cumulative elasticities of endogenous variables: the movie data set.

Empirical Analysis of the Video Game Data

We applied the procedure in Table 7 to the video game data set. We find that the pre-launch period of our video game data also follows the VECM described in Eqs. (1) and (2)—Appendix E provides the results of panel unit-root and cointegration tests. The most appropriate lag length P was again 8. Table 9 shows the estimation results for the video game data set. The substantive findings from the video game data set are consistent with those from the movie data set. The significant, positive estimates for β_1 and β_2 indicate a positive long-run relationship among weekly ad spend, blog volume, and search volume in the video game data set, suggesting that consumers' interest in a video game does not self-develop as the release time approaches. The nonsignificant $\hat{\alpha}_A$ (short-term adjustment of advertising to deviation from the long-run equilibrium) implies that weekly ad spend does not adjust to the previous week's blog and search volume However, consumers' weekly search activities and video game buffs' blogging

Table 9
Estimation results of the video game data.

	Coefficient	Std. Err.	t-Stat	p-Value
(a) Long-run equilibrium relationship among advertising, blog postings and search during pre-launch period				
Long-run relationship between advertising and search (β_1)	0.0742	0.0103	7.2055	0.0000
Long-run relationship between blog postings on search (β_2)	0.7261	0.0269	26.9775	0.0000
(b) Adjustment of firm and consumer activities to deviation from long-run equilibrium during pre-launch period				
Adjustment of advertising to deviation (α_A)	0.0340	0.0609	0.5651	0.5720
Adjustment of blog postings to deviation (α_B)	0.0952	0.0225	4.2229	0.0000
Adjustment of search volume to deviation (α_S)	−0.1102	0.0130	−8.4621	0.0000
Model fit	ΔAd_{it}	ΔBlog_{it}	$\Delta Search_{it}$	
R^2	0.254	0.223	0.093	
Adj. R^2	0.245	0.213	0.081	

activities adjust to recover the long-run equilibrium level because the parameter estimates ($\hat{\alpha}_B$ and $\hat{\alpha}_S$) are significantly different from zero. These findings are consistent with those from the movie data set, in support of our conceptual development.

Fig. 3 shows the GIRFs from the video game data analysis. Fig. 4 summarizes the four-week cumulative elasticities of the focal activities.

Consistent with the movie data analysis results, blog postings are more influential than advertising in generating consumers' interest in upcoming new video games. A 1% increase in ad spend in a pre-launch week produces a 0.093% increase in online search for the first four weeks after the shock (four-week cumulative elasticity: 0.093), while a 1% increase in blog volume in a pre-launch week leads to a 1.306% increase in online search for the first four weeks after the shock (four-week cumulative elasticity: 1.306). Conversely, a 1% increase in online search volume in a pre-launch week produces a 1.126% increase in blog postings for the first four weeks after the shock (four-week cumulative elasticity: 1.126), while a 1% increase in ad spend in a pre-launch week leads to a 0.061% increase in blog postings for the first four weeks after the shock (four-week cumulative elasticity: 0.061). Consistent with the movie data, consumers' interest and video game buffs' blogging activities are mutually highly responsive, and more so than their reactions to advertising.

Opening-week Analysis

Model Development

The purpose of the opening-week model is to determine whether the inclusion of pre-launch blog and search volume

