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The impact of online word-of-mouth on television show viewership: An inverted U-shaped temporal dynamic

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Abstract This article examines the dynamic impact of online word-of-mouth (WOM) on US television show viewership. With WOM data collected from the Internet Movie Database website, we find that the cumulative volume of online WOM has significant explanatory power for viewership over time. Consistent with the mere exposure effect theory, the dynamic impact of the volume of online WOM over time varies according to a curvilinear, inverted U-shaped curve. Due to an initial floor effect, the volume of WOM is not significant in the early episodes. The impact of volume increases over time, before peaking and starting to decrease in the latter part of a show's life. This article demonstrates the differential effects of online WOM over time and thereby suggests that firms' online marketing strategies, such as media planning, must adjust with the product life cycle.

Keywords Internet marketing · Word-of-mouth · Online consumer reviews · Television shows

1 Introduction

Online word-of-mouth (WOM) is a primary source of information for consumers, which evokes a challenge for firms that must understand how online WOM affects consumers' purchase decisions (Godes et al. 2005). Firms' online marketing strategies rarely are effective in every situation (Zhu and Zhang 2010), yet we know little about the differential impacts of online WOM over time. In particular, online marketing strategies generally assume that online WOM influences marketplace performance, mainly by enhancing consumer awareness (Liu 2006) and providing a credible signal of product quality (Zhu and Zhang 2010). Growing empirical literature also demonstrates that online consumer WOM significantly impacts market performance measures, such as television show viewership (Godes and Mayzlin 2004), movie sales (Liu 2006; Duan et al. 2008; Dellarocas et al. 2007), beer sales (Clemens et al. 2006), book sales (Chevalier and Mayzlin 2006), video game sales (Zhu and Zhang 2010), beauty product sales (Moe and Trusov 2011), and even stock market returns (McAlister

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et al. 2012). However, this growing body of research yields mixed findings in terms of the significance of online WOM effects.

Previous research identifies two primary and two additional metrics of online WOM (Moe and Trusov 2011). First, volume, measured as the number of postings, and valence, measured as the average rating or percentage of positivity, represents primary metrics for online WOM. Second, entropy corresponds to the dispersion of the volume of postings, and variance refers to statistical variance in valence ratings. Empirical research into the effects of these metrics offers varying results. For example, in a study of movie reviews, Liu (2006) finds that online WOM has significant explanatory power for box office revenues, but most of this explanatory power comes from the volume of online WOM, not its valence. Godes and Mayzlin (2004) empirically test the relationship between online conversations (i.e., dispersion and volume across different Usenet newsgroups) and viewership and reveal that the dispersion of conversations across communities offers explanatory power for viewership. Surprisingly, though, they also find that the volume of online WOM is not significant, which may be an artifact of their data collection and analysis procedures.

Furthermore, prior findings consistently show that the effect of online WOM on performance measures decreases over time (Godes and Mayzlin 2004; Liu 2006), due to satiation effects. We sense some concern about this result for two reasons though. On the one hand, why should the impact of online WOM theoretically decrease after an initial period? Before achieving such satiation, online WOM should influence behaviors for some period of time. On the other hand, existing literature focuses on single-purchase products with short life cycles (e.g., movies, video games) and uses limited time-series data, such that it ignores issues related to the differential impact of online WOM over time.

Therefore, this study seeks to investigate the impact of different metrics of online WOM that might be managed by the firm. In addition, we explore the dynamics of the relationship between online WOM and viewership. By identifying when the impact of online WOM is particularly high, firms can improve the timing of their online marketing strategies. On the basis of multiple regressions, the empirical findings suggest that the volume of online WOM significantly influences television show viewership. Finally, this study demonstrates for the first time that the impact of online WOM on viewership over time follows an inverted U-shaped curve. Thus, we contribute to growing empirical literature pertaining to the impact of online WOM on performance measures and clarify how online WOM affects purchase decisions, as well as how firms should formulate their online marketing strategies to account for product life cycles.

The remainder of this article is organized as follows: In the next section, we develop the theoretical background, then, present the study data. After we analyze the data using multiple regression analyses of viewership, we summarize the results, present some implications, and discuss both limitations and directions for further research.

