Does Twitter matter? The impact of microblogging word of mouth on consumers' adoption of new movies

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Abstract

This research provides an empirical test of the "Twitter effect," which postulates that microblogging word of mouth (MWOM) shared through Twitter and similar services affects early product adoption behaviors by immediately disseminating consumers' post-purchase quality evaluations. This is a potentially crucial factor for the success of experiential media products and other products whose distribution strategy relies on a hyped release. Studying the four million MWOM messages sent via Twitter concerning 105 movies on their respective opening weekends, the authors find support for the Twitter effect and report evidence of a negativity bias. In a follow-up incident study of 600 Twitter users who decided not to see a movie based on negative MWOM, the authors shed additional light on the Twitter effect by investigating how consumers use MWOM information in their decision-making processes and describing MWOM's defining characteristics. They use these insights to position MWOM in the word-of-mouth landscape, to identify future word-of-mouth research opportunities based on this conceptual positioning, and to develop managerial implications.

“Brüno’s box office decline from Friday to Saturday indicates that…[it] could be the first movie defeated by the Twitter effect.”

Corliss (2009), *Time Magazine*

The “Twitter effect” controversy

The power of microblogging to rapidly spread information among networked individuals has been compellingly demonstrated during recent world events, including the Arab Spring movement (Kassim 2012) and the 2012 U.S. presidential election (Mills 2012). Microblogging is a contemporary phenomenon that refers to the broadcasting of brief messages to some or all members of the sender’s social network through a specific web-based service (Kaplan and Haenlein 2011). Although various microblogging services exist, Twitter has become synonymous with the concept; by November 2013, 232 million consumers actively used Twitter on a monthly basis and shared more than 400 million messages every day (Ahmad 2013). Twitter’s growth is closely linked to the introduction of smartphones, with more than 60 percent of tweets being posted “on the go” using mobile devices (McGee 2012).

Microblogging constitutes a new type of word of mouth (WOM) that we refer to as microblogging word of mouth (MWOM). Through MWOM, consumers can share post-purchase quality impressions about market offerings with a vast number of connected consumers at unprecedented speed, which can influence the early adoption of new products at a point in time when no other post-purchase WOM information is widely available and when consumers must make adoption decisions based primarily on promotional material.

Whether such an influence of MWOM, which has been termed the “Twitter effect” (e.g., Corliss 2009), is economically substantial is the subject of a heated debate. Industry experts have blamed negative MWOM for the instant failure of multimillion-dollar movies, such as *Brüno*, and have attributed the unexpected opening success of others, such as the remake of *Karate Kid*, to positive MWOM (e.g., Corliss 2009; Singh 2009a). Some theaters and opera houses across the U.S. now encourage audience members to tweet during shows from specific "tweet seats," hoping to attract additional consumers through the Twitter effect (Funt 2012).[1] Others, however, dispute the importance of MWOM (Atchity, qtd. in Pomerantz 2009), referring to self-reported commercial survey results (Lang 2010).

If the Twitter effect exists, it would have strong economic implications for products for which "instant" success is essential, such as experiential media products (e.g., movies, music, and electronic games), as well as for other products whose distribution strategy involves a hyped release (e.g., Apple's iPhones and iPads). For example, approximately 50 percent of album sales for popular music (Asai 2009), 46 percent of movie ticket sales for major movies (Hayes 2002), and 40 percent of game revenues (www.vgchartz.com) are generated in the first week of a new product's release. MWOM could diminish the information asymmetry that has existed between producers and consumers in the very early stages of any diffusion process by allowing early consumer adopters to communicate quickly and widely about their experiences with the new product. As such, MWOM could decrease the share of revenue that remains unaffected by consumers' quality perceptions of the new product. Consequently, investments in products for which instant success is essential would become more risky. At the same time, the Twitter effect could open up new ways for entertainment providers to attract customers through "tweet seats" and similar innovations.

In this research, we empirically test the existence of the Twitter effect in the context of motion pictures, a category for which instant success is of particular economic importance. To do so, we

[1] We thank an anonymous reviewer for alerting us to this interesting development.

apply sentiment analysis (e.g., Pang and Lee 2008) and regression analysis to a unique dataset of all MWOM messages sent via Twitter that pertained to 105 widely released movies during their respective North American opening weekends. Finding evidence for the Twitter effect of negative but not positive MWOM, we complement this insight by developing a richer understanding of the effect and of MWOM's role within the decision-making process through an incident study of 600 individual consumers who had forgone watching a movie because of negative MWOM. From these insights, we position MWOM in relation to the established concepts of traditional and electronic word of mouth, highlighting similarities and differences between these WOM types and deriving guidelines for future WOM research. We also offer implications for managers of experiential media products and other products whose distribution strategy involves a hyped release.

The concept of microblogging word of mouth (MWOM): What it is and what we know about it

One of marketing's law-like generalizations states that WOM communication is a key information source in consumer decision making (e.g., Arndt 1967; Godes and Mayzlin 2004). Over the years, technological innovations have created new conversation channels that have deeply affected how consumers communicate with one another (e.g., Godes et al. 2005). The characteristics of each conversation channel shape how, when, and what type of WOM is used (Berger and Iyengar 2013).

Existing research has focused on traditional word of mouth (TWOM) that is exchanged face to face between consumers (e.g., Arndt 1967) and on electronic word of mouth (EWOM) in the form of posts on Internet forums, websites, or blogs by consumers who are mostly unknown to readers (e.g., Hennig-Thurau et al. 2004). The rise of real-time interactive social media channels, fueled by the rapid diffusion of mobile devices, has introduced MWOM as a new type of WOM.

We define MWOM as *any brief statement made by a consumer about a commercial entity or offering that is broadcast in real time to some or all members of the sender's social network through a specific web-based service* (e.g., Twitter). Little is known about how this new type of WOM affects consumer behavior and product success as empirical research on MWOM is still in an early stage.

To date, only three studies have investigated the link between Twitter metrics and movie revenues, but none test the Twitter effect,' which captures the impact of the valence of MWOM messages on the early adoption of new products. Asur and Huberman (2010) find the volume of pre-release tweets about 24 movies to predict the movies' opening weekend success, but they do not consider the role of Twitter valence in this early adoption context. In a separate analysis, they add a valence ratio measure and study its role for the second weekend box office, finding it to be predictive. However, they do not control for other important variables that influence movie success, such as advertising spending. Wong, Sen, and Chiang (2012) link Twitter valence metrics to the total box office revenues of 34 movies, but they include only positive tweets in their analysis. They find that these tweets do "not necessarily translate into predictable box office" (p. 6) results. In addition, like Asur and Huberman (2010), they do not control for other movie success drivers. Finally, Rui, Liu, and Whinston (2013) model the link between tweet metrics and revenues over the lifecycle of 63 movies and find effects for tweet volume and valence measures on weekly box office. Because the authors look at the movies' entire lifecycle (instead of early adoption) and do not control for other information sources, it remains unclear what portion of the observed effect can be attributed to MWOM.

In summary, the limited prior research on MWOM is fragmented and has produced an unclear picture of the effects of MWOM and especially MWOM valence on new product success. No research has yet studied the impact of MWOM valence on early adoption—the context in which the Twitter effect has been argued to take place.

Why MWOM could affect early adoption

The immediacy of MWOM enables consumers to share product evaluations with a large social network in real time, which might influence product success at a point at which other WOM product evaluations have traditionally been scarce. We investigate whether we can expect MWOM to influence early product adoption, and whether this influence can be expected to differ for positive and negative MWOM.

MWOM and early product adoption

At the release of a new experiential media product, consumers face an information asymmetry as a result of the unavailability of quality-related information from other consumers and their dependence on producer-provided quality signals (Akdeniz and Talay 2013; Kirmani and Rao 2000).[2] MWOM reduces this information asymmetry by enabling the immediate spread of evaluative messages from early consumers who have experienced the new product. As a result, quality judgments articulated by consumers through MWOM can affect other consumers' product adoption decisions very early in a new product's life, namely when consumers have been able to experience the product and assess its quality.

We thus expect positive MWOM quality judgments that are articulated after experiencing a new product (hereafter, MWOM reviews) to increase a receiver's preference for the product, whereas we expect negative MWOM reviews to reduce such preference, in line with the results

[2] The only neutral quality-related information that has traditionally been widely available for consumers at the release of a new product is expert reviews (such as movie reviews by professional movie critics). However, there is extensive empirical evidence that such reviews have limited informational value for consumers (Eliashberg and Shugan 1997).

of research on other types of WOM (Arndt 1967; Chevalier and Mayzlin 2006). These preference changes should translate into adoption behavior, such that a new product's early adoption should increase as a function of early positive MWOM reviews and decrease as a function of early negative MWOM reviews. Investigating the effect of MWOM valence on early adoption empirically is particularly interesting because the few existing studies that use Twitter data do not show a clear pattern regarding the effect of tweets' valence on product success, as discussed previously.

Differential effects for positive and negative MWOM

Research on WOM has reported differential effects for positive and negative WOM, predominantly finding that negative WOM is more influential (e.g., Chakravarty, Liu, and Mazumdar 2010). If MWOM valence matters, does such a "negativity bias" also exist for MWOM? The only study that considers the influence of positive versus negative Twitter data does not report differing effect sizes (Rui, Liu, and Whinston 2013). Nevertheless, we expect a negativity bias for MWOM in the context of early adoption in line with existing WOM research, with that bias being further fueled by the context of early adoption.

Arguments for such a negativity bias of MWOM come from diagnosticity of information and prospect theory. Regarding diagnosticity of information, negative information runs counter to consumers' expectations, such that negative messages have a higher diagnostic value for consumers (e.g., Kanouse and Hanson 1972; Chen, Wang, and Xie 2011). Because negative MWOM is rare in the marketplace (positive MWOM messages tend to outnumber negative MWOM messages; see Rui, Liu, and Whinston 2013), this argument should apply to MWOM. The second line of reasoning is based on Kahneman and Tversky's (1979) prospect theory and argues that people assign more importance to negative versus positive information in general (Kanouse 1984). In the context of WOM, consumers are more concerned about ensuring that they do not suffer from an unwise product choice than they are about benefiting from a wise choice (Luo and Homburg 2008); therefore, consumers should be more influenced by negative MWOM.