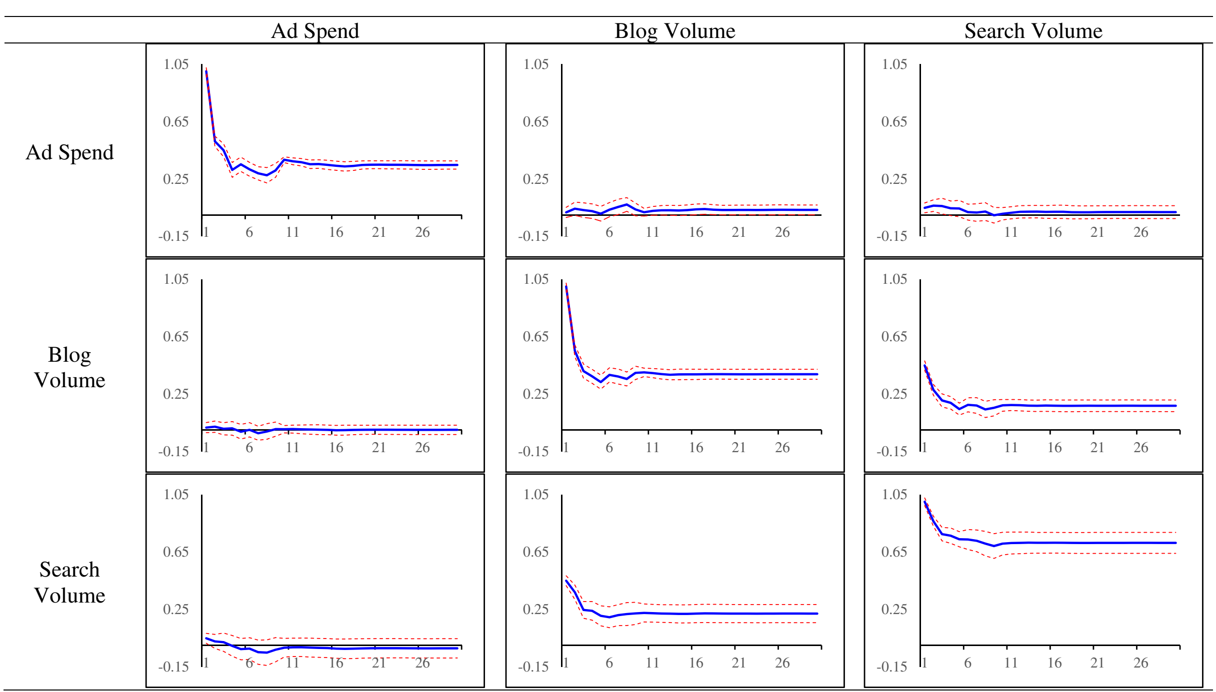


Fig. 3. Weekly elasticities of the row variable to the column variable: the video game data set. (The horizontal axis represents the weeks of and after the shock. 1 represents the week when the shock occurs.)

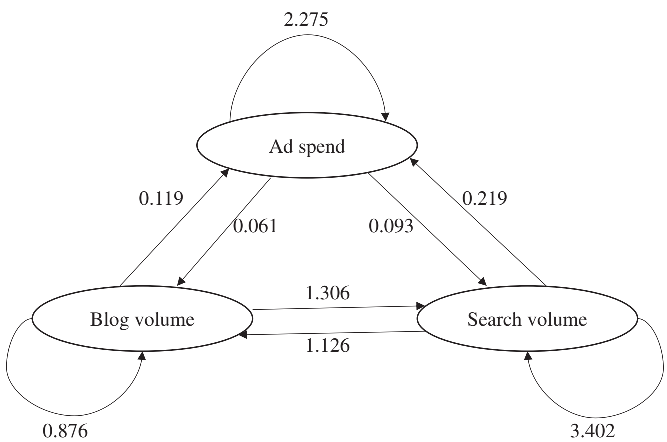


Fig. 4. Four-week cumulative elasticities of endogenous variables: the video game data set.

improves the prediction of opening-week revenue. As such, the model is a cross-section data model in which the dependent variable is the opening-week revenues of movies. To provide early predictions, we include blog and search volume observed in the three weeks before the release.[8] Eq. (4) specifies the model:

$$\ln(Open\_Revenue_i) = Intercept + \boldsymbol{\theta}'[\mathbf{movie\_char}]_i + \phi_1 \ln(Open\_Ad_i) + \phi_2 \ln(Open\_Scrns_i) + \phi_3 \ln(Blog_{i,-3}) + \phi_4 \ln(Search_{i,-3}) + \varepsilon_i, \tag{4}$$

where $Open\_Revenue_i$ is the opening-week revenue of movie i, **[movie_char]** is the vector of movie characteristics in Table 3, $Open\_Ad_i$ is the opening-week ad spend, $Open\_Scrns_i$ is the number of opening-week screens, $Blog_{i,-3}$ is the blog volume observed in the three weeks before release, and $Search_{i,-3}$ is the search volume observed in the three weeks before release. As predetermined variables at the time of movie launch, the variables $Blog_{i,-3}$ and $Search_{i,-3}$ are not influenced by opening-week marketing activities.