2 Theoretical background

2.1 Effect of online WOM on viewership

The two metrics of online WOM (valence and volume) influence purchase decisions though different cognition–behavior routes (Liu 2006). The valence of online WOM influences consumer attitudes. As Anderson (1998) notes, positive (negative) satisfaction leads to positive (negative) online WOM that shapes consumer attitudes. Positive online WOM enhances expected quality and thus consumers' attitudes toward a product. It seems intuitive that positive (negative) online WOM enhances (reduces) attitudes, but whether this effect extends to viewership is uncertain. Previous research indicates that valence is not significant (Liu 2006; Duan et al. 2008; Godes and Mayzlin 2004), because attitudes do not always accurately predict actual behaviors, and situational factors may capture real behaviors better than attitudes (Ajzen and Fishbein 1980).

Conversely, studies using the five stages of innovation adoption (Rogers 1962) indicate that the volume of online WOM can influence product sales through its informative effect on awareness (Liu 2006). Online discussions about television shows increase people's level of information about the shows; many postings with similar information also makes that information seem more accurate and trustworthy (Zhu and Zhang 2010). An increased number of postings better reflects product quality and can be more influential. Therefore, higher volumes of online WOM should influence viewership through awareness and trust.

However, innovation adoption theory focuses on initial innovations and single-purchase products. Zhu and Zhang (2010) specifically introduce their conceptual framework to address single-purchase products, such as information goods (e.g., books, movies, music, computer games) whose characteristics are difficult to observe prior to consumption. Thus, the innovation diffusion framework might not fit the case of repeat purchase products perfectly, because "Many researchers are not interested in repeated use, but only in the first time an innovation was used or implemented ('trial'), regardless of sustained use" (Van den Bulte and Lilien 2003, p.8). Television shows represent a specific form of repeat purchase product, for which a version of the product gets regularly repurchased.

In this situation, consumers might access online WOM from different time periods, such that they are exposed to both daily and cumulative WOM information (Duan et al. 2008). Compared with their assessments of single-purchase products, consumers are more likely to use accumulated, rather than daily, online WOM when considering repeat purchase products. Consider a simple example of a show whose online WOM is extensive and positive. The fact that a single episode yields some minimal amount of negative WOM at time t might not lead to decreased viewership at time t+1 if consumers consider all past information.[1] Janiszewski (1993) also suggests that mere exposure to marketing stimuli (e.g., online WOM) can encourage a consumer to develop a more favorable attitude, even if he or she cannot recall the initial exposure.

2.2 Temporal dynamics

The effect of online WOM on performance measures decreases over time (Liu 2006), and Godes and Mayzlin (2004, p.548) suggest that this decreasing magnitude of the effect of online WOM on viewership reflects satiation, "because as people become better informed about their preferences for different shows, a recommendation is less likely to

[1] Although consumers are more likely to access recent information, the importance of past information likely decreases; so, our model grants greater weight to recent than to older online WOM information.

impact decisions." Dynamic decreases in ratings also may explain this decreasing impact. With respect to sequential dynamics, Godes and Silva (2011) find that ratings decrease with time, as does the ability to assess the diagnosticity of previous reviews.

We agree that such explanations may be valid for products with short life cycles (e.g., movies, video games) but that the effect differs for products with longer life cycles. The satiation effect implies that preferences take time to shape, in which case, the impact of online WOM may not be significant at the beginning of the product life cycle but then might increase, at least temporarily. First, building awareness and trust take time. Repeated positive WOM can increase trust and thus enhance preferences and purchase decisions. Second, psychological studies on the mere exposure effect show that repeated exposures to a stimulus enhance people's attitudes toward that stimulus (Zajonc 1968). Applying this theory to marketing (Janiszewski 1993), repeated exposure to communication stimuli, such as online WOM (Zhu and Zhang 2010), should influence consumer behavior, including a positive effect on purchasing behavior. Moreover, the theory of mere exposure is consistent with a curvilinear relationship between exposure and attitudes, which reflects satiation effects (Zajonc et al. 1972). The repetition of a stimulus may increase attitudes in the first phase, but excessive exposure can inhibit processing of the stimulus through satiation or habituation. This satiation effect is consistent with the notion that people become better informed about their preferences over time and that online WOM is less likely to affect consumers' decisions.