The negativity bias should be particularly strong in the early adoption context studied in this research because consumers already carry a predisposition toward the adoption of new experiential media products upon their release. For such products, the majority of consumers have made their adoption choices before the release based primarily on the producer's marketing efforts and the "buzz" to which these marketing efforts have contributed. In fact, 92 percent of moviegoers reportedly make their movie choices at least two days before going to the theater (*Stradella Road* 2010). Thus, very early positive MWOM reviews (i.e., reviews that are consistent with marketing information) reinforce the choices of the majority of consumers and can only influence the new adoption decisions of a small group of consumers who have not chosen in advance. In contrast, very early negative MWOM messages can influence all consumers' adoption decisions, even changing predetermined choices, as a result of the diagnosticity of information and prospect theory arguments made above.

Testing the Twitter effect: MWOM's impact on the early adoption of movies

Context, research design, and sample

We now report the first empirical test of the Twitter effect, investigating whether positive and negative MWOM reviews affect early adoption behaviors and whether the strength of the effect of MWOM differs between positive and negative reviews. We conducted our analysis in the context of the movie industry because movies are an economically important category of experiential media products featured in the Twitter effect debate and because data on daily revenues and important controls (e.g., advertising spending) are available. Because we are interested in early product adoption, we focus on the revenues generated during the first three days of a movie's release (i.e., the "opening weekend").

Specifically, because movies are generally released in theaters on Fridays in North America, we collected the positive and negative MWOM reviews sent within the first 24 hours after each movie's release and examined whether these reviews influenced the share of opening weekend revenues generated by the movie during the remainder of the weekend (i.e., Saturday and Sunday). We collected such MWOM data on all movies that were widely released in North American theaters (i.e., that were shown simultaneously in more than 800 theaters at their release) between October 2009 and October 2010. We focused on wide releases because their economic success depends in particular on the success of the opening weekend; these films accounted for 98.4 percent of opening weekend revenues and 97.5 percent of total revenues generated in this time frame. We excluded 11 titles that were released on different days of the week to avoid any possible bias.[3] The final sample consists of 105 movie titles.

This research design allowed us to isolate the impact of MWOM reviews on early adoption, whereas other types of WOM for new movies require more time to spread on a large scale. During the period covered by our data, even popular EWOM sites such as the Internet Movie Database (IMDb) did not report consumer opinions before Monday. We provide empirical support for this argument through post-hoc analyses in which we include different EWOM valence measures in the analyses.

Model, variables, and measures

Model and variables The dependent variable is the percentage of North American opening weekend box office revenues generated by a movie on the Saturday and Sunday of its release

[3] Technical issues caused by the Twitter application programming interface (API) lead to the exclusion of 12 additional movies; we were unable to collect all tweets for them on the release day.

weekend. To capture the effect of very early MWOM reviews, the core concept of this research, we included three variables: (1) the share of consumers who saw a new movie on its Friday release day and sent a positive MWOM review about it within 24 hours (hereafter, PMWOM share); (2) the share of consumers who saw a new movie on its Friday release day and sent a negative MWOM review about it within 24 hours (hereafter, NMWOM share); and (3) the ratio of positive to negative MWOM reviews for a movie sent within 24 hours of its Friday release (MWOM ratio). We also included the total number of tweets sent within 24 hours of a movie's Friday release as a measure of MWOM volume.

We included a number of control variables to rule out alternative explanations and confounding effects. Our choice of controls was inspired by extant movie research; however, because our dependent variable was a percentage measure instead of the absolute revenue measure that is generally used in this research, we included only those variables for which a differing impact on Friday versus Saturday/Sunday revenues could be theorized. Specifically, we considered a movie's pre-release buzz (e.g., Karniouchina 2011) and whether a movie was a sequel (e.g., Hennig-Thurau, Houston, and Heitjans 2009) or an adaptation of a book or play (Joshi and Mao 2012). Because these variables build or reflect the hype for a movie that is relatively stronger on the release day, we expected them to exert a stronger influence on Friday revenues and thus to have a negative impact on our dependent variable.

In addition, we included a movie's production budget (Basuroy, Chatterjee, and Ravid 2003), its star power (Elberse 2007), and whether the movie was produced by a major Hollywood studio (e.g., Kim 2013). We expected positive parameters because these variables signal the artistic value of a movie and thus should primarily influence mainstream (rather than opening night) audiences. We used an age rating measure to capture whether a movie was considered to be appropriate for younger audiences by the Motion Picture Association of America (MPAA), as reflected by a rating of G (“general audiences – all ages admitted”) or PG (“parental guidance suggested – some material may not be suitable for younger children”). We expected this variable to have a positive impact on our dependent variable because families are known to prefer Saturday and Sunday screenings over the opening night.

Other controls were movie ratings by professional critics (e.g., Basuroy, Chatterjee, and Ravid 2003), popular genres (e.g., De Vany and Walls 1999), and the pre-release advertising spending for a movie (e.g., Elberse and Eliashberg 2003). The effects of these variables were difficult to anticipate. Critics’ reviews are typically published shortly before or on the day of a movie’s release and could thus influence both the release day and subsequent days. For most genres, arguments could be made for greater attractiveness either on the release day or during the remainder of the weekend. Similarly, advertising for a movie can target opening night audiences, but also those who attend theaters the following days.

To address established relationships among the control variables and to avoid multicollinearity, we conducted two auxiliary regressions. The first auxiliary regression accounts for the fact that advertising spending for movies is a function of a movie producer’s expectations regarding the success of the film to be advertised. Because the producer’s success-related expectations are unobservable, we used advertising spending as the dependent variable and the production budget (which reflects a producer’s success-related expectations and is determined simultaneously with them) as the independent variable. The residuals of this regression were used in the main analyses as a measure of advertising spending.[4] The second auxiliary regression accounts for the influence of a movie’s pre-release buzz on MWOM volume on the release day.

[4] The resulting regression equation was as follows: advertising spending = 9,570.15 + 262.72 × production budget - .76 × production budget^2, with $R^2 = .53$. The coefficient was significant at $p < .01$.

In this case, we used MWOM volume as the dependent variable and pre-release buzz as the independent variable. The residuals of this regression were used as MWOM volume measure in the main analyses.[5]

Equation 1 shows the final model. We log-transformed those variables that were heavily skewed (i.e., the production budget and advertising spending) to approximate a normal distribution, consistent with extant research on WOM and movies (e.g., Chevalier and Mayzlin 2006; Gemser, Leenders, and Weinberg 2012):

$$\begin{aligned} SAT/SUN\_REVPERC_m = {} & ß_0 + ß_1 PRBUZZ_m + ß_2 SEQUEL_m + ß_3 ADAPT_m + ß_4 LN(BUDGET_m) \\ & + ß_5 STARS_m + ß_6 STUDIO_m + ß_7 G/PG\_RAT + ß_8 CRIT_m + ß_9 LN(PRADV_m) + ß_{10} GENRE_m \\ & + ß_{11} PMWOM_m + ß_{12} NMWOM_m + ß_{13} MWOMRATIO_m + ß_{14} MWOMVOL_m + \varepsilon \end{aligned} \tag{1}$$

$SAT/SUN\_REVPERC_m$ is the percentage of a movie *m*'s opening weekend North American theatrical box office revenues generated on Saturday and Sunday of that weekend, $PRBUZZ_m$ is the amount of pre-release buzz for movie *m*, $SEQUEL_m$ (a dummy) indicates whether a movie is the sequel to an earlier movie, $ADAPT_m$ (a dummy) indicates whether a movie is the adaptation of a book or play, $BUDGET_m$ is movie *m*'s production budget in US \$, $STARS_m$ (a dummy) indicates whether one or more major star actors or actresses play a leading role in movie *m*, $STUDIO_m$ (a dummy) indicates whether movie *m* is produced by a major Hollywood studio, G/PG_RAT_m (a dummy) indicates whether a movie *m* is appropriate for younger audiences, $CRIT_m$ is the quality assessment of the movie *m* by a set of professional critics, $PRADV_m$ is movie *m*'s pre-release advertising spending in US \$ (the residual term of an auxiliary regression with $BUDGET_m$), and $GENRE_m$ is a vector of nine major genres (all dummies). $PMWOM_m$ is

[5] The resulting regression equation was as follows: MWOM volume = 321.25 + 22,546.59 × pre-release buzz, with $R^2 = .54$. The coefficient was significant at $p < .01$.

PMWOM share, $NMWOM_m$ is NMWOM share, $MWOMRATIO_m$ is MWOM ratio, and $MWOMVOL_m$ is MWOM volume, all as defined above.

Measures In Table 1, we provide a description of all variables included in our empirical model, their operationalization, their empirical sources, and exemplary studies if applicable. We provide additional details about the operationalization of the MWOM concepts below.

--------------*Table 1 approx. here*--------------

With regard to *PMWOM* and *NMWOM*, we collected all English-language MWOM messages sent via Twitter during the respective opening weekends of the 105 movies in our dataset. We used Twitter messages as a proxy for MWOM messages in general because Twitter was by far the largest microblogging platform when we collected our data; the service is regularly used as a synonym for microblogging in general (Anamika 2009). Twitter allowed us to download all of the tweets shared about a movie during its opening weekend in real time by granting us extended access to their application programming interface (API). This access was essential because for major movies, the amount of Twitter chatter often drastically exceeds the API's normal download limits; no other study has reported a similar rights extension.

Each week from October 2009 to October 2010, we developed a list of search terms for movies that were due to be released on Friday of the respective week. One author generated an initial set of search terms based on an extensive manual Twitter search, which was then discussed jointly to ensure its completeness. Up to 10 search term combinations were considered per movie, taking into account Twitter-specific acronyms and exclusion words. These search term combinations were then manually entered into a script that automatically downloaded all tweets containing the specified search term combinations throughout the opening weekend, beginning on Friday at 10:00 a.m. Eastern Daylight Time (EDT) and ending on Sunday at midnight EDT. Overall, we collected 4,045,350 tweets about the 105 movies in our sample. Our extended access rights ensured that these tweets included all English-language MWOM messages sent via Twitter about the movies in our sample. Although it was impossible to collect information about the number of followers per tweet because of Twitter's privacy policy at the time, the Max Planck Institute (2011) has estimated that the average number of followers per Twitter user is approximately 45, which suggests that the tweets in our sample could have reached approximately 182 million consumers.

Because our approach required us to identify MWOM reviews and to separate positive reviews from negative ones, we ran a multistage sentiment analysis to determine the valence of the individual tweets. Before the actual analysis, we eliminated all tweets with identical content by the same author and those tweets not written in Latin script. The subsequent sentiment analysis involved two steps. First, all remaining tweets were sorted into one of three groups: (1) spam, non-English tweets, and tweets not related to the movie in question; (2) movie-related tweets that contained no post-consumption quality assessment (mostly anticipatory statements that express buzz, e.g., "I look forward watching *MOVIE A* tonight"); and (3) review tweets, our group of interest. Second, we divided the third group into positive and negative reviews using sentiment analysis.