We develop one base model and three test models by varying Eq. (4). For the base model, we omit $Blog_{i,-3}$ and $Search_{i,-3}$; therefore, the base model evaluates the baseline predictive performance of the usual variables for movie revenue prediction. Test Model 1 augments $Blog_{i,-3}$ to the base model to test the predictive improvement of pre-launch blog volume. Test Model 2 augments $Search_{i,-3}$ to the base model to test the predictive improvement of pre-launch search volume. Finally, Test Model 3 augments both $Blog_{i,-3}$ and $Search_{i,-3}$ to the base model.

[8] We also tested models with search and blog volume from one and two weeks before release. These tests showed more improved predictive performance. To save space, we include only the most conservative results (i.e., models with blog and search volume three weeks before release). The detailed estimation results are available from the first author.

Empirical Analysis

Table 10, the correlation matrix of the variables in Eq. (4), shows that opening-week revenue of a movie is more strongly correlated with pre-launch search volume than pre-launch blog volume. Indeed, the correlation between pre-launch search volume and opening-week revenue is comparable to that between opening-week advertising and opening-week revenue, suggesting strong predictive ability of pre-launch search volume.

We estimate each of the four models with 96 randomly selected movies (70% of 137 movies) and test their predictive performance using a holdout sample of the remaining 41 movies. To mitigate the effect of random selection, we repeat the analysis 100,000 times, each time with a randomly selected different sample of movies. This procedure generates 100,000 R-squares, adjusted R-squares for the in-samples, and 100,000 MAPEs for the holdout samples. To control for the endogeneity of the screen decision (Elberse and Eliashberg 2003), we use two-stage least squares estimation. For instrumental variables for the opening-week screens, we use weekly pre-launch search volume and blog volume as well as the movie characteristics as shown in Table 3.

Table 11 shows the 99% confidence intervals of the population means of MAPE of the holdout sample. The population means of the four MAPEs are statistically different at a 1% significance level, with Test Model 2 being the best. Because Test Model 2 includes pre-launch search volume but not pre-launch blog volume, this finding suggests that the information in pre-launch search volume is superior to that of pre-launch blog volume in predicting the opening-week revenue of a movie. Note that because the dependent variable is log-transformed, the improvement of predictive performance is substantial in the original scale.

Conclusions

This study examined how advertising and blog postings affect pre-launch consumer interest in an upcoming experience product, and how information on pre-launch consumer activity (i.e., blogging and searching) improves the prediction of initial sales of an experience product. To answer the research questions, we assembled panel data sets of films and video games and applied persistence modeling and developed a cross-section regression model.

The study's findings should be of interest to marketers of experience products. First, two important findings from the pre-launch analysis are that blogging activities are more effective than advertising in generating consumer search in an upcoming product and that blogging and search activities are mutually highly responsive, creating viral effects between them. This suggests that the current resource allocation between traditional media (e.g., television advertising) and new media (e.g., Internet forums and communities) – most of the pre-launch advertising budget is spent on traditional media such as television – should be revisited to maximize the effectiveness of pre-launch marketing in generating consumers' interest. For example, investing in online communities and WOM may be more effective than investing in traditional advertising as "early" pre-launch marketing activities because the effects of WOM on consumer interests carry well over

Table 10
Correlation coefficients of opening-week revenue and the focal variables.