3 Data

3.1 Viewership data

Consistent with previous research, we collected viewership data from Nielsen ratings. The Nielsen website does not report historical viewership data, but these data are available on a public website (TV by the Numbers, http://tvbythenumbers.com), which indicates the number of viewers per episode (in millions). Our sample includes 41 shows that aired on five major networks (ABC, CBS, NBC, FOX, and CW), of the ten networks in total (see Table 1). More than one quarter (28 %) of the shows had been canceled by the time of the data collection, but the remainder continued to air. The shows in our sample broadcast a mean of 89 episodes, with an average viewership of 8.55 million per episode and a standard deviation of 5.05 million.

Unlike Godes and Mayzlin (2004), who investigate television shows that premiere during the same season (1999–2000), we seek to study the long-term impact of online WOM, so we selected broader, time-series data pertaining to multiple seasons. That is, we explicitly chose to gather data about shows that lasted multiple seasons, to ensure a minimum of time-series data points per show.[2] However, we limited the number of

[2] Our data collection thus might suffer from a selection bias, because we focused on successful products (De Bruyn and Lilien 2008). However, our data set includes a wide range of heterogeneous shows; including unsuccessful shows canceled after as few as 26 episodes. This heterogeneity in product popularity is consistent with the research recommendations formulated by Zhu and Zhang (2010).

Table 1 Sample description

Show name	Date	Network	Season/episode	Mean VIEW	Mean VOL	Mean VAL
30 Rock	2006–2012	NBC	6/106	5.77	217	7.89
90210	2008–2012	CW	4/83	2.00	44	7.11
Bones	2005–2011	FOX	7/130	9.67	226	7.99
Castle	2009–2012	ABC	4/72	10.50	213	8.01
Chuck	2007–2012	NBC	5/91	5.85	377	8.24
Cold Case	2003–2009	CBS	6/130	14.03	68	7.41
Community	2009–2011	NBC	3/59	4.51	340	8.25
Criminal Minds	2005–2011	CBS	6/130	14.30	293	8.01
CSI NY	2004–2010	CBS	6/130	14.07	82	7.82
Desperate Housewives	2004–2010	ABC	6/130	18.99	174	7.93
Fringe	2008–2012	FOX	4/77	6.21	515	8.21
Glee	2009–2012	FOX	3/55	9.89	445	8.15
Gossip Girl	2007–2012	CW	5/100	2.14	153	7.71
Grey’s Anatomy	2005–2010	ABC	7/130	17.84	200	8.19
Heroes	2006–2010	NBC	4/77	9.52	678	7.80
House	2004–2010	FOX	6/130	15.78	734	8.55
How I Met Your Mother	2005–2011	CBS	6/130	9.20	530	8.20
Hung	2009–2011	HBO	3/30	2.18	81	7.06
Justified	2010–2012	FX	3/29	2.56	174	8.29
Lie to Me	2009–2011	FOX	3/50	7.32	191	7.82
Lost	2004–2010	ABC	6/114	15.05	1488	8.56
Modern Family	2009–2012	ABC	3/60	10.98	250	7.94
NCIS	2003–2009	CBS	6/130	15.32	148	7.81
Numb3rs	2005–2010	CBS	6/118	10.59	85	7.39
One Tree Hill	2003–2009	CW	7/130	3.36	93	8.14
Parks and Recreation	2009–2012	NBC	4/59	4.59	121	7.92
Prison Break	2005–2009	FOX	4/79	7.76	653	8.39
Private Practice	2007–2012	ABC	5/89	8.59	32	7.64
Sanctuary	2008–2011	SYFY	4/59	1.42	72	7.95
Southland	2009–2012	TNT	4/26	3.49	55	8.10
Supernatural	2005–2011	CW	7/130	3.09	742	8.68
The Big Bang Theory	2007–2012	CBS	5/103	12.09	501	8.14
The Good Wife	2009–2012	CBS	3/60	11.96	88	8.01
The Mentalist	2008–2012	CBS	4/83	15.20	210	8.14
The O.C.	2003–2007	FOX	4/92	6.98	134	8.02
The Office	2005–2011	NBC	7/131	8.16	406	8.12
The Vampire Diaries	2009–2012	CW	3/57	3.31	356	8.52
True Blood	2008–2011	HBO	4/48	4.05	554	8.31
Two and a Half Men	2003–2009	CBS	6/130	15.59	210	7.81
Veronica Mars	2004–2007	CW	3/64	2.62	339	7.37
White Collar	2009–2012	USA	3/43	4.01	120	8.14