The analysis was executed simultaneously for all movies using the open-source data mining software WEKA (Hall et al. 2009). Initially, we manually coded 51,000 randomly selected tweets into the different aforementioned groups. This time-consuming task was accomplished by human coders who read the tweets and coded them with regard to their content and, for review tweets, their sentiment. Regarding the latter, coders were asked to determine whether a tweet was predominantly positive, indicating that the sender liked the respective movie, or predominantly negative, indicating that the sender did not like the movie. A total of five coders were used; the coders were all master's degree students of media studies/media management at a public research university and were extensively trained for the task by one of the authors. Using 65 percent (i.e., 33,150) of these coded messages as input, we trained the algorithm of a support-vector machine (SVM) to build a model to classify cases into the different groups named above. The manually coded tweets were decomposed into their elements (i.e., single words and word groups), and these elements were used to calibrate the model by identifying each element's discriminatory power (i.e., whether an element helped to discriminate among the different groups of tweets).

More formally, a vector was assigned to all words and word groups and mapped into a multi-dimensional space. Next, the SVM fitted a hyperplane that divided all training points (i.e., vectors) into two classes such that it maximized the distances between the hyperplane and the nearest training points. The SVM then identified those words and word groups whose vectors showed the greatest distance from the hyperplane and assigned a parameter to each, indicating the strength of association with a particular category. The words and word groups with the highest discriminatory power were used for further analysis (Pang, Lee, and Vaithyanathan 2002).

To determine the predictive power of this classification, we ran an out-of-sample test with the remaining 35 percent (i.e., 17,850) of the manually coded tweets that had not been used to calibrate the model. These tweets were classified as positive and negative reviews with an accuracy level of 90.2 percent—higher than most other studies that use sentiment analysis to code consumer comments (e.g., Das and Chen 2007), which may be a result of the brevity of MWOM messages.

We then applied the SVM to classify all other (non-coded) tweets. Using the sequential–minimal–optimization algorithm, the SVM searched for the previously identified words and word groups in each of these tweets. The previously determined parameters of the recognized words and word groups were used to calculate the degree to which each tweet was associated with the different groups, resulting in the final classification of all collected tweets (Platt 1999).

Model estimation

We used ordinary least squares regression to estimate Eq. 1. We used a blockwise approach for entering variables to learn whether adding variables increased the model fit significantly. The first block consisted of the control variables *PRBUZZ, SEQUEL*, *ADAPT*, *BUDGET*, *STARS*, *STUDIO*, *G/PG_RAT*, *CRIT*, and *PRADV*. The second block was composed of the *GENRE* vector; for this block, we used a stepwise mode for entering variables to account for the limited number of data points. The third and final block consisted of the MWOM variables, namely *PMWOM*, *NMWOM*, *MWOMRATIO* and *MWOMVOL*.

Results

Descriptive statistics

Of the approximately four million tweets that we collected, 829,576 were classified as MWOM reviews. The number of MWOM reviews per movie varied; the mean was 38,527. Consistent with previous insight into MWOM, there were clearly more positive than negative review tweets (the positive-to-negative ratio was 8.2). Figure 1 depicts the number of movie-related tweets sent throughout the opening weekend. Friday was the most active day in terms of MWOM; approximately 65 percent of MWOM reviews were sent from Friday through the following

Saturday until noon. During the three days of the opening weekend, MWOM reviews peaked at approximately 11:00 p.m. EDT, which indicates that the majority of MWOM reviews are sent shortly after the show. Table 2 reports basic descriptive statistics and correlations.

--------------*Figure 1 and Table 2 approx. here*--------------

Model fit

The overall model fit when estimating Eq. 1 with *SAT/SUN_REVPERC* as the dependent variable was good. The R-square (adjusted R-square) was .56 (.52) after the first block. No genre was added from the second block. The addition of the MWOM variables as the third block led to an additional increase in explained variance of 5.0 percentage points (significant at $p < .05$), so that the R-square (adjusted R-square) was .61 (.56). Multicollinearity was below critical thresholds; the variance inflation factors (VIFs) for *PMWOM* and *NMWOM* were below 4, and no other VIF was above 2.[6]

Findings

Table 3 reports the results for the estimation of Eq. 1. We find a negative and significant impact of *NMWOM* on *SAT/SUN_REVPERC*. However, although the direction of *PMWOM* on *SAT/SUN_REVPERC* is positive as proposed, the parameter is not significant. In other words, whereas negative Twitter reviews shared on a movie's opening day decreased the movie's revenues on Saturday and Sunday, we cannot claim that positive Twitter reviews shared in the same time frame translated into higher revenues in the next two days. The *MWOMRATIO* variable was insignificant, explaining no variance above and beyond the two percentage measures of *PMWOM* and *NMWOM*. *MWOMVOL* was marginally significant ($p = .063$) with a

[6] An analysis with the unadjusted *MWOMVOL* variable instead of the residuals from the auxiliary regression produced the same results. The only difference was that the VIFs for *MWOMVOL* and *PRBUZZ* were higher. We treated this result as support for the superiority of the used specification.

negative coefficient. Along with other facets of buzz and being a sequel or adapted from a book or play, *MWOMVOL* tends to bias a movie's opening weekend revenues toward the first day.

The parameters for the other controls are mostly as expected. A higher production budget and a less restrictive MPAA rating increase the percentage of opening weekend revenues that are generated on Saturday and Sunday; star power has a positive sign but is non-significant. All other variables (i.e., genres, critics, stars, major studio, and advertising) do not significantly affect the distribution of box office revenues during the first weekend.

--------------*Table 3 approx. here*--------------

To determine the relative strength of the effects of positive and negative MWOM reviews, we conducted a Wald test to compare the absolute size of the regression parameters of *NMWOM* and *PMWOM*. This test constrains the parameters to equality and uses a nested *F*-test to ascertain the resulting change in the model's R-square (Judge et al. 1985). In our case, the *F* value for the comparison is 5.38, which is significant at $p < .05$. We conclude that the effect of negative MWOM reviews dominates that of positive MWOM reviews.

To provide empirical support for our argument that the Twitter effect is based on information that is available through MWOM, but not through other WOM channels at this early point of a movie's release, we replicated our regression analysis by adding proxies for EWOM valence. Specifically, we added the movies' user ratings from IMDb, Netflix, and Yahoo to the model; all three variables are regularly used indicators of EWOM valence (we conducted separate analyses for each proxy to avoid multicollinearity). As we report in the Appendix, none of these EWOM proxies turned out to be significant, and all MWOM variables remained unchanged in all replications, which is in line with our theoretical arguments.

Simulations: What is the size of the impact of MWOM reviews?

To develop a better understanding of the monetary implications of the impact of MWOM reviews on early adoption, we ran different simulation analyses for the opening weekend. In these simulations, we used the regression coefficients from the estimation of Eq. 1 to calculate, for each movie *m* in our dataset, the impact that a higher and lower share of negative MWOM reviews would have on: (1) the movie's percentage of Saturday and Sunday opening weekend revenues, and (2) absolute revenues.

We did not perform any simulations for positive MWOM reviews because of the *PMWOM* coefficient's lack of significance. In all cases, we assumed that all other movie characteristics remain unchanged, modifying only the *NMWOM* parameter. Table 4 presents the relevant summary statistics, showing sample averages and extreme values for different scenarios, including a reduction of 50 percent and 100 percent of an individual movie *m*'s share of *NMWOM* reviews of opening day attendances, an increase of 100 percent, and the sample-maximum of *NMWOM*.

--------------*Table 4 approx. here*--------------

Consider the example of the movie *Nightmare on Elm Street*, which generated US $15.7 million on its release day but was also the subject of 1,592 negative review tweets on that day. Our simulations show that with only half of the negative review tweets, the movie's share of opening weekend revenues generated on Saturday and Sunday would have been +1.3%, which translates into additional revenues of US $1.43 million (+ 3.46%). If there had been no negative tweets about the movie (i.e., *NMWOM* share = 0), *Nightmare* would have generated additional revenues on its opening weekend of US $2.96 million or + 8.17%.

Regarding all movies in the dataset, we find that both higher and lower NWOM shares considerably affect opening weekend success. An *NMWOM* share of .24 (the maximum value found in the sample) leads to an average box office reduction of nearly 15 percent, or \$3.5 million, whereas the absence of *NMWOM* increases the average box office by 4.3 percent, or more than \$1 million (and up to \$6.6 million for a single film). These numbers illustrate that the effect of negative MWOM reviews for movies is not only statistically significant but also of financial relevance, particularly when considering the continuing growth of microblogging platforms, which suggests the absolute number of MWOM reviews will increase—and with it the share of *NMWOM*.

Toward a richer understanding of MWOM's impact on early adoption

Our analysis of MWOM messages sent via Twitter provides evidence that negative MWOM reviews about a movie affect its early adoption. To better understand this effect and the role of MWOM within the decision-making process, we conducted an incident study with consumers who had personally refrained from watching a movie in a theater because of tweets received. We used data from an online survey of U.S. consumers who are active Twitter users. Survey participants were drawn from a representative panel of U.S. consumers operated by a global market research company. We used a combination of closed-ended and open-ended question formats; we employed closed-ended questions for behavioral and demographic information, whereas open-ended questions were used to gather information about consumer decision making and motivations that are unobservable in general.

The survey requested a description of the tweet that influenced the respondent's decision and the situational context (e.g., sender, movie, previous information), followed by questions regarding the respondent's reaction to the tweet, why the tweet made the respondent change his/her mind, and what the role of tweets was in general in the respondent's choice process. We also asked questions regarding the respondent's demographics, Twitter profile, and the role of negative versus positive tweets. We used a coding procedure to analyze the qualitative data collected via the open-ended questions.

Of the 1,545 consumers invited to participate via email, 1,489 were active Twitter users; 698 (or 47 percent) could remember a recent incident during which a tweet had prevented them from watching a movie in the theater that they had planned to see. Ninety-eight of those consumers were unable to recollect the incident in detail (i.e., naming the movie, describing the tweet's text) and were dropped, resulting in a final sample of 600 respondents. The majority of respondents referred to an incident that occurred within the previous month (mode = one month); the median of the time difference between the survey and the incident was two months.

We now report insights derived from this incident study that shed light on: (1) the characteristics of those consumers who are influenced by the Twitter effect, (2) the reasons for the importance of negative MWOM, (3) the role of MWOM within consumers' decision-making processes, and (3) the MWOM characteristics that consumers hold responsible for its relevance.