	Pre-launch blog volume [a]	Pre-launch search volume [a]	Opening week ad spend	Opening screens	Opening revenue
Pre-launch blog volume [a]	1.0000				
Pre-launch search volume [a]	0.3569	1.0000			
Opening-week ad spend	0.0243	0.3738	1.0000		
Opening-week number of screens	0.0990	0.4101	0.5554	1.0000	
Opening-week revenue	0.2009	0.5984	0.6043	0.9230	1.0000

[a] Pre-launch blog volume and search volume of a movie mean the movie's blog and search volume in three weeks before its release.

the launch week. Marketers should also make their marketing efforts as engaging as possible, to both consumers and product experts, to take advantage of the strong mutual response between bloggers and consumers. For example, movie studios can develop engaging blog sites for upcoming movies and implement various online communication activities.

Second, with the findings of a permanent effect of blog postings (vs. temporary effect of advertising), marketers should focus on WOM advertising in the early pre-launch periods rather than full-fledged advertising on television media. In this way, movie studios can improve the returns of their marketing investments in pre-launch periods. We can make this inference because we examined long time series of advertising, blog postings, and online search in pre-launch periods.

Third, early pre-launch advertising should be used to target mainly business partners, in particular the distribution channel—for example, movie exhibitors and video retailers. Indeed, any consumer interest boost of such early advertising is bound to lead to lower levels in subsequent weeks, rather than setting off an enduring positive trend in interest. Firms can avoid this "return-to-equilibrium" behavior in consumer interest by aggressive advertising close to the product launch date. However, it could also lead to excessive expectations on the financial performance of the new product. This was documented in Joshi and Hanssens (2009), who find that even successful opening-weekend attendance levels of heavily advertised movies result in negative stock returns for the studios in the days following launch. The overall conclusion, then, is that pre-launch ad spend needs to be commensurate with the inherent experiential quality of the new product.

Overall, these findings highlight an important limitation of the role and power of pre-launch advertising in generating consumer interest in new experience products. In and of itself, advertising is unable to start or enhance a trend in pre-launch consumer interest. Instead, advertising temporarily boosts interest, as measured by consumer search. At the same time, pre-launch consumer interest does evolve, but the drivers of that evolution lie elsewhere, and the co-evolving metrics are in a long-run equilibrium with each other. So, if aggressive advertising in a pre-launch week boosts these metrics beyond their equilibrium levels, in subsequent weeks the metrics will decrease to restore the equilibrium.

Finally, regarding opening-week revenue prediction, pre-launch search volume contains significantly better information than pre-launch blog volume. Therefore, movie studios should not ignore consumers' online search activities during pre-launch periods.

Several research opportunities remain in this area. First, we analyze two experience goods categories in this study. Analyzing other experience goods categories (e.g., music albums) would be a logical next step. Second, this paper does not include the sentiment of pre-launch blog postings. While previous research finds no significant effects of pre-launch blog sentiment on the opening revenue of movies (e.g., Gopinath, Chintagunta, and Venkataraman 2013), other dimensions of blog content may influence consumer search. For example, high search volume for a product can stem from strong disagreement among bloggers' expectations about the quality of the upcoming product. If search is motivated by uncertainty about product quality, search volume may not be a good indicator of the market success of that product. Therefore, uncovering what motivates consumers to search for a product may shed light on the usefulness of the product's search volume to predict its market success. Third, given that pre-launch search volume influences post-launch sales, determining the optimal allocation of a pre-launch advertising budget to maximize search volume is an important question for management.

Acknowledgement

We thank the editor and reviewers for their invaluable feedback and constructive comments. The first author also acknowledges generous support by the research fund of UCLA and University of Missouri-St. Louis.

Table 11
Predictive performance: 99% confidence intervals. [a]

Models	Covariates	Out-of-sample prediction error (MAPE)
Base model	Base model [b]	[3.4900, 3.4972]
Test Model 1	Base model + Blog volume of three weeks before release	[3.5054, 3.5162]
Test Model 2 [c]	Base model + Search volume of three weeks before release	[3.2012, 3.2079]
Test Model 3	Base model + Blog & search volume of three weeks before release	[3.2327, 3.2395]

[a] The 99% confidence interval is constructed from the 100,000 iterations.
[b] Base model = Movie characteristics + Opening-week ad spend + Opening-week screens.
[c] The best model.