episodes to 130 (even if the show was still airing), which seemed sufficiently long. To collect a large enough sample and still meet these criteria, we could not limit our sample to shows that premiered in a single year and instead gathered data on shows that premiered in different years (see Table 1).

3.2 WOM data

Whereas Godes and Mayzlin (2004) used online conversations from Usenet, our WOM data came from the Internet Movie Database (http://us.imdb.com), including user reviews archived and indexed by episodes. Consistent with previous studies (e.g., Moe and Trusov 2011), we measured the valence of online WOM with a rating scale (each episode rated on a 10-point scale). For the volume of online WOM, we measured the number of votes per episode. These online WOM data are posted on the same website; the question of whether viewers actually access them admittedly is unclear. However, considering the large amount of data on IMDb, we believe online user reviews offer a good indicator of underlying WOM and could significantly drive viewership (Duan et al. 2008; Zhu and Zhang 2010).

The average valence and volume of online WOM per episode, respectively, were 7.99 and 302 (cf. a volume of 28 posts in the sample of Godes and Mayzlin 2004). The standard deviation of valence was low (0.36), whereas that for volume was very high (277) compared with the average value. We also included time-varying binary control variables, such as season premiere (i.e., first episode of the season) and season finale (i.e., last episode of the season), that influence viewership because they highlight specific show development events. We also considered the Super Bowl, a special occasion that traditionally leads to incredible viewership peaks for television shows broadcast immediately following the game.[3]

4 Analyses and results

4.1 Effect of online WOM on viewership

In this section, we describe our panel data analysis, which we used to examine the evolution of television show viewership. Nonlinearities seem likely, so we used a multiplicative model in log-log form. The first independent variable was lagged viewership; we anticipated substantial variance in current viewership to be explained by past viewership. The first objective of this study was to demonstrate that online WOM data provides significant extra information. To measure cumulative online WOM, we used exponentially smoothed variables for both valence and volume of online WOM. Consistent with the assumption of a decrease in the importance of past information, this specification allowed the weight of lagged observations to decrease over time. A greater degree of weighting decrease (α) thus assigned less weight to old changes in the data and more weight to recent observations. We ran several regressions

[3] The data include five Super Bowl events. For example, the episode of *Grey's Anatomy* broadcast on February 5, 2006, was watched by more than 37 million viewers, whereas the show's average viewership for the season was less than 20 million, representing a 185 % increase.

with different high values for α, and they all yielded qualitatively similar results. Thus we only report results with α=0.95. We investigate the following model:

$$\log\left(VIEW_{i,t}\right) = \beta_0 + \beta_1\log\left(VIEW_{i,t-1}\right) + \beta_2\log\left(CVAL_{i,t-1}\right) + \beta_3\log\left(CVOL_{i,t-1}\right) \\ + \beta_4 EPISODE_{i,t} + \sum\nolimits_m \beta_m COV_m + u_i + e_{i,t} \text{ for } t < \tau, \tag{1}$$

- $VIEW_{i,t}$ corresponds to viewership for episode t for show i;
- *CVAL* and *CVOL* represent the cumulative valence and volume of online WOM;
- $EPISODE_{i,t} = t$ serves as a control for time trends in viewership;
- *COV* refer to the three control variables (season premiere, finale, Super Bowl);
- We also included a fixed effect for each show (u_i).[4] This group-specific constant may capture the intrinsic quality of each show, as well as a combination of distribution factors such as network, day of the week, and air time.

