# Interplay between Social Media and Traditional Media: An Empirical Study in the Motion Picture Industry

Research-in-Progress

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#### Abstract

Marketers leverage multiple media outlets to promote products. There are three media types: paid (e.g., advertising on TV), owned (e.g., company website), and earned (e.g., consumers' word-of-mouth) media. The effects of individual media channels and the interrelationships within paid media have been examined by prior literature. However, little is known about interplay across different types of media channels. We investigate how social media marketing (both owned and earned media) and the interplay between traditional paid media and social media affect product sales. We analyze how promotional activities across different media channels influence the box office revenues of 200 movies in their opening weekends and subsequent weeks, respectively. We find empirical evidence that social media marketing is positively associated with product sales, especially in the initial product launch period. Additionally, traditional media and social media.

Keywords: social media marketing, multiple media interplay, motion picture industry

## Introduction

With the proliferation of social media in the past decade, global media landscape is undergoing a revolution and has become more complex than ever before. Stephen and Galak (2012) classify media activities into three categories: paid media (the company pays for the advertising channel), owned media (the company owns the channel), and earned media (other entities generate the media activity). Previous studies have investigated multiple media interplay within one media type, especially paid media (e.g., Naik and Raman 2003; Naik ad Peters 2009; Goldfarb and Tucker 2011a, b); others compare the relative effects of different channels in various contexts (e.g., Stephen and Galak 2012; Trusov et al, 2009). However, much less is known about how the interrelationship across media types would matter, yet such lack of scrutiny neglects the interplay nature of multiple channels and the indirect effects that media may have through one another on business outcomes. Moreover, prior literature has yielded mixed results on whether different paid media outlets complement or substitute each other.

To gain an integrated understanding of the impact of multiple media on sales, we study how social media marketing (including owned and earned media) and its interplay with traditional advertising (paid media) affect product sales. Since firms usually utilize a combination of multiple marketing communication channels and consumers also multi-home across different media, these media channels do not function independently. In this study, we aim to answer the following research questions: How does social media marketing affect product sales? How do traditional media advertising and social media marketing interplay with each other to influence product sales?

We contextualize our study in the motion picture industry, in which there are public and proprietary data available for our research goal. For decades, the movie industry heavily relies on traditional advertising channels such as TV, magazines, and newspapers to reach target audience (Caves 2001). Major movie studios such as Disney, Fox, Paramount, Sony Pictures, Universal, and Warner Bros, to name a few, spend a substantial amount of money on advertising for typical Hollywood movie releases, sometimes exceeding 50% of the actual film-making costs (Gerbrandt 2010). Recently, social media sites, especially Facebook, have become a popular alternative to engage potential consumers (Dorr 2012). Social media marketing, or Facebook marketing in our context, relies on a combination of owned media and earned media. Marketers partially own the media as movie titles create their official Facebook page, post a wealth of content, and orchestrate various activities to engage fans. Consumers then participate in movies' social media community, consume various kinds of information, create word-of-mouth, and spread product information on their own social networks. These consumer generated contents form the earned media. Such coexistence and widespread usage of multi-channels in this industry provide us a great opportunity to study media effectiveness and their interplay on product sales. We sample 200 movies released in the USA in 2012 and grossed more than 1 million US dollars, whose total revenues account for 91.9% of the over 10 billion box office revenue in that year. We construct a longitudinal dataset on movie sales, media activities, and other control variables. Consistent with prior studies (Stephen and Galak 2012; Trusov et al. 2009), we focus on marketing intensity or volume of media activities for each type (e.g., advertising expenditure on paid media and activity intensity on owned and earned media), and analyze the box office revenues in the opening weekends (initial launch) and subsequent weeks, respectively. Our results show that Facebook marketing drives product sales, especially in the initial launch period. Additionally, there is a substitution effect between traditional paid media and social media on movie sales. Our study contributes to the multiple media interplay literature as one of the first papers to investigate cross-media interactions.