Fig. A.1. Example of weekly blog volume.

Appendix A. Collecting Weekly Blog Volume Using Google Blog Search

We collected our data of movie blog postings from Google Blog Search, Google's search engine for blog postings. Note that Google has since disabled the blog search engine. Fig. A.1 illustrates how we collected blog postings from Google, according to which 208 blog postings were made about the movie *Avatar* from October 2 to November 1, 2009. Google Blog Search indexes blog postings not only from the industry's leading magazines (e.g., *The Hollywood Reporter*) but also from lay bloggers who are interested in the new focal movies.

Appendix B. Constructing Cross-sectionally Comparable Search Volume Measures from the Google Search Index

Because the Google search index is normalized, researchers cannot compare the search volume across different keywords with the raw search index. As such, we develop a methodology to transform the weekly search indices from Google into cross-sectionally comparable search volume metrics. The method consists of three steps. The first is the keyword selection step, where basis keywords and movie keywords are selected. Any set of words can be selected for the basis keywords. The only requirement for a basis keyword is that the weekly search volume of the basis keyword should not be high enough to make the weekly search index of a focal movie to be zero. For our analysis of the movie data set, we select the following seven basis keywords for the motion picture industry: "mac os," "lamp", "hello", "windows", "weather", "tomatoes", "video", and "imdb".[9] They are listed in the order of search amount when we restrict the search amount to the U.S. motion picture industry. Then, for each movie, we select a set of keywords that are considered to be used by consumers to search the movie. For example, for the movie *12 Rounds*, we choose "12 Rounds" as the keyword for the movie.

The second step is the keyword matching step. To each product, we assign a basis keyword and collect the Google search index of the movie keyword along with that of the assigned basis keyword to the product. Any basis keyword can be assigned to any product as long as the search index of the movie keyword is comparable to that of the chosen basis keyword for the product. That is, if the search volume of a certain basis keyword is too large compared to the search volume of a movie keyword, that basis keyword should not be used for that product because the product's search index so collected will be reduced to zero for many or all of the weeks.

The last step is the transformation step where we transform each product's search index into a cross-sectionally comparable search volume measure. Taking the motion pictures as an example, the mathematics in this step can be explained as follows. Let k_j be the basis keyword at the *jth* position (i.e., k_1 = "mac os", k_2 = "lamp", …, k_8 = "imdb"), and let $I_t^{k_j}$ represent the search index of the *jth* basis keyword in week *t*. We calculate the ratio of the Google search index of two adjacent basis keywords, $r_t^{j,j-1} = I_t^{k_j}/I_t^{k_{j-1}}$, for each *t* and for all

[9] For the video game industry, we use "technique", "beer", "travel", "wall", "music", and "video game".