We truncated the data set to include only early episodes, defined as the first τ episodes of a show. We estimated our models across a range of τ values (τ= 20, 40, 90, 130 or the full sample). Table 2 contains the regression results from Eq. 1. First, the models for all levels of τ fit the data well. The R^2 value obviously increases when we do not restrict the data set to the early data. Second, the coefficient of lagged viewership is positive and significant for all phases. Both the coefficient and t values seem to increase over time, such that this variable explains most of the variance. This result suggests that, for the latter part of the shows' lives, viewership exhibits strong persistence. Third, the cumulative volume of online WOM provides significant extra information in our model. In particular, there exists a floor effect, such that the cumulative volume of online WOM is not significant when τ<20 and only significant at the 10 % level when τ=20. Then, the coefficient becomes significant at the 1 % level. Moreover, both the coefficient and t value vary in accordance with an inverted U-shaped curve; we explore the temporal dynamics in more detail in the next section. However, the cumulative valence of online WOM is not significant.[5] The episode effect is negative and significant for all data; consistent with decreasing viewership, but the low value of the coefficient suggests that this decrease is quite small. Finally, the control variables were all positive and significant.

In contrast with previous findings for television shows (Godes and Mayzlin 2004), we show that the cumulative volume of online WOM influences viewership. Consistent with previous research though (Liu 2006; Duan et al. 2008), these results suggest that online WOM affects viewership mainly though an informative effect on awareness, not through attitude change. The finding that online WOM influences viewership through

[4] With few time periods and many panel participants, estimation of a fixed effect model with lagged dependent variables may be subject to finite-sample bias (Arellano and Bond 1991). However, the bias is unlikely to be substantial in our sample, because the number of observations per show is not low (M=89) and the number of shows is not large (N=41). We also ran regressions for a random effect model, but the Hausman test revealed that the group-specific term is correlated with the independent variables, which violates the hypothesis of a random effect model and could lead to biased estimates.

[5] We also ran a regression with daily online WOM instead of cumulative information. Consistent with Godes and Mayzlin (2004), both daily volume and valence were not significant in this alternative model.

Table 2 Regression results: truncated sample fixed effect models

	τ=20	τ=40	τ=90	τ=130
Intercept	2.46 (0.80)	3.55*** (3.37)	2.31*** (6.18)	2.72*** (9.21)
log($VIEW_{i,t-1}$)	0.68*** (27.29)	0.72*** (45.59)	0.79*** (76.37)	0.81*** (88.26)
log($CVAL_{i,t-1}$)	0.26 (0.21)	−0.71 (−1.52)	0.26 (1.46)	0.02 (0.17)
log($CVOL_{i,t-1}$)	0.37* (1.82)	0.42*** (5.59)	0.09*** (3.64)	0.05*** (2.79)
Episode	0.002* (1.86)	0.001*** (3.56)	−0.0006*** (−4.36)	−0.0005*** (−5.21)
Premiere	0.04 (1.22)	0.06*** (3.81)	0.05*** (4.85)	0.05*** (5.86)
Finale	0.05 (1.42)	0.03** (2.24)	0.04*** (4.23)	0.04*** (4.90)
Superbowl		0.78*** (10.91)	0.74*** (14.12)	0.74*** (14.50)
R^2	0.72	0.74	0.95	0.96
Number of observations	738	1,526	2,998	3,619
Number of groups	41	41	41	41
F test: all coefficients=0	124.67***	345.45***	1,152.94***	1,568.31***

The t value are in parentheses; dependent variable is log($VIEW_{i,t}$). The regressions are truncated for $t<\tau$

*$p<0.1$; **$p<0.05$; ***$p<0.01$

an awareness effect is surprising because the online reviews we analyze all come from the same website. We thus attribute the effect of IMDb's online reviews to their role as indicators of the intensity of the underlying online WOM (Duan et al. 2008; Zhu and Zhang 2010).

