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Paid and Earned Media, Consumer Interest and Motion Picture Revenue

ABSTRACT

This study examines how consumers’ interest in a new movie develops around paid and earned media in pre-launch periods, how this interest impacts opening-week revenue, and how post-launch revenue of a movie is influenced by advertising and various earned media. The pre-launch, opening-week and post-launch worlds are structurally different and we therefore develop three separate models, two multiple-time series models and one cross-sectional equation. These models are applied to a panel data set of movies consisting of movie descriptors, weekly advertising, blog postings, search volume, user reviews and revenue. We find, first, that consumer interest evolves in the pre-launch periods, as evidenced by non-stationary weekly blogging and searching activity. While commercial advertising plays a role in stimulating consumer information search, blogging by movie buffs is more influential. Managerially, this underscores the value of designing ads that create strong viral effects. Second, we demonstrate the value of pre-launch consumer search as a leading indicator of movie revenue, as it improves the studios’ ability to predict opening-week revenue. Finally, the effects of blog postings change drastically after movie launch. In these post-launch periods, advertising and user review volume have significant effects on movie revenue, while blog postings lose their influence. The paper concludes with a description of several managerial implications of our findings.

Keywords: Paid Media, Earned Media, Advertising, Blogs, Online Search, User Reviews, Motion Pictures, Vector Autoregressive Model, Vector Error Correction Model
1. Introduction

Marketing of a new entertainment product consists of two phases. The first phase is a pre-launch marketing period where firms make efforts to maximize consumers’ awareness and interest in the upcoming product; the second phase is a post-launch sales period where firms try to maximize the sales of their products. This study examines how marketing activities and diverse sources of word-of-mouth (WOM) influence pre-launch consumer interest and post-launch sales of motion pictures. For our focal variables, we consider advertising, blog postings, user reviews (volume and valence), and consumer search activities.

These focal variables have their own unique theoretical and practical meanings. Blog postings are effectively the only earned media in pre-launch periods of a movie, because user reviews are not yet available. Managed by movie enthusiasts or movie buffs—who are generally more knowledgeable about motion pictures than the general public—the pre-launch blog volume reflects the enthusiasts’ interest, excitement and expectations about the new product (Xiong and Bharadwaj, 2014), which can stimulate interest from the general public. Blog postings are conceivably more effective than paid media in generating pre-launch interest, as earned media have been found to be more impactful in influencing market outcomes than paid media for existing and new products (e.g., Trusov, Bucklin, and Pauwels, 2009; Villanueva, Yoo, and Hanssens, 2008;).

Second, user reviews, while also a type of earned media, are distinct from blog postings in several important ways. Firstly, user reviews are written by the moviegoing public, who, compared to bloggers and movie buffs, are more akin to lay consumers. When there is a disagreement between moviegoers and movie critics (or movie buffs), everyday consumers often seek like-minded amateurs’ opinions (Chakravarty, Liu, and Mazumdar, 2008; Holbrook; 1999).
Furthermore, compared to blog postings and forum discussions, user reviews are generally more easily accessed by moviegoers due to the popularity of movie review sites (e.g., Yahoo! Movies). These arguments suggest that user reviews may be more influential on market outcomes than blog postings once the product is in the market.

In addition, the volume and valence of reviews may have a distinct impact on revenue. Review volumes, which reflect the number of consumers who have previously watched the movie, indicate how popular it is with the moviegoing public. Review valence, on the other hand, reflects the movie’s perceived quality by moviegoers (Moon, Bergey, and Iacobucci, 2010). As such, these two indicators may have a different over-time effect on movie revenue. For example, review volume may have a high immediate effect due to herd behavior of moviegoers (Banerjee, 1992), while review valence may take time to influence movie revenue, as product quality takes time to be appreciated (e.g., Mitra and Golder, 2006).

Finally, online search is different from blog postings and user reviews. While blog posting and review writing are media generation activities, consumer search can indicate media consumption activity because consumers use search engines to find other people’s opinions (e.g., blog postings). As blog postings need to be viewed in order to influence sales (Onishi and Manchanda, 2012), search volume—as a measure of consumers’ media consumption activity—may well affect product sales. Furthermore, searching for a product reflects the consumer’s consumption interest (Du and Kamakura, 2012; Hu, Du, and Damangir, 2014; Kulkarni, Kannan, and Moe, 2012). Lastly, consumer search is much more common and prevalent activity than blog postings. 91% of the US adult Internet user use a search engine to find information, while only 32% of them post a comment on the Internet (The Pew Research Center 2012). Therefore, online search volume may be an excellent barometer of the consuming public’s interest in a new
product (Kim and Bruce, 2014; Xiong and Bharadwaj, 2014), and may be a superior predictor of sales than online word-of-mouth.

These distinct features of our focal variables motivate the following substantive questions. First, how is consumer interest in an upcoming movie developed in the pre-launch period? Specifically, how do paid media (advertising) and earned media (blog postings) influence consumer interest (search volume) during that period, and which of the two is more effective in arousing consumer interest? In addition, is there a long-run relationship between paid media, earned media and consumer interest so that the three evolve in parallel to each other?

Second, after a movie is released, moviegoers and critics write reviews while movie buffs continue to post blogs, interested consumers search online, and movie studios advertise. How do these behaviors influence weekly movie revenue? How do review volume and valence differentially impact movie revenue over time?

Third, predicting opening-week revenue is an important and challenging task for movie studios. Can pre-launch consumer activity such as online search and blog postings improve opening-week revenue prediction beyond the accuracy obtainable by using only movie characteristics?

To answer these questions, we examine a panel of 137 movies released in the US, mainly in 2009. We assemble diverse data sources of advertising, blog postings, user reviews, online search, number of screens, revenue and movie characteristics. To incorporate dynamic interdependences between the focal variables, we use the vector autoregressive (VAR) modeling approach (Hanssens, Parsons and Schultz, 2001; Lutkepohl, 2006). Specifically, we develop a vector error correction model (VECM) for the pre-launch period analysis and a VAR model for
the post-launch period analysis. In addition, we estimate a cross-sectional model of opening-week revenue to examine the predictive performance of pre-launch search and blog volumes.

Several interesting findings emerge. First, pre-launch consumer interest, as measured by search and blogging activity, is evolving and therefore difficult to predict. Interestingly, these two metrics are in a dynamic equilibrium with each other. This means that general moviegoers’ search intensity (or interest in the upcoming movie) cannot increase indefinitely for a given level of WOM (i.e. blogging). They can however, move up or down together, for example as a result of pre-launch advertising. Second, word-of-mouth (i.e., blog postings) is more effective in generating pre-launch consumer interest than advertising. Third, after a movie is released, it is not blog postings but user reviews, especially review volume, that influence national-level weekly movie revenue. Lastly, pre-launch blog volume and search volume (measured three weeks before release) improve the prediction of opening-week box office, regardless of other covariates included in the model. Interestingly, search volume is superior to blog volume in predicting opening-week revenue. To the best of our knowledge, most of the above findings are new to the marketing literature on the motion picture industry.

The remainder of the paper is organized as follows. We first selectively review the extant literature and introduce our movie data set. We then discuss the modeling procedure and present our empirical results. The paper concludes with a discussion of the main findings, their managerial implications and proposed future extensions of this work.

2. Literature Review

Our review focuses on pre-launch consumer mindset metrics for entertainment products and WOM factors that influence post-launch sales of movies.

2.1 Pre-Launch Consumer Mindset Metrics
Measuring consumers’ pre-launch awareness, interest in and expectations for new products is important because they may be used as leading indicators for market demand when there is still time to influence that demand through pre-launch marketing activities. In the entertainment industry, the most commonly used online metrics for pre-launch consumer interests and expectations are virtual stock price traded on the Hollywood Stock Exchange (HSX), pre-launch online WOM such as blog postings, and pre-launch consumer search.

