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Television Advertising and Online Word-of-Mouth: An Empirical Investigation of Social TV Activity

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Abstract. In this research, we investigate the relationship between television advertising and online word-of-mouth (WOM) by examining the joint consumption of television programming and production of social media by television viewers, termed social TV. We explore how television advertising impacts the volume of online WOM about advertised brands and about the programs in which the advertisements air. We also examine what encourages or discourages viewers to engage in this particular social TV activity. Using data containing television advertising instances and the volume of minute-by-minute social media mentions, our analyses reveal that television advertising impacts the volume of online WOM for both the brand advertised *and* the program in which the advertisement airs. We additionally find that the programs that receive the most online WOM are not necessarily the best programs for advertisers interested in online engagement for their brands. Finally, our results highlight the brand, advertisement, and program characteristics that can encourage or discourage social TV activity. We discuss the implications of our findings for media planning strategies and advertisement design strategies.

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Keywords: online word-of-mouth • advertising • television • social media • social TV

1. Introduction

Television viewing is rapidly evolving due to the rise of multiscreen activity. Nielsen (2014a) estimates that 84% of U.S. tablet and smartphone users engage in media multitasking while watching television. One prevalent multiscreen activity is the joint consumption of television programming and production of social media by viewers, an activity known as social TV[1] (Benton and Hill 2012). An estimated 36% of multiscreeners in the United States engage in social TV activity (IAB 2015). Among Twitter users active during primetime, 85% have discussed television programming on the platform (Midha 2014). Social TV has caught the attention of both advertisers and television networks for its potential to assess viewers' real-time responses to programming through social media activity (Kantar Media 2014). This interest is reflected in the size of the global social TV industry, which is valued to be more than $100 billion (MarketsandMarkets 2012).[2]

Social TV's rapid rise, however, has also created new challenges for marketers, raising questions of how media multitasking affects viewers' responses to advertising and how advertisers and television networks can leverage this behavior (e.g., Hare 2012, Poggi 2012). Research in this area is in its infancy. Early work presents initial evidence that television advertising can influence online behaviors such as online search (Joo et al. 2014) and online shopping (Liaukonyte et al. 2015). These works, however, have not explored television advertising's impact on online conversations. Online word-of-mouth (WOM) is an important construct beyond online search and shopping as it investigates a social cross-media effect that can amplify the reach of television ad campaigns and offer advertisers real-time feedback on how ads are being received by viewers.

In this research, we aim to address the dearth of work examining the relationship between television advertising and online WOM, presenting the first broad investigation into social TV activity. Specifically, we explore three research questions. First, how does television advertising impact the volume of online WOM? We examine how television advertising influences online chatter about both the brand advertised and the program in which the ad airs. Second, what is the interaction between online engagement with programs and advertised brands? Several reports on social TV argue that shows with high online chatter are more beneficial for advertisers (e.g., Deggans 2016; Flomenbaum 2016; Nielsen 2014b, 2015); however, experimental work on media context effects has shown that more engagement with a program can hurt ad effectiveness (e.g., Lord and Burnkrant 1993, Tavassoli et al. 1995). We explore the interaction between online WOM about programs and advertised brands to empirically assess if programs with high online social activity are beneficial to advertisers in terms of increased online brand engagement. Finally, what are the drivers of social TV activity? We examine how advertisers and television networks can increase the volume of online chatter for their respective brands and programs by examining how various brand, ad, and program characteristics influence online WOM following television advertising.

We contribute to the research on cross-media effects, television advertising, and online WOM in three key ways. First, our examination of social TV activity expands the work on cross-media effects that has investigated the relationship between television advertising and some online behaviors (Joo et al. 2014, Liaukonyte et al. 2015) but has yet to explore the relationship between television advertising and online WOM. Second, we extend the work that has begun to link advertising and WOM (Gopinath et al. 2014) into the contexts of television viewing and media multitasking. This extension allows for the examination of the three research questions of interest. Finally, we contribute to the research on the drivers of online WOM (e.g., Lovett et al. 2013, Toubia and Stephen 2013) by extending this work into the media multitasking context, which allows for the examination of what encourages viewers to engage in social TV activity during programming and sheds light on how advertisers and television networks can use brand, ad, and program characteristics to increase online WOM for their respective brands and programs.

To explore the three research questions of interest, we construct a multisource data set that includes television advertising instances on network broadcasts, minute-by-minute social media data of Twitter conversations mentioning brands and programs, and data on brand, advertisement, and program characteristics. Our data include over 9,000 ad instances for 264 brands across 15 product categories that aired on 84 prime-time programs during the fall 2013 television season. We jointly model the immediate change in online mentions for both the brand and the program following an advertisement's airing using a hierarchical Bayesian framework.

We find evidence of increases in online mentions for both brands and programs following advertisements, illustrating that television advertising can encourage online WOM about both the advertised brand and the program in which the ad airs. This result reveals that social TV activity can be beneficial for advertisers as it can increase brand chatter and sheds light on how viewers converse about television online. Interestingly, we also find that advertising in programs that see higher than expected online program chatter following television ads does not necessarily lead to increases in online WOM for the advertised brand. This suggests, counter to industry reports (e.g., Deggans 2016, Flomenbaum 2016; Nielsen 2014b, 2015), that programs with high online social activity are not necessarily the best programs for advertisers seeking to generate online brand engagement. Our results also reveal the brand, ad, and program characteristics that can encourage or discourage viewers' social TV activity. For example, we find that ads with a hashtag or Web address calls-to-action can increase online brand WOM, but this effect only occurs if the ad is the first ad in a commercial break. These results have implications for ad design strategies and the importance of ad position in media buy negotiations for advertisers interested in increasing online brand WOM. We also find that the product advertised can impact how viewers engage online with the program. For example, relative to movie advertisements, ads for cable providers and ads for nonprofits or public service announcements (PSAs) decrease subsequent program chatter by 2%. These findings suggest that how networks distribute advertisements across their shows can have an important impact on online program WOM.

The remainder of this research is organized as follows. In the next section, we review related work on online WOM, cross-media effects, and television advertising. We then describe the data, present model-free evidence, and discuss the modeling approach for jointly assessing the impact of television advertising on online WOM for brands and programs. We present our results and conclude with a discussion of implications of our research for advertisers and television networks in terms of the media planning process as well as opportunities for future research in the contexts of online WOM and social TV.

2. Background Literature

2.1. Online WOM

Why would marketers want to encourage online WOM? Research shows that online chatter matters. Consumer social media activity has been shown to increase sales, shopping frequency, and profitability (e.g., Kumar et al. 2013, Stephen and Galak 2012, Rishika et al. 2013). Other forms of online WOM such as online reviews (e.g., Chevalier and Mayzlin 2006) and online referrals (Trusov et al. 2009) can increase customer acquisition and sales. Consistent with these findings, surveys estimate that more than 70% of consumers use social media to inform purchase decisions (Hitz 2014, Stadd 2014). Online WOM in the social TV context can offer additional potential benefits for advertisers, including free exposures for the brand online, extended reach of television ad campaigns to the online space, and real-time feedback on how advertisements are being received by viewers.

Research has also illustrated the value of online chatter to television networks and program creators. Godes and Mayzlin (2004) show that online WOM activity relates to program ratings. Gong et al. (2016) find that Tweets from a program's microblog account and influential Retweets also can increase ratings. Additionally, in their study of media activity for one show, Lovett and Staelin (2016) find that off-line and online communications can also increase live viewing. Reports from Kantar Media and Nielsen complement this work and show that Twitter activity about programs correlates with higher ratings (Kantar Media 2014, Subramanyam 2011).

While the above work highlights online WOM's importance, research on how online chatter can be encouraged is still in its early stages. Notably, Lovett et al. (2013) present the first empirical link between brand characteristics and online WOM and find that several brand traits, including excitement and visibility, can impact brand chatter. Toubia and Stephen (2013) further find that image-related utility plays a vital role in motivating users to post content on Twitter. Furthermore, Berger and Milkman (2012) find that online news articles evoking high-arousal emotions are more likely to be shared. Additional work has examined the dynamics in consumer decisions to contribute to online content (e.g., Godes and Silva 2012, Moe and Schweidel 2012). Research on the drivers of online WOM, however, has not considered media multitasking. Thus, we have limited insights into what encourages television viewers to engage in social TV activity and how advertisers, television networks, and program creators can manipulate brand, ad, and program characteristics to increase online WOM for their respective brands and programs.

2.2. Cross-Media Effects

Work on cross-media effects has presented initial evidence that television advertising can impact online behavior as it has been found to affect branded search (Joo et al. 2014), shopping behavior in terms of website traffic and sales (Liaukonyte et al. 2015), and prelaunch blogging activity for movies and wireless services (Onishi and Manchanda 2012). Additionally, Gopinath et al. (2014) consider the relationship between total advertising spend across all media channels in the aggregate and online WOM. They find initial support that advertising in one month can impact online WOM in the next month. This research, however, is not on media multitasking and, as such, does not allow for the examination of the three research questions of interest. We aim to expand on this work on cross-media effects by investigating television advertising's impact on online conversations, examining the relationship between online engagement with programs and advertised brands, and exploring the drivers of social TV activity to provide insights into how advertisers and television networks can leverage viewers' media multitasking activities.

2.3. Television Advertising and Social TV Activity

How might television advertising impact online WOM? Communications about television can enhance coviewing experiences and lead to increased program enjoyment (Lovett and Staelin 2016, Raghunathan and Corfman 2006). Functionally, since ad breaks may offer reduced strain on cognitive resources, media multitasking viewers seeking coviewing experiences may engage in online chatter during ad breaks as they serve as natural pauses in program content (Dumenco 2013). Additionally, research on WOM has shown that brand accessibility and visibility increase brand chatter (Berger and Schwartz 2011, Lovett et al. 2013). Thus, television advertising may stimulate online brand WOM by making the brand more accessible in the viewer's mind. Furthermore, Nielsen (2015) explore the correlation between neurological engagement and Twitter activity for eight television shows and find that viewers' emotion, attention, and memory are positively correlated with online WOM about the programs. Thus, beyond the functional quality of television advertisements serving as a convenient break in program content, the above work suggests that accessibility of a brand or program and/or viewers' emotional arousal, attention, and recall may encourage online WOM following television advertisements. Past research in marketing has illustrated that these factors can be influenced by characteristics of brands, advertisements, and programs. We discuss each in turn.

