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The Role of Online Word-of-Mouth in Brand Strategy

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The Role of Online Word-of-Mouth in Brand Strategy

By

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B.B.A, Millsaps College, 2010

Advisor: David A. Schweidel, Ph.D.

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2016

Abstract

The Role of Online Word-of-Mouth in Brand Strategy

By Beth L. Fossen

Online word-of-mouth (WOM) is playing an increasingly important role in the dissemination of brand information and marketing messages. In my dissertation work, I study online WOM in two broad contexts and provide insights into how online WOM can be productively incorporated into brand strategies, the media planning and buying process, and advertisement design strategies.

I first investigate online WOM in multi-screen media consumption environments. Media consumption is rapidly evolving due to the rise multi-screen media activity. This changing media consumption landscape is creating new challenges for marketers who aim to understand how such multi-screen activities influence consumers' responses to marketing messages. In the first two essays, I address several of these key challenges and explore a new consumer behavior that has emerged due to media multitasking, social TV, which is the interaction of consumer social media participation and television viewing. The first essay explores the relationship between television advertising and online WOM and provides insights into how marketers, television networks, and program creators can (1) increase online WOM for their respective brands and programs through media planning and advertisement design strategies and (2) incorporate online WOM into the media planning and buying process. The second essay investigates how online viewer engagement with the program impacts online shopping behavior following television advertisements. This work address whether social shows are more beneficial to marketers and sheds light on the relationship between social TV, television advertising, and sales.

I additionally explore online WOM in the context of brand publicity. Brand publicity can have a lasting impact on consumer-brand relationships and generate spillover effects to other brands. The third essay of my dissertation examines the evolution of competitive spillover effects from brand publicity using the volume and valence of social media conversations about the brand and its competitors. This work considers the dynamics of consumer generation and consumption of online WOM about brands and sheds light on how brand managers can use online WOM to assess the potential spillover effects from brand publicity.

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Chapter 1: Introduction

Online word-of-mouth (WOM) is playing an increasingly important role in the dissemination of brand information and marketing messages. Research in the marketing literature has established that online WOM matters and can increase new customer acquisition (e.g., Trusov et al. 2009), television ratings (e.g., Godes and Mayzlin 2004), and sales (e.g., Chevalier and Mayzlin 2006; Kumar et al. 2013). Despite the positive consequences of online WOM, marketers still face many challenges in understanding how to incorporate online WOM into brand strategies. Specifically, research into actionable drivers of online WOM is still in its infancy (e.g., Berger and Milkman 2012; Berger and Schwartz 2011). Additionally, in many contexts, such as in television viewing, advertisers struggle with understanding how online WOM can play a valuable role in consumer media consumption experiences (e.g., Copeland 2013).

In my dissertation work, I address research challenges concerning online WOM in two broad contexts – multi-screen media consumption environments and brand publicity. With this research, I am to provide insights into the drivers of online WOM and shed light on how online WOM can be productively incorporated into brand strategies, the media planning and buying process, and advertisement design strategies.

The first two essays of my dissertation investigate online WOM in multi-screen media consumption environments. Consumer media consumption is rapidly evolving due to the rise multi-screen media activity. Nielsen (2014a) estimates 84% of tablet and smartphone users engage in multi-screen behavior while watching television. Joint work from Twitter, FOX, and the Advertising Research Foundation finds that 85% of Twitter users active during primetime programming contribute to online conversations about television and 90% of users exposed to this chatter have taken TV-related action such as switching channels to watch a program or searching online for additional program information (Midha 2014).This changing media consumption landscape is creating new challenges for marketers who aim to understand how such multi-screen activities influence consumers' responses to marketing messages. In the first two essays of my dissertation, I address several of these key challenges, focusing on a new consumer behavior that has emerged in the multi-screen media consumption environment, social TV, which is the interaction of consumer social media participation and television viewing. Overall, the global media industry's interest in social TV is substantial as social-media related television businesses comprise a $100 billion industry (MarketsandMarkets 2012). Despite this rapid growth in social TV activity, advertisers and networks are facing challenges trying to grasp the value of this behavior (e.g., Hare 2012; Copeland 2013).

The first essay of my dissertation explores the relationship between television advertising and online WOM. We first explore if television advertising (1) drives online WOM about the brand advertised and (2) associates with changes in online WOM about the program in which the advertisement airs. We further examine if the media context in which the advertisement appears – the television program – impacts the relationship between television advertising and online WOM. By investigating the integration of consumer social media participation with television programming, known as social TV, we aim to improve the field's understanding of the consumer experience with television, advertising, and social media.

Using data containing over 9,000 television advertising instances and the volume of minute-by-minute social media mentions for 264 brands and 84 programs, we employ a hierarchical Bayesian model to conduct our investigation. The analyses reveal that television advertising impacts 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 aren't necessarily the best programs for advertisers in terms of increasing online engagement for advertised brands. These results suggest the need for social TV activity to be viewed in terms of viewer engagement with both programs and advertisements. Moreover, the results indicate that the program in which the advertisement airs affects the extent of online WOM for both the brand and program following television advertising.

Additionally, the results from the first essay indicate that online program WOM increases substantially following the first advertisement in a commercial break. This may hurt consumer attention to advertisements airing early in the commercial break, ad positions that are often coveted by advertisers, and reveal a potential downside of consumers' multi-screen behavior for marketers. However, we also find evidence that advertisers can increase online WOM for their brands following advertisements airing in the first ad slot by incorporating digital calls-to-action, specifically a hashtag or web address, into the creative. Overall, this first essay sheds light on how marketers, television networks, and program creators can (1) increase online WOM for their respective brands and programs through media planning and advertisement design strategies and (2) incorporate online WOM into the media planning and buying process.

The second essay expands on the analysis in the first essay by also considering online shopping behavior. Specifically, this research investigates the relationship among television advertising, social TV activity, online traffic, and online sales and examines how television viewers' online engagement with programs impacts online shopping behavior at retailers that advertise during the programs. This work aims to address whether television programs with engaged online audiences, so called "social shows," are more beneficial to marketers.

We build a multi-source data set that includes online shopping activity with data on traffic and transactions on retailers' websites, television advertising instances for those retailers in primetime programming on broadcast networks, social media conversations mentioning television programs and the retailers, and data on advertisement and program characteristics. Our data include over 1,600 ad instances for five national retailers that advertise a diverse range of products on 83 television programs during the fall 2013 television season. We jointly model the traffic and purchases on a retailer's website(s) following an ad's airing as a function of social TV activity, ad characteristics, and program characteristics using a hierarchical Bayesian regression. We assess the effects of social TV activity about the program on traffic and sales by considering the change in the volume of online mentions about the program prior to an ad's airing.

We find that that online program chatter has a substantial impact on online shopping behavior following advertisements. While increased online engagement with the program before the airing of a retailer's ad has a negative relationship with subsequent traffic to the retailer's website(s), we find that it increases sales at the retailer's website(s). Overall, this suggests that social shows are more beneficial to advertisers interested in increasing online sales. We also find that online chatter about the retailers following an ad's airing has a positive relationship with subsequent online purchases on the retailer's website, a result consistent with past research on the link between online brand WOM and brand sales (e.g., Babić Rosario et al. 2016; Stephen and Galak 2012; You et al. 2015). Our results further reveal the advertisement characteristics that influence online shopping activity. Of note, we find that advertisements with a funny mood perform best in terms of increasing online sales. In contrast, active, informational, and sexy advertisements result in decreases in subsequent purchases on the retailers' websites relative to ads with a funny mood. Furthermore, we find that advertisements that mention price have a positive impact on subsequent online purchases. These results have implications for ad design strategies for retailers interested in increasing online shopping activity.

Finally, my dissertation work additionally investigates online WOM in the context of brand publicity. Brand publicity can have a lasting impact on consumer-brand relationships and generate spillover effects, either positive or negative, to other brands. The third essay of my dissertation examines the evolution of competitive spillover effects from brand publicity using the volume and valence of social media conversations about the brand and its competitors. To conduct this investigation, we use data on performance-enhancing drug (PED) offenses of Major League Baseball players related to the highly publicized 2013 Biogenesis Scandal and treat each player as a human brand. We employ a hierarchical Bayesian model to estimate individual-level direct and reputational spillover effects stemming from the scandal and empirically find evidence of both collateral damage (negative spillover) and collateral construction (positive spillover) in social media sentiment from the brand scandal. Overall, this work considers the dynamics of consumer generation and consumption of online WOM about brands and sheds light on how brand managers can use online WOM to assess the potential spillover effects from brand publicity.

Taken together, these three essays provide insights into how online WOM can be effectively integrated into brand strategies, the media planning and buying process, and advertisement design strategies.

Chapter 2: Social TV

Introduction

Television viewing is rapidly evolving due to the rise of multi-screen activity. Nielsen (2014a) estimates 84% of U.S. tablet and smartphone users engage in media multitasking while watching television. One prevalent multi-screen activity is the joint consumption of television programing and social media, an activity known as social TV (Benton and Hill 2012). An estimated 36% of multi-screeners in the U.S. 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). Social TV's rapid rise, however, also has created new challenges for marketers, raising questions of how media multitasking affects viewer 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 behavior (Liaukonyte et al. 2015). These works, however, have not explored television advertising's impact on online conversations.

In this research, we aim to address the dearth of work examining the relationship between television advertising and online WOM and present the first broad investigation into social TV activity. Specifically, we explore three research questions. First, how does television advertising impact 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; Nielsen 2015a); 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 social activity are beneficial to advertisers in terms of increased online WOM. Finally, what are the drivers of social TV activity? We examine how advertisers and television networks can encourage online chatter for their respective brands and programs by examining how various brand, ad, and program characteristics influence online WOM following television ads.

We contribute to research on cross-media effects, television advertising, and online WOM in three key ways. First, our examination of social TV activity expands 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 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. Lastly, we contribute to 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, exploring what encourages television viewers to engage in social TV activity during programming and shedding light on how advertisers, television networks, and program creators 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 multi-source 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 primetime 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 doesn't 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; Nielsen 2015a), that programs with high online social activity aren't necessarily the best programs for advertisers seeking to generate online WOM. 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 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 online 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 non-profits or public service announcements (PSAs) decrease subsequent program chatter by 2%. These findings can help guide networks in the distribution of ads across programs as they may want to avoid placing such ads in shows they hope will have high online engagement.

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.

Background Literature

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 (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 brand exposures 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. (2015) 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 offline and online communications also can 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.

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 pre-launch 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.

Television Advertising and Social TV Activity

How might television advertising impact online WOM? Communications about television can enhance co-viewing 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 co-viewing 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 (2015a) explore the correlation between neurological engagement and Twitter activity for eight television shows and find that viewer emotion, attention, and memory are positively correlated with online WOM about the programs. Thus, beyond the functional quality of television advertisements serving as convenient breaks in program content, the above work suggest that accessibility of a brand or program and/or viewer 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, characteristics of advertisements, and characteristic of the 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 viewer 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). In 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 viewer 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 increase 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 viewer 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 towards the show's conclusion, which may increase viewer attention and positive emotional arousal towards the program but have a detrimental impact on attention towards 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 viewer 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 lead 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 exploring the link between program and brand engagement in the social TV context, treating the nature of this relationship as an empirical question.

Data Description

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 (Sept. 1 – Dec. 31, 2013) were gathered from Kantar Media's Stradegy database. Data were collected for ads on the initial airing of recurring programs[1]. We exclude ads that Stradegy identifies as joint promotions, which made up less than 1% of the ad instances in the data, from our analysis so that the data does not contain multi-brand ads. Our final data set consists of 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. We use Twitter data because the majority of public social media chatter about television occurs on Twitter (Schreiner 2013). We

[1] 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, discussed next, allows us to attribute the online WOM to the Eastern/Central time zone programming.

use the number of mentions for brands and programs to assess online WOM[2]. 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)[3]. 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[4]. The exceptions include movies (e.g., parent brand – Warner Brothers; product brand – *Gravity*), books (e.g., parent brand –Little, Brown and Company; product brand – *Gone* by James Patterson), 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 for the advertised brands.

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

[2] Our data captures the volume of mentions and does not distinguish between Tweets and Retweets.
[3] Note that this search strategy does not double count conversations that include more than one of these elements.
[4] The narrow time window and difference structure of the dependent variables used in the analysis, discussed in Model Development, alleviate the concern that we capture chatter about the brand not spurred by the advertisement.

play in influencing social TV activity. We control for the category of the product advertised as online WOM may vary across categories[5]. We account for if a brand has a Twitter profile as it may reflect a brand's interest in online WOM and may affect viewer decisions to discuss the brand online. We further control for ad position in a commercial break (first or last non-promo ad), ad position in a program (relative ad break position and near a half-hour interval), and if an ad runs simultaneously with another ad break on a different broadcast network. Past work has found that viewer attention and ad response varies 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 2015a). 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 viewer attention and recall (e.g., MacInnis et al. 1991; Stewart and Furse 1986; Teixeira et al. 2012), which can impact online WOM (Nielsen 2015a). 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 a auditory brand sign-off (is the brand name repeated

[5] Only one category is featured per ad instance, and only 5% of the brands in the data air ads in more than one category.

within the last 3 seconds of the ad?), as defined by Stewart and Furse (1986)[6]. To identify the actors in each ad, we use ispot.tv, an ad metrics firm which lists the actors that appear in national television ads, and ad content (does the ad contain an actor's name?). 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[7].

Lastly, we control for program characteristics that influence viewer 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 2015a). We account for network, genre, program ratings, and 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. The data for these program characteristics were gathered from Stradegy with the exception of program ratings which were collected from *TV by the Numbers*.

Descriptive Statistics for Television Advertising Data

The average ad break in the data contains eight ads, and programs have on average six ad breaks. The most advertised categories are movies, beauty, and wireless providers, which account for 38% of ad instances. The most advertised brands are Apple, Microsoft, AT&T, Nokia, Sprint, and Bank of America, which account for 20% of ad instances.

[6] 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.

[7] 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.

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

Brand and Advertisement Characteristics			
Parameter	*Description*	*Freq. (%)*	*Mean (SD)*
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 ad that air simultaneously with commercials on a different broadcast network	61.17	
Ad position in a commercial break	% of ads that are the first non-promo ad in a given commercial break	17.83	
	% of ads that are the last non-promo 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 2 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 18-49 demographic		1.85 (0.97)
Season premiere	% of ads that aired during season premieres	9.38	

Table 1 shows summary statistics for the brand, ad, and program characteristics. 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 the data collection. Lastly, 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.

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 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 no change in brand chatter following their ads airing on FOX's *Glee.*

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 non-profit or PSAs, online program WOM decreases by 19% and 11%, respectively. These insights 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[8]. For example, including a celebrity in an ad who is also in the program in which the ad airs increases subsequent online brand chatter by 569% on average. This is an interesting insight because our data suggests that advertisers are not utilizing this strategy.

[8] Table 2 present 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 Appendix 1.

Figure 1: Online WOM for *Scandal* on October 3, 2013

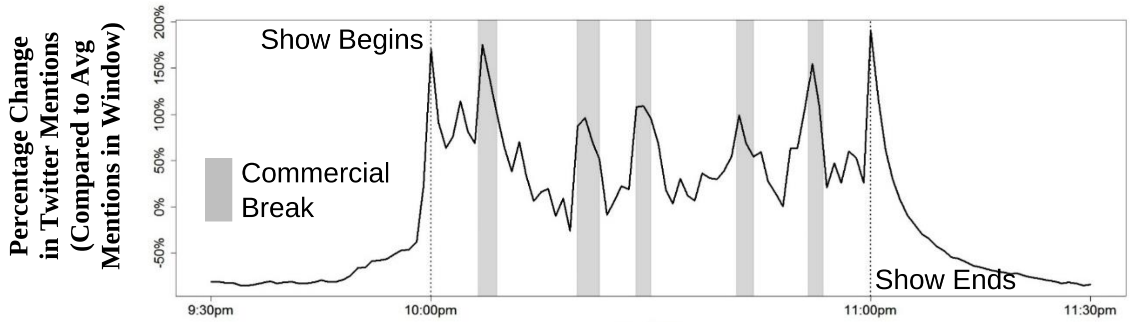
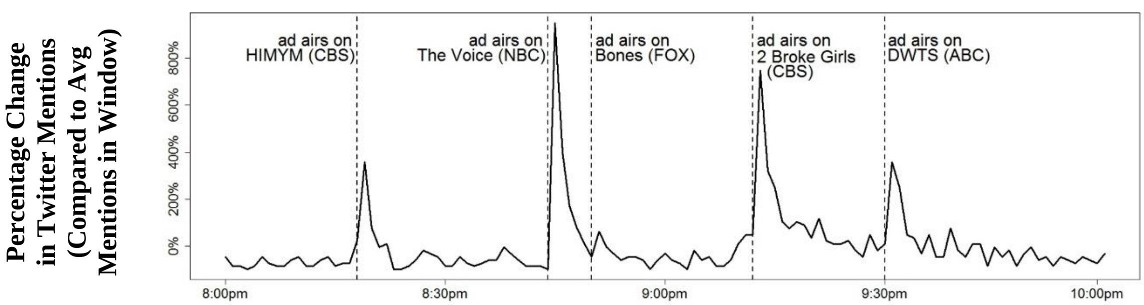
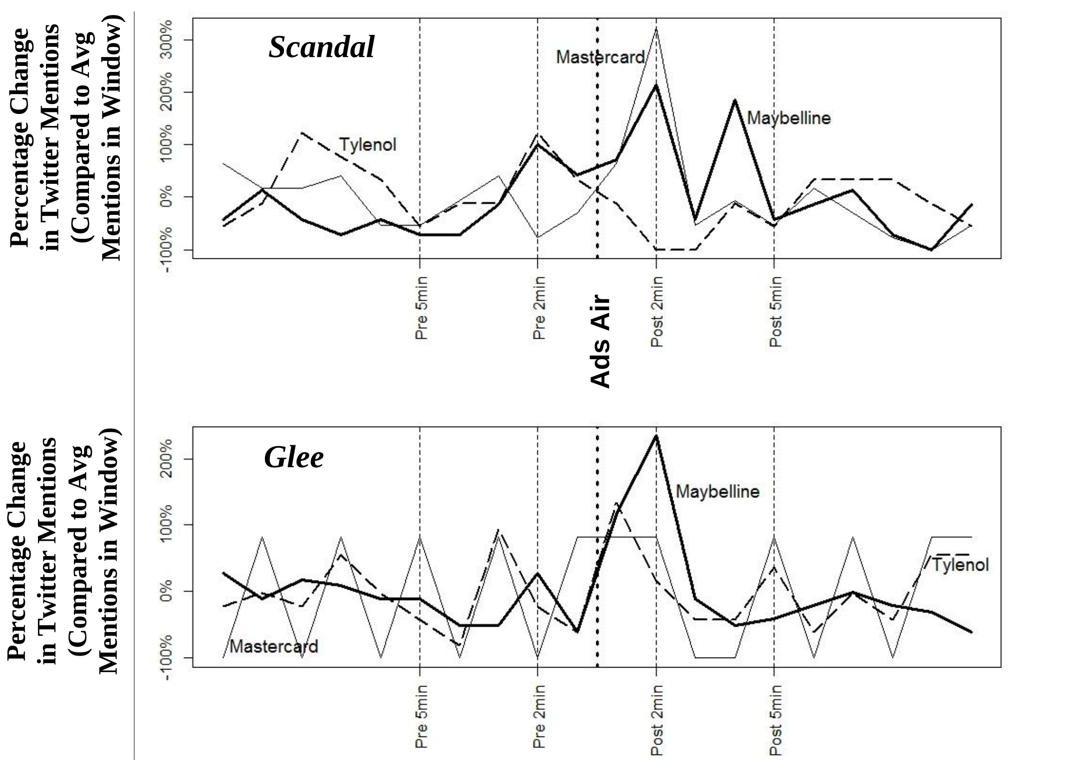


Figure 2: Online WOM following Television Ads for *Gravity* on September 23, 2013



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

Figure 3: Online WOM following Television Ads on ABC's *Scandal* and FOX's *Glee*



While 31% of the ad instances in the data contain a celebrity, less than 1% contain 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 an ad 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 above the average effect (e.g., first ad position, movie ads, ads including a Facebook link or icon). However, other characteristics have the opposite effect (e.g., apparel ads, ads with celebrities also featured in the program, shows on FOX). Furthermore, our data show that the presence of brand-program co-mentions in a single post (e.g., "Did you see the Sprint ad on *Scandal*?") is not prevalent.