Virtual stock prices on the Hollywood Stock Exchange (HSX) were used to measure pre-launch movie advertising effectiveness (Bruce, Foutz, and Kolsarici, 2012; Elberse and Anand, 2007) and to forecast the financial success of movies (Foutz and Jank, 2010). Blog postings were used in Gopinath, Chintagunta, and Venkataraman (2013) to examine how consumer-generated media during pre-launch periods influence opening-day movie revenue. Xiong and Bharadwaj (2014) examine how the evolution patterns in pre-launch buzz can be used to predict market success of new video games, and Kulkarni, Kannan and Moe (2012) use pre-launch search volume to predict market success of movies. Kim and Bruce (2014) use weekly pre-launch search volume of movies to examine dynamic effectiveness of pre-launch advertising.

2.2. Movie Revenue and Word-of-Mouth

There is broad support for the notion that word-of-mouth is a significant driver of motion picture demand, however there is ambiguity around the relative importance of WOM volume and WOM valence. Liu (2006) collects national-level user reviews from Yahoo! Movies and finds that previous weeks’ online review volume is positively related to the current week’s movie revenue. Chintagunta, Gopinath, and Venkataraman (2010) use similar data at the designated market area (DMA) level, and report that review valence, not review volume, influences opening-day movie revenue at the local market level. However, at the national level, their findings are consistent
with those of Liu, i.e. review volume matters to national-level movie revenue. In a follow-up study, Gopinath, Chintagunta, and Venkataraman (2013) collect blog postings and find that release-day movie performance is impacted by pre-launch blog volume, whereas post-release performance is influenced by post-release blog valence. Onishi and Manchanda (2012) collect blog postings data and examine dynamic relationships between daily movie revenue and blog postings. Interestingly, they find that the number of blog postings viewed, a measure of media consumption, has a positive significant relationship with the same-day box-office revenue.

Some studies consider the feedback effects of movie revenues on WOM and examine the dynamic simultaneous relationship between WOM and movie revenue. Duan, Gu, and Whinston (2008ab) model the dynamic relationship between user reviews and movie revenue on a daily basis. Using Yahoo! Movies data, they find that only review volume matters to post-launch movie revenue.

The current paper ventures beyond these earlier studies in several ways. First, we examine how pre-launch interest in new movies develops among general moviegoers (i.e., online search) and how it interacts with paid media (advertising) and earned media (blog postings). In so doing, we examine which of the two media types is more powerful in developing interest in upcoming movies among moviegoers. To the best of our knowledge, this is the first study that examines the dynamics between paid media, earned media and consumer search in pre-launch periods.

Second, we assemble a multitude of variables from various sources and model the dynamic interdependencies among them. This allows us to examine how these variables influence movie revenue over time. In contrast, previous studies collect only a subset of these variables and/or they conduct only cross-sectional analyses (Chintagunta, Gopinath, Venkataraman, 2010; Gopinath, Chintagunta, Venkataraman, 2013; Liu 2006).
Finally, we compare the performance of online search volume and online WOM volume in predicting opening-week revenue and find that search volume is the superior metric. In contrast, previous studies in the motion-picture industry have used only one of these two metrics, or they have excluded supply-side factors such as advertising and number of screens (Dellarocas, Zhang, and Awad, 2007; Kulkarni, Kannan, and Moe, 2012).

3. The Data
Our database consists of 137 movies, most of which were released in 2009. For each of the 137 movies, we collect weekly advertising spending, number of screens, blog volume (number of blog postings), online search volume, theatrical revenue, review volume (number of review postings), and review valence from 60 weeks before their release through 10 weeks after the release. Additionally, we collect various movie characteristics, i.e. genre descriptions, size and timing of distribution and critics’ review scores. Table 1 summarizes the variables and their sources.

3.1 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 average advertising spending of the 137 movies during the analysis period is $22 million, with 79% of the advertising budget spent either before or during the release week. Weekly number of screens and box-office revenue are collected from The Numbers (www.the-numbers.com). The median U.S. box-office revenue in our sample is $58.7 million.

3.2 Blog Postings, Search Volume, and User Review Data
Weekly blog postings for each movie were collected from the Google blog search engine (e.g., Gopinath, Chintagunta, Venkataraman, 2014). As a preliminary analysis, we conducted a series
of experiments with different search conditions and compared the search results. The experiments uncovered that the best search condition is to 1) constrain the search efforts to blogs whose titles contain either the word *movie*, *film*, or *flick*; 2) and within such blogs, search for postings whose title contains the movie title. For example, to find blog postings of the movie *12 Rounds*, we use the following search condition: *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.\(^1\) Figure 1 shows an example of collecting weekly blog volume for the movie *Avatar*.

--- Figure 1 about here ---

To obtain weekly online search volumes of the 137 movies, we use Google Trends (www.google.com/trends), a site where one can examine the weekly search index of keywords entered into the Google search engine. To improve accuracy of search volume, we count search instances that occur only in the US motion picture category using English as the search language.\(^2\) To further improve data accuracy, we use relevant search terms suggested by Google Trends and compare search results.

Note that Google normalizes the Google Trends search index. The normalized index causes a problem when analyzing search volume across movies. Therefore, we develop a method to transform the Google keyword search index into a measure that is comparable across movies and over time. The technical details of this method are shown in the Web Appendix.

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\(^1\) In most cases, the five search results agree with each other. That is, the Google blog search engine gives the same number of blog postings for the same search condition. In rare cases, the five search trials disagree—e.g., with one outlier and four same numbers—perhaps due to the search engine’s imprecision. When they disagree, we use the mode of the search results because, among the five trials, the outliers usually occur once.

\(^2\) Google Trends provides various filters for location, time, language, and industry category. We utilizes those filters to improve search result accuracy.
User reviews are collected from Yahoo! Movies, a popular review site for movies. We collect weekly volume and valence of reviews for each movie, where weekly review valence of a movie is measured as the average number of stars that reviewers gave to the movie during the week. Figures 2 and 3 show how the focal variables typically change over time, by averaging each time series across movies.

== Figure 2 about here ==

== Figure 3 about here ==

3.3 Other Variables

We also collect various movie characteristics such as genre, MPAA rating, monthly seasonality, whether or not the movie is a sequel, average critic rating, and director power. For the director power, we collect two indicators: total revenue of past movies\(^3\) in which the director was involved as either a director, writer, or producer, and the average user rating of such movies. Table 2 shows the descriptive statistics of the main variables.

== Table 2 about here ==

4. Modeling

Because pre-launch periods are structurally different from post-launch periods, we develop separate time-series models to address the two periods. In addition, we estimate a cross-sectional opening-week revenue model to examine the predictive performance of various pre-launch consumer activities.

4.1 Modeling Procedure for Pre- and Post-Launch Periods

For pre- and post-launch periods, multivariate time-series models are developed to account for endogeneity and dynamic relationships among our focal variables (e.g., Trusov, Bucklin, and Pauwels, 2009; Zhang et al., 2012). The model selection procedure is summarized in Figure 4.