Brand and Advertisement Characteristics. Consumers often engage in online WOM to signal something about themselves (e.g., Berger and Milkman 2012, Lovett et al. 2013). As such, television advertisements for product categories that stimulate positive emotions, such as ads for exciting movies or high-end tech products, may increase online brand chatter. Thus, the product category advertised is likely to impact subsequent online WOM. Additionally, a brand's presence on social media may reflect a brand's interest in generating online chatter and its accessibility in the online space, both of which could have a positive impact on online brand WOM.

The content of an advertisement may also influence online chatter. Research on direct response advertising has shown that calls-to-action in television ads can affect viewers' behavior (e.g., Tellis et al. 2000). Ads with a hashtag, a social media call-to-action to join a conversation, may increase online brand WOM by informing or reminding viewers that a dialog exists, a view in line with work on accessibility and WOM (Berger and Schwartz 2011, Lovett et al. 2013). By contrast, featuring a phone number call-to-action may decrease online chatter by encouraging an offline action. Furthermore, ads that feature a visual or auditory brand sign-off may spur online brand WOM as these sign-offs can increase viewers' attention and recall (Stewart and Furse 1986). Research has also found that longer ads (e.g., Teixeira et al. 2012) and ads with a celebrity (e.g., MacInnis et al. 1991) increase consumer attention, which may spur online WOM about the advertised brand following the ad's airing. In addition to ad content, an ad's position may further impact online chatter. Ads airing earlier in an ad break increase viewers' attention and ad response (e.g., Danaher and Green 1997), which may stimulate more social TV activity. Additionally, program content is likely to become more engaging and interesting toward the show's conclusion, which may increase viewers' attention and positive emotional arousal toward the program but have a detrimental impact on attention toward the advertisements.

Program Characteristics. Since younger individuals are more likely to be active on social media (Pew Research 2015), the program an ad airs in and its associated audience characteristics may impact social TV activity. Program ratings also may affect the amount of online chatter after ads air. Furthermore, given that the network, genre, and airing day and time can affect viewers' attention and channel changing behavior (e.g., Schweidel and Kent 2010, Schweidel et al. 2014, Wilbur 2008, Wilbur et al. 2013), these factors also may influence online WOM following television ads. Finally, greater synergy between a program and an advertised brand may increase social TV activity as an ad's fit with the context in which it is shown can increase ad effectiveness and reduce audience decline (e.g., Schweidel et al. 2014, Wang and Calder 2009).

While the above discussion mainly focuses on how television ads can impact online brand WOM, these effects may also influence program chatter. For example, discussing a brand online may distract viewers from engaging with the program. Thus, a rise in online brand WOM after an ad may correspond to a drop in online program WOM. Conversely, an increase in brand chatter may have a positive impact on program chatter. An ad spurring online brand WOM suggests that some viewers are now active online and may now face a reduced cost of discussing other things online, such as the program. Ads that increase brand chatter could also spur online program WOM if viewers regularly discuss brands and shows jointly (e.g., "Did you see the Sprint ad on *Scandal*?"). These opposing ideas on the link between online brand and program WOM during social TV activity relate to research on media context effects that has found that engagement with a television program can either enhance or hurt ad effectiveness (e.g., Feltham and Arnold 1994, Lord and Burnkrant 1993, Murry et al. 1992, Tavassoli et al. 1995, Wang and Calder 2009). We extend this work by studying the link between the program and brand engagement in the social TV context, treating the nature of this relationship as an empirical question.

3. Data Description

3.1. Television Advertising and Social Media Data

Data on national, primetime television advertising on broadcast networks (ABC, CBS, CW, FOX, and NBC) during the fall 2013 television season (September 1–December 31, 2013) were gathered from Kantar Media's Stradegy database. Data were collected for ads on the initial airing of recurring programs.[3] We remove ads identified by Stradegy as joint promotions, which made up less than 1% of the ad instances, to exclude multibrand ads from our analysis. Our final data set contains 9,103 ad instances for 264 brands across 15 categories that aired on 84 television programs.

We combine the television advertising data with minute level data of brand and program mentions on Twitter from Topsy Pro, a certified Twitter partner with comprehensive access to public Twitter posts.[4] We use Twitter data because the majority of public social media chatter about television occurs on Twitter (Schreiner 2013). We use the number of mentions for brands and programs to assess online WOM.[5] A search of program mentions was conducted by tallying Tweets that contain a program's name or nickname (e.g., *Parks and Recreation*, "Parks and Rec"), hashtags with a program's name or nickname (e.g., #parksandrecreation, #parksandrec, #parksandrecnbc), or the program's Twitter handle (e.g., @parksandrecNBC).[6] We use a similar strategy to search brand chatter, capturing Tweets that mention the brand, a hashtag featuring the brand name, a hashtag included in the brand's advertisement, or the brand's Twitter handle. In line with past work on WOM and brands (Lovett et al. 2013), we focus on WOM that uses parent brand names rather than full product brand names (e.g., "Colgate" versus "Colgate Optic White") for almost all brands in the data with the goal of capturing as much chatter as possible about the advertised brand.[7] The exceptions include movies (e.g., parent brand—Warner Bros.; product brand—*Gravity*), books (e.g., parent brand—Little, Brown and Company; product brand—*Gone*), tech products (e.g., parent brand—Amazon; product brand—Kindle), and brands that share a name with a common word (e.g., Nationwide). For these exceptions, product brand names were incorporated into the search of Twitter mentions to better capture brand chatter. Tables A1 and A2 in the online appendix present terms used to search brand mentions for a sample of the 264 brands in our analysis.

3.2. Data on Brand, Advertisement, and Program Characteristics

We supplement this data on television advertising and online WOM with brand, ad, and program characteristics following our discussion on the role these characteristics may play in influencing social TV activity. We control for the category of the product advertised as online chatter may vary across categories.[8] We account for if a brand has a Twitter profile as it may reflect a brand's interest in online WOM and may affect viewers' decisions to discuss the brand online. We further control for ad position in a commercial break (first or last nonpromo ad), ad position in a program (relative ad break position and near a half-hour interval), and if an ad runs concurrently with another ad break on a different broadcast network. Past work has found that viewers' attention and ad response vary across these measures of ad position (e.g., Danaher and Green 1997, Schweidel and Kent 2010, Schweidel et al. 2014, Siddarth and Chattopadhyay 1998), which may impact online chatter (Nielsen 2015). These data on ad position were extracted from Stradegy.

We also account for variables based on ad content. In addition to ad length, which is provided by Stradegy, we code if the ad contains calls-to-action, a brand sign-off, a general celebrity, and/or a celebrity who is in the program in which the ad airs. Past work has shown that these elements can affect viewers' attention and recall (e.g., MacInnis et al. 1991, Stewart and Furse 1986, Teixeira et al. 2012), which can impact online WOM (Nielsen 2015). For the calls-to-action, each ad in the data was viewed by two coders who identified if the ad contained a phone number, Facebook page link or icon, hashtag, and/or Web address. Similarly, each ad was viewed by two coders to classify if the ad has a visual brand sign-off (is the brand name, package, or other obvious identifier of the product visible as the ad ends?) or an auditory brand sign-off (is the brand name repeated within the last three seconds of the ad?), as defined by Stewart and Furse (1986).[9] To identify the actors in each ad, we use ispot.tv, an ad metrics firm that lists the actors that appear in national television ads, and ad content (does the ad contain an actor's name?).[10] IMDb STARmeter and IMDb filmography are used to identify if the actor is a celebrity and whether or not the actor appears in the program episode in which the ad airs.[11]

Last, we control for program characteristics that influence viewers' attention and channel changing behavior (e.g., Danaher and Green 1997, Schweidel et al. 2014, Wilbur 2008, Wilbur et al. 2013), which may affect social TV activity (Nielsen 2015). We account for network, genre, program ratings, day of the week, and time the program airs. We further control for season premieres and fall finales as these episodes may generate more social chatter compared to other episodes. Data for these program characteristics were gathered from Stradegy with the exception of program ratings that were collected from *TV by the Numbers*.

3.3. Descriptive Statistics for Television Advertising Data

The average ad break in the data contains eight advertisements, and programs have on average six ad breaks. The most advertised categories are movies, beauty, and wireless providers, which account for 38% of the ad instances. The most advertised brands are Apple, Microsoft, AT&T, Nokia, Sprint, and Bank of America, which account for 20% of the ad instances. Table 1 shows the summary statistics for the brand, ad, and program characteristics.[12] Of note, only 1% of ad instances in the data are longer than 30 seconds. Additionally, 59% of the ad instances feature a Web address, 17% include a hashtag, 6% contain a phone number, and 5% include a Facebook page link or icon. Given the growth in social TV activity by viewers (IAB 2015) and advertisers' interest in leveraging this behavior (e.g., Hare 2012, Poggi 2012), it is notable that less than 20% of the ad instances in the data include a social media call-to-action (hashtag and/or Facebook page link or icon). This suggests that social TV strategies by advertisers were not widespread at the time of data collection. Finally, we see that while 31% of ad instances include a celebrity, less than 1% include a celebrity who is also in the program episode in which the ad airs.