Who is influenced by negative MWOM?

Our sample resembles both the overall population of U.S. moviegoers and Twitter users in general in that the sample is skewed toward younger consumers (*MPAA* 2012; Bennett 2013). Thirty-one percent of the respondents are younger than 30 years, and 41 percent are younger than 35. However, similar to moviegoers and Twitter users in general, there is also a substantial share of older respondents who have experienced the Twitter effect; of our respondents, 46 percent are 40 years or older, and 28 percent are 50 years or older.

We find the respondents to be active in terms of their Twitter usage when compared to the average Twitter user (*beevolve* 2012). Respondents send out an average of 53 tweets per week, compared to a user average of 3.5 (Smith 2013). Whereas only 19 percent of Twitter users have more than 50 followers (mean = 208), this applies to 55 percent of the respondents (mean = 330;

median = 72); our respondents also follow more users (62 percent follow more than 50 users; mean = 344; median = 100) than the average Twitter user does (only 26 percent do so). The respondents consider their network to be well informed regarding movie-related topics; on a 7-point scale, 85 percent rate their networks' movie expertise as 5 or higher (mean = 5.6).

Those affected by the Twitter effect also characterize themselves as being strongly interested in movies (mean = 6.4 on a 7-point scale), with 79 percent attending the movies at least once per month. The respondents attend early when a new movie is released (i.e., at a point in time when only limited other information via TWOM and EWOM regarding a new movie's quality is available); of the respondents, 49 percent generally see a movie during its opening weekend, and an additional 31% attend during its first week.

Why is negative MWOM particularly influential?

We proposed different arguments regarding a negativity bias in the context of MWOM. In our follow-up incident study, we examined respondents' perception of these reasons. Specifically, we suggested one item for each explanation (i.e., information diagnosticity and prospect theory) and one 'other reason item; respondents could agree with as many of these items as they desired. Additional insight on this issue came from the respondents' description of Twitter's role within the adoption decision-making process.

Sixty-seven percent of the respondents agreed that the higher diagnosticity of negative information (item: "Because negative tweets stand out from all the positive marketing information about a movie") was a reason for its stronger influence. Several open-ended comments from respondents stressed the limited information potential of movie advertising and the role of critical tweets (e.g., "I watch the online trailers and reviews on movies but they are usually really positive so I need to balance that with reactions from real people!"). Negative tweets are also described by respondents as more “honest” and as “not having an agenda.” These responses are in line with negative MWOM messages as rarer and diagnostic.

In addition, 63 percent of the respondents agreed that the costs of making the wrong decision (item: “Because I would hate to waste my time watching a bad movie”) are a primary reason for being more strongly influenced by negative tweets, offering support for the relevance of prospect theory in the context of negative MWOM. Again, various statements from respondents supported this idea, showing that respondents were more concerned about ensuring that they do not suffer from a bad movie than they were about missing out on a good movie choice (e.g., “If there [are many], especially negative, [tweets] I start to wonder if I should even bother wasting my time and money when I can just wait for it to come out later on a movie channel through my satellite company”). These reasons explained the negativity bias well; only 2 percent indicated other reasons.

How does MWOM influence consumers’ early adoption decisions?

To contextualize the Twitter effect, we asked respondents about the information that had initially made them want to see a movie before Twitter feedback changed their minds. Using a closed-ended question (“Why did you want to see this movie in the first place?”) with multiple answer categories to which respondents could agree, respondents said they had planned to see the chosen movie based on a trailer (65 percent) and/or pre-release online buzz (28 percent), and/or because friends or family wanted to see the movie (28 percent). More than half (53 percent) of the respondents had planned to see the movie during the opening weekend, indicating that MWOM is most influential for *early* adoption decisions, as examined in this research.

To enable respondents to recall the decision situation, we asked them to write down the approximate content of the tweet that changed their mind. The majority of tweets contained a clear evaluation of whether the movie was worth the time and money to see (e.g., “A waste of time and I can't even get my money back #Screwed"), and several linked the movie to advertising efforts (e.g., "We are the Millers was stupid and was a waste of my time. The trailer was more exciting!"). To learn about respondents' reactions to the tweet, we used a closed-ended question ("How did you react to this tweet?") in which respondents had to choose the answer that was most appropriate for them. Nearly half (44 percent) of respondents took the tweet at face value, changing their decision based on the tweet without any further discussion or research. In 26 percent of the cases, the negative tweet triggered a conversation about the movie on Twitter, whereas the remaining 31 percent decided to search for additional movie evaluations. Instead of watching the movie in question, 36 percent of respondents watched another movie in the theater instead; others stayed at home to watch a downloaded/rented movie (23 percent).

To better understand how respondents use MWOM when making movie choices, we asked an open-ended question and content analyzed and coded the answers. Specifically, one author developed a classification scheme and a set of codes, which were then discussed by co-authors until agreement on a final scheme was reached. Two coders examined all responses and classified them into a dominant category.[7] We learned that the majority of respondents combine information from multiple sources, particularly different WOM sources, to form an opinion regarding the quality of a new movie.

Specifically, we identified four ways in which Twitter is used in the decision-making process. First, numerous respondents consider Twitter to be a "first resort" for movie information (e.g., "I usually watch movie trailers. When the movie comes out and others have watched it I use Twitter to see what they think before I purchase a ticket"). Respondents either actively ask their

[7] Of the responses, 105 were too short or general and were thus not classified. Inter-coder agreement was 90.4 percent for the MWOM characteristics and 98.0 percent for the ways in which Twitter is used in the decision-making process. The two coders discussed each case in which they disagreed until they reached an agreement on the classification.

Twitter network for information about a particular movie (e.g., “I put the topic out there and get feedback”), or they search to determine whether someone in their network has tweeted about the movie (e.g., “to check other followers if they have seen a movie that is worthwhile”).

Second, multiple respondents resort to Twitter when undecided about whether to see a particular movie, using MWOM as a “tool to sway.” One respondent described this way as follows: “Twitter comes into play on movies I'm not sure about seeing—I use the opinions of people who have seen it as a final tool.” Because the majority of pre-release information about movies is positive, this particular way of usage offers an explanation of negative MWOM’s power to change (predetermined) decisions, serving as a counter weight for positively biased advertising.

Third, several respondents mention Twitter as a “fallback option” for movie information. They look for MWOM when they cannot find any other information about the movie, as exemplified by the following statement: “[I use Twitter] when I don’t know anyone who has seen movie and cannot find any info online or professional websites.” This approach underscores the exclusive availability of movie evaluations via Twitter at a point in time when limited or no other consumer evaluations are obtainable.

Fourth, a number of respondents also report noticing movie-related tweets from their Twitter connections, even though they were not particularly seeking movie information (e.g., “a friend went and saw and tweets about it”). This way of usage differs from the previous three, in that the use of Twitter is not directly linked with the decision to watch a specific movie. Instead, the information obtained via Twitter unintentionally affects the respondent’s decision-making process.

What characteristics of MWOM make it influential?

The ways in which Twitter is used in the decision-making process are linked with particular characteristics of MWOM that set this type of WOM apart. To learn more, we used the qualitative coding approach described above to identify defining characteristics of MWOM.

First, respondents emphasized that MWOM via Twitter provides access to real-time product evaluations from consumers who have actually experienced the product. Some respondents stressed the immediacy of the channel (e.g., Twitter "is usually a good information source because you get information in real time"), whereas others highlighted the type of information that is transmitted at that very early point in time (e.g., Twitter "allows me to see what people who have seen a movie rate it"). A related aspect is the ease of accessibility of the information from mobile devices, which enables consumers to obtain information whenever and wherever they are interested, including the waiting line at the theater (e.g., Twitter "is mobile and easy to read and super fast"). This access to real-time consumer evaluations is valued even by respondents who usually base their decisions on critics' reviews; these respondents take Twitter into account when critics' reviews are not (yet) available.

Second, MWOM via Twitter allows respondents to obtain interesting information without proactively seeking it. Respondents suggest that this passive information receipt (or push) characteristic makes MWOM stand out from EWOM on review websites and from professional reviews, which require the consumer to actively search for them. This characteristic is closely linked with the fourth, more passive method of Twitter usage mentioned above, as evident in the following statement: "I usually do not seek information, but if I notice something on Twitter, I will read it and take it into account."

Third, respondents cite MWOM's ability to have a conversation and ask for feedback as a major factor for its impact on their decisions. In another difference from EWOM, Twitter combines its push element with an active search (or pull) characteristic, a synchronicity that enables consumers to proactively ask their network for feedback, in our case on a particular movie (e.g., “I go to Twitter and ask people who actually saw the movie”).

Fourth, respondents consider their personal connections with the senders of messages as a reason for MWOM’s relevance. Numerous statements reflected the respondents’ trust in the opinions of their Twitter network, as exemplified by the following statement: Twitter “is a perfect way to determine the quality of a movie if you can trust the person's opinion. And I have found a couple of people whose opinions match mine rather well.” This trust in MWOM messages often emanates from the personal relations outside the network: “I mostly listen to feedback from family and friends. Twitter is nice to get information from long-distance friends and family, which are my majority.”

A separate closed-ended question (“Who was the person from whom your received the tweet?”) indicated that 58 percent of tweets that made respondents change their plans were sent by a friend or acquaintance who is also part of the respondent’s offline social network. More surprisingly, trust is not limited to offline relations but generally refers to people whose expertise respondents value (34 percent of decision-changing tweets came from ‘movie experts’), as expressed by the following statement: “I generally trust the recommendations from a select group of people who I know like quality movies. If I am not sure about the plot of the movie, I usually ask my followers' help in deciding whether I should go see it.” The fact that consumers have chosen whom to follow lays the groundwork for their trust in these connections and the impact of MWOM; thus, it is no surprise that 57 percent of the decision-changing tweets came from someone with whom our respondents interact frequently or whose tweets respondents find to be interesting in general.

Finally, respondents commented positively on the brevity of MWOM messages, suggesting that this brevity, instead of reducing the message's informational content, made it easier to digest the information. This observation is expressed in the following respondent statement: "Twitter connects me to people who have seen the movie or experienced something and lets me read what they thought about it in a simple way without having to read a whole article."

Discussion and implications

This research empirically tests the "Twitter effect" of MWOM on the early adoption of new products for a dataset of 105 movies. We find an effect for negative MWOM reviews on early adoption (i.e., the remainder of the opening weekend), but not for positive MWOM reviews. The parameter for negative MWOM reviews dominates that of positive MWOM reviews, indicating a negativity bias for MWOM.