\(^3\) Defined in the time window from 1990 to one year before each movie’s release.
First, because we are dealing with multiple cross-sections, we determine how to deal with individual-specific fixed effects of movies. For this, we examine two commonly used approaches—i.e., 1) including movie-specific fixed effects (fixed effect estimation); and 2) subtracting movie-specific mean from each movie’s time-series (hierarchical centering)—and choose the most appropriate one. The final choice between the two approaches is made after the estimation step by examining residual diagnostics. Second, for each of our focal variables, we conduct a Granger causality test to examine their endogeneity (Granger, 1969). If a variable is Granger-caused by other variables, we treat the former as an endogenous variable in our VAR model. Third, we conduct panel unit root tests assuming an individual unit root process for each cross-section (Im, Pesaran and Shin, 2003; Maddala and Wu, 1999). If the panel unit root tests indicate that at least two endogenous variables are nonstationary, we proceed to a cointegration test; if at most one variable is nonstationary, we estimate a vector autoregressive model after appropriate differencing for any nonstationary variable. Fourth, in case two or more variables are nonstationary, we examine whether there exist long-run equilibria between the nonstationary variables by conducting cointegration tests (Kao, 1999; Pedroni, 1999, 2004). If the cointegration tests find long-run equilibria, we estimate an appropriate vector error correction model. Otherwise, we use a VAR model after appropriate differencing.

After model parameterization we examine the generalized impulse response functions (GIRFs) and forecast error variance decompositions (FEVDs). GIRFs show the total effect of a random shock to an endogenous variable on the other endogenous variables (Dekimpe and Hanssens, 1999; Pesaran and Shin 1998; Trusov, Bucklin, and Pauwels 2009). Since our model is developed in log-transformed units of the original variables, the impulse response values may

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4 Another approach is to difference the time-series (Cameron and Trivedi, 2005). We do not examine this approach because differencing of time-series data has a special meaning of transforming a nonstationary series to a stationary series.
be interpreted as elasticities. We also examine FEVDs, which show the direct over-time impact of one endogenous variable on the other endogenous variables (Joshi and Hanssens, 2010).

4.1.2 The Pre-Launch Model

In pre-launch periods, potential endogenous variables are ad spending, blog volume and search volume. We explain a model development procedure by assuming that we adopt the fixed effect estimation in the first step. We find that Granger causality tests indicate that all the variables are endogenous. Next, we conduct panel unit root tests on the variables. 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, 2003). We find that the appropriate lag lengths are 3, 12, and 3 for log ad spending, log blog volume, and log search volume, respectively. With the chosen lag length, individual unit roots test are conducted (Im, Pesaran and Shin, 2003; Maddala and Wu 1999). The panel unit root tests in Table 3 indicate that the three endogenous variables are integrated of order one.

Next, we examine whether there exists long-run equilibria among the integrated variables by conducting a series of cointegration tests. If at least two of them are cointegrated, we include appropriate error correction terms to incorporate the short-term (weekly in our case) adjustment of the variables (e.g., Dekimpe and Hanssens, 1999; Joshi and Hanssens 2010). Before we conduct cointegration tests, however, we consider an important industry practice regarding advertising decision in the motion picture industry: Most advertising media is bought upfront—at

--- Table 3 about here ---

5 We went through the same procedure with centered variables. The model and estimation results with the centered variables were same as those with the original variables. We think this occurs because the focal variables are eventually first-differenced, which removes individual-specific fixed effects.

6 Note that we do not rely on likelihood-based criteria such as Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn criterion (HQ) because we find that the error terms of the endogenous variables do not follow normal distributions.
least months ago, and it is extremely difficult to buy additional advertising media in an opportunistic market (Elberse and Anand 2007). This implies that it is unrealistic for movie studios to adjust ad spending on a weekly basis. For econometricians, this means it is inconsistent with the industry practice to include weekly ad spending in the cointegration relationship. Therefore, we examine the long-run equilibrium only between blog postings and search volume\(^7\). We use panel cointegration tests developed by Pedroni (1999, 2004) and Kao (1999)\(^8\), assuming individual intercepts for the cross sections. Also, we assume individual autoregressive process for residuals in Pedroni test and use 11 lags to ensure that residuals are serially uncorrelated. The test results in Table 4 show that weekly blog volume and search volume have a long-run equilibrium\(^9\).

\[= \text{Table 4 about here} =\]

The above procedure leads to a vector error correction model (VECM) in (1).

\[
\begin{bmatrix}
\Delta \ln(Ad_{it}) \\
\Delta \ln(Blog_{it}) \\
\Delta \ln(Search_{it})
\end{bmatrix}
= \begin{bmatrix}
\alpha_A \cdot e_{i,t-1} \\
\alpha_B \cdot e_{i,t-1} \\
\alpha_S \cdot e_{i,t-1}
\end{bmatrix} + \sum_{l=1}^p \begin{bmatrix}
\pi_{11}^l & \pi_{12}^l & \pi_{13}^l \\
\pi_{21}^l & \pi_{22}^l & \pi_{23}^l \\
\pi_{31}^l & \pi_{32}^l & \pi_{33}^l
\end{bmatrix} \begin{bmatrix}
\Delta \ln(Ad_{i,t-1}) \\
\Delta \ln(Blog_{i,t-1}) \\
\Delta \ln(Search_{i,t-1})
\end{bmatrix} + \begin{bmatrix}
\Delta \ln(Ad_{i,t-1}) \\
\Delta \ln(Blog_{i,t-1}) \\
\Delta \ln(Search_{i,t-1})
\end{bmatrix} + \begin{bmatrix}
u_{it}^A \\
u_{it}^B \\
u_{it}^S
\end{bmatrix},
\]

where \(Ad_{it}\) is weekly ad spending of movie \(i\) in week \(t\), \(Blog_{it}\) is blog volume and \(Search_{it}\) is search volume. \(e_{i,t-1}\) is the error correction term defined in (2).

\[
e_{i,t-1} = \ln(Search_{i,t-1}) - \beta_0 - \beta_1 \ln(Blog_{i,t-1}).
\]

The parameters \(\alpha_A\), \(\alpha_B\) and \(\alpha_S\), represent short-term (weekly) adjustment to deviations from the long-run relationship defined by (2). Based on our previous reasoning, we expect that \(\hat{\alpha}_A\),

\(^7\) Our VECM estimation results also confirm this by showing that the adjustment parameter in advertising equation is statistically not different from zero. See Table 6.

\(^8\) We do not use Johansen type methods because it requires that the error terms follow normal distributions (Johansen 1991).

\(^9\) We tried different tests with various assumptions and found that the results largely agree.
the estimate of $\alpha_A$, is statistically not different from zero, while $\hat{\alpha}_B$ and $\hat{\alpha}_S$ are significantly different from zero. $x_n$ is the vector of exogenous variables that includes movie characteristics, monthly seasonality dummy variables (Einav, 2007), holiday dummy variable, weekly dummy variables, and a common intercept. The error terms $(\hat{u}^A_n, \hat{u}^B_n, \hat{u}^S_n)$ follow serially uncorrelated white noise processes. The lag length $P$ is determined so that the residuals, $(\hat{\hat{u}}^A_n, \hat{\hat{u}}^B_n, \hat{\hat{u}}^S_n)$, are serially uncorrelated.