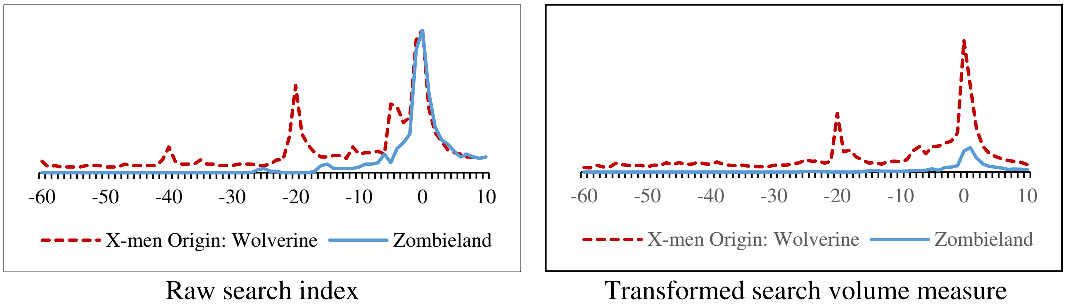


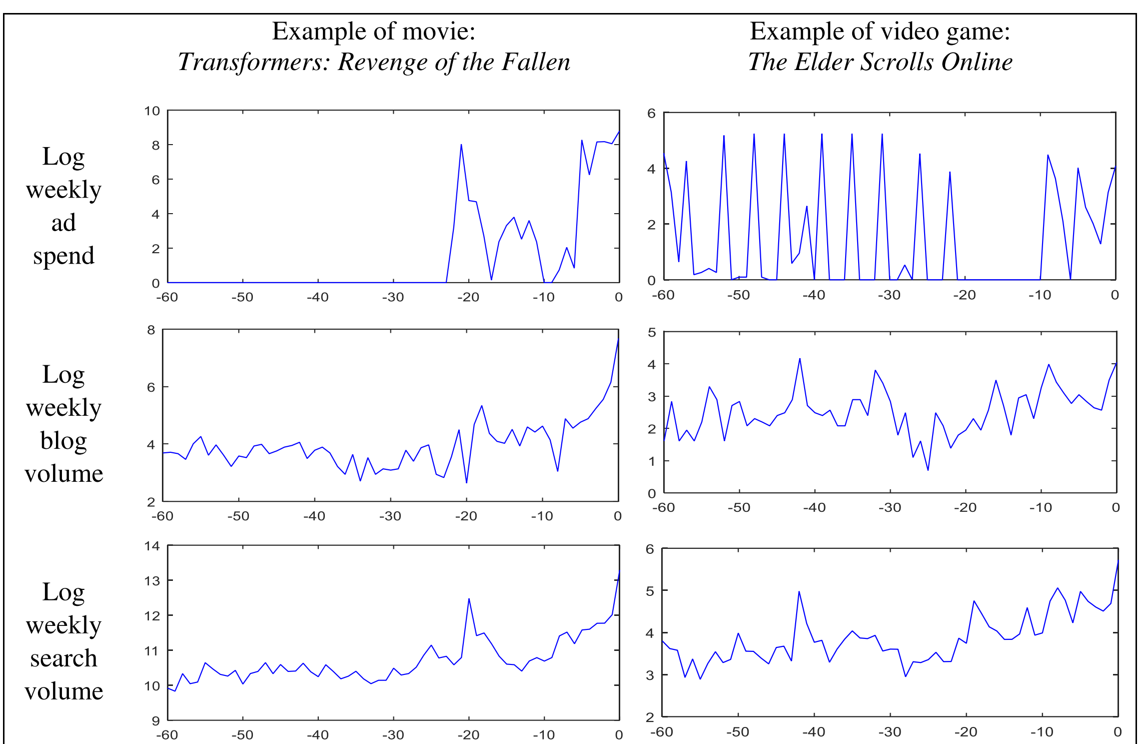
Fig. B.1. Example of raw search index and transformed search measure.

seven pairs of adjacent basis keywords. Let I_{mt} be the search index of movie m in week t. Suppose that, in the second step, the basis keyword of position j was assigned to movie m. Then, for movie m in week t, our cross-sectionally comparable search volume measure, denoted by S_{mt}, is calculated as in Eq. (B.1).

$$S_{mt} = I_{mt} / r_t^{j,j-1} \left(r_t^{j,j-1} \cdot r_t^{j-1,j-2} \dots r_t^{2,1} \cdot r_t^{1,0} \right) \tag{B.1}$$

where $r_t^{1,0}$ is the weekly search index of the basis keyword "mac os" collected together with the keyword "lamp" (the first graph in Fig. B.1). Fig. B.1 exemplifies the raw search indices of Google Trends and their transformed cross-sectionally comparable search volume measures from 60 weeks before the movies' releases to 10 weeks after their releases, for the movies *X-Men Origins: Wolverine* and *Zombieland*. Note that our transformed search volume measures show a substantial difference in consumer search activities between the two movies.

Appendix C. Example of Weekly Ad Spend, Blog Volume, and Search Volume



The horizontal axis is week ($t = -60$–0). Weekly ad spend is measured in thousands of dollars.