We complement this product-level analysis with an incident analysis on the consumer level, which sheds light on the processes underlying the Twitter effect and the role of MWOM and its particular characteristics in the decision-making process. We find that MWOM influences the early adoption decisions of active Twitter users in four different ways, based on five particular characteristics that distinguish MWOM from other types of WOM. We now discuss the implications of these insights for WOM scholars and managers of experiential media products.

Research implications

Because marketing research has dedicated relatively little attention to differences between WOM channels, this research supports previous calls for improved understanding of such WOM channel specifics. Despite significant recent growth in the number and heterogeneity of WOM channels, we do not know enough about the way in which the characteristics of each conversation channel shape how, when, and what type of WOM is used and how it influences consumer decision making (Berger 2012; Berger and Iyengar 2013).

The findings of our empirical research demonstrate the distinct influence of MWOM on early new product adoption and shed light on how MWOM's discriminating characteristics influence decision making. These findings enable us to position MWOM in the overall WOM landscape and to identify future research opportunities based on this conceptual positioning. Figure 2 condenses the insights from our survey study, showing the conceptual similarities and differences among MWOM, TWOM, and EWOM.

--------------*Figure 2 approx. here*--------------

As described by the respondents of the survey study, MWOM is characterized by the real-time transmission of quality information and a personal connection between sender and receiver. MWOM enables feedback and combines, for the receiver of information, the possibilities of active search (or pull) and passive information receipt (or push). These aspects are all established elements of TWOM. MWOM does differ from TWOM, however, in that the receiver of a WOM message is not just an individual person or small group but potentially a very large group and in that the information is delivered in written instead of oral form. MWOM shares its large audience potential and the written form with EWOM, but it also differs in several ways: its real-time character (versus asynchronous, as is the case with EWOM), the personal connection (versus the sender usually being personally unknown to the receiver), the lack of summary signals (versus valence and volume signals), its feedback options (versus discrete articulation), and its combination of push and pull (with EWOM being pull only). Finally, the brevity of MWOM mentioned by our respondents is a unique element that is not typical for either EWOM or TWOM, but that contributes to very clear evaluations that are perceived as unequivocal by our respondents.

The unique combination of these characteristics serves as the basis for MWOM's influence on consumers, particularly at the very early stage of a new product's lifecycle. Figure 2 suggests that MWOM is perceived as conceptually closer to TWOM than EWOM, a conclusion shared by several of our respondents who stressed the personal character of MWOM and the trustworthiness of its content. Although this comparison of the different types of WOM is far from definite and based only on explorative insights, we believe our findings can serve as an inspiration for future research by highlighting, among others, the following questions.

Brevity Under which circumstances does the length of WOM information help, and under which does it hurt information dissemination and effectiveness? Chevalier and Mayzlin (2006) found that in the context of EWOM, longer reviews about a book positively influence the book's market share. Pan and Zhang (2011) suggest that the length of EWOM reviews increases perceived helpfulness. Why then is brevity, in the context of MWOM, considered a virtue by consumers?

Personal connection The influential role of MWOM depends on its perception as personal and trustworthy. Existing research has found that especially weak ties provide important and useful information when they are trusted (Levin and Cross 2004). Why do consumers consider themselves as similarly "close" to people they do not know in person as to those they know? In addition, because the majority of these MWOM connections are experts in the field of interest, when and to what extent does the perceived expertise of a person serve as a substitute for homophily in terms of trustworthiness and tie-strength?

Search strategies The participants in our survey reported that they used different strategies regarding MWOM, from passive consumption and systematic screening of one's network to the active asking of questions. Under what circumstances is a particular strategy used, and does the strategy selection differ based on a consumer's personality and the product type? For example, do these strategies differ for experiential versus utilitarian products?

Interaction/feedback The interaction element of MWOM differs from face-to-face interactions by being device-mediated; however, it is unclear how this difference affects consumers' perception of the information provided. One promising avenue to understand how the interaction element of MWOM affects decisions is the concept of media richness, in which interaction and feedback play focal roles. Although media richness has been developed in the pre-Internet age by organization scholars (Daft and Lengel 1986), this concept deserves to be updated and transferred into the WOM context (for a first step to do so, see Dennis and Kinney 1998). Is interactivity particularly important when the length of messages is restricted, as is the case with MWOM?

Push and pull In addition to enabling consumers to search for information, MWOM also acts as a push medium by exposing consumers to information about new products that they might not have been seeking. This push character resembles advertising, which raises a question regarding situations and contexts in which "unwanted" WOM information influences consumers—when are consumers receptive to such information? This question is particularly interesting given Twitter’s relatively recent introduction of “promoted tweets,” which allow advertisers to target advertising messages to consumers based on what topics they have recently tweeted about. Which targeting strategies are the most effective for advertisers?

On a more general level, our research stimulates further investigations into consumers’ usage of different types of WOM and their respective impacts on the decision-making process. When do the different types of WOM influence behaviors? Although our results suggest that MWOM is particularly important when very limited information is available, such as during early adoption, how does the role of MWOM change when more quality information becomes available over time through other WOM channels? Whose behaviors are affected by which channel? We study the Twitter effect for new products that are simultaneously released nationwide, but does MWOM also play a distinct role for smaller-scale product launches? We need to know much more about the interplay among the industry context, the WOM channel, and the time period (short-term/long-term adoption) and its impact on consumer decisions. Such insight could then be used to extend existing diffusion models which do not account for different WOM types (e.g. Mahajan, Muller, and Kerin 1984).

How do consumers perceive sponsored tweets and similar hybrid formats that combine WOM elements with advertising? Such formats did not exist when we collected our movie-level data but are actively promoted by Twitter today. Other changes since our data collection include an earlier availability of consumer reviews on EWOM sites such as IMDb and the growth of the Twitter network. Does earlier EWOM cannibalize or complement the Twitter effect and/or does the growth of Twitter translate into an even stronger effect of MWOM reviews on early adoption?

Managerial implications

This research offers substantial implications for marketing managers, particularly those who are responsible for the success of experiential media products and other products whose distribution includes a hyped release. We provide evidence that early MWOM reviews reduce the information asymmetry between producers and consumers, spreading evaluative post-purchase quality opinions about experiential media products so quickly and widely that they influence consumers’ early adoption behavior to an economically relevant degree.

This reduced asymmetry poses a threat to producers, particularly to those products that consumers perceive as low in quality. Our findings should motivate producers to increase their focus on developing high-quality products that meet consumer needs and to market the products in a way that truthfully reflects their quality, which has not been the norm for some media producers. The need for high-quality products is increased by the negativity bias that we identified empirically, because only negative MWOM reviews exert an impact during the crucial opening weekend. Whereas “bad” products will be hurt by negative MWOM reviews, “good” products do not benefit equally from positive MWOM reviews above and beyond the behavioral predispositions created by pre-release advertising and buzz. Consequently, a producer that releases an equal number of good and bad products will not be compensated for the losses caused by the negative MWOM reviews of the bad products by the positive MWOM reviews that the good products receive.

However, because of the creative nature of experiential media industries, producing only high-quality products is difficult if not impossible. Thus, the rise of MWOM may have even more fundamental implications. The economic viability of the current “blockbuster” business model (which centers on the production of a small number of very expensive blockbuster products) relies on the information asymmetry between producers and consumers upon the release of the new product, because producers cannot afford their products to “flop” even if they are creative failures. For example, a movie such as Walt Disney’s *John Carter* must be successful because of its U.S. $300 million budget; if the movie is not successful, the producer experiences financial pressure (Nakashima 2012). Before the advent of MWOM, this blockbuster model guaranteed the success of releases to some degree, at least for products that were deemed sufficiently interesting to stimulate strong pre-release buzz; however, it is unclear whether this model will continue to be viable now that consumers have access to early MWOM reviews. Although our findings cannot provide a definitive answer, the findings point to the increasing economic risk of employing the blockbuster model.

Which alternative business models might better account for the influence of MWOM? One approach might be for producers to return to the WOM-driven model that was dominant in the media industries until the mid-1970s, when even major productions such as *Star Wars* were released only in a few theaters before being propelled by WOM (*PBS* 2001). Such a model requires the production of more products with smaller budgets rather than the current reliance on a few high-budget films (the inflation-adjusted budget of the first *Star Wars* movie, for example, was only U.S. $40 million). This approach would allow producers to cope more effectively with the consequences of their inevitable occasional failures. Because the revenues of experiential media products are highly unevenly distributed, with a few extreme successes and numerous failures (e.g., De Vany and Walls 1999), a portfolio approach could be implemented in which successful products compensate for the losses generated by creative failures. One of the challenges of using such a model would be the need to create sufficient awareness and demand for a higher number of products despite smaller advertising budgets; however, digital distribution offers extensive ways to connect new films, games, books, and music with consumers. These channels could be employed to support the new model (Parker 2012).

Moreover, our findings suggest that the type of response to the rise of MWOM that is presently favored by media industries (which focuses on sending tweets through media agencies, e.g., Singh 2009b) will be largely ineffective. We find that positive quality information from other consumers has a limited impact and assume this observation to be particularly true for *industry-fabricated* positive quality information, which lacks the characteristics of influential MWOM identified in our incident study. Such information might stimulate buzz if managers are capable of connecting to consumer networks, although its positive valence will hardly motivate consumers to see a movie. Although other scholars have commended this type of focus on positive news (Wong, Sen, and Chiang 2012), our findings indicate that such strategies are misleading and potentially counterproductive.

Instead, marketers should candidly assess an experiential media product's quality and its popularity with the target audience, tailoring their communications strategy accordingly. Our research implies that it would be unwise to focus a low-quality product's campaign on engaging consumers through microblogging channels such as Twitter. Although it is not possible to prevent consumers from sending MWOM messages about their experiences, movie marketers should at least not encourage Twitter engagement if they expect consumers to be disappointed with the new product.

Limitations

A number of limitations should be noted. Although this research takes a first step toward understanding the strategies that consumers use to combine different types of WOM information by identifying four different ways in which MWOM is used by consumers, our focus on early adoption and movies leaves room for studies regarding the role of other WOM sources in other contexts. While our incident study is a good starting point, personal qualitative interviews might go beyond the insights we gathered through the consumer survey and provide an even richer account of how consumers navigate the different information sources at their disposition when making consumptions decisions. Because we focus on negative MWOM in the incident study, the processes related to positive MWOM and its role beyond early adoption should be explored by further research.