## **Related Literature and Hypotheses Development**

#### Paid, Owned, Earned Media

We adopt the typology from Stephen and Galak (2012) and classify complex media activities into three categories: paid media, owned media, and earned media. Paid media refers to the media channel that requires payment to gain access, for example, advertising on cable TV and newspapers. Owned media is the channel created by the company, such as official websites and social media accounts. Company owns the content on such media. Earned media refers to the media activity generated by entities other than the

company, such as customers, journalists, and third-party critics. Companies have stronger controls over paid and owned media, which in turn could potentially drive earned media activities (Corcoran, 2009).

There is an ample literature on advertising that typically falls in the paid media. In the past decade, earned media activities such as online WOM received plenty of attention, since social media dramatically changed the way consumers acquire and generate information in various contexts (e.g., Chintagunta et al. 2010; Gopinath et al. 2013; Liu 2006; Sun 2012; Zhu and Zhang 2010). More recently, firm initiated social media marketing is receiving increased attention (e.g., Chen et al. 2014; Goh et al. 2013; Rishika et al. 2013); how it operates and affects sales is not well understood, particularly when coexisting with traditional media. In this study, we first examine how social owned and earned media affect product sales (see Figure 1 for the conceptual model of this study).

Advertising through different media serves as a signal for product quality (e.g., Nelson 1974; Kihlstrom and Riordan 1984). Studios send a strong quality signal of films when they engage in owned media activities on Facebook. They disclose both factual information, such as cast teams and release details, and persuasive messages such as ad commercials with emotional cues. All these marketer generated contents help create film awareness, arouse consumers' curiosity, and reduce their purchase uncertainty. Consumers also participate in the community by expressing their attitude and intention to watch the movie, which could potentially be used to predict their theatergoing behavior (e.g., Ajzen 1991). After movie releases, consumer-generated earned media function as another information source, mitigating successors' uncertainty (Liu 2006). Therefore, we propose:

H1a: Owned media is positively associated with product sales.

H1b: Earned media is positively associated with product sales.



#### Multiple Media Interplay

While integrated marketing communications (IMC) are not new, existing studies have largely limited the scope within paid media. The IMC literature suggests that people are likely to consume multiple media sources simultaneously and their retention of advertising messages and purchase likelihood are increased by repeated exposures (Chandra and Kaiser 2014; Naik and Raman 2003; Naik and Peters 2009). In this way, advertising in one outlet increases the effectiveness of the others. For example, Naik and Raman (2003) report a synergy effect between television and print advertising on clothing sales. Furthermore, consumers may actively seek information from one source to complement those acquired from another. For instance, Joo et al. (2014) show that offline television advertising encourages consumers' online search behavior. However, other studies argue that different paid media are substitutes. Bergemann and Bonatti (2011) indicate that multiple advertising messages delivered on different media are redundant and with diminishing effectiveness. Empirical studies, Goldfarb and Tucker (2011 a, b), for example, imply that when offline advertising is restricted, the effectiveness of online advertising becomes more salient, or the pricing of it becomes higher, pointing to the possibility of the online-offline paid media substitution. Some studies compare the relative effectiveness of different media types, but little research has examined their interplay. Among these studies, most of them compare the effect of WOM (earned

media) and traditional marketing vehicle (paid media) (e.g., Dewan and Ramaprasad 2014; Gopinath et al. 2013; Trusov et al. 2009). For example, Trusov et al. (2009) find WOM referrals have a longer carryover effect on customer acquisition and a higher response elasticity compared with traditional media mentions. Stephen and Galak (2012) examine both traditional earned (publicity mentions) and social earned media (blog and online community posts) in the microlending marketplace. In the movie industry, Gopinath et al. (2013) examined how firm-generated media (traditional advertising) and consumer-generated media (blogs) influence the movie's financial performance, respectively.