4.1.3 The Post-Launch Model

In the post-launch model, we include several additional variables that are available in post-launch periods. They are weekly revenue, weekly volume of user reviews, average weekly user rating, and weekly number of screens. To treat individual-specific fixed effects, we compared the two approaches in the pretreatment step—i.e., fixed effect estimation and hierarchical centering—and found that hierarchical centering is appropriate. Thus we describe the following steps with respect to centered variables. First, the Granger causality test (Granger, 1969) indicates that all the centered variables are endogenous except weekly review valence. The review valence neither does Granger cause any other variable nor is Granger-caused by them. As such, we treat review valence as an exogenous variable. Next, we conduct panel unit root tests (Im, Pesaran and Shin, 2003; Maddala and Wu 1999). We find that ad spending is difference-stationary; blog volume and review valence are stationary; and all other variables can be either trend- or difference-stationary (Table 5). Because there is no theory to guide our choice of differencing or detrending, we examine all possible combinations to empirically determine whether the variables (number of screens, search volume and revenue) should be detrended or

10 The residual auto- and cross-correlations of fixed-effect estimation were very poor. We suspect that the fixed effect estimation suffers from incidental parameters problem (Cameron and Trivedi, 2005).
differenced. One such model is specified in (3), which assumes trend-stationary process for screens and difference-stationary processes for search volume, revenue, and review volume.

\[
\begin{bmatrix}
\Delta \ln(Ad_{it}) \\
\ln(No_{-}Scrn_{it}) \\
\ln(Blog_{it}) \\
\Delta \ln(Search_{it}) \\
\Delta \ln(Revenue_{it}) \\
\Delta \ln(Review_{Vol_{it}})
\end{bmatrix}
= \sum_{i=1}^{P} \Pi(l) 
\begin{bmatrix}
\Delta \ln(Ad_{it}) \\
\ln(No_{-}Scrn_{it}) \\
\ln(Blog_{it}) \\
\Delta \ln(Search_{it}) \\
\Delta \ln(Revenue_{it}) \\
\Delta \ln(Review_{Vol_{it}})
\end{bmatrix} + \Gamma x_{it} + u_{it},
\]

where \( \Pi(l) \) is the matrix of coefficients of lag \( l \) endogenous variables and \( x_{it} \) is the vector of exogenous variables such as holiday dummy variable, a deterministic trend, a common intercept, and review valence. Note that we include review valence as an exogenous variable because there may still exist a contemporaneous association between review valence and other variables—e.g., revenue. The lag length \( P \) is determined so that the residuals \( \hat{u}_{it} \) are serially uncorrelated. Note that the variables in (3) are hierarchically centered.

4.2 The Opening-Week Model

The purpose of the opening-week model is to examine whether prediction of opening-week revenue is improved by including pre-launch blog volume and pre-launch search volume. As such, the regression model is a cross-section model whose dependent variable is the opening week revenue of movies. To provide early prediction, we include search volume and blog volume observed in three weeks before the opening week. The model is specified as follows.

\[
\ln(Open_{-}Revenue_{i}) = \phi_{0} + \phi_{1} \ln(Open_{-}Ad_{i}) + \phi_{2} \ln(Open_{-}Scrn_{i}) \\
+ \phi_{3} \ln(Blog_{i-3}) + \phi_{4} \ln(Search_{i-3}) \\
+ \theta' x_{i} + \varepsilon_{i},
\]
where $Open\_Revenue_i$ is the opening-week revenue of movie $i$, $Open\_Ad_i$ is the opening-week advertising spending, $Open\_Scns_i$ is the number of opening-week screens, $Blog_{i,-3}$ is the blog volume of movie $i$ observed in three weeks before the release week, $Search_{i,-3}$ is the search volume of movie $i$ observed in three weeks before the release week, and $x_i$ is the vector of other relevant variables that are observable during the launch week by consumers. The vector $x_i$ includes genre, MPAA rating, monthly seasonality, director power variables and average critic rating.

5. Empirical Analysis

This section describes the estimation of the models and empirical results. The models are estimated with a panel data set of 137 movies. Using a panel data set has several benefits. First, with multitude of data points, we obtain sufficient degrees of freedom. This allows us to add sufficiently many lags to ensure serially uncorrelated residuals in (1) and (3), improving the model validity. Second, by using various movies to estimate the parameters, we reduce the possibility that the estimation results are influenced by idiosyncracy of individual movies, enhancing the generalizability of the estimation results.

5.1. Pre-Launch Period

Estimation. The long-run equilibrium relationship (2) is estimated by the fully modified ordinary least square estimation suggested by Phillips and Moon (1999)\textsuperscript{11}. Then the residuals of (2), $\hat{e}_{i,t-1}$, are substituted for $e_{i,t-1}$ in (1) to estimate the VECM (Enders, 2004; Engle and Granger 1987). The VECM is estimated by the pooled ordinary least squares method. We examined various lag

\textsuperscript{11} We do not use the full-information maximum likelihood method (Johansen 1991) because we found that the residuals do not follow normal distributions.
length for the VECM and determined that 14 is an appropriate lag length that ensures the residuals ($\hat{\alpha}^A_i$, $\hat{\alpha}^B_i$, $\hat{\alpha}^S_i$) are serially uncorrelated. Table 6 shows the estimation results for the long-run relationship parameters and the weekly adjustment parameters. We omit other parameter estimates in the table to avoid clutter.

---Table 6 about here---

**Relationship between media generation and consumption.** The estimates of adjustment parameters ($\alpha_A$, $\alpha_B$ and $\alpha_S$) support our previous reasoning. First, we do not find significant weekly adjustment of ad spending to WOM and search activities (statistically nonsignificant $\hat{\alpha}_A$). Perhaps one week is too short a time period for movie studios to analyze consumers’ search and WOM activities, and make a major adjustment on their ad spending accordingly (Elbserse and Anand, 2007; Onishi and Manchanda, 2012). Therefore, movie studios do not make a significant weekly adjustment for ad spending for their upcoming movies, while they do in the long run—as indicated by the Granger causality test.

Second, the significant positive estimate for $\beta_1$ in (2) indicates a positive long-run relationship between weekly blog volume and search volume. That is, higher search level is associated with higher blogging level and vice versa, i.e. the two time series evolve together. Furthermore, the estimates of adjustment parameters show that weekly blog volume and search volume change in response to the previous week’s deviation from the long-run equilibrium. This relationship is shown in equations (5-1) and (5-2) by substituting the parameter estimates into the corresponding equations in (1):

\[
\Delta \ln(\text{Blog}_i) = 0.0326 \left( \ln(\text{Search}_{i,t-1}) - \hat{\beta}_{10} - 1.7175 \ln(\text{Blog}_{i,t-1}) \right) + \cdots + \hat{\alpha}^B_i.
\]

\[
\Delta \ln(\text{Search}_i) = -0.1645 \left( \ln(\text{Search}_{i,t-1}) - \hat{\beta}_{10} - 1.7175 \ln(\text{Blog}_{i,t-1}) \right) + \cdots + \hat{\alpha}^S_i.
\]
The above equations reveal that, if the previous week’s search volume happened to be larger than its equilibrium level (i.e., if moviegoing public happened to search more than the amount predicted by blog postings), then this week’s search volume would decrease. The opposite holds as well. For example, if the previous week’s search volume happened to be smaller than its equilibrium level, then this week’s search volume would increase.

This cointegration finding does not disclose any specific causes for co-evolution. There could be many external reasons for, say, an increase in both searching and blogging activity, including movie advertising. Overall, the evolving nature of these metrics shows that the pre-launch environment is inherently unpredictable, much like the evolving nature of stock prices. However, the finding that they co-move can be interpreted as evidence that movies are developing flow, a condition where individual interest (search) and group or social engagement (blogging) by consumers reinforce one another. This follows the characterization by Wierenga (2014), based on the flow concept proposed by Csikszentmihalyi (1990). While the degree of a movie’s flow may not be easily predictable, it is important for studios to diagnose and monitor it throughout the pre-launch phase, as we will demonstrate in the opening-week and post-launch models.