3.4. Descriptive Statistics and Model-Free Evidence for Online WOM Data

Figures 1–3 illustrate how television viewers engage in online WOM following ads. Figure 1 shows online mentions about the show *Scandal* during an airing, and we clearly see that program chatter spikes during ad breaks. While this may appear as bad news to advertisers, we need to consider if media multitasking by television viewers is also spurring online brand WOM. Figure 2 suggests that this may be the case as we see that the ads for the movie *Gravity* lead to immediate increases in online WOM for the movie. Figure 2 also presents evidence that the relationship between the brand and program matters when assessing the effects of television advertising on online WOM, as the increases in mentions about *Gravity* vary across the programs in which the ad airs. Figure 3 offers additional model-free evidence that the relationship between the brand and the program is important. For example, Tylenol on average sees increases in online brand WOM following the airing of their ads on FOX's *Glee* but on average experiences decreases in brand chatter after their ads air on ABC's *Scandal*. As another example, MasterCard sees immediate increases in online WOM after their ads air on ABC's *Scandal* but sees little change in brand chatter following their ads airing on FOX's *Glee.*

Table 1. Descriptive Statistics for Brand, Advertisement, and Program Characteristics

Parameter	Description	Freq. (%)	Mean (SD)
Brand and advertisement characteristics			
Ad break position	Ad break position in a given program		3.30 (2.21)
Ad length	Ad length in seconds		25.26 (8.14)
	% of ads less than 30 seconds	33.90	
	% of ads more than 30 seconds	1.18	
Ads on other networks	% of ads that air simultaneously with commercials on a different broadcast network	61.17	
Ad position in a commercial break	% of ads that are the first nonpromo ad in a given commercial break	17.83	
	% of ads that are the last nonpromo ad in a given commercial break	1.57	
Brand sign-offs	% of ads with an auditory brand sign-off	55.84	
	% of ads with a visual brand sign-off	90.40	
Calls-to-action	% of ads with a phone number	6.22	
	% of ads with a hashtag	17.18	
	% of ads with a Facebook icon or URL to a Facebook page	5.03	
	% of ads with a Web address	59.16	
Celebrities	% of ads with a celebrity	30.93	
	% of ads with a celebrity that is in the program episode the ad airs in	0.21	
Half-hour break	% of ads that air within two minutes of a half-hour break	12.94	
No Twitter	% of brands that do not have a Twitter account	18.40	
Program characteristics			
Fall finale	% of ads that aired during fall finale shows	10.49	
Genre	% of ads on Drama/Adventure programs	46.69	
	% of ads on News programs	7.37	
	% of ads on Suspense/Police programs	3.35	
	% of ads on Comedy programs	18.86	
	% of ads on Slice of Life programs	23.73	
Network	% of ads on ABC programs	24.33	
	% of ads on CBS programs	23.97	
	% of ads on CW programs	14.35	
	% of ads on FOX programs	18.68	
	% of ads on NBC programs	18.68	
Program length	Length of program in minutes		62.13 (25.11)
Program ratings	Nielsen program ratings—Reflects % of population of TVs tuned to a program for the 18–49 demographic		1.85 (0.97)
Season premiere	% of ads that aired during season premieres	9.38	

While Figures 1–3 serve as illustrative examples of social TV behavior, Table 2 presents broader preliminary evidence that television advertising may influence online WOM. If we consider the percentage change in online mentions from two minutes before an ad airs to two minutes after, brands in the data see on average a 108% increase in mentions after their ads air. Program chatter on average increases 4% following ads. Both brand and program WOM see larger increases following the first ad in a commercial break, with program chatter increasing 30% on average after the first ad. Across the categories of products advertised, movie ads are associated with the largest increases in online brand WOM (533%) while ads for cable providers are associated with the smallest increases (9%). Interestingly, we also see evidence that program chatter varies based on the category of product advertised. Following ads for computers, notebooks, tablets, or phones, program chatter increase about 10%. However, following ads for cable providers and ads for nonprofit or PSAs, online program WOM decreases by 19% and 11%, respectively. These insights

Figure 1. Change in Online Program WOM for ***Scandal*** October 3, 2013

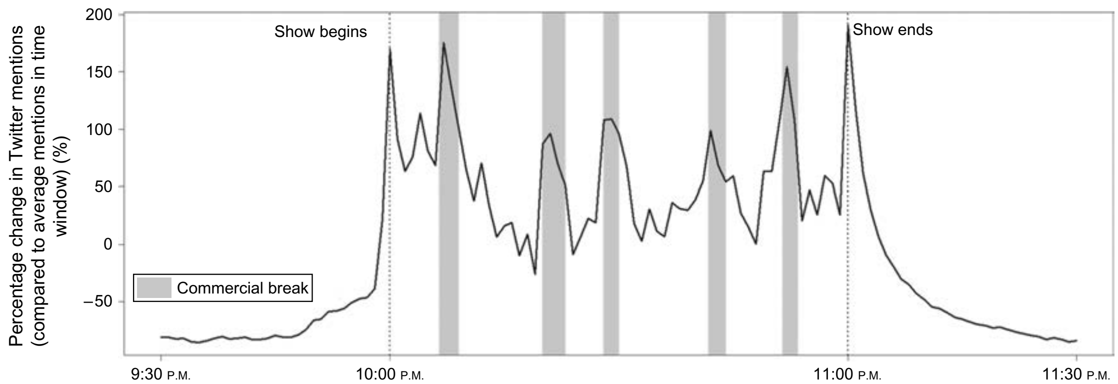
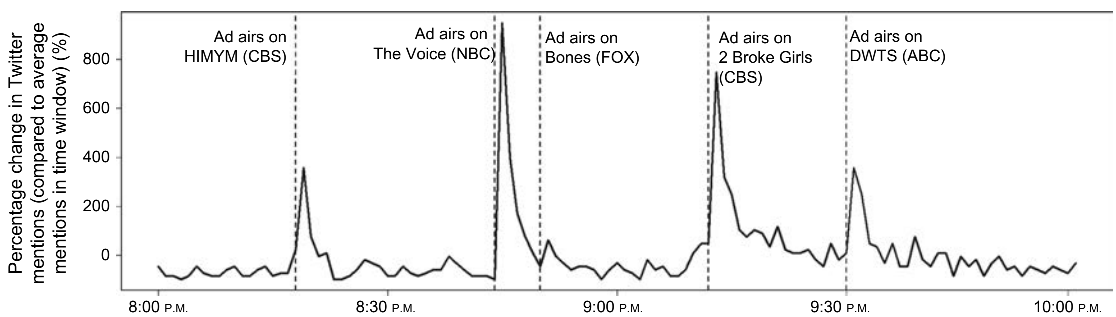


Figure 2. Change in Online Brand WOM Following Television Advertisements for ***Gravity*** on September 23, 2013



Note. The following shows in Figure 2 were abbreviated: *Dancing with the Stars* (DWTS) and *How I Met Your Mother* (HIMYM).

Figure 3. Change in Online Brand Mentions from Television Advertisements Airing on ABC's ***Scandal*** and FOX's ***Glee***