In addition, this research does not include the number of followers of the tweet's sender. Empirical findings indicate that such information is of limited relevance (Cha et al. 2010); however, we must find out more about this metric's role. As is usually the case with secondary data, the majority of measures used in our regression analysis are proxies for certain control variables (e.g., Metacritic as a measure of professional reviews); therefore, replications could further investigate the robustness of our analyses using different or additional proxies. This factor is also relevant for the MWOM measures we use; it is unclear to what extent differences exist among specific MWOM platforms and how the inclusion of services other than Twitter might affect the results. Finally, we find that the buzz about a new product biases adoption, reducing the percentage of consumers who adopt the product in the days following the release. Does this effect also stem from disconfirmed consumer expectations, in that industry-triggered buzz leads to inflated expectations that systematically cause a reduction of attendants over time for products with high buzz, or is it a zero-sum game?

References

Ahmad, I. (2013). 30+ of the most amazing Twitter statistics. Retrieved December 16, 2013, http://socialmediatoday.com/irfan-ahmad/1854311/twitter-statistics-IPO-infographic.

Akdeniz, M. B., & Talay, M. B. (2013). Cultural variations in the use of market signals: a multilevel analysis of the motion picture industry. *Journal of the Academy of Marketing Science*, 41, 601-624.

Anamika S. (2009). *Microblogging sites–40 Twitter like websites list*. Retrieved January 19, 2012 http://anamikas.hubpages.com/hub/40-Microblogging-Sites-list-for-Communication-Twitter-Alternatives.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, 4 (3), 291-295.

Asai, S. (2009). Sales patterns of hit music in Japan. *Journal of Media Economics*, 22, 81-101.

Asur, S., & Huberman, B. A. (2010). Predicting the future with social media. *Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, 1, 492-499.

Basuroy, S., Chatterjee, S. & Ravid, S. A. (2003). How critical are critical reviews? The box office effects of film critics, star power, and budgets. *Journal of Marketing*, 67(4), 103-117.

beevolve (2012). *An exhaustive study of Twitter users across the world.* Retrieved January 17, 2014, http://www.beevolve.com/twitter-statistics/.

Bennett, S. (2013). *Who uses Twitter? 16% of internet users, 18-29 year olds, minorities, men more than women* [REPORT]. Retrieved January 17, 2014, http://www.mediabistro.com/alltwitter/twitter-demographics-2013_b36254.

Berger, J. (2012). Word-of-mouth and interpersonal communication: an organizing framework and directions for future research. *Working paper.*

Berger, J., & Iyengar, R. (2013). Communication channels and word of mouth: How the medium shapes the message. *Journal of Consumer Research*, 40 (3), 567-579.

Cha, M., Haddadi, H., Benevenuto, F., & Gummadi, K. P. (2010). Measuring user influence in Twitter: The million follower fallacy. *Proceedings of 4th International AAAI Conference on Weblogs and Social Media*.

Chakravarty, A., Liu, Y., & Mazumdar, T. (2010). The differential effects of online word-of-mouth and critics’ reviews on pre-release movie evaluations. *Journal of Interactive Marketing*, 24, 185-197.

Chen, Y, Wang, Q., & Xie, J. (2011). Online social interactions: a natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, 48 (April), 238–254.

Chevalier, J., & Mayzlin, D. (2006). The effect of word of mouth on sales: online book reviews. *Journal of Marketing Research*, 43 (August), 345-354.

Corliss, R. (2009). *'Bruno': Did Twitter reviews hurt movie at box office*? Retrieved August 17, 2010 from http://www.time.com/time/arts/article/0,8599,1910059,00.html.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, 32 (5), 554-571.

Das, S. R., & Chen, M. Y. (2007). Yahoo! for Amazon: sentiment extraction from small talk on the Web. *Management Science*, 53 (9), 1375-1388.

Dennis, A. R., & Kinney, S.T (1998). Testing media richness theory in the new media: The effects of cues, feedback, and task equivocality. *Information Systems Research*, 9 (3), 256-274.

De Vany, A., & Walls, W. D. (1999). Uncertainty in the movie industry: does star power reduce the terror of the box office. *Journal of Cultural Economics*, 23, 285–318.

Elberse, A. (2007). The power of stars: do star actors drive the success of movies? *Journal of Marketing*, 71(4), 102-120.

Elberse, A., & Eliashberg, J. (2003). Demand and supply dynamics for sequentially released products in international markets: the case of motion pictures. *Marketing Science*, 22(3), 329-354.

Eliashberg, J., & Shugan, S. M. (1997). Film critics: influencers or predictors? *Journal of Marketing*, 61 (April), 68-78.

Funt, P. (2012). Theater for Twits. *The New York Times*, January 8, p. SR2.

Gemser, G., Leenders, M. A. A. M., & Weinberg, C. W. (2012). More effective assessment of market performance in later stages of the product development process: the case of the motion picture industry. *Marketing Letters*, 23 (4), 1019-1031.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word of mouth communications. *Marketing Science*, 23 (4), 545-560.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., & Verlegh, P. (2005). The firm's management of social interactions. *Marketing Letters*, 16 (3/4), 415-428.

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. (2009). The WEKA data mining software: An update. *SIGKDD Explorations*, 11 (1).

Hayes, D. (2002). Tentpoles fade fast after opening ad blast. *Variety Magazine*, August 4, 2002.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer opinion platforms: what motivates consumer to articulate themselves on the Internet? *Journal of Interactive Marketing*, 18 (1), 38-52.

Hennig-Thurau, T., Houston, M. B., & Heitjans, T. (2009). Conceptualizing and measuring the monetary value of brand extensions: the case of motion pictures. *Journal of Marketing*, 73 (November), 167-183.

Hennig-Thurau, T., Houston, M. B., & Walsh, G. (2006). The differing roles of success drivers across sequential channels: An application to the motion picture industry. *Journal of the Academy of Marketing Science*, 34 (4), 559-575.

Ho, J. Y. C., Dhar, T., & Weinberg, C. B. (2009). Playoff payoff: Super Bowl advertising for movies. *International Journal of Research in Marketing*, 26 (3), 168-179.

Joshi, A. & Mao, H. (2012). Adapting to succeed? Leveraging the brand equity of best sellers to succeed at the box office. *Journal of the Academy of Marketing Science*, 40 (4), 558-571.

Judge, G. G., Griffiths, W. E., Hill, R. C., Lütkepohl, H., & Lee, T.-C. (1985). *The theory and practice of econometrics*. 2nd ed, New York: Wiley.

Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, 47 (March), 263-291.

Kanouse, D. E., & Hanson, L. R. Jr. (1972). Negativity in evaluations. In E. E. Jones, D. E. Kanouse, H. H. Kelley, R. E. Nisbett, S. Valins, & B. Weiner (Eds.), *Attribution: Perceiving the causes of behavior* (pp. 47-62). Morristown, NJ: General Learning Press.

Kanouse, D. E. (1984). Explaining negativity biases in evaluation and choice behavior: theory and research. *Advances in Consumer Research*, 11, 703-708.

Kaplan, A. M., & Haenlein, M. (2011). The early bird catches the news: nine things you should know about micro-blogging. *Business Horizons*, 54, 105-113.

Karniouchina, E. V. (2011). Impact of star and movie buzz on motion picture distribution and box office revenue. *International Journal of Research in Marketing*, 28, 62-74.

Kassim, S. (2012). *Twitter revolution: how the Arab Spring was helped by social media*. Retrieved January 11, 2012 from http://www.policymic.com/articles/10642/twitter-revolution-how-the-arab-spring-was-helped-by-social-media.

Kim, M. H. (2013). Determinants of revenues in the motion picture industry. *Applied Economics Letters*, 20 (11), 1071-1075.

Kirmani, A., & Rao, A. R. (2000). No pain, no gain: a critical review of the literature on signaling unobservable product quality. *Journal of Marketing*, 64 (2), 66-79.

Lang, B. (2010). *Study: the 'Twitter effect' does not exist*. Retrieved on October 12, 2011 from http://www.thewrap.com/media/column-post/thegrill-twitter-effect-myth-21035?page=0,0.

Levin, D. Z., & Cross, R. (2004). The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Management Science*, 50 (11), 1477-1490.

Luo, X., & Homburg, C. (2007). Neglected outcomes of customer satisfaction. *Journal of Marketing*, 71 (April), 133-149.

Mahajan, V., Muller, E., & Kerin, R. A. (1984). Introduction strategy for new products with positive and negative word-of-mouth. *Management Science*, 30 (December), 1389-1404.

Max Planck Institute (2011). *The Twitter project page at MPI-SWS*. Retrieved on December 23, 2011 from http://twitter.mpi-sws.org/.

McGee, M. (2012). *Twitter: 60 percent of users access via mobile*. Retrieved on January 22, 2013 from http://marketingland.com/twitter-60-percent-of-users-access-via-mobile-13626.

Mills, S. (2012). *How Twitter is winning the 2012 US election*. Retrieved on January 11, 2012 from http://www.guardian.co.uk/commentisfree/2012/oct/16/twitter-winning-2012-us-election/.

MPAA (2012). *Theatrical market statistics 2012*. Retrieved on January 17, 2014, from http://www.mpaa.org/resources/3037b7a4-58a2-4109-8012-58fca3abdf1b.pdf.

Nakashima, R. (2012). *'John Carter': Movie to lose $200 million, among biggest Hollywood flops ever*. Retrieved on January 15, 2013 from http://www.csmonitor.com/The-Culture/Latest-News-Wires/2012/0320/John-Carter-Movie-to-lose-200-million-among-biggest-Hollywood-flops-ever.

Pan, Y., & Zhang, J. Q. (2011). Born unequal: a study of the helpfulness of user-generated product reviews. *Journal of Retailing*, 87 (4), 598–612.

Pang, B. & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval*, 2, 1-135.

Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. *Proceedings of EMNLP*. Retrieved on August 10, 2010 from http://www.cs.cornell.edu/home/llee/papers/sentiment.pdf.

Parker, L. (2012). *The digital revolution: how consumers are driving the future of games retail*. Retrieved on January 7, 2012 from http://www.gamespot.com/features/the-digital-revolution-how-consumers-are-driving-the-future-of-games-retail-6396713/.

PBS (2001). *The monster that ate Hollywood*. Retrieved on December 28, 2011 from http://www.pbs.org/wgbh/pages/frontline/shows/hollywood/.

Platt, J. C. (1999). Fast training of support vector machines using sequential minimal optimization. In B. Schölkopf, C. Burghes, & A. Smola (Eds.), *Advances in Kernel methods - support vector learning* (pp. 41-65).Cambridge MA: MIT Press.