Effectiveness of paid media and earned media in pre-launch periods. In pre-launch periods, blog postings (and forum discussions) are the only earned media because user reviews are not yet available. Then, one important question is, of paid and earned media, which is more influential in raising general consumers’ pre-launch interests in upcoming movies? We answer this question by examining the dynamic relationship between search volume (moviegoing public’s interest), advertising (paid media) and blog volume (earned media) around upcoming movies. Table 7 and Figures 5 exhibit select GIRFs and their 95% confidence bands, which show the total effects of a
shock to an endogenous variable on the other endogenous variables. Figure 6 exhibits select
FEVDs with 95% confidence bands. FEVDs show the direct (not total) impacts of advertising
and blog postings on search volume.\footnote{Unlike the GIRFs, FEVDs require temporal orders between endogenous variables. We examine various temporal orders and found that the results are very robust.}

The GIRFs reveal several interesting findings. First, movie consumers’ interests in upcoming
movies are influenced by blog postings as well as advertising. More importantly, blog postings
(the predominant earned media in pre-launch periods) are much more effective than advertising
(paid media) in promoting moviegoers’ interest in upcoming movies. During the first two weeks,
where the effects of both advertising and blog postings on consumer search are significantly
positive, their respective elasticities are 0.125 and 0.31. The blog postings effect is greater than
the advertising impact at the 1% significance level. Based on these figures, blog postings are
about 2.5 times more effective (in the short run) than advertising in generating consumer search.
This result is confirmed in the FEVDs shown in Figure 6. To the best of our knowledge, this is
the first reported result on the effectiveness of paid and earned media in promoting consumer
interests in pre-launch periods.

Another important finding is the strong effect of moviegoers’ search activities on movie
buffs’ blogging activities. For the first three weeks, where the effect of consumer search on
blogging is significantly positive, the elasticity of blog postings to consumer search is 0.19. The
advertising elasticity of blog postings is only 0.07 (during the first two weeks of positive effects),
which is significantly smaller than 0.19. In other words, moviegoers’ interest and movie buffs’
buzz activities are mutually highly responsive, and much more so than their reactions to paid media. This has an important implication for movie studios’ pre-launch advertising strategy. That is, movie studios should make their advertisements as interesting as possible, both to general consumers and movie bloggers, so that the ads create strong viral effects.

Lastly, pre-launch advertising, through the ecosystem of the endogenous variables, not only arouses moviegoing public’s interests in upcoming movies but also promotes movie buffs’ buzz activities around these upcoming movies. Thus, the role of advertising in the pre-launch period is similar to that for existing products where advertising induces WOM (e.g., Yang et al., 2013) and consumer search (Joo et al., 2013).

5.2. Post-Launch Period

The post-launch VAR model is estimated with a pooled least squares method. By examining all eight specifications, we find that the model specified in (3) offers superior residual diagnostics, and that a lag-structure of three periods is appropriate. Figure 7 shows select GIRFs and 95% confidence bands, focusing on the response of log weekly revenue to a one standard-deviation change in the endogenous variables. Figure 8 shows FEVDs of differenced log weekly revenue.

First, movie revenue is evolving, as was consumer interest in the pre-launch periods. This implies that post-launch marketing activities and WOM can exhibit long-run effects on movie revenue, so the game (of generating life-cycle revenue) is not over after opening week.

Second, consider how revenue is influenced by two types of earned media—blog postings and user reviews. GIRFs in Figure 7 show that review volume, through the dynamic interdependence between the endogenous variables, has significant effects on revenue, while
blog postings do not. FEVDs in Figure 8 indicates that blog volumes do not have direct impact on movie revenue, while the volume of user reviews does. Thus, we find that, while blog postings are important drivers of consumer interest during pre-launch periods, they are taken over by user reviews as significant drivers of movie revenue in post-launch periods.

There are several possible reasons for the differential effects of user reviews and blog postings on movie revenue. Firstly, movie blog sites are generally less well-known among general movie consumers than user review sites such as Yahoo! Movies and Rotten Tomatoes. Thus, when a random consumer wants to make a moviegoing decision, it is easier for him or her to visit one of movie review sites than a blogger’s page. In other words, a greater digital distance exists between the moviegoing public and movie blog pages as opposed to user review sites.

Secondly, because movie bloggers are considered to be more knowledgeable than general movie consumers, a blogger’s opinion may be perceived more as a critic’s review than as a lay consumer’s opinion. In the same vein, blog volume may be regarded to reflect movie buffs’ excitement or controversy, while review volume is viewed as reflecting that of lay consumers. As lay consumers tend to appreciate like-minded amateurs’ opinions more than critic reviews (Chakravarty, Liu, and Mazumdar, 2008; Holbrook; 1999), the volume of user reviews may be more persuasive to moviegoers than that of blog postings.

Third, our Granger causality tests reveal that review valence neither Granger causes the other variables nor is it Granger caused by them. Therefore, the impulse responses of the other variables to an innovation in review valence is negligible (Lutkepohl, 2006). By explicitly modeling dynamic interdependences between a comprehensive set of variables, we find review volume has over-time effects on movie revenue, whereas review valences does not. This finding
extends previous studies on cross-sectional data (Chintagunta, Gopinath, Venkataraman, 2010; Lui 2006) and studies that include reviews and revenues only (Duan, Gu, Whinston, 2008ab).

Fourth, ad spending is more important than blog volume in influencing weekly movie revenue (GIRFs in Figure 7 and FEVDs in Figure 8). This contrasts with the pre-launch finding that consumers’ interests in an upcoming movie are more sensitive to blog volume than to advertising. Thus, after a movie is released, the effects of blog volume or movie buff’s WOM diminish, whereas advertising maintains its effectiveness and user reviews emerge as a new driver of movie revenue.

Lastly, online search is an important consumer activity that influences movie consumption. Our findings—high elasticity of revenue to search volume shown by GIRFs and the direct impact of search on revenue shown by FEVDs—are in line with the notion that consumers’ search activity reflects their interest and potential consumption desire for the searched product (Kulkarni, Kannan, Moe, 2012; Xiong and Bharadwaj, 2014). This suggests that online search volume can be an important consumer-mindset metric (e.g., Hanssens et al. 2014; Hu, Du, and Damangir, 2014; Srinivasan, Vanhuele, and Pauwels; 2010) to help measure marketing effectiveness, especially when there are no sales data (e.g., pre-launch periods of new products as in Xiong and Bharadwaj, 2014).

5.3. Opening Week

How useful are pre-launched consumer interest data for opening-week revenue prediction? We examine the predictive performance of model (5) with various combinations of explanatory variables—i.e., movie characteristics only, movie characteristics and search/blog volume, movie characteristics, search/blog volume and marketing activities and so forth. We first estimate the model with randomly selected 96 movies (about 70% of 137 movies), and test the predictive
performance of the model using a hold-out sample of 41 movies. Because the randomness of the sampling may influence the results, we adopt a bootstrap approach by conducting this analysis 50,000 times, each time with a randomly selected sample of 96 movies for estimation and the remaining 41 movies (the movies not selected for estimation) for prediction.

Table 8 shows the 95% highest probability density intervals (HDPIs) of $R^2$ and adjusted $R^2$ for in-sample estimation, and mean absolute percentage error (MAPE) for hold-out sample prediction\textsuperscript{13}.

Let us focus on the median values of the performance measures. First, comparing scenarios 2 and 3 shows that *pre-launch search volume has more predictive power than blog volume* of the same period. Including search volume observed three weeks before release (scenario 3) improves the average predictive performance of the model with only movie characteristics (scenario 1) but also that with movie characteristics and blog volume. Second, pre-launch search volume has better predictive power than the opening-week advertising spending (scenarios 3 and 5). Third, the number of screens is the most important of all to predict opening week revenue, consistent with Neelamegham and Chintagunta (1999). This is not surprising because the number of screens influences the availability of the movie to consumers, imposing the ceiling on movie consumption. In this case too, we find that adding pre-launch search and blog volume further improves the predictive performance of model (4) (scenario 8 vs. 7).