Because of the prevalence of multi-channel marketing, and also in line with the call for inspection of whether paid media strengthen earned media in affecting sales (Stephen and Galak, 2012), we investigate the interplay across channels. Based on the signaling theory, we determine the interplay between different media types by assessing whether the advertising signals sent through different media are similar to one another. Kirmani and Rao (2000) classify signals into two broad categories (e.g., default-independent and default-contingent signals), and argue that it is more reasonable to combine dissimilar signals to fully take advantages of their complementary properties. In contrast, similar signals attenuate each other. Based on our observations, movie studios currently use Facebook page as a channel to mainly disseminate film information but rarely interact with consumers. In this regard, Facebook page plays a similar role as traditional advertising. Thus, we propose paid media and owned media substitute each other. In contrast, paid media and earned media are generated by different sources with different emphases. Checking out both channels helps consumers form a comprehensive evaluation that would reduce their purchase uncertainty (Urbany et al. 1989). Consumer engagement on social media platforms could also potentially amplify the effect of a firm's marketing efforts, as consumers may be more likely to look for firmgenerated information when they hear from their friends talking about a product. Hence, we propose paid media and earned media are complementary.

H2a: There is a substitution effect between traditional paid media and owned media on product sales.

H2b: There is a complementary effect between traditional paid media and earned media on product sales.

## Data

Our dataset combines information from multiple sources, including dependent variables of movie ticket sales from Box Office Mojo, social media activity collected from Facebook, traditional marketing expenditure acquired from Kantar Media, and movie characteristics from IMDb and The Numbers, earned media (customer reviews) outside Facebook from Fandango, and critical reviews from Rotten Tomatoes. We select movies released in the USA in 2012 that received box office revenue of at least 1 million US dollars as our sample (200 movies), which covers both large budget/Hollywood blockbusters and small budget/independent films<sup>1</sup>.

#### **Box Office Revenue**

Weekly movie box office revenue is our dependent variable, denoted as WEEKLYGROSS<sub>it</sub>. Given the importance of the opening week performance in the movie industry, we pay special attention to the opening weekend box office, OPENINGGROSS<sub>i</sub>. Following prior studies (e.g., Chintagunta et al. 2010, Liu 2006), we also include theater count (THEATRES<sub>it</sub>: the number of theatres showing movie *i* in week *t*) and competition (COMPETITION<sub>i</sub>: the number of other movies in theatres in the same week as the focal movie) as control variables in our analyses.

#### Social Media and Traditional Media

We collect social media marketing data from Facebook. Facebook is the most popular social media site in the USA<sup>2</sup>, for both individual and commercial usage (Stelzner 2014). In the movie industry, Facebook has

<sup>&</sup>lt;sup>1</sup>We exclude the re-release and/or 3D version of prior movies. The highest grossing movie in 2012, Marvel's The Avengers, achieved \$623 million box office revenue in the USA. The mean and median box office revenue is \$50.47 million and \$19.65 million, respectively. Our choice of \$1 million threshold thus excludes only the lowest grossing (and perhaps insignificant) films from the population.

<sup>&</sup>lt;sup>2</sup> http://newsroom.fb.com/company-info/

become the dominant social media avenue (Jonson 2013). We manually identify the official Facebook page for each of the 200 movies in our sample by searching the movie titles. 180 movies have an official presence on Facebook<sup>3</sup>. We also search each movie title on Twitter, but only 24 out of 200 movies (i.e., 12%) have official Twitter accounts. This suggests that Facebook was the most popular social media outlet for movie studios in 2012. We download all Facebook data, such as page profile information, posts submitted by the page, and users' comments/shares/likes, through Facebook API. The page profile information includes page ID (numeric), username (distinct web address for a page), description, and the date when the page joined Facebook. Owned media activities of movie studios are captured primarily by their posts on Facebook over time. The information we collect about each post includes the following items: post ID, page username, date of publication, post type, and content. Our explanatory variable for owned media, OWNED<sub>it</sub>, is the number of posts submitted by movie page *i* in week *t*. Users can respond to each post by making a comment, sharing the post with his/her friends, or simply hitting the "Like" button. We use the volume of comments per post within the same week (EARNED<sub>ii</sub>) to measure earned media activities. Our results remain similar if we use the total volume of comments in a week or replace comments with shares or likes. Movie studios usually utilize various traditional advertising outlets to promote their films, such as cable TV, magazines, and radio stations, etc. We use the sum of advertising expenditure on all traditional paid media, PAID<sub>it</sub>, to capture their influences. In our data set, 14 movies do not allocate any advertising expenses on paid media.