Table 2: Descriptive Statistics for Online WOM

	Change in Brand WOM		**Change in Program WOM**			**Change in Brand WOM**		**Change in Pro WOM**
	Mean/*SD*		Mean/*SD*			Mean/*SD*		Mean/*SD*
Overall	108%	*1411%*	4%	*73%*	**Ad position in ad break**			
Ad length					First ad	169%	*1014%*	30%
< 30 seconds	52%	*199%*	1%	*82%*	Last ad	21%	*78%*	-17%
30 seconds	129%	*1716%*	5%	*68%*	**Calls-to-action**			
> 30 seconds	511%	*2340%*	10%	*45%*	Facebook	137%	*325%*	8%
Category					Facebook in 1st ad	170%	*300%*	20%
Movies	533%	*3793%*	5%	*47%*	Hashtag	259%	*2930%*	4%
Apparel	114%	*322%*	1%	*37%*	Hashtag in 1st ad	324%	*964%*	23%
Insurance	76%	*247%*	3%	*44%*	Phone	44%	*167%*	6%
Hair care	78%	*507%*	-1%	*35%*	Phone in 1st ad	67%	*204%*	29%
Beauty	58%	*199%*	3%	*45%*	Web	83%	*423%*	4%
Financial	45%	*151%*	6%	*132%*	Web in 1st ad	150%	*541%*	31%
Other	39%	*89%*	2%	*45%*	**Genre**			
Wireless prov.	36%	*105%*	6%	*52%*	Comedy	91%	*544%*	-2%
Phones	32%	*118%*	9%	*53%*	Drama/Adv.	132%	*2014%*	9%
Computer accessories	37%	*137%*	5%	*44%*	News	21%	*82%*	13%
Meds/vitamins	30%	*89%*	0%	*46%*	Slice of Life	109%	*406%*	-3%
Non-profits/PSA's	27%	*131%*	-11%	*31%*	Suspense/Police	52%	*155%*	2%
Computers /tablets	19%	*89%*	10%	*131%*	**Network**			
Dental care	14%	*63%*	3%	*37%*	ABC	198%	*2776%*	4%
Cable providers	9%	*54%*	-19%	*24%*	CBS	53%	*204%*	11%
Celebrity					CW	54%	*173%*	13%
Celebrity	53%	*199%*	5%	*88%*	FOX	128%	*657%*	-7%
Celebrity in program	569%	*1435%*	-5%	*33%*	NBC	83%	*311%*	-1%

Note: Percentage change is calculated as (PostWOM-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

Only 2% of the ad instances in the data see posts with brand-program co-mentions within two minutes after the ad airs. 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 our empirical analysis.

Overall, Figures 1-3 and Table 2 show support that television advertising can influence online chatter and show evidence of 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.

Model Development

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:

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

where i indexes the ad instance in the data, $PostBWOM_i$ 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, the specificity of timing of when an 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). Furthermore, networks commonly order advertisements across commercial breaks at random (Wilbur et al. 2013). Therefore, it is not plausible to time an ad to air during a specific four minute period to influence 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[9]. We select a difference structure for the dependent variables because we are interested in how an advertisement's insertion – and its associated characteristics – alter online WOM for a brand or program from its baseline levels. We use log specifications as there is large variance in these differences across brands and programs[10].

[9] We test sixteen alterative time windows varying from three minutes to one hour. The substantive results for these analyses are highly consistent with those from our main model.

[10] 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

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

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

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

μ_{brand} and μ_{prog} are respective intercepts. We account for brand-specific effects ($\alpha_{b.}$) and program-specific effects ($\gamma_{p.}$) 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. Furthermore, $\alpha_{b.}$ and $\gamma_{p.}$ 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). $X_{i.}$is a vector of ad instance-specific brand, ad, and program characteristics detailed in the data section. $X_{i.}$ also includes a measure to capture if 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. Lastly, to account for potential correlation between the two dependent variables of interest, we allow for contemporaneous covariance in T.

$BPSynergy_{bp}$ is a latent measure that functions like a brand-program interaction as it assesses if the synergy between brand b and program p affects online WOM for b and p beyond the main effects of the brand ($\alpha_{b.}$) and the program ($\gamma_{p.}$). 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

of the online mentions and the presence of brand-program co-mentions in a single Tweet. The substantive results for these alternative analyses do not differ from those of our main model.

program p is stated as 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:

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

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

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

where B_{b1} (P_{p1}) and B_{b2} (P_{p2}) specify the location of brand b (program p) in the two-dimensional Euclidean space[11]. We use the estimates of these locations to construct the brand-program synergy measures ($BPSynergy_{bp}$), which we assume to be inversely related to $LatentDist_{bp}$:

(7) $$BPSynergy_{bp} = \frac{1}{LatentDist_{bp}}$$

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 ($\alpha_{b.}$) and the program ($\gamma_{p.}$)[12].

Advertisers' program selection, however, is expected to have little impact on the relationship between television advertising and online WOM, largely due to the nature of

[11] 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.
[12] 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}.

advertiser-network media buy negotiations. Advertisers commonly buy ad time for a set of programs on a network or for a general program type (e.g., comedies) rather than for just one program (Katz 2013, pg. 152). About 80% of these ad buys take place in May, 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 ordered randomly across commercial breaks (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 re-running the ad in a comparable spot on the same or similar program to make up the remaining ratings point (Katz 2013, pg. 200). This process does not offer advertisers much control over selecting a specific program to air an ad in to affect immediate online WOM.

Additionally, if advertisers were interested in influencing online Twitter mentions for their brands through program selection, these advertisers would be interested in online engagement on Twitter and would likely have a Twitter profile for their brand. However, as shown in Appendix 1, online brand WOM following an ad's airing does not appear to vary considerably based on whether or not the brand has a Twitter profile. Thus, the nature of media buy practices and a comparison of brands with and without Twitter profiles appear to suggest that advertisers' program selection may not play a substantial part in affecting television advertising's impact on online WOM. Nevertheless, we incorporate advertisers' program selections into our analysis to account for its potential impact on online chatter.

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 $\alpha_{b1} \sim N(0,\tau_{\alpha 1})$, $\alpha_{b2} \sim N(0,\tau_{\alpha 2})$, $\gamma_{p1} \sim N(0,\tau_{\gamma 1})$, and $\gamma_{p2} \sim N(0,\tau_{\gamma 2})$, with diffuse inverse-gamma priors for the variances. We specify μ_{brand}, μ_{prog}, $\eta_{.}$, and $\theta_{k.}$ 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 $\bar{\lambda}$, $\bar{B}_{.}$, and $\bar{P}_{.}$ 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.

Results

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 ($X_{i.}$), 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 upon 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.

Table 3: Model Comparison

Model	*Description*	*What's Included*	*DIC*	*Brand MAE*	*Program MAE*
Model 1	Baseline: no cross-effects	μ_{brand}, μ_{prog}, $X_{i\cdot}$, $\alpha_{b,1}$, $\gamma_{p,2}$	96467	1.102 (1.095, 1.109)	2.888 (2.869, 2.908)
Model 2	Brand cross-effects only	μ_{brand}, μ_{prog}, $X_{i\cdot}$, $\alpha_{b,1}$, $\alpha_{b,2}$, $\gamma_{p,2}$	96395	1.102 (1.095, 1.109)	2.879 (2.859, 2.900)
Model 3	Program cross-effects only	μ_{brand}, μ_{prog}, $X_{i\cdot}$, $\alpha_{b,1}$, $\gamma_{p,1}$, $\gamma_{p,2}$	96371	1.098 (1.091, 1.105)	2.888 (2.869, 2.908)
Model 4	Main model without $BPSynergy_{bp}$	μ_{brand}, μ_{prog}, $X_{i\cdot}$, $\alpha_{b,1}$, $\alpha_{b,2}$, $\gamma_{p,1}$, $\gamma_{p,2}$	96371	1.098 (1.091, 1.105)	2.879 (2.859, 2.900)
Model 5	Main model	Model 4 + $BPSynergy_{bp}$	96292	1.096 (1.089, 1.103)	2.874 (2.854, 2.895)

Note: 95% highest posterior density (HPD) intervals are shown with MAE.

What Impacts Online Brand WOM?

Tables 4 and 5 show that brand and ad characteristics have substantial impacts on 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 WOM after an ad's airing. All categories see less online brand chatter than movies. Next to movie advertisements, ads for phones and ads for computers, notebooks, or tablets spur the most online brand WOM while apparel, non-profit or PSA, and dental care ads generate the least 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 product, other ads may interrupt these experiences, such as ads for non-profits 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 is a notable finding as advertisers are not commonly employing this strategy. While 31% of ad instances in the data contain a celebrity, less than 1% include a celebrity who is also in the program episode in which an ad airs. The latter strategy is likely effective at amplifying consumer attention toward the ad (e.g., MacInnis et al. 1991), which may explain the effect.

Calls-to-action also can impact an ad's effect on online brand WOM. Specifically, including a phone number in an ad reduces subsequent brand chatter by 2%. This may decrease online brand WOM by encouraging an offline action (e.g., Tellis et al. 2000). 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 a web address in the first ad increasing online brand WOM by 2%. The interaction with ad position may occur

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*
μ_{brand} / μ_{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 acc.	-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%**
Non-profit/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)	

Note: 95% HPD intervals are shown. ** (*) indicate the 95% (90%) HPD interval excludes zero. 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).

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 viewer attention (e.g., Teixeira et al. 2012), which can increase social TV activity (Nielsen 2015a).

Table 5: Impact of Ad 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%**

Note: Table 5 presents posterior mean estimates with the 95% HPD intervals. We denote 95% HPD intervals that exclude zero with a double asterisk (**) and 90% HPD intervals that exclude zero with a single asterisk (*). See note under Table 4 about percentage change calculations.

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 larger base may spur more online WOM for advertised brands. Higher rated programs also may attract higher quality ads, which could also explain this positive effect. We further see that ads airing on CBS generate less online brand WOM that ads airing on FOX, which is consistent with the descriptive statistics presented in Table 2.

What Impacts Online Program WOM?

The results in Table 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 non-profits 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 non-profit 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 of 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 program content is more engaging as the program 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.

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 ($\vec{\lambda} > 0$). 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 online viewer engagement with advertised brands and program. 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 decreases 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, suggesting that online viewer engagement with advertised brands and programs may not always have a positive relationship.

Using our posterior inferences of $\gamma_{p.}$, we can further examine this relationship and explore if brands that advertise in programs with high online activity also experience more online brand WOM. Work on media context effects has found that viewer program engagement can either improve ad response (e.g., Murry et al. 1992; Feltham and Arnold

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%**

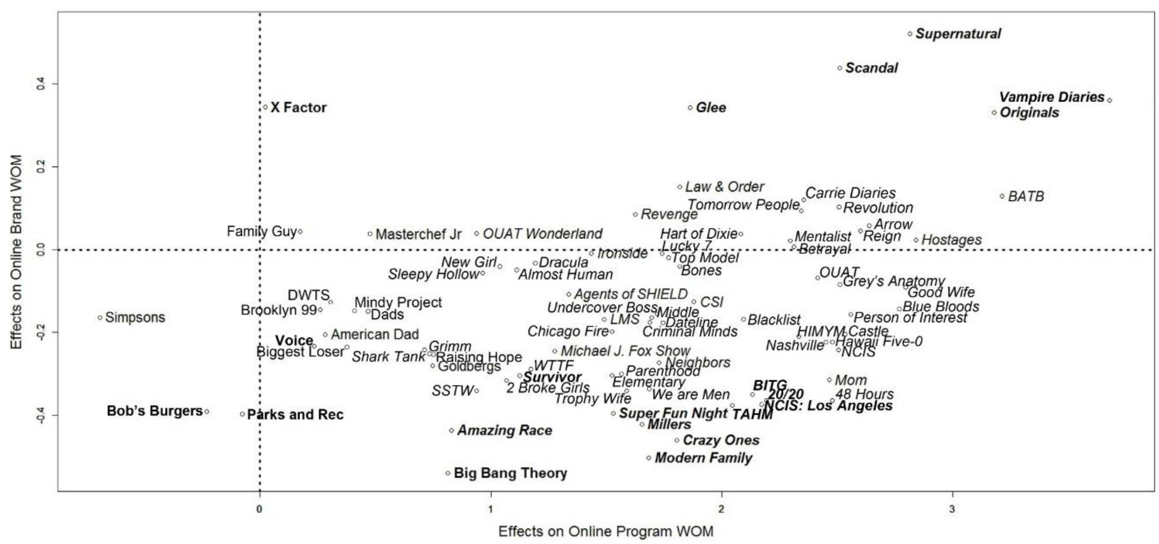
	Brand WOM Model		*Program WOM Model*	
Variable	*Parameter*	*Posterior Mean*	*Parameter*	*Posterior Mean*
Variance for $\log(Y_{i1})$ and $\log(Y_{i2})$	τ_{11}	2.38** (2.31, 2.45)	τ_{22}	11.79** (11.45, 12.15)
Covariance for $\log(Y_{i1})$ and $\log(Y_{i2})$	τ_{12}	-0.01 (-0.12, 0.10)	τ_{21}	-0.01 (-0.12,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

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

Note: Posterior mean estimates are presented with 95% HPD intervals. We denote 95% HPD intervals that exclude zero with a double asterisk (**) and 90% HPD intervals that exclude zero with a single asterisk (*). See note under Table 4 about percentage change calculations.

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. Twenty-one programs in our data (25%) 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*.

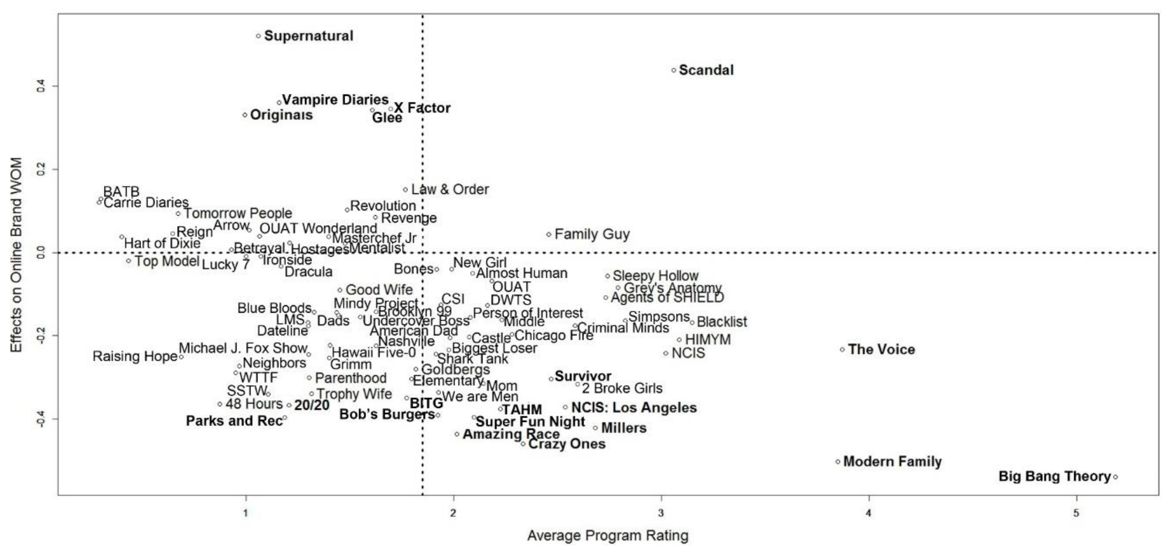
Figure 4: Impact of Combined Program-specific Effects, Genre Effects, and Network Effects on Online Program and Brand WOM following Television Ads



Note: 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. The quadrant lines are drawn at zero.