\textsuperscript{13} Scenarios 7 and 8 include the number of opening week screens as an explanatory variable. To control for the endogeneity of the screen decision (Elberse and Eliashberg, 2003), we use two-stage least squares estimation for scenarios 7 and 8. For instrumental variables for screens, we use weekly pre-launch search volume and blog volume from four weeks before release up to one week before release. We also estimated these scenarios with the ordinary least squares and found that the model fit and predictive performance are virtually the same.
6. Conclusions

This study has examined how consumer interest in a new movie is developed by advertising and word-of-mouth, and how subsequent movie revenue responds to advertising and various user generated media. To this end, we created a panel data set of movies by assembling multiple data sources so that each of the included variables not only has a unique conceptual meaning, but also offers practical implications for studio executives. We developed two separate multiple time-series models for the pre- and post-launch periods, as well as a cross-section model for predicting opening-week box office.

Overall, we find that the pre-launch movie environment is in a state of evolution, where the key evolving variables, blogs and searches, reflect consumer interest and are in a dynamic equilibrium with each other. While this state of evolution implies that post-launch revenue prediction will be difficult, movie executives can and should monitor the public interest in their product and influence it with advertising. This advertising generates searches and thus consumer interest, but is not as impactful as the level of blogging activity. Movies that grow both individual interest (searches) and group or social engagement (blogging) are developing “flow” that bodes well for their future success. Overall, both searches and blogs can be viewed as “latent demand” indicators, offering vigilant studios an opportunity to predict revenue when there is still time to act.

Next, we find that the accuracy of box office prediction in the launch week is enhanced by including pre-launch consumer interest data, i.e., online search volume. In the post-launch period, movie revenue is evolving and the significant drivers of demand are different. In particular, the impact of blogging activity diminishes and a new important variable emerges, user reviews. However, advertising still plays a role in impacting box office. This implies that advertising and
user reviews have persistent effect on movie revenue, as this revenue, like pre-launch consumer interest, is in the state of evolution.

The findings in this study should interest both academics and industry practitioners, especially in the motion picture industry. For example, one finding from the pre-launch analysis is that blog volume is more effective in generating consumer search than commercial advertising. This implies that merely increasing ad spending is not an efficient way of developing pre-launch consumer interest in an upcoming movie. Instead, movie studios should make their advertisements as engaging as possible, both to general consumers and movie bloggers, so that the ads create strong viral effects. This finding also implies that movie studios should take pre-launch blogging activity serious as they seek to improve the returns to their marketing communication investments.

These relationships drastically change in the post-launch periods. Like pre-launch consumer interest, movie revenue is in a state of evolution. This evolution is impacted by advertising and user review volume, but not by blog postings. Also, we do not find significant effects of review valence on movie revenue, as the former neither Granger causes, nor is Granger caused by the latter. Lastly, in a separate analysis of opening-week revenue, we find that search volume is a more important metric than blog volume (or earned media) to predict opening-week revenue. We also find that the predictive performance of search volume is, on average, better than that of opening-week advertising spending alone.

Several research opportunities remain in this area. The content of blogs may influence consumer search. For example, large search volumes for a product can result from strong disagreement among bloggers about the quality of the product. If search is motivated by
uncertainty about the quality of a product, then 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. Second, 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.
References


### Table 1. Variables and Data Sources

<table>
<thead>
<tr>
<th>Category</th>
<th>Variable</th>
<th>Source of Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal variables</td>
<td>Weekly advertising spending</td>
<td>Nielsen</td>
</tr>
<tr>
<td></td>
<td>Weekly number of screens</td>
<td>The numbers</td>
</tr>
<tr>
<td></td>
<td>Weekly blog postings</td>
<td>Google blog search engine</td>
</tr>
<tr>
<td></td>
<td>Weekly search volume</td>
<td>Google Trends</td>
</tr>
<tr>
<td></td>
<td>Weekly revenue</td>
<td>The Numbers</td>
</tr>
<tr>
<td></td>
<td>Weekly user review (volume and valence)</td>
<td>Yahoo! Movie</td>
</tr>
<tr>
<td>Movie characteristics and other variables</td>
<td>Genre, MPAA rating, Sequel, Director power variables</td>
<td>IMDb</td>
</tr>
<tr>
<td></td>
<td>Average critic rating</td>
<td>Metacritic</td>
</tr>
<tr>
<td></td>
<td>Monthly Seasonality: January-April; May-August; September-October, November-December</td>
<td>Einav (2007)</td>
</tr>
<tr>
<td></td>
<td>National holiday</td>
<td></td>
</tr>
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</table>

### Table 2. Descriptive Statistics (N = 137)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ad spending ($000)</td>
<td>22,210</td>
<td>22,198</td>
<td>11,962</td>
<td>13</td>
<td>50,781</td>
</tr>
<tr>
<td>Ad spending up to release week ($000)</td>
<td>12,314</td>
<td>12,829</td>
<td>8,400</td>
<td>0.17</td>
<td>31,557</td>
</tr>
<tr>
<td>No. of blog postings</td>
<td>1,314</td>
<td>402</td>
<td>3,565</td>
<td>14</td>
<td>32,390</td>
</tr>
<tr>
<td>Google search volume (index, 000)**</td>
<td>1,156</td>
<td>470</td>
<td>2,665</td>
<td>16</td>
<td>21,617</td>
</tr>
<tr>
<td>No. of daily average screens</td>
<td>1,492</td>
<td>1,497</td>
<td>815</td>
<td>84</td>
<td>3,837</td>
</tr>
<tr>
<td>Box-office revenue ($000)</td>
<td>82,961</td>
<td>58,716</td>
<td>94,967</td>
<td>2,708</td>
<td>760,505</td>
</tr>
<tr>
<td>No. of user reviews</td>
<td>62.9</td>
<td>32.4</td>
<td>97.7</td>
<td>1.5</td>
<td>774.5</td>
</tr>
<tr>
<td>Review valence (No. of starts, [1 ~ 5])</td>
<td>3.63</td>
<td>3.70</td>
<td>0.64</td>
<td>1.88</td>
<td>4.87</td>
</tr>
<tr>
<td>Critic rating (Metascore, [0 ~ 100])</td>
<td>57.7</td>
<td>58.3</td>
<td>15.2</td>
<td>23.8</td>
<td>92.7</td>
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<tr>
<td>Production budget ($ 000)</td>
<td>59,041.1</td>
<td>40,000</td>
<td>54,694.9</td>
<td>11</td>
<td>250,000.0</td>
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<tr>
<td>Past movie box-office revenue of the focal director ($ M)</td>
<td>$942</td>
<td>$516</td>
<td>$1,097</td>
<td>$0.013</td>
<td>$6,518</td>
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<tr>
<td>Average director rating from the past</td>
<td>6.72</td>
<td>6.77</td>
<td>0.63</td>
<td>5.22</td>
<td>8.71</td>
</tr>
<tr>
<td>Genre (%)</td>
<td>Action: 22.6, Comedy: 27.7, Drama: 19.0, Others: 30.7%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MPAA (%)</td>
<td>G: 2.2, PG: 21.9, PG13: 41.6, R: 34.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sequel</td>
<td>15 movies (10.9%) are sequels.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* These statistics are based on a maximum of 71 weeks per movie: from 60 weeks before release to up to 10 weeks after release.

** Google search volume is an index. The computation is explained in detail in Web Appendix.
Table 3. Panel Unit Root Test for Pre-Launch Periods

H0: The variable follows a unit-root process.