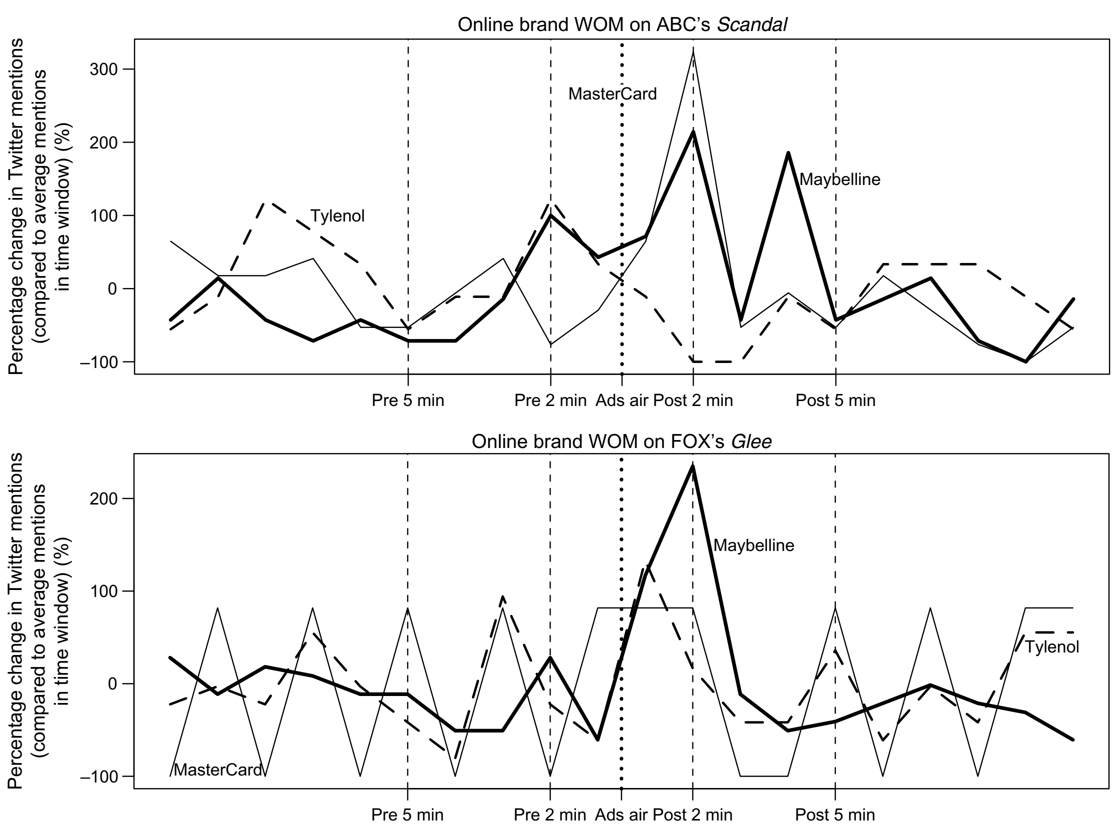


Table 2. Descriptive Statistics for Online WOM

	Change in brand WOM (%)		Change in program WOM (%)			Change in brand WOM (%)		Change in program WOM (%)	
	Mean	(SD)	Mean	(SD)		Mean	(SD)	Mean	(SD)
Overall	108	(1,411)	4	(73)	Ad position in a commercial break				
Ad length					First ad	169	(1,014)	30	(108)
Less than 30 seconds	52	(199)	1	(82)	Last ad	21	(78)	−17	(27)
30 seconds	129	(1,716)	5	(68)	Calls-to-action				
More than 30 seconds	511	(2,340)	10	(45)	Facebook	137	(325)	8	(56)
Category					Facebook in first ad	170	(300)	20	(38)
Movies	533	(3,793)	5	(47)	Hashtag	259	(2,930)	4	(46)
Apparel	114	(322)	1	(37)	Hashtag in first ad	324	(964)	23	(51)
Insurance	76	(247)	3	(44)	Phone number	44	(167)	6	(53)
Hair care	78	(507)	−1	(35)	Phone number in first ad	67	(204)	29	(62)
Beauty	58	(199)	3	(45)	Web address	83	(423)	4	(86)
Financial	45	(151)	6	(132)	Web address in first ad	150	(541)	31	(126)
Other	39	(89)	2	(45)	Genre				
Wireless providers	36	(105)	6	(52)	Comedy	91	(544)	−2	(49)
Phones	32	(118)	9	(53)	Drama/Adventure	132	(2,014)	9	(44)
Computer accessories	37	(137)	5	(44)	News	21	(82)	13	(71)
Meds/Vitamins	30	(89)	0	(46)	Slice of life	109	(406)	−3	(121)
Nonprofits/PSAs	27	(131)	−11	(31)	Suspense/Police	52	(155)	2	(42)
Computers/Notebooks/Tablets	19	(89)	10	(131)	Network				
Dental care	14	(63)	3	(37)	ABC	198	(2,776)	4	(45)
Cable providers	9	(54)	−19	(24)	CBS	53	(204)	11	(127)
Celebrity					CW	54	(173)	13	(50)
Celebrity	53	(199)	5	(88)	FOX	128	(657)	−7	(30)
Celebrity in program	569	(1,435)	−5	(33)	NBC	83	(311)	−1	(45)

Notes. Percentage change is calculated as $(PostWOM\text{-}PreWOM)/(PreWOM+1)$ at each ad instance. *PostWOM* is the number of mentions about a brand or program between when the ad airs to two minutes after it airs, and *PreWOM* is the number of mentions between two minutes before the ad airs to when it airs.

may have implications for how networks distribute advertisements across their highly social programs and their less social programs.

Table 2 also shows that ad characteristics may affect social TV activity.[13] For example, including a celebrity in an ad who is also in the program in which the ad airs increases online brand chatter following the ad by 569%, on average. This is an interesting insight because our data suggest that advertisers are not utilizing this strategy, with less than 1% of ads containing a celebrity who is also in the program in which the ad airs. Table 2 also suggests that longer ads are associated with more online brand chatter than shorter ads, with ads longer than 30 seconds increasing online brand WOM by 511%, on average. While running longer ads introduces additional costs for advertisers, we also see that including a hashtag in an ad, a relatively costless change to ad design, increases brand chatter by 259%, on average. Hashtags are particularly effective if they appear in the first ad of a commercial break.

Beyond when an ad airs in a commercial break and the effects of the category advertised, online program WOM seems to be influenced most by program characteristics. Table 2 provides evidence that program chatter following ads varies across genre. News (13%), Drama/Adventure (9%), and Suspense/Police (2%) shows see increases in WOM following ads while Comedy (−2%) and Slice of Life (−3%) shows see decreases. Program chatter also seems to vary across networks with shows airing on CW (13%), CBS (11%), and ABC (4%) seeing subsequent increases in program WOM and shows on NBC (−1%) and FOX (−7%) seeing decreases.

Table 2 does not present a clear picture on the relationship between online engagement with advertised brands and programs. Some brand, ad, and program characteristics that increase online brand WOM above the average effect also have a positive impact on online program WOM (e.g., first ad slot, movie ads, Facebook calls-to-action). However, other characteristics have the opposite effect (e.g., apparel ads, ads with a celebrity also in the program, ads on FOX). Furthermore, our data show that the presence of brand-program comentions in a single post (e.g., "Did you see the Sprint ad on *Scandal*?") is not prevalent, with only 2% of the ad instances having posts with brand-program comentions within two minutes of the ad's airing. Thus, the data do not present a clear picture of the relationship between online engagement with programs and advertised brands. We will explore this relationship in more detail in Sections 4 and 5.

Overall, Figures 1–3 and Table 2 suggest that television advertising can influence the volume of online chatter and that there is substantial heterogeneity in online brand and program WOM across brand, ad, and program characteristics. However, these figures do not account for multiple factors and do not explore the association between online brand and program WOM. Moreover, the large standard deviations in Table 2 may suggest that online WOM varies greatly across specific brands and programs. Thus, a formal model is needed to explore the relationship between television advertising and online WOM and account for brand- and program-specific effects. Toward this end, we next describe our modeling framework.

4. Model Development

4.1. Joint Model of Online WOM About Brands and Programs

We jointly model the immediate change in online brand and program WOM following the airing of a television advertisement. We measure this change using two minute windows before and after the ad airs. We specify the dependent variables for our primary analysis as follows:

$$Y_{i1} = \begin{cases} \log(PostBWOM_i - PreBWOM_i + 1), \\ \qquad PostBWOM_i - PreBWOM_i \geq 0; \\ -\log(|PostBWOM_i - PreBWOM_i| + 1), \\ \qquad PostBWOM_i - PreBWOM_i < 0; \end{cases} \tag{1}$$

where i indexes the ad instance, $PostBWOM_i$ is the number of online mentions for the brand in ad i from when ad i airs till two minutes after ad i airs, and $PreBWOM_i$ is the number of brand mentions two minutes before ad i airs till ad i airs. We specify Y_{i2} in the same manner with $PostPWOM_i$ and $PrePWOM_i$, the number of online mentions for the program in which ad i airs two minutes after and two minutes before, respectively, ad i airs. We attribute the changes in brand and program online WOM between these pre- and post-measures to the ad's insertion (Liaukonyte et al. 2015).

The two minute window is chosen for three main reasons. First, narrow, minute level windows are commonly used to explore the effects of television programming or advertising on online behaviors (e.g., Benton and Hill 2012, Kantar Media 2014, Liaukonyte et al. 2015, Wallenstein 2015). Second, our model-free evidence in Figures 1–3 illustrates that the changes in online WOM commonly occur within two minutes of an ad's airing. Third, the narrow event window alleviates concerns that advertisers or networks could choose a certain time window to air an ad to impact online WOM. In television media buy negotiations, advertisers commonly purchase ad time for a set of programs on a network or for a general program type (e.g., comedies) (Katz 2013, p. 152). The ability to specify when a specific ad will air is limited to the quarter-hour level, and this timing is not stipulated in the advertiser-network contracts, 80% of which are completed in the May upfront market several months prior to the start of the fall television season (Liaukonyte et al. 2015). Once ad time is purchased, networks distribute ads across programs, and these ads are then commonly ordered across commercial breaks at random (Wilbur et al. 2013). If an ad does not reach the number of viewers paid for by the advertiser, networks deliver a "make-good" by rerunning the ad in a comparable spot on the same or a similar program to make up the remaining ratings point (Katz 2013, p. 200). This process does not offer advertisers much control over selecting a specific program to air an ad in to affect immediate online WOM, let alone timing an ad to air during a specific four minute period to influence the volume of social media activity. Given these three reasons, we utilize the two minute windows both before and after an ad airs to assess the impact of television advertising on online WOM.[14]

We select a difference structure for the dependent variables because we are interested in how an advertisement's insertion—and its associated characteristics—change the volume of online WOM for a brand or program from its baseline levels. We use log specifications as there is a large variance in these differences across brands and programs.[15]

We model the immediate change in brand b's online mentions (Y_{i1}) and program p's online mentions (Y_{i2}) following a television advertisement instance i as follows:

$$\begin{pmatrix} Y_{i1} \\ Y_{i2} \end{pmatrix} \sim N\left(\begin{pmatrix} \hat{Y}_{i1} \\ \hat{Y}_{i2} \end{pmatrix}, \mathrm{T}\right), \tag{2}$$

$$\begin{pmatrix} \hat{Y}_{i1} \\ \hat{Y}_{i2} \end{pmatrix} = \begin{pmatrix} \mu_{\text{brand}} \\ \mu_{\text{prog}} \end{pmatrix} + \begin{pmatrix} \alpha_{b[i],1} \\ \alpha_{b[i],2} \end{pmatrix} + \begin{pmatrix} \gamma_{p[i],1} \\ \gamma_{p[i],2} \end{pmatrix} + \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix} BPSynergy_{b[i],p[i]} + \sum_{k=1}^{57} \begin{pmatrix} \theta_{k1} \\ \theta_{k2} \end{pmatrix} X_{ik}, \tag{3}$$

where μ_{brand} and μ_{prog} are respective intercepts. We account for brand-specific effects ($\alpha_{b\cdot}$) and program-specific effects ($\gamma_{p\cdot}$) in each equation to explore (1) if brand b or program p experiences changes in online WOM after ad i airs and (2) cross-effects—that is, if brand b (program p) impacts online WOM for p (b) after ad i airs.[16] Furthermore, $\alpha_{b\cdot}$ and $\gamma_{p\cdot}$ control for potential unobservables related to advertisers and programs, respectively, that may influence Y_{i1} and Y_{i2} (e.g., audience characteristics valued by advertisers). The vector $X_{i\cdot}$ contains the ad instance-specific brand, ad, and program characteristics detailed in Section 3. This vector also includes a measure to capture if the volume of online WOM following ad i is influenced by the online brand chatter generated by the ads airing before ad i in the same commercial break. A summary of the variables in $X_{i\cdot}$ is presented in Table A3 in the online appendix. Finally, to account for potential correlations between the two dependent variables of interest, we allow for contemporaneous covariance in T.