Interestingly, we find that the majority of the programs in our data (71%) fall in the lower right quadrant. These programs see higher than expected online program WOM after ads, but online WOM for brands that advertise in these shows is less than expected. Audiences that talk online about these shows may be doing so at the expense of engaging with advertised brands. This finding presents compelling evidence that programs that receive the most online WOM aren't necessarily the best programs for advertisers interested in online engagement. This result contrasts industry reports (e.g., Deggans 2016; Flomenbaum 2016; Nielsen 2014b; Nielsen 2015a) 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.

Figure 5: Relationship between Program Ratings and Combined Program-specific Effects, Genre Effects, and Network Effects on Online Brand WOM following Television Ads



Note: 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. The vertical quadrant line is drawn at the overall mean program rating in our sample (1.85), and the horizontal quadrant line is drawn at zero.

We consider the relationship between program ratings and the program-specific effects on online brand WOM, again paired with the program's genre and network effects, in Figure 5. Ratings currently dictate the cost of advertising, with higher ratings equating to higher 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, which have below average ratings, experience higher than expected online WOM following ads. The higher online WOM, 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, 23% of the programs in the data fall in the upper left quadrant, and some examples of such programs include CW's *Supernatural*, CW's *Vampire Diaries,* and FOX's *Glee*.

Conclusion

Using multi-source 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.

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; Nielsen 2015a), we find that programs that receive the most online WOM aren't 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 advertisers can influence online WOM for their brands through further media planning strategies by avoiding airing ads on CBS (decreases brand WOM 1%) and considering 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, pg. 71; Wilbur et al. 2013).

While viewers' multi-screen 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 for not only 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 should consider the cast of programs in which they hope to air ads when choosing a celebrity spokesperson as ads that include a celebrity who is also in the show in which the ad airs increases online brand WOM substantially by 112%. Lastly, our results suggest further ad design strategies that can increase 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).

Implications for Television Networks

We find that the products advertised can influence viewers' online engagement with programs. Our results suggest that networks may want to avoid distributing ads for cable providers, non-profits, and PSAs across programs they desire to have high online social activity as these ads decrease subsequent online program chatter by 2%. 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.

Directions for Future Research

This work is subject to limitations that may be rich avenues of 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 provides limited information on what is being said about the brands and programs. 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 upon this foundation to explore the relationship between television advertising, social TV, and other brand performance measures, such as sales or brand health.

Chapter 3: Social TV and Sales

Introduction

Multi-screen activity by television viewers is on the rise with an estimated 80% of U.S. television viewers simultaneously using another device while watching television (IAB 2015; Nielsen 2014a). Social TV, the joint viewing of television programming alongside the production and/or consumption of social media chatter about the programming (Benton and Hill 2012), is one of the most prevalent multi-screen activities with nearly 40% of multi-screeners in the U.S. engaging in this behavior (IAB 2015). Furthermore, joint work from Twitter, FOX, and the Advertising Research Foundation finds that 90% of Twitter users exposed to social TV chatter on the platform have taken action related to the programming, such as switching channels to watch a show or searching online for additional program information (Midha 2014). The interest in social TV is substantial, with social media-related television businesses having grown to be more than a $100 billion industry (MarketsandMarkets 2012).

The rapid growth of social TV, however, has raised new questions for advertisers. On the one hand, social TV behavior may be beneficial for advertisers. Viewers' participation in online conversations may engage viewers, making them more tuned-in and committed to the programming they are viewing, which in turn may improve the effectiveness of subsequent advertisements (Deaggans 2016; Flomenbaum 2016; Nielsen 2015a). Research on media context effects has shown that increased attention toward or involvement with a television program can improve brand attitudes and increase purchase intent of advertised brands (e.g., Feltham and Arnold 1994; Kilger and Romer 2007; Norris and Colman 1993) as well as reduce channel-changing behavior (e.g., Teixeira et al. 2010). The positive effects of program involvement on ad response are argued to be the result of a halo effect: the increased attention, arousal, and/or interest generated by the program carries over to the subsequent processing of the advertisements (e.g., Feltham and Arnold 1994; Schweidel et al. 2014; Wang and Calder 2009). Additionally, online media multitasking activities such as social TV may be beneficial for advertisers as these activities offer a lens into viewers' real-time responses to television programming (Liaukonyte et al. 2016), allowing advertisers the potential to assess ad effectiveness quickly.

On the other hand, social TV activity may distract viewers from watching advertisements and processing information in the ads. As a result, "social shows" – programs with high volumes of social TV activity – may be less attractive to advertisers. Research on media context effects has found that high levels of involvement with a television program can have a negative impact on ad recall (Norris and Colman 1993; Tavassoli et al. 1995). Additionally, in Chapter 2 we find evidence to suggest that television viewers that discuss programs online as part of social TV activity may be doing so at the expense of engaging with advertised brands online. Consistent with these findings, recent studies have found that online activities and television viewing can be substitute activities rather than complementary (e.g., Hinz et al. 2016; Seiler et al. 2015).

In this research, we empirically examine these contrasting theories on the impact of online program engagement on ad effectiveness by presenting the first examination of the relationship among television advertising, social TV activity[13], online traffic, and online sales. Specifically, we explore two research questions. First, how does social TV

[13] In this work, we focus on one type of social TV activity: online chatter about television programming.

activity impact online shopping behavior? We examine how online engagement with programs impacts both web traffic and online purchasing for retailers following their television advertisements. We additionally explore the effect of the volume of online chatter about the retailers on traffic and purchases on the retailers' websites following their advertisements. Examining this research question allows us to (1) extend research on cross-media effects that has yet to consider the joint relationship among television advertising, online WOM, and online shopping and (2) extend work on media context effects that has not explored media multitasking environments.

Second, how can television advertising increase online shopping activity? We investigate how retailers can use ad design strategies as well as media planning and buying strategies to encourage online traffic and purchases following their television advertisements, extending recent research examining the relationship between television advertising and online shopping (Liaukonyte et al. 2016) by incorporating the role of social TV behavior. Overall, our investigation of these two research questions allows us to (1) examine how the prominent media multitasking activity social TV affects viewers' responses to television advertisements in terms of subsequent traffic to and purchases on the advertisers' websites, (2) explore whether social shows are good for advertisers, and (3) shed light on how advertisers can use ad design and media planning and buying strategies to encourage online shopping activity on their websites in the age of multi-screen consumers.

To explore the relationship among television advertising, social TV, online traffic, and online sales, we build a multi-source data set that includes online shopping activity with data on traffic and transactions on retailers' websites, television advertising instances for those retailers in primetime programming on broadcast networks, social media conversations mentioning television programs and the retailers, and data on advertisement and program characteristics. Our data include over 1,600 ad instances for five national retailers that advertise a diverse range of products on 83 television programs during the fall 2013 television season. We jointly model the traffic and purchases on a retailer's website(s) following an ad's airing as a function of social TV activity, ad characteristics, and program characteristics using a hierarchical Bayesian regression. We assess the effects of social TV activity about the program on traffic and sales by considering the change in the volume of online mentions about the program prior to an ad's airing.

We find that that online program chatter has a substantial impact on online shopping behavior following advertisements. While increased online engagement with the program before the airing of a retailer's ad has a negative relationship with subsequent traffic to the retailer's website(s), we find that it increases sales at the retailer's website(s). We suggest that these results are consistent with past research on media context effects (Lord and Burnkrant 1993; Murry et al. 1992) that has found that increased viewer involvement with the program has different impacts on ad response depending on the viewer's interest in the advertised product. Overall, this suggests that social shows are more beneficial to advertisers interested in increasing online sales.

We also find that online chatter about the retailers following an ad's airing has a positive relationship with subsequent online purchases on the retailer's website, a result consistent with past research on the link between online brand WOM and brand sales (e.g., Babić Rosario et al. 2016; Stephen and Galak 2012; You et al. 2015). Our results further reveal the advertisement characteristics that influence online shopping activity. Of note, we find that advertisements with a funny mood perform best in terms of increasing online sales. In contrast, active, informational, and sexy advertisements result in decreases in subsequent purchases on the retailers' websites relative to ads with a funny mood. Furthermore, we find that advertisements that mention price have a positive impact on subsequent online purchases. These results have implications for ad design strategies for retailers interested in increasing online shopping activity.

The remainder of this research is organized as follows. In the next section, we review related research on program engagement and media context effects to discuss what influence social shows may have on ad effectiveness. We then describe the data and discuss the modeling approach for assessing the impact of social TV on online traffic and purchases. We present our results and conclude with a discussion of implications of our research for retailers and television networks as well as opportunities for future research in the contexts of media context effects and cross-media effects.

Television Program Engagement and Media Context Effects on Advertisements

Are social shows good for advertisers? Research on media context effects and cross-media effects has not yet explored the impact of online program engagement on sales of advertised brands. However, this body of work has established that television content can impact viewers' online behaviors (e.g., Joo et al. 2014; Liaukonyte et al. 2016) and has explored the relationship between other measures of program involvement and ad effectiveness. Additionally, industry studies from Nielsen have begun to explore how social TV activity impacts viewers' attention and ad response (Nielsen 2015a; Nielsen

2015b; Nielsen 2015c). We use the insights from these works to discuss why social shows may be good for advertisers and why social shows may be bad for advertisers. While our intent in the current research is not to test a particular behavioral theory, we use the proceeding discussion to motivate our subsequent empirical analysis.

Why Social Shows May Be Good for Advertisers

Past research on media context effects and cross-media effects suggest three key reasons why television viewers' online engagement with programs may be beneficial to advertisers. First, viewers' participation in online conversations about television shows may indicate that the viewers are more engaged with and more attentive to the programming relative to viewers of shows with less social TV activity. Nielsen (2015a) finds a positive correlation between Twitter conversations about television programs and neurological measures of engagement (attention, memory, and emotional arousal) for the program's general audiences. Experimental research on media context effects and ad processing supports these findings, arguing that heightened program involvement can increase viewers' cognitive arousal and attention, which enhances viewers' opportunities to process advertisements (e.g., Dahlén 2005; Lord and Burnkrant 1993; Maclnnis et al. 1991). Additional studies have illustrated that these increases in viewer attention, engagement, and/or involvement with television programming is good news for advertisers as these measures relate to better ad recall (Singh and Hitchon 1989), improved ad attitudes (Feltham and Arnold 1994; Murry et al. 1992), reduced ad skipping behavior (Teixeira et al. 2010; Woltman Elpers et al. 2003), and increased purchase intent (Feltham and Arnold 1994; Kilger and Romer 2007; Norris and Colman 1993). These positive effects of increased viewer program involvement on ad effectiveness are argued to be driven by a halo effect in which the increased attention, arousal, and/or interest generated by the program carries over to the subsequent processing of the advertisements (e.g., Dahlén 2005; Feltham and Arnold 1994; Schweidel et al. 2014; Wang and Calder 2009).

Second, heightened online program engagement also may encourage a more committed viewing audience, another behavior that is beneficial to advertisers. Programs with high online social activity commonly have viewers who watch multiple program episodes and are more likely to watch those episodes live (Nielsen 2015b). Such viewer loyalty factors are very important to advertisers (Atkinson 2008) and can help programs avoid cancellation (Lynch 2015). Lastly, social TV may be good news for advertisers because it can increase production and consumption of brand-related earned media. Television viewers who engage in online social activity about programs may also take time to discuss advertisements online, an activity that increases earned media for the advertised brand and also provides advertisers with real-time ad responses that can be used to assess ad effectiveness quickly (Nielsen 2015c). Additionally, viewers engaged on social media during programming may be more likely to be exposed and be attentive to such ad-related – and potentially consumption-oriented – earned media, which can prime a shopping mindset (Zhang et al. 2016).

Why Social Shows May Be Bad for Advertisers

While numerous studies on media context effects and cross-media effects present evidence that increased program engagement is good news for advertisers, other research suggests that the relationship between viewer program involvement and ad effectiveness may be negative. Higher levels of viewer engagement and/or entertainment with a program can distract viewers from ad information (Teixeira et al. 2014; Sternthal and Craig 1973) and create cognitive competition for the viewer, resulting in lower attentional, arousal, and/or informational capacity to process advertisements (e.g., Feltham and Arnold 1994; Hinz et al. 2016; Lord and Burnkrant 1993; Tavassoli et al. 1995). Additionally, increased engagement with the program also may enhance viewers' perceptions of advertisements as harmful intrusions (Calder and Malthouse 2008). These negative side effects of increased program involvement can result in reduced ad recall (Norris and Colman 1993; Pavelchak et al. 1988; Tavassoli et al. 1995), diminished attitudes toward the ad (Tavassoli et al. 1995), damaged ad persuasiveness (Teixeira et al. 2014), and lowered effectiveness of direct response advertising (Danaher and Green 1997). However, both Tavassoli et al. (1995) and Teixeira et al. (2014) only find these effects at very high levels of program involvement or program entertainment, respectively, not at moderate levels.

Consistent with the idea that social shows may be bad for advertisers, recent empirical investigations have found evidence that television viewing and online activity may be substitute behaviors rather than complementary. In Chapter 2, we find evidence that viewer online engagement with television programs may occur at the expense of viewer online engagement with advertised brands. Hinz et al. (2016) suggest that big television events, such as World Cup coverage and news coverage of recent natural disasters, can reduce online activity on bidding websites. Finally, Seiler et al. (2015) find that the ability (or inability) of viewers to engage social TV activity about the program does not impact program viewing, suggesting that these may not be complementary activities.

Role of Ad Relevance to the Viewer

The impact of program engagement on ad response may vary across viewer characteristics. Lord and Burnkrant (1993) and Murry et al. (1992) both find that the relationship between program involvement and ad effectiveness depends on how relevant the advertisement is to the viewer. If an advertisement has low relevance to a viewer (e.g., ad for a nutritional product shown to a non-health conscious consumer), then this viewer will likely have low motivation to switch her processing of the high involvement program to the advertisement content (Celsi and Olson 1988; Lord and Burnkrant 1993), which can result in reduced ad effectiveness (Lord and Burnkrant 1993; Murry et al. 1992). In our empirical context, this effect would likely manifest in a negative effect of online program engagement on traffic to and purchases on the retailer's website(s) following an ad's airing. Consistent with this argument albeit not in the context of program involvement, Liaukonyte et al. (2016) similarly contend that television advertisements that feature a product with low fit to the viewers' needs will have a negative impact on subsequent online shopping activity for the advertised product.

On the other hand, if an ad has high relevance to a viewer (e.g., ad for a nutritional product shown to a health conscious consumer), then this viewer will likely have the motivation to redirect the high attentional, arousal, and/or informational cognitive processing from the engaging program to the processing of the advertisement (Lord and Burnkrant 1993; Murry et al. 1992), resulting in improved ad effectiveness (e.g., Feltham and Arnold 1994; Kilger and Romer 2007; Murry et al. 1992). We anticipate that, in our empirical context, this effect would manifest as a positive relationship between online program engagement and both online traffic and purchases.

Social TV and Online Shopping

What hasn't been examined in prior research is what impact program involvement will have on viewers' ad response when (1) the program engagement happens in the online context that involves some viewers' media multitasking and (2) ad response is studied in terms of actual online sales rather than other ad effectiveness measures such as attitudes, recall, and purchase intent. Given the unknowns noted above, we treat the investigation of the net effect of social TV activity on online shopping behavior and, subsequently, interpretation of whether social shows are good for advertisers as empirical questions in our investigation.

Data Description

Online Shopping Data

To investigate the relationship among television advertising, social TV activity, online traffic, and online sales, data on online shopping behavior were gathered from comScore, Inc.'s Web Behavior Database. These data contain online browsing behavior for a panel of 100,000 active U.S. internet users and include machine- and minute-level data on new sessions to a website and website transactions (if applicable). Our data include online traffic and purchases for five large, national retailers[14]. We track new sessions and purchases on the retailers' websites and on the websites mentioned in the retailers' advertisements. Each of these retailers – or the retailer's parent company in one case – appeared on the 2013 Fortune 500 list of top companies and netted at least $10 billion in sales in the 2013 fiscal year.

[14] Due to our agreement with comScore, we cannot disclose the names of the retailers.

Television Advertising Data

The online shopping measures are combined with minute-level data on television advertising instances for the five retailers, which is gathered from Kantar Media's Stradegy database. These data include national, primetime, broadcast (ABC, CBS, CW, FOX, and NBC) advertisements that aired during the fall 2013 television season (early September to late December) on the initial airing of recurring programs[15]. The retailers advertise a diverse range of products including apparel accessories, computers and computer accessories, fragrances, make-up and skin care products, smartphones and smartphone accessories, software, and tablets and tablet accessories. Overall, our data include 1,685 ad instances for the five retailers that aired on 83 television programs.

Social Media Data

We further supplement this data on online shopping activity and television advertisements for the five large retailers with minute-level Twitter mentions about the 83 television programs in which the advertisements air as well as minute-level Twitter mentions about the five retailers. Program Twitter mentions were collected via Topsy Pro and retailer Twitter mentions were collected via Crimson Hexagon. At the time of data collection, both Topsy Pro and Crimson Hexagon were certified Twitter partner with comprehensive access to the public firehose of Twitter posts[16]. We focus on Twitter

[15] This advertising data contains 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). Programming in the pacific time zone is not deemed an initial broadcasting since it airs three hours after Eastern/Central programming. The comScore data is also filtered to exclude consumers in the Pacific time zone. The granular level of the social media data, discussed next, allows us to attribute the online WOM to the Eastern/Central time zone programming.

[16] Topsy Pro was acquired by Apple following our collection of program Twitter mentions but prior to the collection of retailer Twitter mentions. Since public access to Topsy Pro was no longer available following the acquisition, we acquired data on retailer Twitter mentions from Crimson Hexagon. These platforms offered comparable access to public Twitter posts. The only difference is that Crimson Hexagon's minute-level volume numbers are truncated if a given search query tallies more than 10,00 posts a day. If this

mentions because the vast majority of public social media conversations about television occur on Twitter (Schreiner 2013). Twitter mentions for programs and retailers were gathered by tallying Tweets that contain the program/retailer's name, a hashtag(s) with a program/retailer's name, or the Twitter handle of the program/retailer. For program mentions, we expanded the above search criteria to include nicknames as well (e.g., *DWTS* for *Dancing with the Stars*) to capture as much chatter as possible about the programs.