4.2 Temporal dynamics

These findings offer some insights into the temporal dynamics (i.e., coefficient and t value for volume follow an inverted U-shaped curve); in this section, we also present a more detailed analysis. That is, we aim to specify temporal dynamics in terms of a continuous functional form. To capture the evolution of such a function, we first ran truncated regressions from Eq. 1 for every period,[6] from τ=5 to 130. We plotted the values of the coefficient for the cumulative volume of online WOM (see Fig. 1a). Then, we selected a continuous functional form that fit the data, using the CURVEFIT procedure in Stata. Graphically, the curvilinear function F yielded two phases: In the first phase, the curve was rapidly increasing and concave, and in the second phase, it was slowly decreasing and convex. To study the dynamic impact over time, we interacted this function of the time trend with the cumulative volume of online WOM, such that we added the independent variable $F_K(EPISODE) \times \log(CVOL_{i,t-1})$ to Eq. 1. In doing so, we could continually vary the effect of cumulative volume over time. Moreover, we estimated four models with different parameter values for the function F, indexed by $K=A$, B, C, and D, such that the magnitude of the curvilinear trend decreased (see Fig. 1b).

The estimation results of the regressions for the full sample with the episode–volume interaction appear in Table 3. The coefficient of the interaction term was significant,

[6] We start with τ=5, or the shortest period that includes enough data to estimate the model.

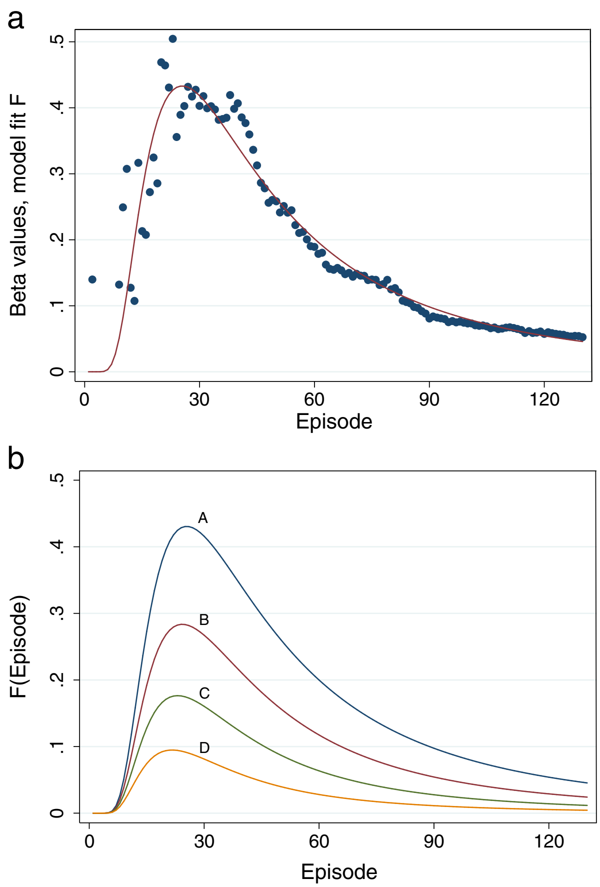

Fig. 1 **a** We ran truncated regressions from Eq. 1 for every period, from τ=5 to 130. *Dots* correspond to the values of beta coefficients for the cumulative volume of WOM. The *curve* represents curvilinear model fit. **b** We modified the parameters of the curvilinear function F to reduce its magnitude

consistent with the hypothesis that the effect of the cumulative volume of WOM varied over time, in an inverted, U-shaped curve. The magnitude of the curvilinear trend influenced the estimation results. Although the coefficient of the interaction term increased with a weaker curvilinear trend, the *t* value for the interaction term seemed to peak around model *C*. This result suggested that the interaction term would not be significant if the curvilinear trend were too strong or too weak. Again, the effect of valence of online WOM was not significant. Finally, the positive and significant coefficient of past viewership that we uncovered was consistent with our previous finding that viewership has strong persistence throughout the lifespan of a show.