Pomerantz, D. (2009). Movie critics vs. the audience. *Forbes Online*. Retrieved January 21, 2014 at http://www.forbes.com/2009/08/27/movies-twitter-matt-atchity-business-entertainment-tomatoes.html.

Rui, H., Liu, Y., & Whinston, A. (2013). Whose and what chatter matters? The effect of tweets on movie sales. *Decision Support Systems*, forthcoming.

Singh, A. (2009a). Inglourious Basterds a box office hit 'thanks to the Twitter effect', *The Telegraph*. Retrieved December 16, 2013, at http://www.telegraph.co.uk/news/celebritynews/6081711/Inglourious-Basterds-a-box-office-hit-thanks-to-the-Twitter-effect.html.

Singh, T. (2009b). *How Hollywood embraced social media*. Retrieved on December 28, 2011 from http://www.ngonlinenews.com/article/hollywood-and-social-media.

Smith, C. (2013). (December 2013*) By the numbers: 68 amazing Twitter stats.* Retrieved on January 17, 2014 from http://expandedramblings.com/index.php/march-2013-by-the-numbers-a-few-amazing-twitter-stats/#.UtlsfxCwbYg.

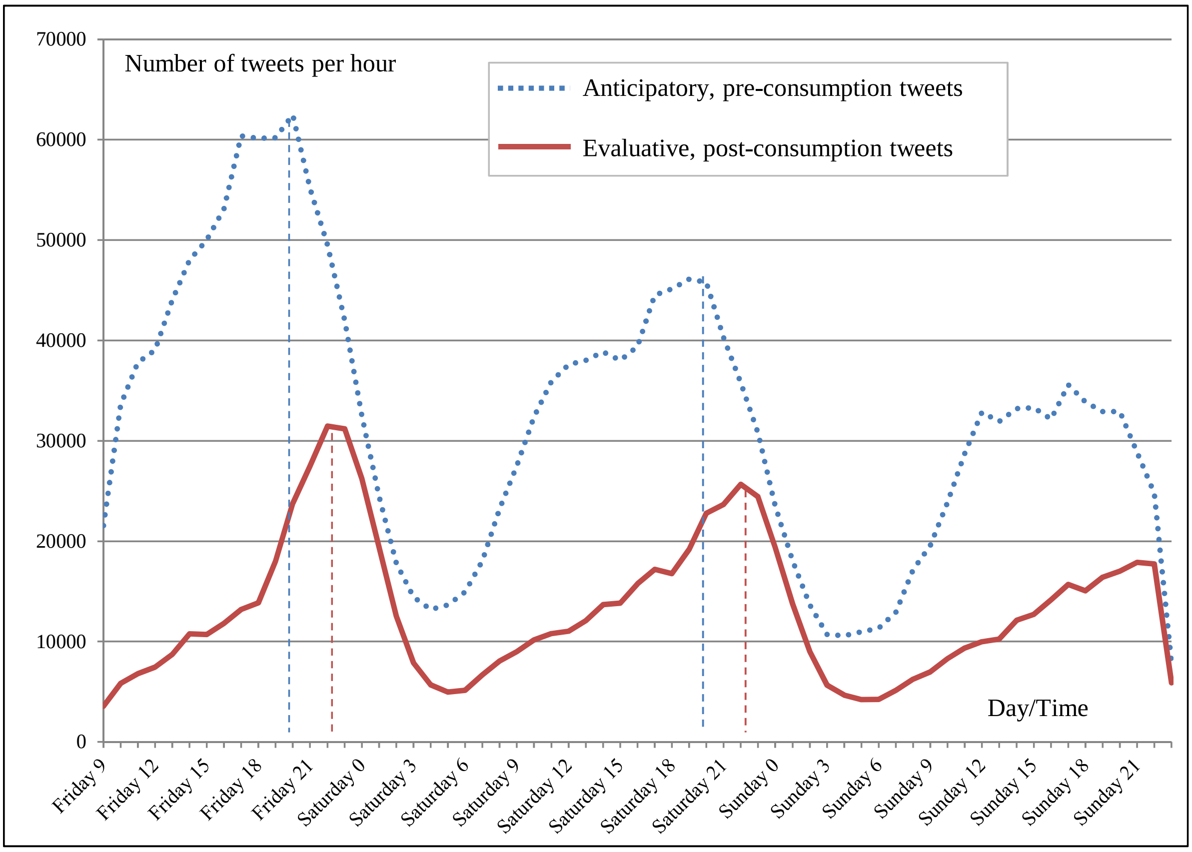
Stradella Road (2010). Moviegoers 2010. *Company report.*

Swami, S., Eliashberg, J., & Weinberg, C. B. (1999). SilverScreener: A Modeling Approach to Movie Screens Management. *Marketing Science*, 18 (3), 352-372.

Wong, F. M. F., Sen, S., & Chiang, M. (2012). Why watching movie tweets won't tell the whole story? *Proceedings of the WOSN Conference*, 1-6.

Figure 1

Distribution of tweets throughout movies' opening weekend



Notes: All time data refer to Eastern Daylight Time.

Figure 2

Types of word of mouth and their characteristics

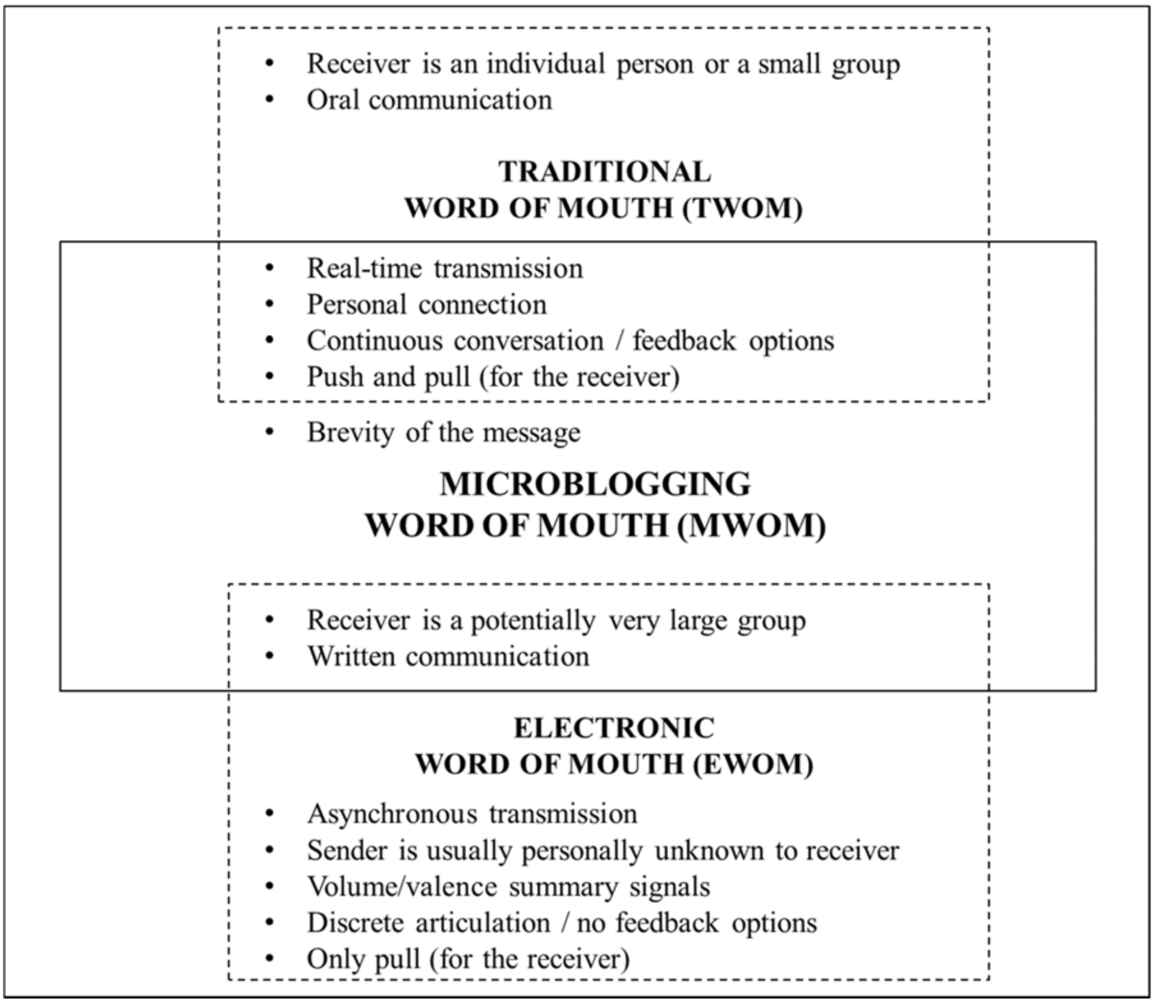


Table 1

Variable operationalization

Variable	Label	Operationalization	Data Source	Exemplary studies
Percentage of subsequent days' revenues earned during opening weekend	*SAT/SUN_REVPERC*	Sum of North American box office revenues for a movie generated on Saturday and Sunday of its opening weekend (in US $), divided by total box office revenues generated by a movie during its opening weekend (in US $), multiplied by 100	Boxofficemojo.com	n.c.
Positive MWOM share	*PMWOM*	The number of positive evaluative, post-purchase MWOM messages sent via Twitter within the first 24 hours after a movie's Friday release divided by the number of consumers who have seen the movie in a theater on Friday. The valence of messages was determined by sentiment analysis (for details, see text); the number of consumers who have seen a particular movie was estimated based on the movie's Friday box office and an average ticket price of $7.89 for 2010.	Twitter, own processing; boxofficemojo.com	n.c.
Negative MWOM share	*NMWOM*	The number of negative evaluative, post-purchase MWOM messages sent via Twitter within the first 24 hours after a movie's Friday release divided by the number of consumers who have seen the movie in a theater on Friday. See *PMWOM* for details.	Twitter, own processing; boxofficemojo.com	n.c.
MWOM ratio	*MWOMRATIO*	The ratio of positive and negative MWOM reviews for a movie sent within 24 hours of its Friday release; the valence of messages was determined by sentiment analysis (for details, see text).	Twitter, own processing	n.c.
MWOM volume	*MWOMVOL*	The total number of tweets sent within 24 hours of a movie's Friday release	Twitter	Rui, Liu, & Whinston (2013)
Pre-release movie buzz	*PRBUZZ*	Inverted rank in the Movie-Meter on IMDb at a movie's release	IMDb.com	Ho, Dhar, & Weinberg (2009)
Sequel	*SEQUEL*	Movie is a sequel (= 1, 0 otherwise)	IMDb.com	Hennig-Thurau, Houston, & Heitjans (2009)
Adaptation of book or play	*ADAPT*	Movie is an adaptation of a book or play (=1, 0 otherwise)	IMDb.com	n.c.[a]
Production budget	*LN(BUDGET)*	Log-transformed production budget of a movie, in US $	IMDb/Boxofficemojo	Basuroy, Chatterjee, & Ravid (2003)