The latent measure $BPSynergy_{bp}$ functions like a brand-program interaction as it assesses if the synergy between brand b and program p affects the volume of online WOM for b and p beyond the main effects of the brand ($\alpha_{b\cdot}$) and the program ($\gamma_{p\cdot}$). We construct $BPSynergy_{bp}$ using a proximity model (Bradlow and Schmittlein 2000, Schweidel et al. 2014) of advertisers' program selection where the probability that brand b advertises in program p is a function of the latent distance between b and p in a Euclidean space ($LatentDist_{bp}$). We let $Z_{bp}=1$ if brand b advertises in program p during the 2013 fall television season and 0 otherwise. The probability that b advertises in p and the latent distance between b and p are specified as follows:

$$Z_{bp} \sim \text{Bernoulli}(q_{bp}), \tag{4}$$

$$q_{bp} = \frac{1}{1+(LatentDist_{bp})^{\lambda_b}}, \tag{5}$$

$$LatentDist_{bp} = \sqrt{(B_{b1}-P_{p1})^2+(B_{b2}-P_{p2})^2}, \tag{6}$$

where B_{b1} (P_{p1}) and B_{b2} (P_{p2}) specify the location of brand b (program p) in the two-dimensional Euclidean space.[17] We use the estimates of these locations to construct the brand-program synergy measures ($BPSynergy_{bp}$), which we assume to be inversely related to $LatentDist_{bp}$:

$$BPSynergy_{bp} = \frac{1}{LatentDist_{bp}}. \tag{7}$$

By jointly modeling Equations (1)–(7), our model framework parsimoniously constructs a measure of brand-program synergy based on advertisers' program selection, which may affect online WOM beyond the main effects of the brand ($\alpha_{b\cdot}$) and the program ($\gamma_{p\cdot}$). However, as discussed above, we anticipate that advertisers' program selection will not play a substantial role in affecting television advertising's impact on online WOM because of the nature of advertiser-network media buy negotiations that gives advertisers limited control over selecting a specific program to air an ad in to influence social TV activity.[18]

4.2. Estimation

The above equations are estimated jointly using a Bayesian hierarchical regression and Markov Chain Monte Carlo techniques in WinBUGS (http://www.mrc-bsu.cam.ac.uk/bugs/). We assume that $\alpha_{b1} \sim N(0,\tau_{\alpha1})$, $\alpha_{b2} \sim N(0,\tau_{\alpha2})$, $\gamma_{p1} \sim N(0,\tau_{\gamma1})$, and $\gamma_{p2} \sim N(0,\tau_{\gamma2})$, with diffuse inverse-gamma priors for the variances. We specify μ_{brand}, μ_{prog}, $\eta_{\cdot}$, and $\theta_{k\cdot}$ with diffuse normal priors, and T with a diffuse inverse Wishart prior. Additionally, we assume that $\lambda_b \sim N(\bar{\lambda},\tau_\lambda)$, $B_{b1} \sim N(\bar{B}_1,\tau_{B1})$, $B_{b2} \sim N(\bar{B}_2,\tau_{B2})$, $P_{p1} \sim N(\bar{P}_1,\tau_{P1})$, and $P_{p2} \sim N(\bar{P}_2,\tau_{P2})$, with diffuse normal priors for $\bar{\lambda}$, $\bar{B}_{\cdot}$, and $\bar{P}_{\cdot}$ and diffuse inverse-gamma priors for the variances. The above equations are estimated from three independent chain runs of 40,000 iterations with the first 20,000 iterations discarded as a burn-in. Our inferences are based on the remaining 20,000 draws from each chain. Model convergence is assessed through the time series plots of the posterior draws for each parameter, and these plots provide evidence consistent with model convergence.

5. Results

5.1. Model Comparison

To assess the importance of accounting for cross-effects and brand-program synergy in our model of television advertising's impact on online WOM, we compare our proposed model to four alternative models. Deviance information criterion (DIC), a likelihood-based measure that penalizes complex model specifications, and the mean absolute error (MAE) are used to compare our proposed model to these alternatives. Lower DIC and MAE indicate better model fit.

We first consider a baseline model (Model 1) that includes intercepts, characteristic variables ($X_{i\cdot}$), brand-specific effects to control for brand unobservables that can impact brand WOM ($\alpha_{b,1}$), and program-specific effects to control for program unobservables that can impact program WOM ($\gamma_{p,2}$). We then evaluate how accounting for cross-effects impacts model fit. We build on Model 1 to assess model fit when only brand cross-effects are accounted for (Model 2) or only program cross-effects are accounted for (Model 3). Finally, we consider a model in which $BPSynergy_{bp}$ is withheld from Equation (3) (Model 4). Adding $BPSynergy_{bp}$ to Model 4 gives us our proposed model (Model 5). The DIC and MAE estimates in Table 3 establish that including cross-effects in our model of television advertising's impact on online WOM improves model fit. We also find that incorporating brand-program synergy into Model 5 improves overall model fit. As Model 5 is our best fitting model, we focus our discussion on the results from this model estimation.

5.2. What Impacts Online Brand WOM?

Tables 4 and 5 show that brand and ad characteristics have substantial impacts on the volume of online brand WOM following television ads while program characteristics play a limited role. The category of product advertised has a sizeable effect on online brand chatter after an ad's airing. All categories see less online brand WOM than movies. Next to movie advertisements, ads for phones, computers, notebooks, and tablets spur

Table 3. Model Comparison

Model	Description	What's included	DIC	Brand MAE	Program MAE
Model 1	Baseline: No cross-effects	$\mu_{\text{brand}}, \mu_{\text{prog}}, X_{i\cdot}, \alpha_{b,1}, \gamma_{p,2}$	96,467	1.102 (1.095, 1.109)	2.888 (2.869, 2.908)
Model 2	Brand cross-effects only	$\mu_{\text{brand}}, \mu_{\text{prog}}, X_{i\cdot}, \alpha_{b,1}, \alpha_{b,2}, \gamma_{p,2}$	96,395	1.102 (1.095, 1.109)	2.879 (2.859, 2.900)
Model 3	Program cross-effects only	$\mu_{\text{brand}}, \mu_{\text{prog}}, X_{i\cdot}, \alpha_{b,1}, \gamma_{p,1}, \gamma_{p,2}$	96,371	1.098 (1.091, 1.105)	2.888 (2.869, 2.908)
Model 4	Main model without $BPSynergy_{bp}$	$\mu_{\text{brand}}, \mu_{\text{prog}}, X_{i\cdot}, \alpha_{b,1}, \alpha_{b,2}, \gamma_{p,1}, \gamma_{p,2}$	96,371	1.098 (1.091, 1.105)	2.879 (2.859, 2.900)
Model 5	Main model	Model 4 + $BPSynergy_{bp}$	96,292	1.096 (1.089, 1.103)	2.874 (2.854, 2.895)

Notes. 95% highest posterior density (HPD) intervals are shown with MAE. We use DIC estimated by WinBUGS.

Table 4. Impact of Brand Characteristics on Online WOM Following Television Ads

	Brand WOM model		Program WOM model	
Variable	Posterior mean	Change in WOM (%)	Posterior mean	Change in WOM (%)
$\mu_{\text{brand}}/\mu_{\text{prog}}$	1.10** (0.60, 1.51)	3.82	−1.80** (−2.76, −0.77)	−1.13
Category (baseline: Movies)				
Apparel	−1.34** (−1.69, −0.98)	−820.19	−0.25 (−0.87, 0.36)	
Beauty	−1.56** (−1.76, −1.36)	−319.07	−0.30* (−0.66, 0.05)	−0.07
Cable provider	−1.59** (−2.02, −1.14)	−193.26	−1.93** (−2.68, −1.18)	−1.89
Computer accessories	−1.83** (−2.18, −1.49)	−90.87	−0.55* (−1.20, 0.09)	−0.11
Computer/Notebook/Tablet	−1.80** (−2.04, −1.55)	−3.66	−0.29 (−0.71, 0.13)	
Dental care	−1.56** (−1.86, −1.25)	−350.88	−0.08 (−0.62, 0.47)	
Financial	−1.73** (−1.96, −1.49)	−184.38	−0.46** (−0.86, −0.06)	−0.13
Hair care	−1.53** (−1.83, −1.23)	−150.33	−0.36 (−0.94, 0.21)	
Insurance	−1.39** (−1.67, −1.11)	−208.02	−0.54** (−1.03, −0.05)	−0.20
Meds/Vitamins	−1.46** (−1.68, −1.24)	−196.81	−0.82** (−1.21, −0.43)	−0.36
Nonprofit/PSAs	−1.61** (−1.92, −1.30)	−728.36	−1.42** (−2.01, −0.84)	−1.91
Other	−1.48** (−1.77, −1.19)	−135.54	−0.63** (−1.17, −0.09)	−0.21
Phones	−1.73** (−2.01, −1.45)	−1.38	−0.39* (−0.85, 0.06)	−0.09
Wireless providers	−1.57** (−1.86, −1.27)	−19.43	−0.22 (−0.66, 0.22)	
No Twitter	−0.04 (−0.19, 0.12)		0.03 (−0.24, 0.30)	

Notes. 95% HPD intervals are shown. Percentage changes are calculated as *TransformedPM*/*PreWOM*. The posterior means are transformed from the specification in Equation (1) at each iteration and averaged to calculate *TransformedPM*, which is the change in mentions following ad i. *PreWOM* is the average number of mentions for a brand or program two minutes before an ad airs from the data. For dummy variables, *PreWOM* is specific to the variable. For example, the percentage change for apparel is calculated as *TransformedPM*/(*PreWOM* for apparel ads).