While we collect program mentions to model the impact on online program engagement on online sales, we also include data on online retailer chatter to control for the impact it may have on online shopping. While a number of past studies find evidence of a positive relationship between online brand WOM and brand sales (e.g., Babić Rosario et al. 2016; Stephen and Galak 2012; You et al. 2015), online conversations about advertisements may also distract viewers from engaging in social TV activity about the program and from engaging in online shopping following ads. Thus, we account for online retailer chatter in our analysis.

Advertisement and Program Characteristics

Lastly, we supplement our data with ad and program characteristics to control for the impact that they may have on online shopping and to provide additional insights into our second research question – how can television advertising increase online shopping activity? We account for several measures of ad position as past work on television advertising has found that viewer attention and ad response varies across assorted measures of ad position (e.g., Danaher and Green 1997; Schweidel et al. 2014; Siddarth

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occurs, Crimson Hexagon reports a random sample of 10,000 posts from that day. We use a relative change measure of online retailer chatter in our model, which alleviates effects from this data truncation.

and Chattopadhyay 1998). We control for the time the ad airs, the position of the ad in the commercial break, the position of the ad in the program, whether the ad airs near a half-hour interval or not, and whether the ad runs concurrently with another ad break on a different broadcast network or not. These data were extracted from Stradegy.

We further account for a number of measures of ad content that can influence ad effectiveness and ad response (e.g., Liaukonyte et al. 2016; Stewart and Furse 1986), including ad length, ad mood, whether the ad features a website call-to-action or not, whether the ad refers to a price or not, and whether the ad is comparative or not. Ad length is provided by Stradegy. We use ispot.tv, a television advertising metrics firm, to identify the mood of the advertisements. They label national advertisements as active, emotional, funny, informational, or sexy using a layered process of "automation, in-house editorial and crowd sourcing on our public website." Furthermore, each ad in the data was viewed by two coders to identify if the ad contains a web address, refers to price, and is comparative in nature[17].

Descriptive Statistics and Model-free Evidence

Table 7 shows descriptive statistics for the online shopping data. Across the ad instances in the data, more than 36,000 web sessions on the retailers' websites were initiated within thirty minutes of the ads' airings, and the users that initiated those sessions generated more than 2,000 purchases. Consistent with Liaukonyte et al. (2016), Table 7 shows evidence that television advertising can increase immediate online traffic and sales. On average, ad instances in the data spur a 20% increase in web traffic to the retailers'

[17] The coders followed definitions from Stewart and Furse (1986) to define if the ad referred to price and was comparative. Initial coder agreement was 99% on whether or not the ad contained a web address, 100% on whether or not the ad referred to price, and 83% on whether or not the ad was comparative. Differences were reconciled through discussion and review of the ad.

websites when comparing the number of sessions initiated from the five-minute period before the ad airs to the number of sessions initiated from the five-minute period after the ad airs. Furthermore, ad instances in the data spur about a 4% increase in purchases on the retailers' websites on average when comparing the number of online purchases from the five-minute period before the ad airs to the number of online purchases from the five-minute period after the ad airs. This grows to a 9% increase when we include purchases generated within twenty-four hours on the retailers' website by users that initiated sessions between when the ads air until five minutes after the ads air.

Table 7: Descriptive Statistics for Online Shopping Data

Parameter	*Description*	*Count*	*Mean*	*(SD)*
Online traffic	Sum of sessions at retailers' websites that were initiated between when the ads air until five minutes after the ads air	6,287		
	Sum of sessions at retailers' websites that were initiated between when the ads air until thirty minutes after the ads air	36,553		
Online purchases	Sum of purchases generated within twenty-four hours by machine users that initiated sessions on the retailers' websites between when the ads air until five minutes after the ads air	338		
	Sum of purchases generated within twenty-four hours by machine users that initiated sessions on the retailers' websites between when the ads air until thirty minutes after the ads air	2,070		
Change in online traffic	Percentage change in traffic to retailers' websites from five minutes before ads air to five minutes after ads air		20.25%	(85.79%)
Change in online purchases	Percentage change in purchases to retailers' websites from five minutes before ads air to five minutes after ads air		3.50%	(35.97%)
	Percentage change in purchases on the retailers' websites five minutes before ads air to five minutes after, including purchases generated within twenty-four hours by machine users that initiated sessions on the retailers' website between when the ads air until five minutes after the ads air		9.07%	(56.13%)

Note: Percentage changes are calculated as (activity in post ad window – activity in pre ad window)/(activity in pre ad window +1).

Table 8: Descriptive Statistics for Social Media Data

Parameter	*Description*	*Mean*	*(SD)*
Average program mentions	Average per minute online program chatter per episode	221.72	(455.99)
Program chatter before ads	Average per minute chatter before ads air relative to average program mentions (calculated as number of program mentions one minute before ad/average program mentions per minute in program episode)	1.10	(0.53)
Change in retailer mentions	Percentage change in retailer mentions from one minute before ads air to one minute after ads air	21.02%	(98.47%)
	Percentage change in retailer mentions from five minutes before ads air to five minutes after ads air	7.76%	(46.66%)

Note: Percentage changes are calculated as (activity in post ad window – activity in pre ad window)/(activity in pre ad window +1).

Table 8 presents descriptive statistics for the social media data. Episodes in the data average about 220 program mentions per minute, and online program chatter, on average, increases in the minute prior to the ads' airings. We also see evidence that television advertising generates increases in online chatter about advertised brands, with the retailers experiencing an 8% increase in WOM when comparing the number of mentions in the five minutes preceding an ad to the number of mentions five minutes after the ad airs. Tables 9 and 10 overview the advertising data, ad characteristics, and program characteristics. Of note, the majority of ad instances in the data have an active mood (72%) followed by an informational mood (14%), funny mood (11%), sexy mood (2%), and emotional mood (1%). Additionally, 46% of ad instances contain a web address and 32% mention price.

To explore the relationship between online program engagement and online shopping behavior, Table 11 shows the average change in online traffic and purchases on the retailers' websites relative to the amount of online program chatter that occurs in the minute before the ads air. We see some evidence that, as online program engagement

Table 9: Descriptive Statistics for Advertising Data, Advertisement Characteristics, and Program Characteristics

	Advertising Data and Advertisement Characteristics			
Parameter	*Description*	*Frequency (%)*	*Mean*	*(SD)*
Ad instances	% ads by retailer 1	9.44%		
	% ads by retailer 2	15.07%		
	% ads by retailer 3	0.24%		
	% ads by retailer 4	29.50%		
	% ads by retailer 5	45.76%		
Ad length	Length of ad (in seconds)		30.20	(5.71)
Ad mood	% ads with active mood	72.40%		
	% ads with emotional mood	0.65%		
	% ads with funny mood	11.34%		
	% ads with informational mood	13.59%		
	% ads with sexy mood	2.02%		
Ad position	Relative ad position in an ad break (calculated as ad position in break/number of ads in break)		0.42	(0.25)
	Relative ad position in a program (calculated as ad break position/number of ad breaks in program)		0.60	(0.30)
	% of ads that air within two minutes of a half-hour break	11.99%		
	% of ads that air simultaneously with commercials on a different broadcast network	62.43%		
Comparative	% of ads that are comparative	31.57%		
Price	% of ads that refer to price	32.40%		
Web address	% of ads that contain a web address	45.99%		
	Program Characteristics			
Program genre	% of ads on comedy programs	21.54%		
	% of ads on drama/adventure programs	52.82%		
	% of ads on news programs	3.03%		
	% of ads on slice of life programs	19.64%		
	% of ads on suspense/police programs	2.97%		
Program network	% of ads on ABC programs	21.25%		
	% of ads on CBS programs	20.77%		
	% of ads on CW programs	15.96%		
	% of ads on FOX programs	23.74%		
	% of ads on NBC programs	18.28%		
Program rating	Nielsen program ratings		1.89	(0.99)
Special episodes	% of ads that aired during season premieres	11.22%		
	% of ads that aired during fall finale shows	10.68%		

Table 10: Time Ad Instances Air

Parameter	*Description*	*Frequency (%)*
Month	% of ads aired in September	14.48%
	% of ads aired in October	35.31%
	% of ads aired in November	31.75%
	% of ads aired in December	18.46%
Day of the week	% of ads aired on Monday	19.05%
	% of ads aired on Tuesday	18.87%
	% of ads aired on Wednesday	15.67%
	% of ads aired on Thursday	21.13%
	% of ads aired on Friday	11.28%
	% of ads aired on Saturday	0.47%
	% of ads aired on Sunday	13.53%
Time	% of ads aired between 8:00-8:14pm EST	7.54%
	% of ads aired between 8:15-8:29pm EST	11.34%
	% of ads aired between 8:30-8:44pm EST	11.16%
	% of ads aired between 8:45-8:59pm EST	9.79%
	% of ads aired between 9:00-9:14pm EST	7.42%
	% of ads aired between 9:15-9:29pm EST	9.38%
	% of ads aired between 9:30-9:44pm EST	10.98%
	% of ads aired between 9:45-9:59pm EST	10.92%
	% of ads aired between 10:00-10:14pm EST	4.87%
	% of ads aired between 10:15-10:29pm EST	5.28%
	% of ads aired between 10:30-10:44pm EST	4.39%
	% of ads aired between 10:45-10:59pm EST	6.94%

Table 11: Model-free Evidence on the Relationship between Online Program Engagement and Online Shopping Activity

Program Chatter in Minute before Ads Air	*Average Change in Online Traffic*	*Average Change in Online Purchases*
1st Quartile (0.00-0.81)	24.41%	7.32%
2nd Quartile (0.82-1.01)	16.77%	8.78%
3rd Quartile (1.02-1.26)	21.16%	14.58%
4th Quartile (1.27-10.76)	20.89%	6.62%

Note: *Program Chatter in Minute before Ads Air* is the (number of program mentions in the minute before ads air)/(average per minute program mentions in the episode in which the ads air). *Average Change in Web Traffic* is the percentage change in traffic to retailers' websites from five minutes before ads air to five minutes after. *Average Change in Purchases* is the percentage change in purchases on the retailers' websites five minutes before ads air to five minutes after, including purchases generated within twenty-four hours by users that initiated sessions on the retailers' website between when the ads air until five minutes after the ads air. Both percentage changes are calculated as (activity in post ad window – activity in pre ad window)/(activity in pre ad window +1).

increases prior to an ad's airing, the subsequent change in web traffic to the retailers' websites seems to decrease. However, the subsequent change in online purchasing appears to increase with some evidence of diminishing returns. This model-free evidence seems to suggest that online engagement with a program as measured from the volume of program-related Twitter mentions has a negative effect on traffic to the advertised retailers' websites but a positive effect on purchases from the websites. However, this evidence does not control for others factors that may impact this relationship, such as advertisement and program characteristics. Moreover, it does not examine the net effect of online program engagement on online purchasing following television advertisements, resulting from online program engagement's direct effect on online purchasing and its indirect effect through its impact on online traffic. Thus, a formal model is needed to explore the relationship between online program engagement and online shopping behavior. Toward this end, we next describe our modeling framework.

Model

To assess the relationship among television advertising, social TV, and online shopping activity, we model both online traffic and online purchases following the airing of television advertisement *i* as follows:

$$\begin{pmatrix} \text{SessionsPostAd}_i \\ \text{PurchasesPostAd}_i \end{pmatrix} \sim N\left(\begin{matrix} \hat{Y}_{i1} \\ \hat{Y}_{i2} \end{matrix}, \mathrm{T} \right) \tag{8}$$

$$\begin{aligned} \hat{Y}_{i1} = \mu_{ses} + \alpha_{r[i],1} + \gamma_{p[i],1} + \beta_{1,1} \cdot \text{ProgramWOMPreAd}_i + \beta_{2,1} \cdot \text{ProgramWOMPreAd}_i^2 + \\ \beta_{3,1} \cdot \text{SessionsPreAd}_i + \beta_{4,1} \cdot \text{PurchasesPreAd}_i + \sum_{k=1}^{45} \left(\theta_{k,1}\right) \cdot X_{ik} \end{aligned} \tag{9}$$

$$\hat{Y}_{i2} = \mu_{pur} + \alpha_{r[i],2} + \gamma_{p[i],2} + \beta_{1,2} \cdot \text{ProgramWOMPreAd}_i + \beta_{2,2} \cdot \text{ProgramWOMPreAd}_i^2 + \beta_{3,2} \cdot \text{SessionsPreAd}_i + \beta_{4,2} \cdot \text{PurchasesPreAd}_i + \beta_5 \cdot \text{SessionsPostAd}_i + \sum_{k=1}^{45} \left(\theta_{k,2}\right) \cdot X_{ik} \quad (10)$$

*SessionsPostAd*i (*SessionsPreAd*i) is the log of the number of new web sessions initiated at the website(s) for the retailer advertised in ad *i* between when ad *i* airs until five minutes after ad *i* airs (between five minutes prior to ad *i* airs until ad *i* airs). *PurchasesPreAd_i* is the log of the number of purchases on the advertised retailer's website(s) between five minutes prior to ad *i* airs until ad *i* airs. *PurchasesPostAd*i is the log of the number of purchases generated within twenty-four hours by users that initiated sessions on the advertised retailer's website(s) between when ad *i* air until five minutes after ad *i* airs[18]. The one-day period for *PurchasesPostAd*i acknowledges that purchase decisions take time to occur once a website visit is initiated. This construction of *PurchasesPostAd*i and our overall model framework in equations (8)-(10) are consistent with past research on the impacts of television advertising on online shopping (Liaukonyte et al. 2016).

$\alpha_{r.}$ are retailer-specific effects for the five retailers, and $\gamma_{p.}$ are program-specific effects for the 83 programs. These effects account for potential unobservable differences across retailers and programs that may influence the outcomes of interest. We assess the effects of social TV activity about the program on online traffic and sales by considering the change in the volume of online mentions about the program prior to ad *i*'s airing, which we denote *ProgramWOMPreAd*$_{i.}$:

[18] We take the log of these online shopping variables plus one to avoid taking the log of zero. We test a number of alternative specifications for these measures, including varying the time from the ad from five minutes to thirty minutes and excluding the one-day period for *PurchasesPostAd*i. The substantive results for these analyses, which are detailed in the results discussion, are highly consistent with those from our main model.

$$\text{ProgramWOM PreAd}_i = \log\left(\frac{\text{Program Mentions 1min Pre Ad}_{\text{i}}}{\text{Average Program Mentions}_{\text{ i}}} + 1\right) \tag{11}$$

where the numerator is the number of online program mentions between one minute before ad *i* airs until ad *i* airs and the denominator is the average (per minute) program mentions in the program episode in which ad *i* airs[19]. This measure captures changes in online program chatter right before ad *i* airs relative to the average program chatter in the episode. We include a quadratic term of *ProgramWOMPreAd*$_i$ in equations (9)-(10) to allow the impact of program engagement on viewer ad response to be non-linear (e.g., Tavassoli et al. 1995).

Lastly, X_i.is a vector of ad instance-specific advertisement and program characteristics detailed in the data section as well as two measures (linear and quadratic) of online chatter about the retailers. These variables are summarized in Table 12.

In line with past research on the effects of television programming on online behaviors (e.g., Liaukonyte et al. 2016), we focus on a narrow time window around when the ad airs to better attribute any changes in the online shopping variables to the focal variables of interest. As the nature of the television media ad buying process restricts advertisers' control of when and where their advertisements will air, the narrow time windows used in our analysis prevent bias in the results that could arise from advertisers choosing a certain time window to air an advertisement to impact online shopping behavior. To elaborate, advertisers buy the vast majority of ad time in the upfront markets, which occur months prior to the start of the fall television season. At best, the

[19]We test a number of alternative specifications for online program engagement, including varying the time from the ad's airing and testing different operationalizations of online program chatter. The substantive results for these analyses, which are detailed in the results discussion, are highly consistent with those from our main model.

ability to stipulate when a specific ad will air is restricted to the quarter-hour level; however, this timing is rarely stated in the advertiser-network contracts, and even which program the ads will air on is not often stipulated (Liaukonyte et al. 2016). Networks further restrict any jurisdiction over when an advertisement will air by commonly ordering ads at random across commercial breaks and by employing "make-good" policies that allow ads that have not reached the number of viewers paid for by the advertisers to be re-run on different programs on different days (Katz 2013; Wilbur et al. 2013). This process not only impedes advertisers control over selecting a specific program to air an ad in, but it also alleviates the concern that advertisers could time an ad to air during a specific minute-level time window to influence online traffic and sales.

Equations (8)-(10) 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 specify μ_{ses}, μ_{pur}, $\beta_{1.}$, $\beta_{2.}$, $\beta_{3.}$, $\beta_{4.}$, β_{5}, and $\theta_{k.}$ with diffuse normal priors. We assume that $\alpha_{r,1} \sim N(0, \tau_{\alpha 1})$, $\alpha_{r,2} \sim N(0, \tau_{\alpha 2})$, $\gamma_{p,1} \sim N(0, \tau_{\gamma 1})$, and $\gamma_{p,2} \sim N(0, \tau_{\gamma 2})$, with diffuse inverse-gamma priors for the variances. Lastly, we allow for contemporaneous covariance in T and specify T with a diffuse inverse Wishart prior. Equations (8)-(10) are estimated from three independent chain runs of 60,000 iterations with the first 30,000 iterations discarded as a burn-in. Our inferences are based on the remaining 30,000 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.