5 Discussion and conclusion

Online marketing strategies may not be effective for all product types and all periods of a product's life. Understanding how online WOM influences consumer decisions is

Table 3 Regression results: full sample with episode–volume interactions

	Model A	Model B	Model C	Model D
Intercept	2.78*** (9.39)	2.78*** (9.39)	2.74*** (9.28)	2.75*** (9.30)
log($VIEW_{i,t-1}$)	0.80*** (87.60)	0.80*** (87.62)	0.80*** (87.83)	0.80*** (87.77)
log($CVAL_{i,t-1}$)	0.01 (0.06)	0.01 (0.07)	0.02 (0.16)	0.02 (0.11)
log($CVOL_{i,t-1}$)	0.06*** (2.88)	0.06*** (2.84)	0.06*** (2.86)	0.06*** (2.95)
$F_K(EPISODE)$ × log($CVOL_{i,t-1}$)	0.008*** (3.03)	0.01*** (3.16)	0.06*** (3.18)	0.11*** (2.96)
Episode	−0.0004*** (−4.16)	−0.0004*** (−3.99)	−0.0004*** (−3.83)	−0.0004*** (−4.16)
Premiere	0.05*** (5.69)	0.05*** (5.68)	0.05*** (5.68)	0.05*** (5.69)
Finale	0.04*** (4.74)	0.04*** (4.73)	0.04*** (4.74)	0.04*** (4.75)
Superbowl	0.73*** (14.45)	0.73*** (14.45)	0.73*** (14.45)	0.73*** (14.44)
R^2	0.96	0.96	0.96	0.96
Number of observations	3,619	3,619	3,619	3,619
Number of groups	41	41	41	41
F test: all coefficients=0	1,376.58***	1,376.98***	1,377.03***	1,376.36***

The t value are in parentheses; dependent variable is log($VIEW_{i,t}$)

*p<0.1; **p<0.05; ***p<0.01

essential for firms that rely on the Internet to spread information about their products. We find that for television shows, online WOM is extremely influential in the first phase of a show's life, but its impact declines during the latter part of the show's life. Take the example of the CBS sitcom *The Big Bang Theory*, which started with an average viewership of 8.3 million during its first season in 2007. Viewership numbers increased every year, until they exceeded 16 million in the show's fifth season (2012). Consistent with our results, press reports attributed this viewership growth to unprecedentedly high WOM (Idato 2011). Although the show initially received lukewarm reviews from professional critics, the huge volume of positive, dispersed information from consumers spread via the Internet. These communications generated higher awareness and more positive attitudes, which contributed to the show's ongoing success.

Our empirical results also support the notion that the impact of online WOM on performance measures (e.g., sales, viewership) depends on product characteristics (Zhu and Zhang 2010). Thus, firms' online marketing strategies, such as media planning, should be contingent on the products' life cycle. The informational role of online WOM appears more salient at the beginning of a product's life cycle. In turn, marketers likely would benefit from allocating resources to managing online WOM early in a product's life cycle. For example, prior to its official airing on CBS, the pilot episode of *The Big Bang Theory* was distributed on iTunes free of charge. Firms' online marketing strategies should not focus solely on the phase prior to product release though; on the contrary, online strategies must involve repeated actions over time, to build continually increasing product awareness and trust. For example, networks could develop interactive websites with exclusive content and online games to help fans share content about the show online. Consistent with previous research, our results also suggest that firms' online strategies may not be as effective later in a show's life cycle.

Although our findings illuminate a growing stream of research, we acknowledge several limitations of this study as well. First, we only measured the final outcome of online communications (i.e., viewership) and ignored intermediate stages in the decision process. We have demonstrated that online reviews influence viewership, but we did not empirically determine how they affected purchase decisions. Additional research using survey data might help clarify the underlying consumer decision process better. Research using disaggregated data also could expand the investigation to identify the causality between online reviews and purchase decisions. Second, we collected our data retrospectively, sometimes long after the communications occurred. Such retrospective data are subject to erroneous recollection, post-interpretation, and hindsight biases (De Bruyn and Lilien 2008). Moreover, the user ratings and number of votes on IMDb might not be representative of all online information. However, this potential bias would have reduced the relationship between online WOM and viewership, rather than overestimating it. Third, our model did not account for several potentially important factors. For example, it excluded data about pre-release online communications. We also could not gather exhaustive data on potentially important control variables, such as advertising or production budgets for each show. Accordingly, we cannot rule out the possibility that online WOM and viewership were generated through production budget or advertising effects.

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