*90% HPD interval excludes zero; **95% HPD interval excludes zero.

the most online brand chatter while apparel, nonprofit or PSA, and dental care ads generate the least online brand chatter. These results appear consistent with the idea that exciting brands spur more online WOM (Lovett et al. 2013). Moreover, while certain ads may complement the hedonic or transportation experiences of watching television, such as ads for movies and tech products, other ads may interrupt these experiences, such as ads for nonprofits or PSAs (Wang and Calder 2006), which may explain the observed effects. Table 5 also shows that including a celebrity in an ad who is also in the program in which the ad airs increases online WOM for the advertised brand by 112%. However, including a general celebrity in an ad increases online brand WOM by less than 1%. This finding, which may stem from amplifying consumer attention toward the ad (e.g., MacInnis et al. 1991), is notable for advertisers as the strategy of featuring a celebrity in an ad who is also in the program in which the ad airs is not commonly employed.

We see that calls-to-action can impact an advertisement's effect on online brand WOM. Specifically, including a phone number in an ad reduces subsequent brand chatter by 2%. Featuring a hashtag or Web address in an ad increases subsequent online brand WOM, but this effect only occurs when the ad airs in the first ad slot of a commercial break, with a hashtag in the first ad increasing online brand WOM by 3% and

Table 5. Impact of Advertisement and Program Characteristics on Online WOM Following Television Ads

	Brand WOM model			Program WOM model		
Variable	Posterior mean		Change in WOM (%)	Posterior mean		Change in WOM (%)
	Advertisement characteristics					
Ad break position	−0.14*	(−0.29, 0.02)	−0.27	0.92**	(0.58, 1.27)	0.30
Ad length	0.02**	(0.01, 0.02)	0.03	−0.01	(−0.02, 0.00)	
Ad near half-hour	−0.04	(−0.14, 0.06)		−0.12	(−0.34, 0.10)	
Ads on other networks	0.02	(−0.04, 0.09)		0.04	(−0.12, 0.19)	
Auditory sign-off	−0.01	(−0.11, 0.08)		−0.19**	(−0.38, −0.00)	−0.04
Celebrity	0.14**	(0.05, 0.23)	0.31	−0.00	(−0.20, 0.19)	
Celebrity in program	0.84**	(0.11, 1.57)	112.09	−0.62	(−2.18, 0.93)	
Facebook	0.05	(−0.15, 0.26)		0.19	(−0.22, 0.59)	
Facebook × First ad	−0.04	(−0.43, 0.35)		−0.67	(−1.52, 0.18)	
First ad	−0.14*	(−0.30, 0.01)	−0.19	3.06**	(2.71, 3.40)	4.54
Hashtag	−0.02	(−0.16, 0.12)		−0.12	(−0.39, 0.15)	
Hashtag × First ad	0.37**	(0.15, 0.59)	2.64	−0.01	(−0.50, 0.47)	
Phone	−0.20**	(−0.39, −0.01)	−1.68	0.11	(−0.29, 0.51)	
Phone × First ad	−0.05	(−0.39, 0.30)		−0.21	(−0.96, 0.55)	
Last ad	0.02	(−0.26, 0.30)		−0.71**	(−1.31, −0.11)	−0.29
Visual sign-off	−0.04	(−0.19, 0.10)		−0.20	(−0.49, 0.09)	
Web	−0.03	(−0.14, 0.07)		−0.08	(−0.28, 0.12)	
Web × First ad	0.17*	(−0.01, 0.36)	2.17	0.05	(−0.34, 0.45)	
	Program characteristics					
Fall finale	−0.09	(−0.20, 0.02)		0.33**	(0.09, 0.57)	0.08
Genre (baseline: Slice of life)						
Drama/Adventure	0.09	(−0.11, 0.30)		1.19**	(0.68, 1.70)	0.43
News	−0.10	(−0.47, 0.28)		1.29**	(0.25, 2.30)	9.93
Suspense/Police	0.24	(−0.12, 0.60)		1.04**	(0.08, 1.98)	0.85
Comedy	−0.14	(−0.38, 0.11)		0.47	(−0.13, 1.06)	
Network (baseline: FOX)						
ABC	−0.15	(−0.34, 0.05)		0.91**	(0.42, 1.42)	0.25
CBS	−0.27**	(−0.46, −0.07)	−0.70	1.20**	(0.69, 1.71)	1.80
CW	0.08	(−0.16, 0.33)		1.59**	(0.92, 2.25)	0.93
NBC	−0.20*	(−0.41, 0.02)	−0.47	0.41	(−0.15, 0.98)	
Program length	−0.00	(−0.00, 0.00)		0.00	(−0.01, 0.01)	
Program ratings	0.25**	(0.17, 0.32)	0.50	−0.11	(−0.29, 0.06)	
Season premiere	0.09	(−0.03, 0.21)		1.05**	(0.78, 1.31)	0.22

Notes. Table 5 presents posterior mean estimates with the 95% HPD intervals. See note under Table 4 about percentage change calculations. Time and day of the week effects are shown in Table A7 in the online appendix.
*90% HPD interval excludes zero; **95% HPD interval excludes zero.

a Web address in the first ad increasing online brand WOM by 2%. This suggests that calls-to-action can stimulate online brand engagement, while calls for offline action may decrease the volume of online WOM (e.g., Tellis et al. 2000). The interaction with ad position may occur because consumers feel as if they have more time to respond to a call-to-action and engage in online WOM at the beginning of the ad break without interrupting program viewing (Danaher and Green 1997). Our results also show that ad length affects subsequent brand chatter, with longer ads seeing more online WOM. This result appears consistent with past work that has found that ad length increases viewers' attention (e.g., Teixeira et al. 2012), which can increase social TV activity (Nielsen 2015).

We find that limited program characteristics affect online brand WOM after ads. We see a positive association between program ratings and online brand chatter. Higher ratings indicate larger viewing audiences, and this greater base may spur more online WOM for advertised brands. Higher rated programs also may attract better quality ads, which could also explain this positive effect. We further see that ads airing on CBS generate less online brand WOM than ads airing on FOX, which is consistent with the descriptive statistics presented in Table 2.

5.3. What Impacts Online Program WOM?

The results in Tables 4 and 5 show that brand and advertisement characteristics can impact online program WOM following television ads. Notably, we find that program chatter varies across the categories of products advertised in the program. Relative to movie ads, ads for cable providers and ads for nonprofits or PSAs have the largest effect, decreasing subsequent online program WOM by 2%. Given that several programs in the data average more than 50,000 Twitter mentions each episode (e.g., ABC's *Scandal*, FOX's *Glee*, NBC's *The Voice*), a 2% decrease is substantial. These results suggest that how networks distribute advertisements across programs can have a meaningful impact on online program chatter. The content of nonprofit and PSA ads, as well as the content of the other categories of ads in Table 4 that have a negative effect on program chatter, may disengage viewers from the hedonic experience of watching television and may explain why we observe decreases in social TV activity following these ads. Exploring the behavior mechanisms behind this effect may be a fruitful avenue for future research.

We also find that more (less) online program WOM is seen following advertisements that air in the first (last) ad slot of a commercial break. Program chatter after the first ad occurs early in the commercial break, whereas such chatter following the last ad of a break occurs during the program content. Thus, this finding is consistent with the argument that viewers are more likely to engage in online WOM during commercials, possibly because they are natural pauses in program content (Dumenco 2013). To avoid interrupting program viewing, such actions are more likely to be taken following ads that occur earlier in a break (Danaher and Green 1997). We further find that program WOM increases following ads airing in later ad breaks in the program, potentially because show content becomes more interesting to discuss as it approaches its conclusion.

Table 5 illustrates that program characteristics influence online program WOM following television ads. We see variation in program chatter across genres. Compared to Slice of Life shows, Drama/Adventure, News, and Suspense/Police shows all experience more online program WOM after ads. We also find variations across networks with programs on ABC, CBS, and CW experiencing more online mentions following advertisements (relative to programs on FOX). These results are consistent with our model-free evidence in Table 2 and may reflect variations in characteristics of the program in each genre or network or differences in characteristics of the viewers that each genre or network attracts. Finally, ads airing in season premieres and fall finales are associated with more subsequent online program WOM than ads that air on episodes in the middle of the season because these special episodes likely have more engaging content.

5.4. Relationship Between Online Brand and Program WOM

Table 6 shows, as expected, that as the proximity between brand b and program p increases, the probability that b advertises in p increases ($\bar{\lambda} > 0$). We find a positive relationship between brand-program synergy and online WOM for both brands and programs after ads air, illustrating that it is important to consider the relationship between advertised brands and programs in assessments of social TV. Some examples of brand-program pairs with high synergy include Amazon–ABC's *Grey's Anatomy*, *Gravity* (movie)–ABC's *Scandal*, and *Frozen* (movie)–FOX's *X Factor*. Some examples of brand-program pairs with low synergy include Coach–CBS's *We are Men*, Microsoft–CW's *Carrie Diaries*, and *Romeo & Juliet* 2013 (movie)–CBS's *We are Men*. Future research can explore potential explanations for these high and low brand-program synergy pairs, which may be driven by the characteristics of the viewers (e.g., demographics and psychographics) and/or characteristics of the program content (e.g., product placements).

Table 6 also shows that while the covariance between Y_{i1} and Y_{i2} is negative, it cannot be distinguished from zero, providing limited insights into the relationship between viewers' online engagement with advertised brands and programs. However, we do find that if ads airing in the same commercial break as ad i before ad i airs result in increases in online brand WOM, this decreases subsequent online WOM for the brand advertised in i and reduces online WOM for the program in which the ad i airs. This latter finding indicates that engaging with advertisements online decreases viewer's propensity to engage with the program online, suggesting that viewers' online engagement with advertised brands and programs may not always have a positive relationship.