(a) $\ln(Ad_{it})$

<table>
<thead>
<tr>
<th></th>
<th>in levels with intercept</th>
<th>in levels with trend</th>
<th>in first differences</th>
</tr>
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<tr>
<td></td>
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<td>p-value</td>
<td>test stat.</td>
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<tr>
<td>Im, Pesaran, and Shin</td>
<td>18.75</td>
<td>1.00</td>
<td>18.25</td>
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<tr>
<td>Maddala and Wu</td>
<td>107.35</td>
<td>1.00</td>
<td>112.98</td>
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(b) $\ln(\text{Blog}_{it})$

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<th>in first differences</th>
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<tr>
<td>Im, Pesaran, and Shin</td>
<td>21.04</td>
<td>1.00</td>
<td>13.72</td>
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<tr>
<td>Maddala and Wu</td>
<td>48.29</td>
<td>1.00</td>
<td>101.35</td>
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(c) $\ln(\text{Search}_{it})$

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<td>p-value</td>
<td>test stat.</td>
</tr>
<tr>
<td>Im, Pesaran, and Shin</td>
<td>11.72</td>
<td>1.00</td>
<td>5.09</td>
</tr>
<tr>
<td>Maddala and Wu</td>
<td>146.03</td>
<td>1.00</td>
<td>236.02</td>
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</table>

Table 4. Cointegration Tests for Pre-Launch Blog and Search

H0: No cointegration relationship between pre-launch blog and search

<table>
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<tr>
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<th>test statistic</th>
<th>p-value</th>
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</thead>
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<tr>
<td>Pedroni $\rho$-statistic</td>
<td>-34.66</td>
<td>0.00</td>
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<tr>
<td>Kao t-statistic</td>
<td>5.54</td>
<td>0.00</td>
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</table>
Table 5. Panel Unit Test for Post-Launch Periods

H0: The variable is a unit-root process.

(a) \( \ln(Ad_a) \)

<table>
<thead>
<tr>
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<th>in levels with trend</th>
<th>in first differences</th>
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<tbody>
<tr>
<td></td>
<td>test stat.</td>
<td>p-value</td>
<td>test stat.</td>
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<tr>
<td>Im, Pesaran, and Shin</td>
<td>3.30</td>
<td>1.00</td>
<td>1.10</td>
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<tr>
<td>Maddala and Wu</td>
<td>245.15</td>
<td>0.89</td>
<td>256.42</td>
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(b) \( \ln(No_Scrns_a) \)

<table>
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<th>in levels with intercept</th>
<th>in levels with trend</th>
<th>in first differences</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>test stat.</td>
<td>p-value</td>
<td>test stat.</td>
</tr>
<tr>
<td>Im, Pesaran, and Shin</td>
<td>1.33</td>
<td>0.91</td>
<td>-12.66</td>
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<tr>
<td>Maddala and Wu</td>
<td>356.26</td>
<td>0.00</td>
<td>717.09</td>
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(c) \( \ln(Blog_a) \)

<table>
<thead>
<tr>
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<th>in levels with trend</th>
<th>in first differences</th>
</tr>
</thead>
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<td>470.95</td>
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(d) \( \ln(Search_a) \)

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<tbody>
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<td></td>
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<td>p-value</td>
<td>test stat.</td>
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<td>Im, Pesaran, and Shin</td>
<td>3.64</td>
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<td>Maddala and Wu</td>
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<td>319.21</td>
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</table>

(e) \( \ln(Revenue_a) \)

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<th>in levels with trend</th>
<th>in first differences</th>
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<td>p-value</td>
<td>test stat.</td>
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<td>12.43</td>
<td>1.00</td>
<td>-3.71</td>
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<td>Maddala and Wu</td>
<td>132.79</td>
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<td>409.70</td>
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(f) \( \ln(Review_Vol_a) \)

<table>
<thead>
<tr>
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<th>in levels with trend</th>
<th>in first differences</th>
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<tr>
<td></td>
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<td>test stat.</td>
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<tr>
<td>Im, Pesaran, and Shin</td>
<td>1.48</td>
<td>0.93</td>
<td>-2.15</td>
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<td>Maddala and Wu</td>
<td>237.27</td>
<td>0.95</td>
<td>383.95</td>
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(g) \( \ln(Review_Val_a) \)

<table>
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<th>in first differences</th>
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<tbody>
<tr>
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<td>p-value</td>
<td>test stat.</td>
</tr>
<tr>
<td>Im, Pesaran, and Shin</td>
<td>-8.78</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Maddala and Wu</td>
<td>562.73</td>
<td>0.00</td>
<td></td>
</tr>
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</table>
Table 6. Parameter Estimates of the Pre-Launch VECM

(a) Long-run equilibrium equation

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t-Stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{i0}$</td>
<td>To avoid clutter, the individual fixed intercepts are not reported.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>1.7175</td>
<td>0.0479</td>
<td>35.8885</td>
</tr>
</tbody>
</table>

$R^2$ | 0.743 |
Adj-$R^2$ | 0.736 |

(b) Adjustment Parameters

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Err.</th>
<th>t-Stat</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_A$</td>
<td>-0.0201</td>
<td>0.0233</td>
<td>-0.8598</td>
</tr>
<tr>
<td>$\alpha_B$</td>
<td>0.0326</td>
<td>0.0075</td>
<td>4.3626</td>
</tr>
<tr>
<td>$\alpha_S$</td>
<td>-0.1645</td>
<td>0.0138</td>
<td>-11.895</td>
</tr>
</tbody>
</table>

Model fit

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>$\Delta \ln(Ad_{it})$</th>
<th>$\Delta \ln(Blog_{it})$</th>
<th>$\Delta \ln(\text{Search}_{it})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.312</td>
<td>0.326</td>
<td>0.139</td>
<td></td>
</tr>
<tr>
<td>0.303</td>
<td>0.317</td>
<td>0.128</td>
<td></td>
</tr>
</tbody>
</table>
Table 7. Select GIRFs of the Pre-Launch Period Model
(a) Response of log(Blog volume) to __________

<table>
<thead>
<tr>
<th>Week</th>
<th>log(Ad spending)</th>
<th>log(Blog volume)</th>
<th>log(Search volume)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1*</td>
<td>0.0371</td>
<td>0.6095</td>
<td>0.1179</td>
</tr>
<tr>
<td></td>
<td>(0.0076)</td>
<td>(0.0055)</td>
<td>(0.0071)</td>
</tr>
<tr>
<td>2</td>
<td>0.0340</td>
<td>0.2321</td>
<td>0.0457</td>
</tr>
<tr>
<td></td>
<td>(0.0085)</td>
<td>(0.0102)</td>
<td>(0.0101)</td>
</tr>
<tr>
<td>3</td>
<td>0.0027</td>
<td>0.1560</td>
<td>0.0285</td>
</tr>
<tr>
<td></td>
<td>(0.0089)</td>
<td>(0.0096)</td>
<td>(0.0110)</td>
</tr>
<tr>
<td>4</td>
<td>-0.0009</td>
<td>0.1210</td>
<td>0.0136</td>
</tr>
<tr>
<td></td>
<td>(0.0091)</td>
<td>(0.0097)</td>
<td>(0.0121)</td>
</tr>
<tr>
<td>5</td>
<td>-0.0010</td>
<td>0.1019</td>
<td>-0.0090</td>
</tr>
<tr>
<td></td>
<td>(0.0093)</td>
<td>(0.0094)</td>
<td>(0.0134)</td>
</tr>
</tbody>
</table>