Table 12: Online Retailer WOM and Ad and Program Characteristics in X_{ik}

Parameter	*Variable*	*Description*
Ad break position in program	X_{i1}	Relative ad break position in program calculated as position of the ad break in the program/number of ad breaks in the program
Ad length	X_{i2}	Ad length in seconds
Ad mood	X_{i3}-X_{i6}	Dummy variables for ad mood: active, emotional, information, or sexy (Baseline: funny)
Ads on other networks	X_{i7}	Dummy variable if an ad runs simultaneously with another ad break on a different broadcast network
Ad position in ad break	X_{i8}	Relative ad position in the ad break calculated as position of the ad in ad break/number of ads in the ad break
Comparative	X_{i9}	Dummy variable for if the ad is comparative
Day of the week	X_{i10}-X_{i15}	Dummy variables for day of the week ad airs (Baseline: Friday)
Half-hour break	X_{i16}	Dummy variable for if ad airs within two minutes of a half-hour break
Month	X_{i17}-X_{i19}	Dummy variables for month ad airs: September, October, or November (Baseline: December)
Online retailer WOM	X_{i20}-X_{i21}	Change in online retailer WOM for the retailer in ad *i* following ad *i*'s airing; calculated as (number of retailer mentions between when ad *i* airs and 1 minute after ad *i* airs/number of retailer mentions between one minute before ad *i* airs until ad *i* airs +1). We take the log of this measure plus one. We include both a linear and quadratic effect.
Price	X_{i22}	Dummy variable for if the ad refers to price
Program genre	X_{i23}-X_{i26}	Dummy variables for if the program is a drama/adventure, news, suspense/police, or slice of life (Baseline: comedy program)
Program network	X_{i27}-X_{i30}	Dummy variables for network: ABC, CBS, FOX, or NBC (Baseline: CW)
Program rating	X_{i31}	Nielsen program rating
Special episodes	X_{i32}-X_{i33}	Dummy variables for season premiere and fall finales episodes
Time	X_{i34}-X_{i44}	Dummy variables for time in quarter-hour increments from 8:00-10:59pm (Baseline: 10:45-10:59pm)
Web adders	X_{i45}	Dummy variable for if the ad contains a web address

Results

Model Comparison

Table 13 compares our proposed model to two alternatives in which retailer-specific effects, program-specific effects, and online program engagement are not taken into account. We use the deviance information criterion (DIC), a likelihood-based measure that penalizes complex model specifications, and the mean absolute error (MAE) 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, online shopping variables as predictors, and the variables in X_{ik}. Model 2 builds on Model 1 by incorporating retailer- and program-specific effects. Adding our measures of online program engagement to Model 2 results in our proposed model, Model 3.

Table 13: Model Comparison

Model	*Description*	*DIC*	*Online Traffic MAE*	*Online Purchases MAE*
Model 1	Baseline: Intercepts (μ_{ses}, μ_{pur}), online shopping variables as predictors ($SessionsPreAd_i$, $PurchasesPreAd_i$, $SessionsPostAd_i$ in online purchases model only), variables in X_{ik}	2776.88	0.42 (0.41, 0.42)	0.18 (0.14, 0.27)
Model 2	Model 1 + retailer- ($\alpha_{r\cdot}$) and program-specific effects ($\gamma_{p\cdot}$)	1647.99	0.37 (0.37, 0.38)	0.11 (0.09, 0.16)
Model 3	Model 2 + online program chatter measures ($ProgramWOMPreAd_i$ + $ProgramWOMPreAd_i^2$)	1631.12	0.37 (0.37,0.37)	0.11 (0.09, 0.16)

Note: Table 13 presents posterior mean estimates for MAE with 95% HPD intervals.

The estimates in Table 13 indicate that accounting for retailer- and program-specific effects is crucial in investigations of the relationship between television advertising and online shopping activity, as including these effects in Model 2 improves model fit over Model 1. Table 13 also highlights the importance of accounting for online program engagement when considering the relationship between television advertising and online shopping activity, as Model 3 has a superior model fit compared to Model 2. We focus the discussion of our results on the findings from Model 3.

Impact of Online Program Engagement on Online Traffic and Purchases

Our results show that social TV activity about television programs has a substantial impact on online shopping activity. Table 14 presents the effects of program-related social media posts on online traffic and online purchases. We also present the net effect of social TV activity on online sales, calculated as the combination of the direct effect of social TV activity on sales and the indirect effect of social TV activity on sales through its impact on online traffic[20]. We find that increases in online chatter about television programs in the minute before an ad airs leads to decreases in online traffic to the advertised retailers' websites. This is consistent with our results in Chapter 2 that found that increases in online program chatter can decrease other media multitasking activities by viewers, such as online engagement with advertised brands. However, we also find that increases in online program engagement have a positive impact on subsequent online purchases on the retailers' websites. When we evaluate the net effect of program-related social TV activity on online purchases at different levels of online program chatter, we find a significant positive relationship between social TV activity and online purchases at almost all observed values of program chatter[21].

To summarize, we find that increases in social TV activity about programs, a media multitasking activity, distract viewers from initiating web browsing, another multitasking activity; however, if online program engagement is high, new web traffic that does occur on the retailers' websites following an ad's airing generates more online purchases than when online program engagement is low. The positive impact on online purchases outweighs the negative effect on online traffic. These findings provide strong evidence that, in terms of increasing online sales, social shows are good for advertisers.

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[20] This net effect is calculated as $\beta_5 * \beta_{1,1} * \mathit{ProgramWOMPreAd}_i + \beta_5 * \beta_{2,1} * \mathit{ProgramWOMPreAd}_i^2 + \beta_{1,2} * \mathit{ProgramWOMPreAd}_i + \beta_{2,2} * \mathit{ProgramWOMPreAd}_i^2$ for different values of $\mathit{ProgramWOMPreAd}_i$.

[21] This significant relationship is found for 92% of the observations in the data when considering the 90% confidence level (90% HPD intervals exclude zero) and for 73% of the observations in the data at the 95% confidence level (95% HPD intervals exclude zero). While Table 14 does show a quadratic effect in which very high values of online program chatter have a negative impact on online sales, these levels of program chatter are present for less than 1% of the observations in the data.

Table 14: Impact of Viewers' Online Program Engagement on Online Shopping

	Online Traffic Model			Online Purchases Model		
Variable	*Posterior Mean*			*Posterior Mean*		
ProgramWOMPreAd$_i$	-0.41	**	(-0.80, -0.02)	0.28	**	(0.08, 0.47)
ProgramWOMPreAd$_i^2$	0.29	**	(0.07, 0.51)	-0.19	**	(-0.30, -0.07)

Net Impact on Online Purchases						
ProgramWOMPreAd$_i$ *Value (without log transformation)*		*Percent of Observations*	*Posterior Mean*			*Estimated Effect Size on Online Purchases for U.S.*
0.10	(0.11)	0.47%	0.02	**	(0.01, 0.04)	19.94
0.20	(0.22)	0.47%	0.04	**	(0.01, 0.07)	37.36
0.30	(0.35)	0.71%	0.06	**	(0.01, 0.10)	52.11
0.40	(0.49)	1.90%	0.07	**	(0.01, 0.13)	64.04
0.50	(0.65)	8.90%	0.08	**	(0.01, 0.14)	73.04
0.60	(0.82)	26.17%	0.08	**	(0.01, 0.16)	79.05
0.70	(1.01)	50.50%	0.09	**	(0.01, 0.17)	81.99
0.80	(1.23)	72.58%	0.09	**	(0.01, 0.17)	81.84
0.90	(1.46)	84.63%	0.08	*	(-0.00, 0.17)	78.60
1.00	(1.72)	92.46%	0.08	*	(-0.01, 0.16)	72.31
1.10	(2.00)	96.14%	0.07		(-0.02, 0.15)	
1.20	(2.32)	97.86%	0.05		(-0.03, 0.14)	
1.30	(2.67)	98.75%	0.04		(-0.04, 0.12)	
1.40	(3.06)	99.35%	0.02		(-0.06, 0.10)	
1.50	(3.48)	99.53%	-0.00		(-0.08, 0.08)	
1.60	(3.95)	99.58%	-0.03		(-0.11, 0.05)	
1.70	(4.47)	99.76%	-0.06		(-0.14, 0.03)	
1.80	(5.05)	99.82%	-0.09	*	(-0.18, 0.00)	-75.75
1.90	(5.69)	99.88%	-0.12	**	(-0.22, -0.02)	-104.00
2.00	(6.39)	99.94%	-0.16	**	(-0.28, -0.05)	-133.70
2.10	(7.17)	99.94%	-0.20	**	(-0.33, -0.07)	-164.71
2.20	(8.03)	99.94%	-0.24	**	(-0.40, -0.09)	-196.62
2.30	(8.97)	99.94%	-0.29	**	(-0.47, -0.12)	-229.36
2.40	(10.02)	99.94%	-0.34	**	(-0.54, -0.14)	-262.60
2.50	(11.18)	100.00%	-0.39	**	(-0.63, -0.16)	-296.14

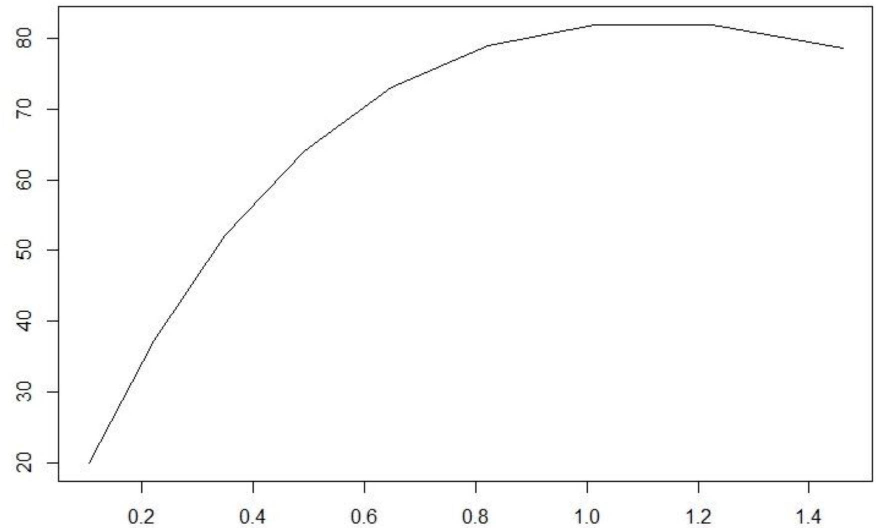
Note: Table 14 presents posterior mean estimates with the 95% HPD intervals. We denote 95% HPD intervals that exclude zero with a double asterisk (**) and 90% HPD intervals that exclude zero with a single asterisk (*). The net effect is calculated as $\beta_5 * \beta_{1,1} * ProgramWOMPreAd_i + \beta_5 * \beta_{2,1} * ProgramWOMPreAd_i^2 + \beta_{1,2} * ProgramWOMPreAd_i + \beta_{2,2} * ProgramWOMPreAd_i^2$ for different values of *ProgramWOMPreAd*$_i$ observed in the data. To estimate effect size for U.S. population, we transform the posterior mean estimates to account for our original log transformation (exp(*Posterior Mean*) -1) and then extrapolate our findings from comScore's panel of 100,000 active U.S internet users to the 91,109,500 households in the U.S. had internet in 2013.

We contend that our empirical findings about program-related social TV activity decreasing online traffic but increasing online purchasing are consistent with experimental research that has found that high program involvement has different effects on viewers' ad response depending on their interest in the advertised product (Lord and Burnkrant 1993; Murry et al. 1992). Specifically, the negative relationship between online program chatter and web traffic may suggest that increases in online program engagement distract consumers with low interest in an advertised product from seeking more information about the product online. This effect may occur because these viewers do not have sufficient motivation to switch their cognitive processing of the high involvement program to processing ad information for advertised products with low relevance to them (Celsi and Olson 1988; Lord and Burnkrant 1993). The positive relationship between online program engagement and online sales indicates that increased online program engagement is effective at spurring high interest consumers to purchase. This may occur because viewers with high interest in an advertised product will have the motivation to redirect their high involvement with the program to processing ad information, which can result in improved ad effectiveness (e.g., Feltham and Arnold 1994; Kilger and Romer 2007; Lord and Burnkrant 1993; Murry et al. 1992). This is also consistent with Liaukonyte et al. (2016)'s empirical findings that suggest that television advertising may affect ad response differently depending on whether the ad is viewed by low-fit or high-fit consumers.

To provide an illustration of the estimated effect size of our results of the impact of online program engagement on online purchases beyond comScore's panel of 100,00 active U.S. internet users, we utilize data from the United States Census Bureau which estimates that 91,109,500 households in the U.S. had internet in 2013 (File and Ryan 2014; United States Census Bureau 2013). Using this estimate, we extrapolate our findings from comScore's panel of 100,000 active U.S internet users to assess what the effects might be for the U.S population and present these estimates in Table 14 and Figure 6. If online program chatter is about one quarter of the average per minute program chatter in the episode in the minute before an advertisement airs ($ProgramWOMPreAd_i$ without the log transformation equals 0.25), the ad would generate an estimated forty incremental purchases from users who initiated web sessions on the advertised retailer's website(s) between when the ad airs and five minutes after the ad airs (above and beyond the effects of other variables in the model). If online program chatter is about one half of the average per minute program chatter in the episode in the minute before an advertisement airs, the ad would generate an estimated sixty-five incremental purchases from users who initiated web sessions on the advertised retailer's website(s) between when the ad airs and five minutes after the ad airs. If online program chatter is either (1) equal to the average per minute program chatter in the episode or (2) one and a half times the average per minute program chatter in the episode in the minute before an advertisement airs, the ad would generate an estimated eighty incremental purchases from users who initiated web sessions on the advertised retailer's website(s) between when the ad airs and five minutes after the ad airs[22]. This increase in purchases as online program engagement increases is illustrated in Figure 6 and is one of the largest net effects on online sales in our investigation.

[22] This range of $ProgramWOMPreAd_i$ without the log transformation from 0.25 to 1.50 covers 85% of the observed values in the data.

Figure 6: Net Impact of Online Program Engagement on Online Purchases



Note: Figure 6 plots the net effects of online program chatter (defined on X-axis) on online purchases for values of online program chatter ranging from one quarter of the average per minute program chatter to one and a half times the average per minute program chatter in the episode in the minute before an ad airs. The range of online program chatter on the X-axis account for 85% of the observations in the data. See Table 14 for calculation of the estimated effect size on online purchases for U.S. population.

Impact of Online Retailer Chatter, Advertisement Characteristics, and Program Characteristics on Online Traffic and Purchases

Tables 15 and 16 and Figure 7 show our results for the impacts of online retailer chatter, advertisement characteristics, and program characteristics on online traffic and purchases. Of note, while we do not find evidence of a significant relationship between online WOM about retailers and online traffic to the retailer's website(s), we do see a positive relationship between online retailer chatter and online sales both in terms of the direct effect on online purchases (Table 15) and on the net effect (Figure 7). This result may indicate that advertisements that spur online WOM about advertised brands also increase online sales for the advertised brand. Figure 7 considers the net effect of online retailer chatter on online sales and shows that when online retailer mentions in the minute after the ad airs spike either to one and a half times or two times the number of online retailer mentions in the minute before the ad airs, this correlates with an increase of forty purchases (above and beyond the effects of the other model variables) from users who initiated web sessions on the advertised retailer's website(s) between when the ad airs and five minutes after the ad airs. Overall, this finding is consistent with past research that has found a positive relationship between online brand WOM and brand sales (e.g., Babić Rosario et al. 2016; Stephen and Galak 2012; You et al. 2015).

We further observe in Tables 15 and 16 that ad characteristics can significantly impact online shopping activity. We find some interesting impacts of ad mood on the direct effect on online purchases (Table 15) and on the net effect (Table 16). Ads with an active, informational, or sexy mood have a negative impact on online sales relative to advertisements with a funny mood. Holding the effects of other model variables constant, we find that active, informational, and sexy ads generate an estimated sixty, fifty, and eighty (respectively) fewer online purchases than funny ads from users who initiated web sessions on the advertised retailer's website(s) between when the ad airs and five minutes after the ad airs. Advertisements with a funny mood may perform well in the age of media multitasking because humor appeals have been shown to be very effective at increasing consumer attention (e.g., Eisend 2009; Sternthal and Craig 1973; Zillmann et al. 1980). Furthermore, our result that sexy advertisements perform the worst in terms of increasing online sales for retailers provides empirical support to recent experimental research that has found that increases in sexual ad content reduce brand favorability and purchase intentions (Lull and Bushman 2015). These findings have implications for advertisement design strategies for retailers interested in increasing online sales.