#### **Other Variables**

Several movie and cast characteristics are widely considered as impact factors of movie sales and controlled for in previous studies. We therefore gather related information from two popular movie web sites: IMDb (www.imdb.com) and The Numbers (www.the-numbers.com). These data include production budget (BUDGET<sub>i</sub><sup>4</sup>), genre (GENRE<sub>i</sub>: Action, Adventure, Animation, Comedy, Drama, Thriller, and Documentary), MPAA ratings (MPAA<sub>i</sub>: G, PG, PG-13, and R), whether the movie is a sequel of an earlier movie (SEQUEL<sub>i</sub>), and the star power (STAR\_POWER<sub>i</sub><sup>5</sup>: a dummy variable equals one if at least one of the movie's cast members won the Oscar Award prior to this movie and zero otherwise (Basurov et al. 2003)). Scholars show great interest in the role played by consumer generated WOM (word-of-mouth) in the movie industry (e.g., Chintagunta et al, 2010; Gopinath et al, 2013; Liu 2006; Moon et al, 2010). Besides earned media generated on Facebook, consumers also provide reviews on other platforms. To control for this influence, we incorporate WOM on Fandango (www.fandango.com), which accounts for 70 percent of the online and mobile movie ticketing market in the USA (Lang 2012). We collected user ID, review date, star rating, and content, for each customer review. Volume and valence of WOM are measured by the number of customer reviews (WOM VOL<sub>it</sub>), and the average rating (WOM VAL<sub>it</sub>). following prior studies (Chintagunta et al. 2010)<sup>6</sup>. Finally, the effects of third-party opinions issued by movie critics have been investigated by prior studies (e.g., Basuroy et al, 2003; Chen et al, 2011). Critical reviews are found to have a significant influence on investors' expectation and a movie's financial performance. In line with these studies, we only consider critical reviews issued prior to the movie release to ensure their credit. Critical reviews information is gathered from Rotten Tomatoes (www.rottentomatoes.com), which aggregates professional opinions posted by critics on a movie and classifies them as "fresh" (positive) or "rotten" (negative). The variable CRITIC\_VOL<sub>i</sub> is the total number of critical reviews. Following Basuroy et al. (2003), we use the percentage of positive critic reviews, CRITIC POS<sub>i</sub>, to measure valence. Season dummies are also included to account for time effects.

<sup>&</sup>lt;sup>3</sup> We exclude community and fan pages, as they do not represent movie studios' marketing activities; we also limit our search to official pages for the US market and do not consider international pages.

<sup>&</sup>lt;sup>4</sup> In our OLS regression analyses, our sample size is reduced to 161 movies because of the missing data on product budget.

<sup>&</sup>lt;sup>5</sup> Our results remain largely the same when we measure star power in a different way as discussed in prior studies such as Liu (2006) and Basuroy et al. (2003): STAR\_POWER equals 1 if at least one of the cast members appears on the list of "Top 100 Stars of 2012" from IMDb.

<sup>&</sup>lt;sup>6</sup> When we use different measures for WOM\_VAL, e.g., the percentage of positive reviews, as in Liu (2006), we obtain very similar results.

# **Models and Preliminary Results**

The motion picture industry has a strong emphasis on a movie's box office performance in the opening weekend, which could account for nearly 30% of the total gross (The Hollywood Quantifier, 2013). An impressive opening can absorb attentions from the media and movie fans and pave the way for the movie's long-term success (Gopinath et al. 2013). To investigate the effects of different advertising media on the box office performances in different time periods, we split our analyses into two sets of regressions and test our hypotheses in terms of how different advertising media help predict the box office performance in the opening week and subsequent weeks after the movie release, respectively.