(b) Response of log(Search volume) to __________

<table>
<thead>
<tr>
<th>Week</th>
<th>log(Ad spending)</th>
<th>log(Blog volume)</th>
<th>log(Search volume)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1*</td>
<td>0.0505</td>
<td>0.2179</td>
<td>1.1268</td>
</tr>
<tr>
<td></td>
<td>(0.0144)</td>
<td>(0.0132)</td>
<td>(0.0101)</td>
</tr>
<tr>
<td>2</td>
<td>0.0746</td>
<td>0.0939</td>
<td>0.9117</td>
</tr>
<tr>
<td></td>
<td>(0.0180)</td>
<td>(0.0208)</td>
<td>(0.0203)</td>
</tr>
<tr>
<td>3</td>
<td>0.0256</td>
<td>0.0362</td>
<td>0.9234</td>
</tr>
<tr>
<td></td>
<td>(0.0216)</td>
<td>(0.0248)</td>
<td>(0.0274)</td>
</tr>
<tr>
<td>4</td>
<td>0.0173</td>
<td>-0.0024</td>
<td>0.9425</td>
</tr>
<tr>
<td></td>
<td>(0.0257)</td>
<td>(0.0287)</td>
<td>(0.0360)</td>
</tr>
<tr>
<td>5</td>
<td>0.0067</td>
<td>-0.0382</td>
<td>0.9621</td>
</tr>
<tr>
<td></td>
<td>(0.0289)</td>
<td>(0.0322)</td>
<td>(0.0448)</td>
</tr>
</tbody>
</table>

standard error in ( )
* 1 indicates the same week when the random shock is given; 2 is one week after the shock is given, and so forth.
** Because the model is developed in log-transformed units of the original variables, the impulse response functions measure elasticity.
<table>
<thead>
<tr>
<th>Scenario</th>
<th>Covariates Included</th>
<th>In-sample fit</th>
<th>Hold-out sample prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$R^2$</td>
<td>Adjusted $R^2$</td>
</tr>
<tr>
<td>1</td>
<td>Movie characteristics only</td>
<td>0.490</td>
<td>0.554 0.627</td>
</tr>
<tr>
<td>2</td>
<td>Movie char. + Blog volume 3 weeks before release</td>
<td>0.498</td>
<td>0.563 0.637</td>
</tr>
<tr>
<td>3</td>
<td>Movie char. + Search volume 3 weeks before release</td>
<td>0.590</td>
<td>0.656 0.741</td>
</tr>
<tr>
<td>4</td>
<td>Movie char. + Blog &amp; search volume 3 weeks before release</td>
<td>0.592</td>
<td>0.657 0.743</td>
</tr>
<tr>
<td>5</td>
<td>Movie char. + Opening week advertising</td>
<td>0.564</td>
<td>0.634 0.815</td>
</tr>
<tr>
<td>6</td>
<td>Movie char. + Opening week advertising + Blog &amp; search volume 3 weeks before release</td>
<td>0.643</td>
<td>0.715 0.851</td>
</tr>
<tr>
<td>7</td>
<td>Movie char. + Opening week advertising &amp; Screens</td>
<td>0.915</td>
<td>0.933 0.949</td>
</tr>
<tr>
<td>8</td>
<td>Movie char. + Opening week advertising &amp; no. of screens + Blog &amp; search volume 3 weeks before release</td>
<td>0.930</td>
<td>0.946 0.958</td>
</tr>
</tbody>
</table>
Figure 1 Collecting Weekly Blog Volume

Figure 2. Mean Time-Series of Variables during Pre-Launch Periods

(a) Ad Spending ($ 000)

(b) Blog Volume

(3) Search Volume
Figure 3. Mean Time-Series of Variables during Post-Launch Periods

(a) Ad Spending ($000)  
(b) Screens

(c) Blog Volume  
(d) Search Volume (000)

(e) Review Volume  
(f) Review Valence

(g) Revenue ($M)
Figure 4. Model Development

Determining how to treat movie-specific fixed effects

Panel Granger causality test (Granger, 1969)

Panel unit-root test (Im, Pesaran, Shin, 2003; Maddala and Wu, 1999)

If at least two variables are nonstationary

Cointegration test (Kao, 1999; Pedroni, 2004)

If cointegrated

Vector error correction model

If not cointegrated

If at most one variable is nonstationary

Vector autoregressive model after appropriate differencing

Two approaches
1) Including movie-specific dummy variables
2) Mean centering
Figure 5. Select GIRFs of Pre-Launch Endogenous Variables

(a) Response of $\ln(\text{Blog})$ to $\ln(\text{Ad})$

(b) Response of $\ln(\text{Blog})$ to $\ln(\text{Search})$

(c) Response of $\ln(\text{Search})$ to $\ln(\text{Ad})$

(d) Response of $\ln(\text{Search})$ to $\ln(\text{Blog})$
Figure 6. Select FEVDs of the Pre-Launch Model:
% Variation of $\Delta \ln(\text{Search})$

(a) explained by $\Delta \ln(Ad)$
(b) explained by $\Delta \ln(Blog)$
(c) explained by $\Delta \ln(\text{Search})$
Figure 7. Select GIRFs of the Post-Launch Model: Response of ln(Revenue)

(a) to Δln(Ad)

(b) to ln(Blog)

(c) to Δln(Search)

(d) to Δln(Review_Vol)

(e) to ln(No_Scrns)
Figure 8. Select FEVDs of the Post-Launch Model:
% Variation of $\Delta \ln(Revenue)$

(a) explained by $\Delta \ln(Ad)$  
(b) explained by $\ln(Blog)$

(c) explained by $\Delta \ln(Search)$  
(d) explained by $\Delta \ln(Review\_Vol)$

(e) explained by $\ln(No\_Scrns)$  
(f) explained by $\Delta \ln(Revenue)$
Web Appendix: Constructing Cross-Sectionally Comparable Search Volume Measure from the Google Search Index

Because the Google search index is normalized, researchers cannot compare the search volumes 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, we select the following seven basis keywords: “mac os,” “lamp”, “hello”, “windows”, “weather”, “tomatoes”, “video”, and “imdb”. They are listed in the order of search amount when we restrict the search amount to the US motion picture industry. That is, the keyword “mac os” is the least searched and “imdb” is the most searched within the US 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. For the movie *Paul Blart: Mall Cop*, we choose “blart + mall cop,” which means either blart or “mall cop.”¹⁴

The second step is the keyword matching step. To each movie, 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 movie. Any basis keyword can be assigned to any movie as long as the search index of the movie keyword is comparable to that of the chosen basis keyword for the movie. That is, if the search volume of a certain basis keyword is too large compared to the search

¹⁴ The selection of movie keywords is guided by the “Related terms” section of Google Trends.
volume of a movie keyword, that basis keyword should not be used for that movie because the movie’s search index so collected will be shrunk to zero for many or all of the weeks.

The last step is the transformation step where we transform each movie’s search index into a cross-sectionally comparable search volume measure. The mathematics in this step can be explained as follows. Let \( k_j \) be the basis keyword at the \( j^{th} \) position (i.e., \( k_1 = “mac\ os”, \ k_2 = “lamp”, \ldots, \ k_8 = “imdb” \)), and let \( I_t^{k_j} \) represent the search index of the \( j^{th} \) basis keyword in week \( t \). We calculate the ratio of the Google search index of two adjacent basis keywords,

\[
r_t^{j,j-1} = \frac{I_t^{k_j}}{I_t^{k_{j-1}}} , \text{ for each } t \text{ and for all seven pairs of adjacent basis keywords.}
\]

Let \( I_t^m \) 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 (A-1).

\[
(A-1) \quad S_{mt} = I_t^m (r_t^{j,j-1} \times \cdots \times r_t^{2,1} \cdot r_t^{1,0})
\]

, 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 Figure A.1). Figure A.1(a) shows the weekly multiplier associated with each basis keyword, i.e., \( (r_t^{j,j-1} \times \cdots \times r_t^{2,1} \cdot r_t^{1,0}) \). Figure A.1(b) 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 Zombieland and X-Men Origins: Wolverine. Note that our transformed search volume measures show a substantial difference in consumer search activities between the two movies.
Figure A.1 Transforming Search Index into Search Volume

(a) Weekly Multiplier Associated With the Basis Keywords

(b) Raw Search Indexes and Transformed Search Volume Measures of *Zombieland* and *X-Men Origins: Wolverine*

Transformed Search Volume Measures of *Zombieland* and *X-Men Origin: Wolverine*