Table 15: Impact of Online Retailer Chatter, Advertisement Characteristics, and Program Characteristics on Online Shopping Activity

	Impact on Online Traffic			Impact on Online Purchases		
Variable	*Posterior Mean*			*Posterior Mean*		
Ad mood (Baseline: funny)						
Active	-0.02		(-0.14, 0.09)	-0.07	**	(-0.12, -0.01)
Emotional	-0.13		(-0.44, 0.18)	-0.08		(-0.22, 0.06)
Informational	-0.07		(-0.20, 0.05)	-0.05	*	(-0.11, 0.01)
Sexy	-0.07		(-0.29, 0.15)	-0.09	*	(-0.18, 0.01)
Ad position						
Airs near half-hour interval	-0.01		(-0.08, 0.06)	0.04	**	(0.01, 0.07)
Relative ad position in break	-0.02		(-0.11, 0.07)	0.01		(-0.04, 0.05)
Relative ad position in program	0.06		(-0.07, 0.19)	0.01		(-0.06, 0.07)
Day of the week (Baseline: Friday)						
Monday	0.17	**	(0.04, 0.29)	0.01		(-0.07, 0.08)
Tuesday	0.19	**	(0.07, 0.32)	-0.02		(-0.09, 0.06)
Wednesday	0.10		(-0.03, 0.23)	0.03		(-0.04, 0.10)
Thursday	0.10		(-0.02, 0.22)	0.01		(-0.06, 0.08)
Saturday	-0.38		(-0.84, 0.07)	0.09		(-0.17, 0.35)
Sunday	0.11		(-0.03, 0.24)	0.01		(-0.07, 0.09)
Fall finale episodes	-0.06		(-0.16, 0.04)	-0.06	**	(-0.10, -0.01)
Month (Baseline: December)						
September	-0.06		(-0.19, 0.06)	-0.05	*	(-0.11, 0.006)
October	-0.13	**	(-0.22, -0.29)	-0.02		(-0.07, 0.026)
November	-0.11	**	(-0.21, -0.02)	-0.05	*	(-0.10, 0.00)
Online retailer WOM	0.06		(-0.12, 0.24)	0.07	*	(-0.01, 0.16)
Online retailer WOM^2	-0.06		(-0.16, 0.04)	-0.03		(-0.08, 0.02)
Price	0.05		(-0.02, 0.13)	0.04	**	(0.00, 0.08)
Time (Baseline: 10:45-10:59pm)						
8:00-8:14pm	0.34	**	(0.16, 0.53)	-0.06		(-0.18, 0.06)
8:15-8:29pm	0.32	**	(0.16, 0.48)	-0.06		(-0.17, 0.05)
8:30-8:44pm	0.22	**	(0.07, 0.37)	-0.04		(-0.13, 0.05)
8:45-8:59pm	0.25	**	(0.11, 0.39)	-0.04		(-0.13, 0.05)
9:00-9:14pm	0.29	**	(0.12, 0.46)	-0.05		(-0.16, 0.06)
9:15-9:29pm	0.19	**	(0.04, 0.35)	-0.05		(-0.15, 0.03)
9:30-9:44pm	0.11		(-0.03, 0.25)	-0.04		(-0.12, 0.03)
9:45-9:59pm	0.13	*	(-0.01, 0.27)	-0.04		(-0.12, 0.03)
10:00-10:14pm	0.23	**	(0.07, 0.39)	0.01		(-0.08, 0.10)
10:15-10:29pm	0.10		(-0.05, 0.25)	-0.02		(-0.09, 0.05)
10:30-10:44pm	0.03		(-0.11, 0.17)	0.03		(-0.04, 0.09)

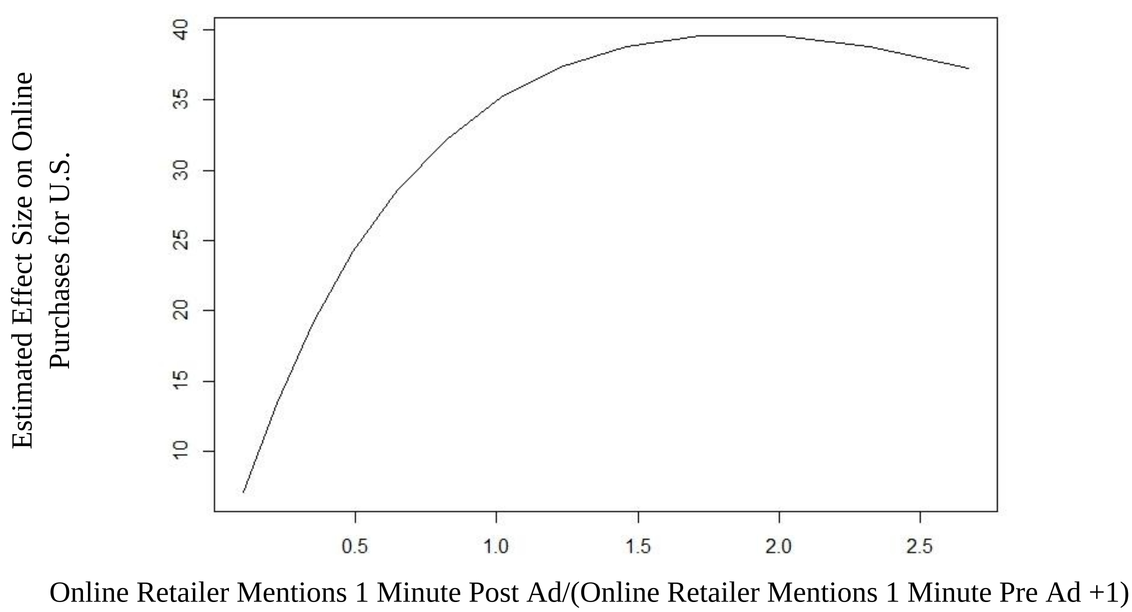
Note: Posterior mean estimates are presented with 95% HPD intervals. ** (*) indicate the 95% (90%) HPD interval excludes zero. Effects of program network, genre, ratings, season premiers, and ad length as well as if the ad is comparative in nature, contains a web address, and/or runs simultaneously with another ad break on a different network were not significant.

Table 16: Net Impact of Ad and Program Characteristics on Online Purchases

	Net Impact on Online Purchases			
Variable	*Posterior Mean*			*Estimated Effect Size on Online Purchases for U.S.*
Ad mood (Baseline: funny)				
Active	-0.07	**	(-0.12, -0.02)	-60.46
Emotional	-0.09		(-0.22, 0.04)	
Informational	-0.06	**	(-0.11, -0.01)	-52.53
Sexy	-0.09	*	(-0.12, 0.00)	-81.42
Ad position				
Airs near half-hour interval	0.04	**	(0.01, 0.07)	34.17
Fall finale episodes	-0.07	**	(-0.11, -0.02)	-57.73
Month (Baseline: December)				
September	-0.06	**	(-0.11, -0.01)	-52.92
October	-0.04	*	(-0.08, 0.00)	-33.98
November	-0.06	**	(-0.10, -0.02)	-53.02
Price	0.05	**	(0.01, 0.08)	42.20

Note: Posterior mean estimates are presented with 95% HPD intervals. Double asterisks ** (single asterisk *) indicate the 95% (90%) HPD interval excludes zero. See Table 14 for details on calculations of net impact on online purchases and estimated effect size on online purchases for U.S. population. Table 16 only displays the significant net impacts on online purchases.

Figure 7: Net Impact of Online Retailer Chatter on Online Purchases



Note: Figure 7 plots the net effects of online retailer chatter (as defined on the X-axis) on online purchases only for the values for which the posterior mean of this effect has a 90% HPD interval that excludes zero. The range of values for online retailer chatter on the X-axis account for 97% of the observations in the data. See Table 14 for details on calculations of the estimated effect size on online purchases for U.S. population.

Consistent with a recent Nielsen study that finds that price is one of the largest drivers of e-commerce activity (Boyte 2015), we also find that advertisements that mention price increase immediate online sales following the ad's airing both in terms of the direct effect on online purchases (Table 15) and on the net effect (Table 16). Additionally, advertisements that air within two minutes of a half-hour interval increase online sales following the ad's airing both in terms of the direct effect on online purchases (Table 15) and on the net effect (Table 16). This result is interesting as advertisements that air near a half-hour interval (e.g., 8:28pm, 9:02pm, 9:58pm) are thought to suffer from increased channel changing behavior (Schweidel and Kent 2010). However, while these advertisements may air to fewer viewers, media multitasking viewers engaging in online shopping following such advertisements may face higher cognitive capacity as the show they were watching or the show they plan to watch has likely either just ended or not yet begun. Thus, these ad positions may be more desirable to advertisers than previously believed.

Our results further suggest that advertisements airing earlier in primetime generate more subsequent online traffic for the advertised retailers but do not have a significant impact on online purchases. This result may be driven by the characteristics of the programs that air earlier in primetime and/or by the characteristics of the media multitasking behavior of television viewers that occurs earlier in the primetime. Lastly, we find that advertisements airing in earlier months of the fall television season (September, October, and November relative to December) as well as ads airing on fall season finale episodes (compared to ads airing in other episodes) have less of an impact on subsequent online purchases on the advertised retailer's websites both in terms of the direct effect on online purchases (Table 15) and on the net effect (Table 16). These results highlight that when an advertisement airs can influence viewers' ad response in terms of subsequent online shopping activity.

Robustness Checks

We test additional specifications of the online shopping variables $SessionsPreAd_i$, $SessionsPostAd_i$, $PurchasesPreAd_i$, and $PurchasesPostAd_i$ varying the time window from when the ad airs from five minutes to alternative time lengths of six to fifteen minutes and thirty minutes for a total of eleven alternative specifications. Our key results are directionally consistent in all eleven of these alternative specifications. Of note, we find a significant positive relationship between viewer online program engagement and online purchases (in which the 90% HPD intervals exclude zero) at almost all observed values of program chatter (at least 73% of the observations in the data) in ten out of the eleven specifications. We also evaluate a different operationalization of $PurchasesPostAd_i$ without the one-day period where $PurchasesPostAd_i$ is defined as the log of the number of purchases on the retailer's website(s) between when the ads air until five minutes after the ads air (plus one to avoid taking the log of zero). The results from this alternative specification are also directionally consistent with those of our main analysis. In particular, we find that viewer online engagement with the program has a positive impact on the net effect of online purchases (in which the 90% HPD intervals exclude zero) for nearly all the observed values of program chatter (99% of the observations in the data).

Additionally, our results are directionally consistent if we change the operationalization of $ProgramWOMPreAd_i$. in equation (11) such that the numerator varies from one minute prior the ad's airing to three minutes prior to the ad's airing.

However, the results are less significant as the time prior to the ad's airing increases, which indicates that changes in online program engagement right before an advertisement airs matters most in terms of influencing subsequent online shopping activity on the websites of advertised retailers. Furthermore, if we change the operationalization of *ProgramWOMPreAd*$_{i}$. in equation (11) such that the denominator is the average per minute program mentions in the episode *up until ad i airs* (rather than the average per minute program mentions in the whole episode in which ad *i* airs), the results from this alternative specification are nearly identical to those in our main model specification.

Discussion

Using multi-source data on online shopping activity, television advertising, and social media conversations for five large retailers, we investigate the relationship among television advertising, social TV activity, and online shopping behavior and examine the impact of television viewer's online program engagement on online traffic and sales. We find that increases in online program chatter prior to an advertisement's airing lead to decreases in online web traffic but increases in online purchases for the advertised retailers with an overall net positive effect on online sales. These results present evidence that, in terms of increasing online sales, social shows are good for advertisers. We additionally find that a number of advertisement design strategies and media planning strategies can influence online shopping behavior following advertisements. We discuss the implications of our key results for both retailers and television networks.

Implications for Retailers

Our results contribute to the debate that media multitasking by television viewers is not necessarily bad news for advertisers (e.g., Liaukonyte et al. 2016). The primary implication from our investigation for retailers is that advertising in social shows may be a good strategy for retailers interested in increasing online sales, validating industry reports that social shows offer more engaged, committed, and tuned-in audiences (e.g., Nielsen 2015a; Nielsen 2015b; Lynch 2015).

Our investigation additionally suggests insights for retailers on how to improve ad design strategies to increase online sales. Our findings recommend that retailers implement ad design strategies that increase immediate online chatter, as advertisements that result in subsequent increases in online retailer mentions also result in subsequent increases in online purchases at the retailers' websites. Retailers should also consider referring to price in their advertisements and avoiding creating advertisements with a predominant active, informational, or sexy mood. Our results suggest that advertisements with a funny mood may be most effective at increasing immediate online retail purchases while sexy advertisements may be the least effective.

Implications for Television Networks

The media planning process has faced many challenges in incorporating program engagement into media buys as there has been much discussion of the definition and value of media engagement to advertisers (e.g., Berman et al. 2015; Calder et al. 2009). Our findings suggest that programs with more program-related social media activity may offer added value to advertisers by contributing to incremental sales. This result highlights the importance of television networks having a social strategy for their programs that encourages viewers to engage in social TV activity about their shows.

Additionally, television networks can utilize this finding to provide support as to why program engagement should be incorporated into the media buying process and to advocate for higher ad rates in their programs that have high online social activity. A fruitful avenue of future research may be to explore what content strategies of television programs increase social TV activity about the program.

Limitations and Directions for Future Research

Our investigation of the relationship among television advertising, social TV activity, and online shopping activity is subject to limitations that we hope may encourage future examinations of media context effects and cross-media effects. First, our data does not allow for the direct observation of a specific television viewer's behavior. Such individual-level data would allow for an examination of a rich set of viewer characteristics that may influence the relationship between the viewer's online engagement with the program and her response to the advertisements in that program. Additionally, while our analysis includes advertisements for a range of products, it is limited to the investigation of the online shopping activity for five large retailers. Future examinations may explore if the relationship between viewer online program engagement and online shopping activity varies for different sets of brands. Furthermore, while some of our key results are consistent with past research, future lab and/or field experiments may allow researchers to tease out the underlying behavioral mechanism driving the results we observe in our empirical analysis.

Chapter 4: Assessing Collateral Damage and Construction from Brand Publicity through Social Media Conversations

Introduction

Brand scandals and the publicity such events generate can have a deleterious impact on consumer-brand relationships. From product safety recalls to socially unacceptable remarks made by executives, such events draw reactions from the news media, customers, and investors. The effects of negative brand information can be dire and result in serious damages to brand sales, performance, and reputation. For example, Target's earnings slid 46% following its well-publicized data breach, which exposed the company's mismanagement of private customer records (Jayakumar 2014). Additionally, political research has shown that political scandals can substantially diminish incumbent vote share (e.g., Levitt 1994).

Such events, however, may also have ripple effects beyond the brand involved. These spillover effects may be either positive or negative. In some situations, a brand's competitors may benefit from shifts in public opinion, as was the case with Tiger Woods' 2009 affair scandal which profited some of the key competitors of his main endorsers (Knittel and Stango 2014). In other cases, though, a publicized event affecting one brand may tarnish a broader set of brands. Such a scenario emerged in the beef industry in Europe in 2013 when recalls of beef-labeled products found to contain horsemeat hurt public perceptions of the European beef industry as a whole, including brands that did not issue recalls (Reuters 2013). Similarly, the detrimental effects of Paula Deen's 2013 discrimination lawsuit spread to her endorsement partners, the other subsidiary companies with which she was associated, and their employees (Greenblatt 2013).

Brand information being disseminated through news media, WOM, and other forms of publicity signifies that brand meanings are not shaped by brand managers alone but also by brand users (e.g., Muniz and O'Guinn 2001; Thompson et al. 2006). This highlights the importance of understanding how disseminated brand information functions as a reflection or potential driver of shifts in consumer brand perceptions. While such co-created brand meaning can make a brand's image and reputation more susceptible to cultural backlash, these shifts in public opinion can also be beneficial, functioning as a diagnostic tool to uncover potential brand image problems (Thompson et al. 2006).

The vast growth in research on WOM, brand publicity, and other earned media highlights the important role disseminated brand information plays in shaping marketing outcomes, consumer perceptions, and consumer actions. Investigations have shown that positive publicity, WOM, and visual influence from social groups can improve customer acquisition (Trusov et al. 2009) and sales (Chevalier and Mayzlin 2006; McShane et al. 2012). Meanwhile, negative publicity can damage brand attitudes (Ahluwalia et al. 2000), reduce purchase likelihoods and sales (Berger et al. 2010), and impair endorsement-related profits (Chung et al. 2013). Research has also shown, however, that publicity and WOM, regardless of their valence, are capable of improving sales (Berger et al. 2010; Liu 2006; Stephen and Galak 2012).

While existing research highlights the importance of exploring the effects of publicity and other forms of earned media, questions concerning how disseminated brand information influences the consumer-brand relationship over time remain unanswered. Specifically, when a brand is publicly linked to an event or scandal, how does it directly impact the consumer-brand relationship? Do these direct effects persist in the long-term, or are they merely short-lived? We aim to extend research on brand transgressions (e.g., Aaker et al. 2004; Roehm and Tybout 2006), which has begun investigating the first of these questions, by empirically exploring how scandal-related brand publicity impacts the consumer-brand relationship over time.

In the context of our previous examples of scandal-related brand publicity, reports from Reuters and Businessweek have argued that Target has already begun to rebound only four months out from when their data breach was initially reported (Dudley 2014; Skariachan and Finkle 2014). Yet, nearly 10 months following the dissemination of Paula Deen's legal woes, the celebrity chef is still searching for ways to rebuild her damaged brand image (Klara 2014). These examples illustrate the importance of delineating both short- and long-term effects of negative brand information to understand its overall impact on the consumer-brand relationship. Additionally, they suggest that the short- and long-term effects may vary across brands.

While research on earned media has begun to explore the direct impact of disseminated brand information, limited research has been conducted on the potential spillover effects that such publicity can have on other brands, and key questions remain unanswered. For example, how does publicized brand information, such as that generated by a brand scandal, affect a brand's competitors or allies? Under what circumstances do these potential spillover effects have a primarily positive impact on other brands, and when is the impact primarily negative? Finally, how do these potential spillover effects vary in the short- versus long-term periods following the dissemination of the brand information? Recent investigations of publicity have called for further research on such spillover effects (Berger, Sorensen, and Rasmussen 2010). Previous work on competitive spillover has begun to explore the first of these questions (Janakiraman et al. 2009; Roehm and Tybout 2006). We contribute to extant research by empirically investigating both positive and negative brand-level spillover effects of negative brand information and by exploring how these spillover effects vary in the short- versus long-term.

In this research we focus on scandal-related brand publicity and investigate how being publicly linked to a brand scandal affects public sentiment toward the brand over time. We also examine the extent of reputational spillover, which captures the impact of the scandal on consumer sentiment toward brands that are not directly linked to the transgression. We employ social media conversations as a means of assessing brand sentiment (e.g., Schweidel and Moe 2014; Tirunillai and Tellis 2012). Akin to Janakiraman et al. (2009) and Roehm and Tybout (2006)'s work on competitive spillover, we draw on Feldman and Lynch's (1988) accessibility-diagnosticity framework and posit that the extent of the reputational spillover will depend on how similar a brand is to the brand involved in the scandal. In doing so we contribute to research on the effects of publicity by presenting a modeling approach to examine spillover from disseminated brand information using the sentiment of social media conversations. Our approach is easily generalizable to contexts in which the publicity is not generated by a brand scandal but rather arises from other forms of earned media or news coverage.