Using our posterior inferences of $\gamma_{p\cdot}$, we can further examine this relationship and explore if brands that advertise in programs with high online social activity also experience more online brand WOM. Work on media context effects has found that viewers' program engagement can either improve ad response (e.g., Murry et al. 1992, Feltham and Arnold 1994) or hurt ad response (e.g., Lord and Burnkrant 1993, Tavassoli et al. 1995). Figure 4 shows the posterior mean estimates of the program-specific effects ($\gamma_{p\cdot}$) combined with the specific genre and networks effects for each program and their impacts on online brand and program WOM. Fifteen programs have estimates that are distinguishable from zero for both of these effects (90% highest posterior density (HPD) intervals exclude zero).[19] These programs may have meaningful impacts on both online WOM about advertised brands and online WOM about the program because of the program's audience characteristics and/or social

Table 6. Results on the Relationship Between Online Brand and Program WOM

Variable	Mean (SD)
Summary statistics for $LatentDist_{bp}$	2.19 (0.77)
Summary statistics for $BPSynergy_{bp}$	0.54 (0.33)

Variable	Posterior mean from brand WOM model	Change in WOM (%)	Posterior mean from program WOM model	Change in WOM (%)
$BPSynergy_{bp}$	0.09** (0.03, 0.15)	0.17	0.15** (0.06, 0.25)	0.03
Brand WOM from ads prior	−0.02* (−0.04, 0.00)	−0.03	−0.15** (−0.19, −0.10)	−0.03

	Brand WOM model		Program WOM model	
Variable	Parameter	Posterior mean	Parameter	Posterior mean
Variance for $\log(Y_{i1})$ *and* $\log(Y_{i2})$	τ_{11}	2.38** (2.31, 2.45)	τ_{22}	11.79** (11.45, 12.15)
Covariance for $\log(Y_{i1})$ *and* $\log(Y_{i2})$	τ_{12}	−0.01 (−0.12, 0.10)	τ_{21}	−0.01 (−0.12, 0.10)
Heterogeneity for α_{b1} *and* α_{b2}	$\tau_{\alpha 1}$	0.07** (0.04, 0.10)	$\tau_{\alpha 2}$	0.08** (0.03, 0.15)
Heterogeneity for γ_{p1} *and* γ_{p2}	$\tau_{\gamma 1}$	0.04** (0.02, 0.07)	$\tau_{\gamma 2}$	0.39** (0.23, 0.60)

Variable	Mean parameter	Posterior mean	Heterogeneity parameter	Posterior mean
Brand location on dimension 1	$\bar{B}_{b1}$	1.99** (1.41, 2.74)	τ_{B1}	2.08** (1.54, 2.76)
Brand location on dimension 2	$\bar{B}_{b2}$	0.69** (0.10, 1.34)	τ_{B2}	0.40** (0.17, 0.88)
Program location on dimension 1	$\bar{P}_{p1}$	2.21** (1.63, 2.98)	τ_{P1}	0.63** (0.39, 0.99)
Program location on dimension 2	$\bar{P}_{p2}$	−0.62* (−1.25, 0.04)	τ_{P2}	0.31** (0.20, 0.48)
Slope	$\bar{\lambda}$	3.94** (3.43, 4.48)	τ_{λ}	4.66** (3.39, 6.26)

Notes. Posterior mean estimates are presented with 95% HPD intervals. See note under Table 4 about percentage change calculations.

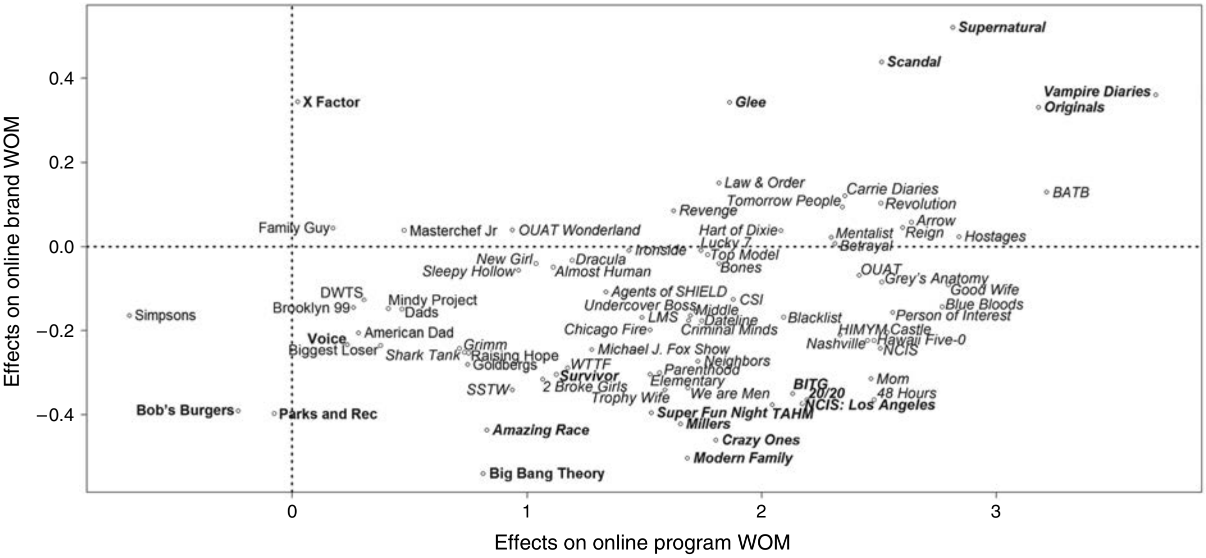
*90% HPD interval excludes zero; **95% HPD interval excludes zero.

TV strategy (Kantar Media 2014, Weinstein 2014). Of those programs for which the program effects on both online brand chatter and online program chatter are distinguishable from zero, 33% fall in the upper right quadrant, indicating that when ads air in these programs, both the advertised brand and the program see more online WOM than one would expect given the other model variables. Some examples of such programs include CW's *Supernatural*, ABC's *Scandal*, and FOX's *Glee*.

Interestingly, we find that the vast majority of the programs in our data fall in the lower right quadrant, including 67% of those programs for which the program effects on both online brand and program chatter are distinguishable from zero. These are programs that see higher than expected online program WOM after ads, but online WOM for brands that advertise in these programs is less than expected. Audiences that talk online about these programs may be doing so at the expense of engaging with advertised brands online. This finding presents compelling evidence that programs that receive the most online WOM are not necessarily the best programs for advertisers interested in increasing online brand engagement. This result contrasts industry reports (e.g., Deggans 2016; Flomenbaum 2016; Nielsen 2014b, 2015) and importantly illustrates that how engaged a program's audience is online does not indicate how the audience will engage with the advertised brands online. Overall, advertisers seeking to amplify their audience through social media, all else being equal, may want to avoid programs that fall in the lower right quadrant. Some examples of such programs include ABC's *Modern Family*, CBS's *NCIS*: *Los Angeles*, CBS's *Two and a Half Men*, and ABC's 20/20.

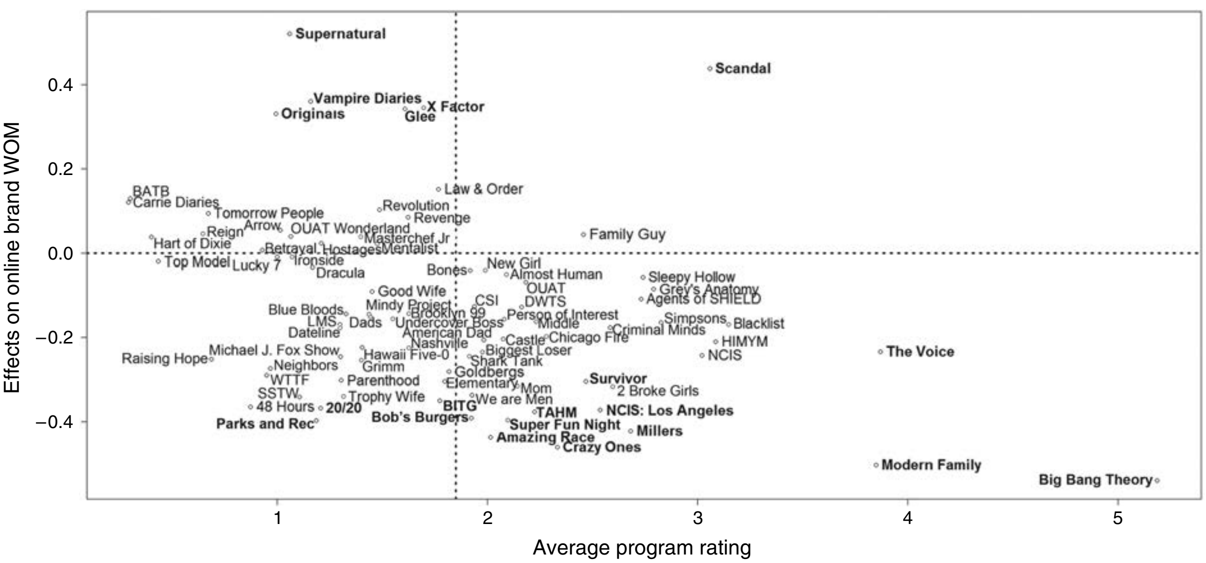
We consider the relationship between program ratings and the program-specific effects on online brand WOM, again paired with the program's genre and

Figure 4. Impact of Combined Program-Specific Effects, Genre Effects, and Network Effects on Online Program WOM and Online Brand WOM Following Television Ads



Notes. The combined impacts of the program-specific effects for program p ($\gamma_{p\cdot}$) plus p's genre and network effects on both online program and brand WOM were estimated at each iteration to obtain posterior mean and HPD interval estimates. Programs in **bold** indicate that the 90% HPD interval for this effect on online brand WOM excludes zero. Programs in *italics* indicate that the 90% HPD interval for this effect on online program WOM excludes zero. Programs in ***bold italics*** indicate that the 90% HPD intervals for both the online brand WOM and online program WOM effects excludes zero. These posterior mean and HPD interval estimates are presented in Table A8 in the online appendix. The quadrant lines are drawn at zero. The following shows in Figure 4 were abbreviated as follows: *Back in the Game* (BITG), *Beauty and the Beast* (BATB), *Dancing with the Stars* (DWTS), *How I Met Your Mother* (HIMYM), *Last Man Standing* (LMS), *Once Upon a Time* (OUAT), *Once Upon a Time in Wonderland* (OUAT Wonderland), *Sean Saves the World* (SSTW), *Two and a Half Men* (TAHM), and *Welcome to the Family* (WTTF).