Variable	Label	Operationalization	Data Source	Exemplary studies
Star power	*STARS*	Movie contains one or more major stars (= 1, 0 otherwise)	Quigley Publishing	Swami, Eliashberg, & Weinberg (1999)
Major studio	*STUDIO*	Movie is produced by one of the six major Hollywood studios (Warner, Fox, Universal, Sony, Paramount, Disney)	IMDb.com	Elberse & Eliashberg (2003)
Age rating	*G/PG_RAT*	Movie was rated either G (General audiences – all ages admitted) or PG (Parental guidance suggested – some material may not be suitable for younger children) by the MPAA (= 1, 0 otherwise)	MPAA	Swami, Eliashberg, & Weinberg (1999)[b]
Professional reviews	*PROREV*	Average rating of a movie by up to 40 professional critics, weighted according to the influence of the experts as expressed by the Metascore (scale ranges from 1 to 10)[c]	Metacritic.com	Hennig-Thurau, Houston, & Walsh (2006)
Pre-release advertising spending	*LN(PRADV)*	Log-transformed advertising spending for a movie before its release, in US $	Kantar Media	Akdeniz & Talay (2013)
Genres	*GENRE*	Vector of nine major movie genres, movie is: family, comedy, drama, action, adventure, horror, thriller/crime, romance, and science fiction/fantasy (each genre was set to 1 if appropriate or 0 otherwise)	IMDb.com	Ho, Dhar, & Weinberg (2009)

Note: n.c. = to the best of our knowledge, variable was not considered in previous research. [a]This variable was only considered as part of a larger composite construct. [b]Movie's age rating based on the MPAA classification has been measured in multiple ways; for the logic behind the measure used in this research, see text. [c]This measure captures the perceptions of the most influential individual reviewers/publications in North America. Using a separate sample of 1,806 movies released in North America between 1998 and 2006, the average correlation of the Metascore measure and 152 individual reviewers and publications (i.e., magazines, newspapers) was .70, and the standard deviation of these correlations is only .06.

Table 2

Correlations and descriptive statistics

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*SAT/SUN_REVPERC*	64.337	4.749	1	-.312**	-.300**	-.008	.256**	.133	.125	.491**	.006	.089	-.274**	-.437**	.107	-.303**
2	*PRBUZZ*	.216	.280	-.312**	1	.192*	-.015	.509**	.116	.282**	-.231*	.309**	.069	.381**	.219*	-.007	.735**
3	*SEQUEL*	n.a.	n.a.	-.300**	.192*	1	-.067	.138	-.095	-.110	.046	.033	-.335**	-.027	-.078	-.025	.252**
4	*ADAPT*	n.a.	n.a.	-.008	-.015	-.067	1	.128	.174	.149	.188	.211*	.014	-.091	-.088	.128	.023
5	*LN(BUDGET)*	3.696	.892	.256**	.509**	.138	.128	1	.319**	.443**	.082	.275**	.072	.023	-.192*	.009	.401**
6	*STARS*	n.a.	n.a.	.133	.116	-.095	.174	.319**	1	.187	-.108	.152	.134	-.102	-.137	-.092	.093
7	*STUDIO*	n.a.	n.a.	.125	.282**	-.110	.149	.443**	.187	1	.082	.142	.069	.045	-.082	-.055	.189
8	*G/PG_RAT*	n.a.	n.a.	.491**	-.231*	.046	.188	.082	-.108	.082	1	-.014	-.027	-.215*	-.339**	.184	-.061
9	*CRIT*	4.895	1.512	.006	.309**	.033	.211*	.275**	.152	.142	-.014	1	.066	.313**	.036	.358**	.386**
10	*LN(PRADV)*[a]	9.388	1.050	.089	.069	-.335**	.014	.072	.134	.069	-.027	.066	1	-.013	.027	.013	.020
11	*PMWOM*	.339	.327	-.274**	.381**	-.027	-.091	.023	-.102	.045	-.215*	.313**	-.013	1	.649**	.154	.609**
12	*NMWOM*	.047	.0423	-.437**	.219*	-.078	-.088	-.192*	-.137	-.082	-.339**	.036	.027	.649**	1	-.358**	.329**
13	*MWOMRATIO*	9.466	7.071	.107	-.007	-.025	.128	.009	-.092	-.055	.184	.358**	.013	.154	-.358**	1	.116
14	*MWOMVOL*[b]	.000	5815.392	-.108	.000	.163	.051	.039	.012	-.027	.160	.235*	-.046	.486**	.248*	.179	1

Notes: SD = standard deviation. ** p < .01, * p < .05. [a] = Unstandardized residuals from a regression with *BUDGET* were used for this variable. [b] = Unstandardized residuals from regressions with *PRBUZZ* were used for this variable. n.a. = not applicable because variable is a dummy.

Table 3

OLS estimation results

Model		**1**			**2**	
	Coef. (Std. Err)	**Beta**	**VIF**	**Coef. (Std. Err)**	**Beta**	**VIF**
DV = SAT/SUN_REVPERC						
Constant	56.340** (3.490)			57.575** (3.573)		
PRBUZZ	-7.056** (1.495)	.416	1.678	-6.896** (1.608)	.406	2.098
SEQUEL	-4.812** (1.139)	.324	1.273	-4.600** (1.154)	.310	1.412
ADAPT	-2.147** (.795)	.196	1.140	-1.914* (.780)	.175	1.186
LN(BUDGET)	2.551** (.488)	.479	1.821	2.256** (.492)	.424	1.992
STARS	.810 (.783)	.077	1.212	.658 (.782)	.063	1.306
STUDIO	-.298 (.742)	.032	1.331	-.517 (.723)	.055	1.368
G/PG_RAT	4.427** (.791)	.419	1.212	4.331** (.813)	.410	1.384
CRIT	.172 (.232)	.055	1.186	.273 (.250)	.087	1.481
LN(PRADV)[a]	-.105 (.332)	.023	1.167	-.047 (.322)	.010	1.184
PMWOM	-			2.800 (1.801)	.193	3.593
NMWOM	-			-31.843* (13.592)	.284	3.432
MWOMRATIO	-			-.061 (.063)	.090	2.052
MWOMVOL[b]	-			-.000132 (.000070)	.161	1.718
R^2 =	.561			.611		
Adjusted R^2 =	.520			.555		

Notes: ** p < .01, * p < .05. No genre variables were significant. VIF = Variance Inflation Factor. [a] = Unstandardized residuals from a regression with *BUDGET* were used for this variable. [b] = Unstandardized residuals from regressions with *PRBUZZ* were used for this variable.

Table 4

Financial simulations for negative MWOM reviews

		Difference in *SAT/SUN_REVPERC* (in percentage points)			Difference in Opening Weekend Revenues (in US $ million)	
NMWOM value substituted by	Mean Deviation (among sample movies)	Maximum Deviation (among sample movies)	For movie *Nightmare on Elm Street*	Mean Deviation (among sample movies)	Maximum Deviation (among sample movies)	For movie *Nightmare on Elm Street*
Reduction by 50%	+ .74	+ 3.82	+ 1.27	+ .51	+ 3.19	+ 1.43
Increase by 100%	- 1.48	- 7.64	- 2.55	- .92	- 16.95	- 2.59
Sample maximum (.24)	- 6.16	- 7.64	- 5.09	- 3.55	- 16.95	- 4.88
No *MWOM*	+ 1.48	+ 7.64	+ 2.55	+ 1.05	+ 6.56	+ 2.96

Note: The sample means for *SAT/SUN_REVPERC* and opening weekend revenues are 64% and US $24.2 million, respectively.

Appendix

Post-hoc analyses of regression model with EWOM quality measures

EWOM measure:	IMDb		Netflix		Yahoo	
	Coef. (Std. Err)	**Beta**	**Coef. (Std. Err)**	**Beta**	**Coef. (Std. Err)**	**Beta**
DV = SAT/SUN_REVPERC						
Constant	57.561** (3.592)		58.631** (5.789)		60.510** (5.204)	
PRBUZZ	-6.867** (1.619)	.405	-6.872** (1.620)	.405	-6.822** (1.614)	.402
SEQUEL	-4.607** (1.161)	.310	-4.543** (1.186)	.306	-4.541** (1.159)	.306
ADAPT	-1.889* (.789)	.172	-1.914* (.784)	.175	-1.833* (.789)	.167
LN(BUDGET)	2.275** (.498)	.427	2.267** (.496)	.426	2.288** (.494)	.429
STARS	.707 (.803)	.068	.654 (.786)	.062	.598 (.788)	.057
STUDIO	-.500 (.729)	.053	-.535 (.731)	.057	-.541 (.726)	.057
G/PG_RAT	4.290** (.829)	.406	4.382** (.847)	.415	4.428** (.825)	.419
CRIT	.329 (.315)	.105	.280 (.253)	.089	.298 (.253)	.095
LN(PRADV)[a]	-.019 (.337)	.004	-.048 (.324)	.011	-.032 (.323)	.007
PMWOM	2.783 (1.811)	.192	2.991 (1.987)	.206	3.504 (2.019)	.241
NMWOM	-31.530* (13.702)	.281	-33.118* (14.721)	.295	-36.660* (14.964)	.327
MWOMRATIO	-.058 (.064)	.086	-.054 (.069)	.081	-.048 (.065)	.072
MWOMVOL[b]	-.000135 (.000071)	.165	-.000131 (.000070)	.160	-.000132 (.000070)	.162
IMDB	-.105 (.358)	.032	-		-	
NETFLIX	-		-.161 (.693)	.026	-	
YAHOO	-		-		-.442 (.568)	.079
R^2 =	.611		.611		.613	
Adjusted R^2 =	.520		.555		.553	

Notes: ** p < .01, * p < .05. No genre variables were significant. VIF = variance inflation factor. [a] = Unstandardized residuals from a regression with *BUDGET* were used for this variable. [b] = Unstandardized residuals from regressions with *PRBUZZ* were used for this variable. IMDB = rating of movie quality from registered IMDb users. NETFLIX = rating of movie quality from registered Netflix users. YAHOO = rating of movie quality from registered Yahoo users.