In line with Knittel and Stango's (2014) analysis of scandals and celebrity endorsement risk, we use the human brand context to explore the direct and reputational spillover effects of brand-related publicity. Specifically, we investigate the highly publicized 2013 Biogenesis Clinic scandal involving the use of performance-enhancing drugs (PEDs) in Major League Baseball (MLB). Treating each MLB athlete as his own human brand, we employ a hierarchical Bayesian model to estimate individual-level direct effects of being publicly linked to the scandal as well as individual-level effects of the reputational spillover generated by those players named in the PED scandal by the news media. These effects are assessed over a 10-month period.

We find that the sentiment expressed in social media for those human brands publicly linked to the scandal experiences short-term declines; however, these direct negative effects do not persist in the long-term throughout the 10-month period. In addition to the scandal's impact on those individuals who were directly associated with the scandal, we observe reputational spillover effects. Operationalizing similarity between players based on their team, field position, and salary level, we find that the similarity of players to those named in the PED scandal is associated with shifts in social media sentiment. Our results show that some players experience a decline in social media sentiment, suggesting that their brands are hurt by being similar to those publicly associated with the scandal. While some players experience collateral damage from this negative reputational spillover, others who are similar to those involved in the scandal experience collateral construction and see an increase in their social media sentiment. Thus, we see evidence of both positive and negative spillover from the scandal-related brand publicity.

Furthermore, we find that the relationship between reputational spillover and player similarity varies over time. While we largely see negative reputational spillover effects on player sentiment in the short-term, indicating collateral damage effects, we observe the opposite relationship in the long-term. Specifically, we find that the relationship between long-term spillover and similarity is positive, suggesting that players who are more similar to those publicly linked to the scandal predominantly experience positive reputational spillover or collateral construction effects in the long-term. This shift from collateral damage in the short-term to collateral construction in the long-term may stem from changes in consumer perceptions of brand culpability over time (Roehm and Tybout 2006; Votolato and Unnava 2006) and, to the best of our knowledge, has not previously been documented.

From the perspective of human brands, our work shows that individuals' brands are susceptible to the actions of others. More broadly, our research indicates that brand managers should be vigilant about the actions of their allies and competitors, as the spillover effects from the transgressions of other brands can vary over time. While managers may seize the opportunity to benefit from the missteps of their competitors, they should be cognizant that consumers may paint similar brands with the same brush, especially in the short-term. Furthermore, our work demonstrates that brand managers can leverage social media conversations about their brands to evaluate the direct or indirect impacts of publicized brand events or scandals.

The remainder of this research is organized as follows. We next discuss the empirical context of our analysis in which we overview performance-enhancing drugs, the 2013 Biogenesis Scandal, and the data employed in our empirical analysis. We then describe our modeling approach for evaluating both the short- and long-term impacts of the highly publicized PED scandal. We conclude with a discussion of implications of our research in the context of publicity, brand transgressions, and spillover effects, as well as opportunities for future research.

Empirical Context

Performance-Enhancing Drugs and the Biogenesis Scandal

We choose the context of athletes and performance-enhancing drug use to investigate the effects of scandal-related brand publicity on the consumer-brand relationship. The use of PEDs by athletes constitutes a transgression as it violates ethical norms and is a form of cheating that gives the potential for performance enhancement. PED use is, additionally, a violation of a legal contract in most major sports leagues, including the MLB. Furthermore, a poll of MLB fans showed that 79% of those surveyed care about PED use in baseball, 72% perceive PED use to be a serious problem in the MLB, and 62% take baseball records less seriously due to the rise of steroid allegations in the sport (GfK Roper Public Affairs and Media 2009). Thus, it appears that PED use is also seen as a transgression by sports consumers.

The MLB amplified their crackdown on PED use in 2002 with the unveiling of the Joint Drug Prevention and Treatment Program and continued to set stricter monitoring requirements and punishments for PED use during the next 10 years (MLB.com 2014). Prior to the 2013 season, the MLB issued 600 suspensions for PED violations, but only 39 of these suspensions were given to major league players (USA Today 2012). On January 29th, 2013, the Miami New Times published a report stating that the Miami-based Biogenesis of America Clinic had supplied several MLB players with PEDs (Elfrink 2013). This report spurred an immediate investigation by the MLB which continued through the 2013 season.

We use the highly publicized Biogenesis scandal as the context for our empirical analysis. In total 21 players were linked by the news media to the Biogenesis scandal, and these players comprise our list of focal players that we use to investigate the direct effects of scandal-related brand publicity on the consumer-brand relationship. This focal list of players was constructed by analyzing all articles related to Biogenesis from two of the most frequented online sports journalism sources, ESPN and Bleacher Report, from January 2013 until August 2013 when the MLB announced its final sanctions against the PED offenders from the Biogenesis scandal. These 21 players enter the focal list at different times based on when they were first linked to the scandal by the news media. Table 17 presents this list of focal players, the date each player entered the focal list, and the publicity source linking the player to the Biogenesis scandal. Table 18 shows important dates in our estimation window including descriptions of these key publicity reports linking players to the scandal as well as other major baseball-related events.

Publicity plays a key role in our empirical context as the news media and general public perceptions serve as the source linking players to the Biogenesis scandal. During the MLB's investigation, no focal list players admitted to being involved in the scandal; most chose not to comment, while the remaining few chose to deny any connection to Biogenesis Clinic. Over six months passed between the initial report breaking the scandal and the MLB's announcement of the majority of the Biogenesis-related suspensions. Thus, our analysis has a particular emphasis on how being publicly linked to a brand scandal impacts consumer sentiment toward a brand as true culpability was unknown during most of our estimation window. In addition to the 21 focal list players linked to the brand scandal, the remaining 848 MLB players on major league rosters at the start of the 2013 season are considered for model estimation to investigate reputational spillover from this scandal-related publicity. This brings our full list of players to 869.

Table 17: Focal List Players Linked to the Biogenesis Scandal by the News Media

Focal List Player	*Date Entered Focal List*	*Publicity Source*
Melky Cabrera	January 29, 2013	*Miami New Times*
Cesar Carrillo	January 29, 2013	*Miami New Times*
Bartolo Colon	January 29, 2013	*Miami New Times*
Nelson Cruz	January 29, 2013	*Miami New Times*
Gio Gonzalez	January 29, 2013	*Miami New Times*
Yasmani Grandal	January 29, 2013	*Miami New Times*
Alex Rodriguez	January 29, 2013	*Miami New Times*
Ryan Braun	February 5, 2013	*ESPN* and *Bleacher Report*
Francisco Cervelli	February 5, 2013	*ESPN* and *Bleacher Report*
Jesus Montero	February 5, 2013	*ESPN* and *Bleacher Report*
Jhonny Peralta	February 5, 2013	*ESPN* and *Bleacher Report*
Danny Valencia	February 5, 2013	*ESPN* and *Bleacher Report*
Everth Cabrera	February 19, 2013	*ESPN* and *Bleacher Report*
Fautino de los Santos	February 19, 2013	*ESPN* and *Bleacher Report*
Fernando Martinez	February 19, 2013	*ESPN* and *Bleacher Report*
Jordan Norberto	February 19, 2013	*ESPN* and *Bleacher Report*
Cesar Puello	February 19, 2013	*ESPN* and *Bleacher Report*
Robinson Cano	April 22, 2013	*ESPN* and *Bleacher Report*
Antonio Bastardo	August 5, 2013	*MLB.com*
Sergio Escalona	August 5, 2013	*MLB.com*
Jordany Valdespin	August 5, 2013	*MLB.com*

Data

Measuring consumer sentiment. We assess how the Biogenesis scandal affects the public perception of human brands in the MLB using the sentiment of social media conversations. Data on daily tweet volume and valence were accessed through Topsy. To maintain consistency in how data were collected, each player's first and last name was used to construct the search of social media conversations; thus, only tweets in which a player's full name is used (e.g., Alex Rodriguez as opposed to A-Rod) are included in our analysis.

Table 18: Key Dates in the Biogenesis Scandal and the 2013 MLB Season

Date	*Description of Key Date*
January 29, 2013	*Miami New Times* links Melky Cabrera, Cesar Carrillo, Bartolo Colon, Nelson Cruz, Gio Gonzalez, Yasmani Grandal, and Alex Rodriguez to the Biogenesis Clinic.
February 5, 2013	Reports from *ESPN* and *Bleacher Report* link Ryan Braun, Francisco Cervelli, Jesus Montero, Jhonny Peralta, and Danny Valencia to the Biogenesis Clinic.
February 19, 2013	Reports from *ESPN* and *Bleacher Report* link Everth Cabrera, Fautino de los Santos, Fernando Martinez, Jordan Norberto, and Cesar Puello to the Biogenesis Clinic.
March 2 - March 19, 2013	World Baseball Classic (WBC) tournament is played.
March 15, 2013	*MLB.com* reports that the MLB suspends first player (Cesar Carrillo) for his PED use in connection with the Biogenesis Clinic.
March 31, 2013	MLB regular season begins.
April 22, 2013	Reports from *ESPN* and *Bleacher* Report link Robinson Cano to the Biogenesis Clinic.
July 15 - July 16, 2013	MLB All-Star events are held.
July 22, 2013	*MLB.com* reports that the MLB suspends Ryan Braun for PED use in connection with the Biogenesis Clinic.
August 5, 2013	*MLB.com* reports that the MLB suspends Antonio Bastardo, Everth Cabrera, Francisco Cervelli, Nelson Cruz, Fautino de los Santos, Sergio Escalano, Fernando Martinez, Jesus Montero, Jordan Norberto, Jhonny Peralta, Cesar Puello, Alex Rodriguez, and Jordany Valdespin for PED use in connection with the Biogenesis Clinic.
September 29, 2013	MLB regular season ends.

Topsy codes tweets as positive, negative, or neutral by analyzing the weighted sentiment of words and phrases using an automated process which they continually validate through manual checks of tweet content. We utilize Topsy's valence coding to construct a daily sentiment measure using the difference between the proportion of positive tweets and the proportion of negative tweets. This sentiment measure is collected from January 1, 2013 to September 29, 2013. This window includes the four week period prior to the scandal being initially reported and ends the final day of the 2013 MLB regular season. As we note in the following section, we control for variation across players using data on several player and team characteristics in order to capture baseline differences in sentiment.

Model controls. Roehm and Tybout (2006) note that context may impact how salient a scandal is in the consumer's mind. Thus, we control for special events in baseball that are likely to draw more public attention to the sport. Specifically, dummy variables for the World Baseball Classic (WBC) and MLB's All-Star events are included in our analysis to control for the effects that these events may have on the social media conversation about a particular human brand.

Given that a player's characteristics may also impact social media conversation about him, data were collected for several player attributes. Information on player position and salary was collected from Newsday, and data on a player's previous PED suspensions were collected from ESPN.com and thesteriodera.com. Two of the 869 players in our sample, both playing primarily in the minor leagues, did not have salary data available for the 2013 season. Thus, we use the league minimum to represent their salaries. Additionally, information on a player's previous award history (including whether a player is a former MVP, Cy Young, or Gold Glove award winner) was collected from MLB.com. Furthermore, data on player injuries and player transactions were collected from MLB.com; we use the latter to control for when a player changes teams throughout the course of the season.

In addition to player characteristics, attributes of a player's team may also impact social media conversation about the player. Data on team payroll were collected from Newsday, and the metropolitan population for each team's city was gathered from the United States Census Bureau and Canada Census. Finally, daily-level team measures were collected as such variables could impact daily social media conversation about a player. Data on whether a team played a game on a given day, whether they won a game on a given day, team run differential, current winning streak of a team, and team standing (number of games behind the division leader) were collected from ESPN.com. If a player included in our estimation becomes a free agent over the course of the season, these team characteristic variables are defined based on the team the player was with just prior to becoming a free agent. This occurs for only 1% of the observations in our data.

Summary Statistics

Table 19 presents descriptive statistics for social media sentiment, player characteristics, and team characteristics across our 10 month estimation window for the 21 players linked to the Biogenesis scandal in the news media (focal list players) as well as for the remaining 848 players in our analysis not publicly linked to the scandal (non-focal list players). As seen in Table 19, the mean social media sentiment for the players on the focal list is substantially lower than the mean sentiment of non-focal list players. This offers model-free evidence that the scandal may have adversely affected the consumer-human brand relationship for those players directly linked to the PED scandal by the news media. We will explore in greater depth the direct impact of the scandal on the focal list of players in the forthcoming analysis.

Table 19 also shows descriptive statistics for player and team characteristics. Of note, the mean player salary is higher for focal list players than for non-focal list players. The focal list contains a higher proportion of major award winners and previous PED offenders. Additionally, the percentage of players that get injured over the course of the season (placed on the disabled list) is similar for both the focal list and non-focal list. Finally, the focal list sees a smaller share of players change teams (e.g., get traded or released) and has a smaller proportion of pitchers compared to the non-focal list.

Table 19: Descriptive Statistics for Player Sentiment, Player Characteristics, and Team Characteristics

		Focal List		*Non-focal List*	
Parameter	*Description*	*Mean*	*(SD)*	*Mean*	*(SD)*
Player Sentiment	Social media sentiment	.03	(.15)	.06	(.19)
Player Characteristics	Salary (in millions)	4.58	(6.85)	3.70	(4.98)
	% of players that are pitchers	33.33%		51.18%	
	% of players that are major award winners	19.05%		8.73%	
	% of players with previous PED suspensions prior to 2013 season	14.29%		1.06%	
	% of players that are placed on the disabled list at least once throughout the season	38.10%		35.50%	
	% of players who change teams	4.76%		16.51%	
Team Characteristics	Metro size (in millions)	7.84	(6.40)	6.00	(4.67)
	Team payroll (in millions)	109.00	(62.84)	107.00	(47.15)
	Games behind division leader	5.56	(7.78)	4.61	(6.87)
	Run differential	-9.14	(54.62)	1.90	(48.60)
	Winning streak	-.07	(2.11)	.04	(2.10)

For the team characteristics, mean metro size is slightly larger for the focal list compared to the non-focal list while mean team payroll is similar for both lists. Additionally, team characteristics for the players on the focal list imply that these teams have lower performance than the teams of non-focal list players. This is suggested because the mean number of games behind the division leader is higher and the run differential and winning streak means are lower for the focal list team characteristics than the non-focal list team characteristics. These summary statistics indicate that player and team characteristics do vary across focal list and non-focal list players, highlighting the importance of controlling for these characteristics in our analysis of the impact of scandal-related brand publicity on the consumer-brand relationship.

Model-Free Evidence

We anticipate that being directly linked to the scandal by the news media will have a negative impact on social media sentiment. The model-free evidence presented in Table 20 provides support for this expectation. Table 20 shows the average social media sentiment for focal and non-focal list players before and after Miami New Times initially reported the PED scandal. The average sentiment for the focal list drops in both the short- and long-term periods following this initial report with the short-term effect being more evident. The list of non-focal players, which will be used to help gauge reputational spillover, sees less pronounced effects with a small increase in average sentiment in the short-term and a small decrease in the long-term.

Figure 8 shows the average social media sentiment for focal and non-focal list players from the beginning of our estimation window (January 1st) to three weeks after the initial scandal was reported (Feb. 19th) helping to illustrate potential short-term effects of the negative publicity. Following the initial publication of the scandal on January 29th, the average sentiment for focal list players drops substantially while the average sentiment for non-focal list players does not see a pronounced change. This figure may suggest that the Biogenesis scandal has a direct short-term negative impact on social media sentiment for focal list players; however, the possible short-term reputational spillover effects from the scandal are less discernible from Figure 8.

Table 20: Average Short- and Long-term Social Media Sentiment Following the Brand Scandal

		Focal List Average Sentiment		*Non-focal List Average Sentiment*	
Date	*Description*	*Mean*	*(SD)*	*Mean*	*(SD)*
Jan. 1- Jan. 28	Pre-scandal (4 weeks prior)	.047	(.166)	.061	(.179)
Jan. 29 - Feb. 19	Short-term (1-3 weeks following scandal)	.001	(.164)	.073	(.195)
Feb. 20 - Sept. 29	Long-term (4-35 weeks following scandal)	.036	(.143)	.057	(.190)

Figure 9 plots the average player social media sentiment for each day in our estimation window (January 1st – September 29th), with a handful of key dates labeled, to help illustrate the potential long-term impacts of the Biogenesis scandal. The first major punishment issued by the MLB as a result of this scandal occurred on July 22nd, 2013, when Ryan Braun was suspended for the rest of the 2013 season and foreshadowed the remaining suspensions which were issued by the MLB on August 5th, 2013. After Braun's suspension, the average sentiment scores for the focal list players drops substantially, but such a drop in sentiment does not immediately follow the group of suspensions announced on August 5th. Both the focal and non-focal lists show slight negative trends in social media sentiment in Figure 9. The negative sentiment trends for focal list players appears to be less prominent in the long-term than seen in the short-term (shown in Figure 8) which provides some support that a formal model of the effects of scandal-related brand publicity should account for how these effects vary over time.

Figures 8 and 9 provide less guidance on the expected reputational spillover effects from the Biogenesis publicity as these figures do not account for how similar an individual is to those publicly linked to the PED scandal, which we speculate will drive spillover. As we will discuss in the next section, we operationalize similarity between players based on their team, position, and salary level (measured in quartiles). We initially explore the potential spillover effects from the scandal based on player similarity by constructing a list of players (1) on the same team, (2) playing the same position, and (3) with the same salary level as at least one of the players on the focal list. This list, which we call the match list, is composed of 48 non-focal list players that are more similar (relative to the non-focal list players) to the focal list players.