#### Effect of Social Media Marketing

To test the main effects of different media (H1a and H1b), we specify the following two regression models.

$$\begin{split} Ln(OPENINGLYGROSS_i) &= \alpha_0^1 + \alpha_1^1 Ln(PAID_i) + \alpha_2^1 Ln(OWNED_i) + \alpha_3^1 Ln(EARNED_i) + \alpha_4^1 Ln(THEATRES_i) \\ &+ \alpha_5^1 COMPETITION_i + \alpha_6^1 CRITIC_VOL_i + \alpha_7^1 CRITIC_POS_i + \alpha_8^1 Ln(BUDGET_i) + \\ &\alpha_9^1 STAR_POWER_i + \alpha_{10}^1 SEQUEL_i + MPAA Dummies + GENRE Dummies + \\ &SEASON Dummies + \varepsilon_i^1 \end{split}$$

 $\ln(WEEKLYGROSS_{it}) = \beta_0^1 + \beta_1^1 \ln(PAID_{it}) + \beta_2^1 \ln(OWNED_{it}) + \beta_3^1 \ln(EARNED_{it}) + \beta_3^1 \ln(EARNED_{$ 

 $\beta_4^1 \operatorname{Ln}(WEEKLYGROSS_{i,t-1}) + \beta_5^1 \operatorname{Ln}(THEATRES_{it}) + \beta_6^1 COMPETITION_{it} + \beta_7^1$ 

 $Ln(WOM_VOL_{it}) + \beta_8^1 WOM_VAL_{it} + SEASON Dummies + \mu_i^1 + \xi_{it}^1$ (2)

The dependent variable in Equations (1) is the opening weekend gross for movie *i*. The main variables of interest are  $Ln(PAID_i)$ ,  $Ln(OWNED_i)$ , and  $Ln(EARNED_i)$ , which capture the influence of three types of media. On the Facebook platform, owned media and earned media activities are positively correlated with each other. To deal with this potential problem, we employ the average number of consumer comments per post to measure the earned media activity. A set of control variables introduced above, including theatre counts, competition variable, critical review information, movie characteristics, and season dummies are included. We take natural logarithms of the sales, media activities, and count variables (e.g.,  $THEATRES_i$ ) to reduce the skewness of data and improve the model fit. All the independent variables are calculated for the period of twelve weeks to one week prior to the release of movie *i*, which eliminates the concern of reverse causality between marketing efforts and movie sales. We run OLS regressions for Equation (1).

After the movie release, marketing activities and box office revenues could potentially influence each other. This is because there could be a reverse causality between marketing efforts and movie sales. For instance, movie studios could promote more on different media channels when good sales are observed earlier. The exhibition decisions (e.g., the number of theatres allocated to the movie) are also endogenous since exhibitors make their decisions according to the movie's prior performance (Basuroy et al, 2006). In addition, a movie's weekly grosses could be serially correlated. In the absence of strong exogenous instruments, we turn to the Arellano-Bond system generalized method of moments (GMM) estimator to account for these issues (Arellano and Bond 1991, Arellano and Bover 1995). We consider the first eight weeks since movie release including the opening week in our analyses, as previous studies suggest that the first eight weeks account for more than 90% of the total movie box office revenue (e.g., Liu 2006; Moon et al. 2010). The dependent variable in Equations (2) is the weekly gross of movie *i* in week *t*.  $Ln(WEEKLYGROSS_{i,t-1})$  is the lagged dependent variable to adjust for serial correlation. The main variables of interest are still main effects of media activities. Fandango WOM is included only in subsequent period analysis because consumers submit reviews on Fandango only after a movie's release. To control for any time effects such as seasonality, we include season dummies. All time-invariant characteristics such as budget, MPAA rating, genres are absorbed into the movie fixed effects  $\mu_i^1$ . Following prior IS studies (e.g., Bardhan et al. 2013) that also adopt the system GMM estimator, we perform the standard testing procedures before estimating our model. The Arellano-Bond tests for autocorrelation are performed, and the results show no evidence of serial correlation in the errors. The Hansen tests show that the null hypothesis of exogeneity of instruments fails to be rejected.