Appendix D. Panel Unit Root Tests and Cointegration Tests for the Movie Data Set

Appendix D shows the panel unit root test result and cointegration test results for the movie data set. To select the appropriate lag length for each variable, we turn to two criteria: the serial correlation of the residuals and the significance of lagged dependent variables (Enders 2004). We find that the appropriate lag lengths are 3, 12, and 3 for Ad_{it}, Blog_{it} and $Search_{it}$, respectively. We conduct individual unit root tests developed by Im, Pesaran, and Shin (2003) and Maddala and Wu (1999).

Table D.1
Panel unit root test.
H_0: The variable follows a unit-root process.

	In levels with intercept		In levels with trend		In first differences	
	Test stat.	p-Value	Test stat.	p-Value	Test stat.	p-Value
(a) Ad_{it}						
Im, Pesaran, and Shin	26.79	1.00	26.84	1.00	−26.55	0.00
Maddala and Wu	61.19	1.00	65.04	1.00	1,320.05	0.00
(b) $Blog_{it}$						
Im, Pesaran, and Shin	19.86	1.00	12.63	1.00	−6.78	0.00
Maddala and Wu	43.62	1.00	92.18	1.00	404.30	0.00
(c) $Search_{it}$						
Im, Pesaran, and Shin	10.92	1.00	4.37	1.00	−34.09	0.00
Maddala and Wu	137.65	1.00	226.71	0.99	1,748.77	0.00

We use panel cointegration tests developed by Pedroni (1999, 2004) and Kao (1999)[10], assuming individual intercepts for the cross sections. Also, we assume individual autoregressive process for residuals in the Pedroni test and use 11 lags to ensure that residuals are serially uncorrelated.

Table D.2
Cointegration tests for Ad_{it}, $Blog_{it}$ and $Search_{it}$.
H_0: No cointegration relationship between Ad_{it}, $Blog_{it}$ and $Search_{it}$.

	Test statistic	p-Value
Pedroni ρ-statistic	−26.14	0.00
Kao t-statistic	3.98	0.00

Appendix E. Panel Unit Root Tests and Cointegration Tests for the Video Game Data Set

Appendix E shows the panel unit root test result and cointegration test results for the video game data set. To select the appropriate lag length for each variable, we turn to two criteria: the serial correlation of the residuals and the significance of lagged dependent variables (Enders 2004). We find that the appropriate lag lengths are 3, 12, and 3 for Ad_{it}, $Blog_{it}$ and $Search_{it}$, respectively. We conduct individual unit root tests developed by Im, Pesaran, and Shin (2003) and Maddala and Wu (1999).

Table E.1
Panel unit root test.
H_0: The variable follows a unit-root process.

	In levels with intercept		In levels with trend		In first differences	
	Test stat.	p-Value	Test stat.	p-Value	Test stat.	p-Value
(a) Ad_{it}						
Im, Pesaran, and Shin	7.42	1.00	7.30	1.00	−18.81	0.00
Maddala and Wu	72.10	0.95	78.24	0.87	590.79	0.00
(b) $Blog_{it}$						
Im, Pesaran, and Shin	4.29	1.00	−0.41	0.34	−6.59	0.00
Maddala and Wu	101.78	0.97	126.01	0.63	216.88	0.00
(c) $Search_{it}$						
Im, Pesaran, and Shin	8.56	1.00	2.67	0.99	−25.04	0.00
Maddala and Wu	49.09	1.00	98.44	0.98	893.64	0.00

We use panel cointegration tests developed by Pedroni (1999, 2004) and Kao (1999)[11], assuming individual intercepts for the cross sections. Also, we assume individual autoregressive process for residuals in the Pedroni test and use 11 lags to ensure that residuals are serially uncorrelated.

Table E.2
Cointegration tests for Ad_{it}, $Blog_{it}$ and $Search_{it}$.
H_0: No cointegration relationship between Ad_{it}, $Blog_{it}$ and $Search_{it}$.

	Test statistic	p-Value
Pedroni ρ-statistic	−17.44	0.00
Kao t-statistic	10.08	0.00

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[10] We do not use Johansen type methods because they require that the error terms follow a normal distribution (Johansen 1991).

[11] We do not use Johansen type methods because they require that the error terms follow a normal distribution (Johansen 1991).

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