Figure 5. Relationship Between Average Program Ratings and Combined Program-Specific Effects, Genre Effects, and Network Effects on Online Brand WOM Following Television Ads



Notes. The combined impacts of the program-specific effects for program $p(\gamma_{p\cdot})$ plus p's genre and network effects on online brand WOM were estimated at each iteration to obtain posterior mean and HPD interval estimates. Programs in **bold** indicate that the 90% HPD interval for this effect on online brand WOM excludes zero. These posterior mean and HPD interval estimates are presented in Table A8 in the online appendix. The vertical quadrant line is drawn at the overall mean program rating in our data (1.85), and the horizontal quadrant line is drawn at zero. See note under Figure 4 for program abbreviations.

network effects, in Figure 5. Ratings currently dictate the cost of advertising, with higher ratings equating to greater costs. Advertisers looking to capitalize on increased online brand chatter following ads without paying for higher ratings could look to advertise in programs that fall in the upper left quadrant of Figure 5. Brands that advertise in these programs experience higher than expected online WOM following ads, and this increased volume of online chatter, which creates free exposures for the brand online, could offset the lower ratings making these programs potential bargains for advertisers. Networks could also leverage the findings in Figure 5 to negotiate higher ad rates in programs that offer increased online brand engagement. Overall, 25% of the programs in the data for which the program effect on online brand WOM is distinguishable from zero fall in the upper left quadrant. Some examples of such programs include CW's *Supernatural*, CW's *Vampire Diaries*, and FOX's *Glee*.

6. Conclusion

Using multisource data on television advertising and social media conversations, we examine television viewers' social TV activity to investigate the relationship between television advertising and online WOM. Overall, our results suggest that television advertising can influence online chatter for both the brand advertised and the program in which the ad airs. We discuss the implications of our key results for both advertisers and television networks.

6.1. Implications for Advertisers

Our findings show that social TV can be valuable to marketers as it can result in increases to online WOM for advertised brands. This chatter creates free exposures for the brand online, extends the reach of television ad campaigns to the online space, and offers real-time feedback to advertisers on how their ads are being received. Our results suggest a number of media planning strategies and ad design strategies that advertisers can implement to increase online brand WOM. Notably, contrary to industry reports (e.g., Deggans 2016, Flomenbaum 2016; Nielsen 2014b, 2015), we find that programs that receive the most online WOM are not necessarily the best programs for advertisers. This result stresses the importance of considering ad engagement in assessments of social TV as program engagement does not tell the whole story. Figures 4 and 5 provide general guidance on programs that can offer increased engagement for advertised brands. Our findings also indicate that, all else being equal, advertisers may influence the volume of online WOM for their brands through further media planning strategies such as through network selection (e.g., airing ads on CBS decreases brand WOM 1%) and program rating selection (e.g., airing ads on programs with higher ratings increases brand WOM 0.50% per rating point). We also find that online program WOM increases following the first ad in a commercial break, which may hurt consumer attention to ads airing early in the break. This is relevant to media buying strategies as the first ad slot in a commercial break is considered to be the most coveted ad position by advertisers (Katz 2013, p. 71; Wilbur et al. 2013).

While viewers' multiscreen behavior reveals a potential downside for ads airing in the first ad slot, we also find evidence that advertisers can increase online WOM for their brands following ads airing in the first ad slot by incorporating calls-to-action, specifically a hashtag or Web address, into the ad design, which increases subsequent online brand WOM by 3% and 2%, respectively. These results have implications not only for ad design strategies but also for the importance that ad position should play in media buy negotiations for advertisers interested in online WOM. Our results also suggest that advertisers interested in online brand engagement may want to consider the cast of programs in which they hope to air ads when choosing a celebrity spokesperson as we find that ads that include a celebrity who is also in the show in which the ad airs increases online brand WOM substantially by 112%. However, these results are based on a small sample as less than 1% of ads in our data include a celebrity who is also in the program in which the ad airs. Further research may want to explore the impact of this strategy and more detailed implications for advertisers with a larger sample. Finally, our results suggest further ad design strategies that, all else being equal, can increase the volume of online brand chatter such as avoiding using a phone number call-to-action in the ad (decreases online brand WOM 2%) and running longer ads (increases online brand WOM 0.03% per second of ad length).

6.2. Implications for Television Networks

We find that the products advertised can influence viewers' online engagement with programs. Our results suggest that how networks distribute ads across programs can have a meaningful impact on online program engagement. All else being equal, networks may want to avoid distributing ads for the categories of products that have negative effects in Table 4 across programs they desire to have high online social activity as these ads decrease subsequent online program chatter. Alternatively, networks may look to charge higher ad rates for such ads when possible. Furthermore, our results in Figure 5 can be leveraged by networks in media buy negotiations to charge higher ad rates for their low-rated programs that offer increased online engagement for advertised brands. Networks can use these results to offer more program-specific recommendations to advertisers interested in finding the right balance between engaged viewing audiences or program ratings and increases in online brand chatter.

6.3. Directions for Future Research

This work is subject to limitations that may be rich avenues for future research. First, we do not observe if a television viewer sees an ad and then engages in online WOM. Such individual-level data could let us attribute changes in online WOM to television ads over longer time periods. The narrow time windows used in our analysis help us avoid potential unobservable impacts of this limitation. Second, we focus on the volume of online chatter as our social media data provide limited information on what is being said about the brands and programs.[20] Future analysis of WOM content could permit a more nuanced study of television advertising and different online WOM types (e.g., recommendation, emotion, and attribute oriented WOM investigated by Gopinath et al. 2014). Finally, while our examination of social TV has focused on television advertising's role as a driver of online WOM, future research may build on this foundation to explore the relationship between television advertising, social TV, and other brand performance measures, such as sales or brand health.

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Endnotes

[1] Social TV can describe many activities at the intersection of television and social media. In this work, we focus on one type of social TV activity, the joint consumption of television and social media by television viewers (henceforth social TV activity).

[2] The social TV industry includes hardware (e.g., Smart TVs), technology/platforms (e.g., social TV analytics), and end user technology (e.g., social check-in, TV-specific social networks) (MarketsandMarkets 2012).

[3] This includes only live programming in the Eastern and Central time zones, which accounts for 76% of the U.S. population (based on U.S. Census Bureau 2013 State Population Estimates). Pacific time zone programming is not deemed an initial airing since it airs three hours after Eastern/Central programming. The granular level of the social media data allows us to attribute the online WOM to the Eastern/Central time zone programming.

[4] Topsy Pro was acquired by Apple in late 2013 and is no longer available to the public.

[5] Our data capture the volume of mentions and does not distinguish between Tweets and Retweets.

[6] Note that this search strategy does not double count conversations that include more than one of these elements.

[7] The narrow time window and difference structure of the dependent variables used in the analysis, discussed in Section 4, alleviate the concern that we capture chatter about the brand not spurred by the advertisement.

[8] Table A3 in the online appendix details the 15 categories and shows the top advertisers in each category. Only one category is featured per ad instance, and only 5% of the brands in the data air ads in more than one category.

[9] Initial coder agreement was 84% on whether or not the ad had specific calls-to-action and 93% on whether or not the ad had a visual or auditory brand sign-off. Differences were reconciled through discussion and review of the ad.

[10] We additionally identified the mood of each ad (e.g., funny, informational) in the data using ispot.tv. However, ad mood was not found to impact social TV activity. Details of these analyses can be found in the online appendix.

[11] An ad is said to contain a celebrity if an actor identified in the ad has an IMDb STARmeter rank, a measure of popularity based on a propriety algorithm of IMDb user behavior, fall in the top 5,000 sometime before the ad airs. If an actor is classified as a celebrity, IMDb filmography is used to identify if the actor appears in the program episode in which the ad airs. Ads for movies and television shows are not considered ads with celebrities.

[12] The frequency of ad instances by program rating, day of the week, and time is shown in Figure A1 in the online appendix. More details on the 84 programs can be found in Table A4 in the online appendix.

[13] Table 2 presents descriptive statistics for changes in online WOM for a subset of the characteristics in the data. Descriptive statistics for the remaining characteristics can be found in Table A5 in the online appendix.

[14] We test 16 alterative time windows varying from 3 minutes to 1 hour. The substantive results for these analyses, which are detailed in the online appendix, are highly consistent with those from our main model.

[15] We consider several alternative specifications for robustness. We evaluate dependent variables that are the number of Twitter mentions for brands and programs, mentions relative to program ratings, and percentage change in mentions. We also consider additional alternative models that take into account the content of the online WOM, albeit in a restricted fashion given the limits of our data. We consider valence of the online mentions and the presence of brand-program comentions in a single Tweet. The substantive results for these alternative analyses do not differ from those of our main model and are detailed in the online appendix.

[16] The subscripts $b[i]$ and $p[i]$ are used to refer to the brand and program, respectively, associated with ad instance i. These effects are brand- and program-specific, respectively, not ad instance-specific.

[17] To avoid axes shifts and rotations, we assume the locations for three brands prior to estimation. We position brand 1 at the origin ($B_{11} = B_{12} = 0$) to avert an axis shift, brand 2 on the positive x-axis ($B_{21} > 0$, $B_{22} = 0$) to prevent rotation over the y-axis, and brand 3 such that $B_{32} > 0$ to avoid rotation over the x-axis.

[18] Consistent with this belief, our results hold whether we account for advertisers' program selection or not. That is, we find the same substantive results when we estimate Equations (1)–(7) as shown and when we assume $\eta 1 = \eta 2 = 0$ in Equation (3), thereby not incorporating advertisers' program selection, which enters Equation (4) through Z_{bp}.

[19] The posterior mean and HPD interval estimates for these effects for all 84 programs are presented in Table A8 in the online appendix.

[20] In the online appendix, we discuss additional models in which we consider the valence of the online WOM and brand-program comentions. The substantive results from these analyses do not differ from those of the main model.

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