The first three columns in Tables 1 show the regression results of Equation (1). Columns (4) to column (6) report the results of Equation (2). Our results show that social media marketing, especially social earned media, is positively associated with the opening weekend box office revenue. This result is consistent with

Gopinath et al. (2013), who find that blog volume drives movie sales on the opening day, but does not influence post-release sales. This finding provides important implications for studios to build buzz before movie release. It is a little surprising that the effects of paid media in Columns (1) to (3) are insignificant. However, it is not uncommon that some heavily promoted movies failed at the very beginning, so it is possible that on average advertising expenditure on paid media may not be a good predictor of the box office performance in the opening week. The coefficient estimates on control variables are largely consistent with prior studies' results. The number of theaters is closely related to movie revenues (Chintagunta et al. 2010; Liu 2006). In Columns (1) to (3), the coefficient estimates on the volume of critical reviews are positive and statistically significant at the 5% level. Additionally, consistent with Eliashberg and Shugan (1997), the percentage of positive reviews shows no significant influence on the beginning box office revenue. Product budget is positively related to the opening week gross (Liu 2006). Competition, star power and sequel are not found to be very informative of sales. In dynamic panel data analyses (Columns 4 to 6), lagged weekly gross is significantly correlated with the box office in the current week, suggesting a strong serial correlation in weekly movie sales. WOM on Fandango does not have a significant influence on weekly box office revenues.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	0	pening Weeke	end Subsequent Weeks			eeks
$Ln(PAID_{it})$	0.055	0.064	0.062	0.120***	0.208***	0.174***
	(0.055)	(0.058)	(0.056)	(0.033)	(0.041)	(0.054)
Ln(OWNED <sub>it</sub> )	0.076***		0.052*	0.205***		0.104
	(0.027)		(0.027)	(0.063)		(0.113)
Ln(EARNED <sub>it</sub> )		1.841***	1.748***		-0.013	-0.020
		(0.400)	(0.392)		(0.019)	(0.020)
Ln(THEATRES <sub>i</sub> )	0.628***	0.626***	0.617***	0.172	0.324*	0.340**
	(0.058)	(0.059)	(0.058)	(0.153)	(0.171)	(0.149)
COMPETITION <sub>i</sub>	0.007	0.004	0.004	-0.002	0.002	0.003
	(0.007)	(0.006)	(0.006)	(0.010)	(0.011)	(0.009)
CRITIC_VOL <sub>i</sub>	0.004**	0.004**	0.004**			
	(0.002)	(0.002)	(0.002)			
CRITIC_POS <sub>i</sub>	0.390	0.351	0.358			
	(0.237)	(0.233)	(0.232)			
Ln(BUDGET <sub>i</sub> )	0.223***	0.179**	0.192***			
	(0.073)	(0.070)	(0.071)			
STAR_POWER <sub>i</sub>	-0.068	-0.0004	-0.019			
	(0.111)	(0.105)	(0.106)			
SEQUEL <sub>i</sub>	0.100	0.126	0.131			
	(0.168)	(0.165)	(0.164)			
MPAA Dummies	Yes	Yes	Yes			
GENRE Dummies	Yes	Yes	Yes			
Ln(WEEKLYGROSS <sub>it-1</sub> )				0.663***	0.648***	0.638***
				(0.134)	(0.123)	(0.108)
Ln(WOM_VOL <sub>it</sub> )				0.117	0.024	0.020
				(0.105)	(0.134)	(0.149)
WOM_VAL <sub>it</sub>				0.010	-0.035	-0.034
				(0.030)	(0.038)	(0.033)
SEASON Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	10.28***	10.55***	10.59***	3.190**	2.689**	2.747**
	(0.615)	(0.605)	(0.604)	(1.278)	(1.153)	(1.099)
Observations	161	161	161	1,297	1,297	1,297
#Movies	161	161	161	200	200	200
Adj. R-squared	0.925	0.933	0.933			

Table I Media Effect off Movie Sales	Table	1 Media	Effect o	on Movie	Sales
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Note: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

(1)(2)(3)(4)(5)(6)VARIABLESOpening WeekendSubsequent Weeks	
VARIABLES Opening Weekend Subsequent Weeks	
	.11.
$Ln (PAID_{it})   0.054   0.050   0.050   0.159^{***}   0.198^{***}   0.170^{*}$	**
(0.055) $(0.061)$ $(0.065)$ $(0.020)$ $(0.017)$ $(0.032)$	)
$Ln(OWNED_{it})    0.076^{**}    0.049    0.083^{*}    0.102$	
(0.030)  (0.030)  (0.050)  (0.087)	)
$Ln(EARNED_{it})$ 2.546*** 2.338** 0.014 -0.019	
(0.847) $(1.101)$ $(0.014)$ $(0.017)$	1
$\ln(PAID_{it}) \times \ln(OWNED_{it})$ 0.0004 0.004 -0.038** -0.047	**
(0.006)  (0.009)  (0.016)  (0.021)	)
$Ln(PAID_{it}) \times Ln(EARNED_{it})$ -0.480 -0.390 -0.023*** -0.017	ķ
(0.464) $(0.622)$ $(0.005)$ $(0.009)$	)
$Ln(THEATRES_{it})    0.628^{***}   0.616^{***}   0.611^{***}   0.152^{**}   0.099   0.350^{*}$	**
(0.058) $(0.052)$ $(0.052)$ $(0.075)$ $(0.087)$ $(0.110)$	1
COMPETITION <sub>i</sub> $0.007$ $0.004$ $0.004$ $-0.005$ $-0.001$ $0.001$	
(0.007) $(0.006)$ $(0.006)$ $(0.005)$ $(0.005)$ $(0.006)$	)
$CRITIC_VOL_i    0.004^{**}    0.005^{***}    0.005^{**}$	
(0.002) $(0.002)$ $(0.002)$	
$CRITIC_POS_i$ 0.390 0.300 0.320	
(0.237) $(0.232)$ $(0.234)$	
$Ln(BUDGET_i)$ 0.224*** 0.171** 0.186***	
(0.074) $(0.067)$ $(0.070)$	
$STAR_POWER_i$ -0.069 -0.013 -0.029	
(0.111) $(0.107)$ $(0.108)$	
$SEQUEL_i$ 0.100 0.117 0.121	
(0.168) $(0.167)$ $(0.166)$	
MPAA Dummies Yes Yes Yes	
GENRE Dummies Yes Yes Yes	
$Ln(WEEKLYGROSS_{it-1})    0.674^{***}   0.726^{***}   0.579^{*}$	**
(0.074) $(0.075)$ $(0.100)$	)
$Ln(WOM_VOL_{it})$ 0.115** 0.109* 0.068	
(0.053) $(0.056)$ $(0.062)$	)
$WOM_VAL_{it}$ 0.029 0.014 0.011	
(0.024) $(0.025)$ $(0.035)$	)
SEASON Dummies Yes Yes Yes Yes Yes Yes	
Constant         10.28***         10.64***         10.66***         3.215***         2.653***         3.355*	**
(0.619) $(0.563)$ $(0.576)$ $(0.731)$ $(0.620)$ $(0.794)$	)
Observations 161 161 161 1,297 1,297 1,297	
#Movies 161 161 161 200 200 200	
Adj. R-squared 0.923 0.933 0.934	

 Table 2 the Effect of Multiple Media Interplay on Movie Sales

Note: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### Interplay between Traditional Media and Social Media

To examine the interplay between traditional media and social media, we add two interaction terms,  $Ln(PAID_{it}) \times Ln(OWNED_{it})$  and  $Ln(PAID_{it}) \times Ln(EARNED_{it})$ , in Equations (3) and (4). All the other explanatory variables are the same as previous specifications.

$$\begin{split} Ln(OPENINGLYGROSS_i) &= \alpha_0^1 + \alpha_1^1 Ln(PAID_i) + \alpha_2^1 Ln(OWNED_i) + \alpha_3^1 Ln(EARNED_i) + \alpha_4^1 Ln(PAID_i) \times \\ Ln(OWNED_i) + \alpha_5^1 Ln(PAID_i) \times Ln(EARNED_i) + \alpha_6^1 Ln(THEATRES_i) + \alpha_7^1 \\ COMPETITION_i + \alpha_8^1 CRITIC_VOL_i + \alpha_9^1 CRITIC_POS_i + \alpha_{10}^1 Ln(BUDGET_i) + \alpha_{11}^1 \\ STAR_POWER_i + \alpha_{12}^1 SEQUEL_i + MPAA Dummies + GENRE Dummies + \\ SEASON Dummies + \varepsilon_i^1 \end{split}$$
(3)

$$\begin{split} \text{Ln}(WEEKLYGROSS_{it}) &= \beta_0^1 + \beta_1^1 \operatorname{Ln}(PAID_{it}) + \beta_2^1 \operatorname{Ln}(OWNED_{it}) + \beta_3^1 \operatorname{Ln}(EARNED_{it}) + \\ & \beta_4^1 \operatorname{Ln}(PAID_{it}) \times \operatorname{Ln}(OWNED_{it}) + \beta_5^1 \operatorname{Ln}(PAID_{it}) \times \operatorname{Ln}(EARNED_{it}) + \\ & \beta_6^1 \operatorname{Ln}(WEEKLYGROSS_{i,t-1}) + \beta_7^1 \operatorname{Ln}(THEATRES_{it}) + \beta_8^1 COMPETITION_{it} + \beta_9^1 \\ & \operatorname{Ln}(WOM\_VOL_{it}) + \beta_{10}^1 WOM\_VAL_{it} + SEASON Dummies + \mu_i^1 + \xi_{it}^1 \end{split}$$
(4)

The Columns (1) to (3) in Table 2 show the results of Equation (3), in which the dependent variable is the opening weekend movie box office revenue. Columns (4) to (6) show the estimation results of Equation (4). We obtain negative and statistically significant interactions in the analyses for subsequent weeks. The results for the opening week are similar but not statistically significant. Therefore, H2a is partially supported. As to the reason why we observe a substitution effect between traditional paid media and social earned media, instead of a complementary effect as we expected in H2B, we suspect one possible explanation is that consumers may substitute between different media channels for their information sources (e.g., Berman et al., 2006; Liebowitz and Zentner 2012). Attention is a scarce resource; different media essentially compete for it. When consumers spend some time on one channel and have their needs satisfied, they may choose to skip other media.

## **Conclusion and Work-in-Progress**

Our study investigates how social media marketing and cross-media interplay affect product sales in the motion picture industry. Our results inform a growing literature on firm initiated social media marketing. We find social media marketing has a positive influence on product sales, especially during a product's initial launch period. These findings confirm the importance of investing in social media marketing for firms. Our study further contributes to the literature of multi-channel marketing. We find a substitution effect between paid media and owned media, which suggests that it is better for marketer to invest most of the resources in the channels with higher marginal returns to maximize the payoff. However, there could be a synergy between them, if owned media are utilized distinctively, such as interacting more with consumers, rather than repeating what has been done on paid media. The interrelationship between paid media is also found to be substitution. This finding is beneficial for marketers because they can potentially save money on traditional paid media after earned media takes shape.

This study is currently a work-in-progress. Since previous studies yield mixed results on multiple media interrelationship (complementarity or substitution), we intend to further investigate this topic. We propose that the multiple media interplay may be contingent on contextual factors like environment, consumer characteristics, and product features. We will focus on product characteristics in our ongoing analyses. Specifically, we inspect how multiple media interplay varies across different types of product appeals. Product appeal measures the range of tastes the product is designed to cater to (Tucker and Zhang, 2011). Broad appeal products are tailored to the mass market and traditional mass media have already covered most of their target audiences. As they are already near the point of diminishing returns of advertising, additional value added by social media advertising may be limited. In contrast, narrow appeal products are hard to get noticed by potential consumers through either traditional media or social media. Multiple media advertising deliver the information to heterogeneous consumers, which increases the likelihood for matched consumers to find niche products. In this regard, multiple media interplay may benefit narrow appeal products more. In line with Sun (2012), we plan to use the variance of consumer ratings as a proxy for product appeal. Our dataset enables us to explicitly test whether the interaction among multiple media varies for different product types.

This study also has a number of limitations. First, we focus on Facebook marketing and do not control for activities on other social media channels such as Twitter. Second, for all the three media we only consider the volume of media activities. However, earned media also have other characteristics, such as message sentiment. In our ongoing research projects, we will try to take these issues into consideration.

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