Figure 8: Average Social Media Sentiment for Focal List and Non-focal List Players in the Short-term Period Following the Brand Scandal

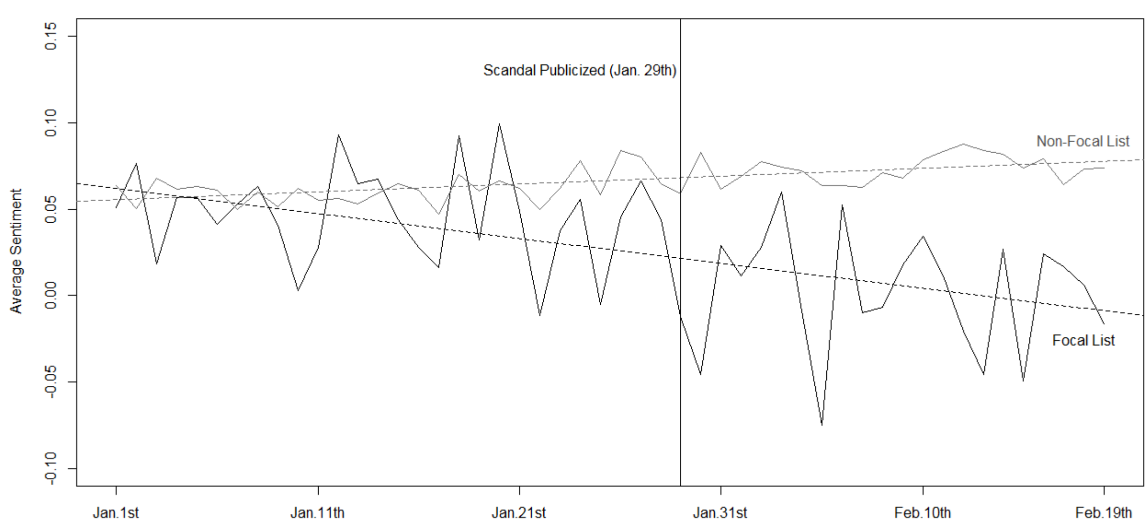


Figure 9: Average Social Media Sentiment for Focal List and Non-focal List Players Following the Brand Scandal

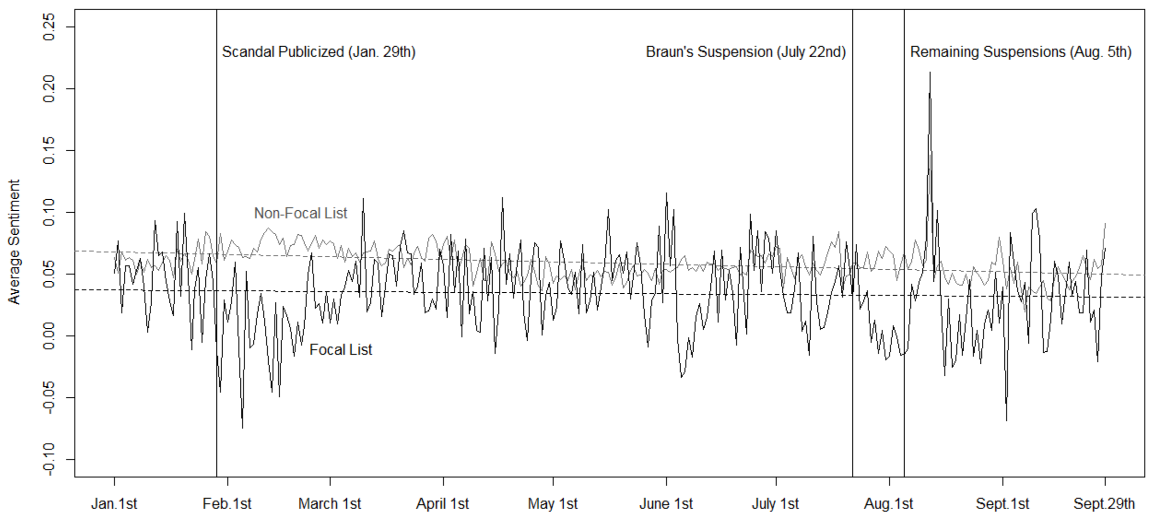
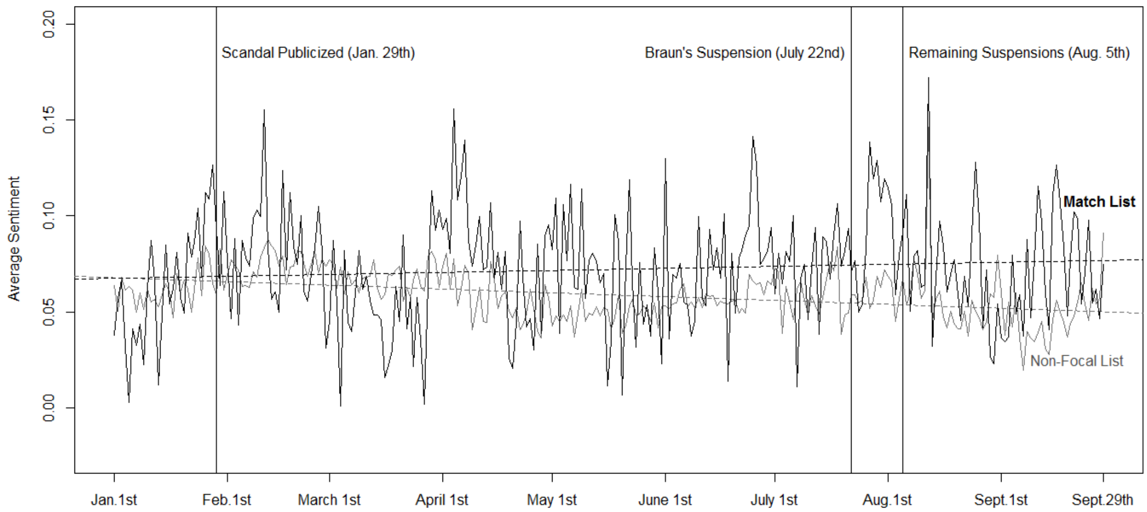


Figure 10 plots the average social media sentiment for each day in our estimation window (January 1st – September 29th, 2013) for the match and non-focal lists. As can be seen in the trends lines, the match and non-focal lists have similar average sentiment immediately following the initial report that broke the scandal on January 29th. Interestingly, we observe that the average sentiment for the match list players is substantially higher than the average sentiment of the non-focal list players in the long-term period following the scandal. This may suggest a long-term positive reputational spillover effect from the scandal for players who are more similar to those publicly linked to the scandal. These insights further highlight the importance of considering brand similarity and the evolution of spillover effects in investigations of scandal-related publicity. As this model-free analysis only considers those players who match a focal list player on all three dimensions, a formal model is needed to assess the importance of each dimension in the extent of reputational spillover. Toward this end we next describe our modeling framework.

Figure 10: Average Social Media Sentiment for Non-focal List and Match List Players Following the Brand Scandal



Model

Model Development

We measure consumer sentiment using the valence of social media conversation. The social media sentiment (Yit) for brand *i* at time *t* can be captured as follows:

(12)
$$Y_{it} = \frac{PosPosts_{it} - NegPosts_{it}}{TotalPosts_{it} + 1}$$

where $PosPosts_{it}$ and $NegPosts_{it}$ are the number of positive and negative social media posts or mentions, respectively, for brand *i* at time *t*. This sentiment score can take values from -1 to 1 with a positive value indicating that the social media conversation is more positive than negative on day *t* while a negative score indicates that the conversation is more negative than positive.

Direct effects of brand-related publicity. We first investigate the short- and long-term direct effects of brand-related publicity on sentiment toward the brand. Figure 11 provides an illustration of how such short- and long-term direct effects may look for a social media sentiment trend line. We assume that short-term effects decay over time and operationalize the short-term effect of publicity coverage as:

$$ShortTermDirect_{it} = Publicity_{it}\delta_1^{DaysSince_{it}} \tag{13}$$

where δ_1 is a decay rate in the interval (0,1) and $Publicity_{it}$ is a dummy variable indicating if an event about brand *i* has been covered in the news media by time *t*. For example, in the case of a brand scandal, this variable would equal zero until the scandal about brand *i* was initially reported in the news media and one thereafter. If brand *i* is not named in the scandal-related publicity, this term will always be zero for brand *i*. $DaysSince_{it}$ captures the number of days since the initial publicity about brand *i* was reported. As $DaysSince_{it}$ increases, $ShortTermDirect_{it}$ will approach zero; thus, we use this term to help capture the short-term direct effect of publicity.

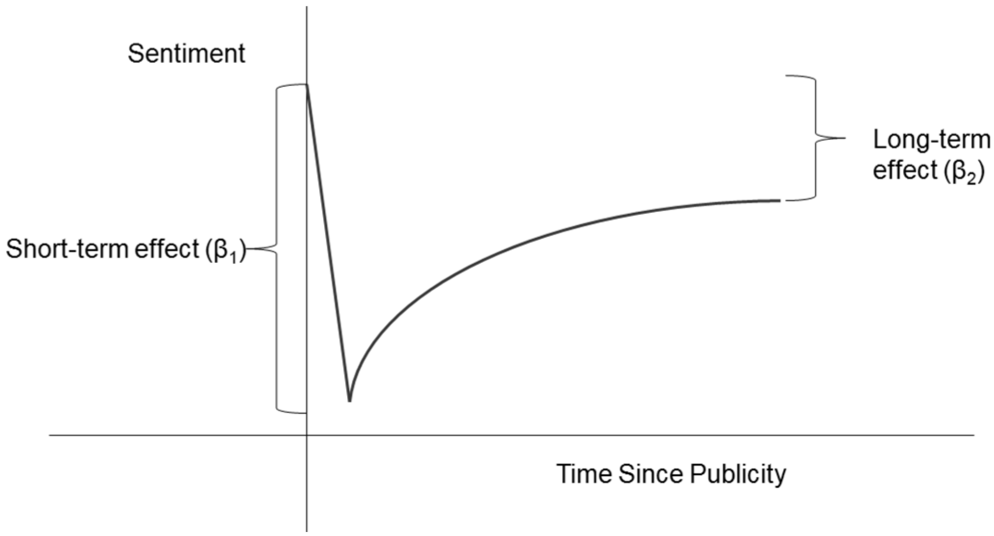
While short-term effects on brand sentiment are expected to dissipate with time, long-term direct effects of brand publicity are expected to remain. We operationalize this as follows:

$$LongTermDirect_{it} = Publicity_{it}(1-\delta_1^{DaysSince_{it}}) \tag{14}$$

In this case as the days since the initial brand-related publicity about brand *i* ($DaysSince_{it}$) increases, the term ($1-\delta_1^{DaysSince_{it}}$) approaches one. Thus, $LongTermDirect_{it}$ helps us capture the long-term direct effects of publicity.

Modeling similarity. In addition to our interest in the direct effects of disseminated brand information, we also investigate the short- and long-term spillover effects of brand-related publicity on the consumer-brand relationship for brands that are not publicly associated with the brand event. We posit that the extent of spillover will depend on how similar a brand is to those involved, an approach in line with Feldman and Lynch's (1988) accessibility-diagnosticity framework and past research on competitive spillover (Janakiraman et al. 2009; Roehm and Tybout 2006). We first describe our approach to measuring the similarity between brands linked to an event or scandal by the news media (which, for the purpose of this example, we call focal brands *j*) and a brand that is not named in the brand-related publicity (brand *i*). We then discuss how we account for the short- and long-term effects of reputational spillover.

Figure 11: Illustration of Short- and Long-term Effects of the Scandal on a Social Media Sentiment Trend Line



We operationalize the similarity between brands *i* and *j* through a feature matching approach (e.g., Tversky 1977). We evaluate pairwise attribute matches between brands and estimate a weighted-and-summed similarity measure. This approach is in line with past work on similarity (e.g., Hutchinson and Mungale 1997; Schweidel et al. 2006). Specifically, to express the similarity between brands *i* and *j*, we define $M_{ijk} = 1$ if brands *i* and *j* match on attribute *k*, and $M_{ijk} = 0$ otherwise. In our empirical context, we assess similarity between two players on three attributes: team, field position, and salary quartile. If player *i* is on the same team (k=1) as focal player *j*, then that match attribute is coded as a $M_{ij1} = 1$; if the players are not on the same team, this is coded as $M_{ij1} = 0$.

To construct a similarity measure on attribute *k* between player *i* and a set of focal players *j*, we average across those players on the focal list at time *t*. Let $FocalList_{jt}$ be a dummy variable equal to one if player *j* has been linked to a brand event or scandal by the news media by time *t*. We operationalize the similarity between player *i* and those players on the focal list at time *t* along dimension *k* as:

(15)
$$Similarity_{ikt} = \frac{\sum_j M_{ijk} FocalList_{jt}}{\sum_j FocalList_{jt}}$$

where the numerator sums the attribute match variable M_{ijk} across those players on the focal list at time *t* and the denominator reflects the number of players on the focal list at time *t*. Thus, $Similarity_{ikt}$ counts the number of players on the focal list at time *t* that match player *i* along attribute *k* and scales this by the size of the focal list, yielding the average similarity between player *i* and those players on the focal list at time *t* on attribute *k*.

Consider the similarity between player *i* and focal list player 1, and assume player 1 has already entered the focal list ($FocalList_{1t} = 1$) and is the only player to do so at time *t*. If player *i* and focal list player 1 match on dimension *k* (k = 1), then $Similarity_{i1t} = 1$. Now assume that the initial publicity also mentions focal list player 2 and that both focal list players 1 and 2 have entered the focal list ($FocalList_{1t} = 1$ and $FocalList_{2t} = 1$) and are the only players to do so at time *t*. While player *i* and focal list player 1 match on attribute *k* ($M_{i11} = 1$), suppose that player *i* and focal list player 2 do not match on this attribute ($M_{i21} = 0$). Thus, in this case $Similarity_{i1t} = .5$.

We construct a weighted average similarity measure across all attributes as follows:

(16) $$AvgSimilarity_{it} = \sum_k \eta_k Similarity_{ikt}$$

where η_k is a vector of attribute weights to be estimated such that $\Sigma\eta_{\cdot} = 1$. The weights of each attribute, η_k, are treated as parameters to be estimated. This specification allows us to assess the degree to which different brand attributes affect the extent of reputational spillover.

Spillover effects of brand-related publicity. With similarity defined we next describe the short- and long-term reputational spillover effects of disseminated brand information on the consumer-brand relationship for brands not publicly linked to the brand event. We operationalize the short-term reputational spillover effects of publicity on brand *i* at time *t* as follows:

(17) $$ShortTermSpillover_{it} = AvgSimilarity_{it}\,\delta_2^{DaysSinceIP_t}$$

where δ_2 is a decay parameter in the interval (0,1) and $DaysSinceIP_t$ captures the number of days since a brand event or scandal was initially reported in the news media. Similar to the short-term direct effect, equation (17) approaches zero as $DaysSinceIP_t$ increases.

We operationalize the long-term effects of reputational spillover from publicity for brand *i* at time *t* as follows:

(18) $$LongTermSpillover_{it} = AvgSimilarity_{it}(1 - \delta_2^{DaysSinceIP_t})$$

As the number of days since the initial brand-related publicity ($DaysSinceIP_t$) increases, the term ($1-\delta_2^{DaysSinceIP_t}$) approaches one. Thus, $LongTermSpillover_{it}$ helps us capture the long-term reputational spillover effects of publicity.

Assessing the Direct and Spillover Effects of Brand-related Publicity

We apply this modeling framework to our empirical context in which the brand-related publicity is generated by a brand scandal. Specifically, we explore the highly publicized Biogenesis scandal which exposed PED use in Major League Baseball. Treating each player as his own human brand *i*, we employ a hierarchical Bayesian model that enables us to estimate individual-level direct and reputational spillover effects generated by those players named in the PED scandal by the news media. We measure consumer sentiment (Y_{it}) toward brand *i* at time *t* using the valence of social media conversation on Twitter, accessed through Topsy, to represent the consumer-human brand relationship as specified in equation (12).

To model both the short- and long-term direct and reputational spillover effects of the scandal-related publicity, the following model of social media sentiment (Y_{it}) is specified for player *i* at time *t*:

(19) $$Y_{it} \sim N(\hat{Y}_{it}, \tau_y)$$

(20) $$\hat{Y}_{it} = \alpha_i + Direct_{it} + Spillover_{it} + MLBHalo_t + \sum_{k=1}^{14} \gamma_k Z_{ikt}$$

where:

(21) $$Direct_{it} = \beta_{i1} ShortTermDirect_{it} + \beta_{i2} LongTermDirect_{it}$$

and:

(22) $$Spillover_{it} = \theta_{i1} ShortTermSpillover_{it} + \theta_{i2} LongTermSpillover_{it}$$

and:

(23) $$MLBHalo_t = \gamma_{15} ScandalDummy_t + \gamma_{16} LogNumFL_t$$

where α_i is a vector of player-specific intercepts, $\beta_{i\cdot}$ is a vector of coefficients capturing the direct effects of being publicly linked to the scandal on consumer sentiment toward brand *i*, and $\theta_{i\cdot}$ is a vector of coefficients accounting for the spillover effects related to brand *i*'s similarity to those publicly associated with the scandal. In our context Publicity_{it} is a dummy variable indicating if player *i* was named in the scandal-related publicity (had entered the focal list) by time *t*, and DaySince_{it} represents the days since player *i* was initially connected to the Biogenesis scandal by the news media. By construction these variables equal zero for all players not on the focal list.

To control for the overall halo effect of the scandal and its related negative publicity on Major League Baseball, we calculate MLBHalo_t which is composed of a dummy variable that equals 0 prior to the scandal being publicized on January 29th and 1 thereafter (ScandalDummy_t) and the log transformation of the number of player on the focal list at time *t* (LogNumFL_t). Finally, γ_k is a vector of coefficients that captures the impacts that control variables Z_{ikt} have on consumer sentiment for brand *i* at time *t*. Z_{ikt} includes controls for special events (WBC and All-Star events), player characteristics (salary and dummy variables for pitchers, previous PED suspension, major award winners, and injury status) and team characteristics (team payroll, metro size, run differential, current winning/losing streak, games behind divisional leader, and dummy variables for game day and game won) which are described in the previous section.

Model Estimation

The model is estimated using a Bayesian hierarchical regression and Markov chain Monte Carlo techniques using WinBUGS (http://www.mrc-bsu.cam.ac.uk/bugs/). The focal list is included in the estimation along with a random sample of half the remaining players for the purpose of computational efficiency. Our final sample for estimation included 410 players. We specify Y_{it}, α_i, $\beta_{i\cdot}$, $\theta_{i\cdot}$, $\gamma_{i\cdot}$, logit($\delta_\cdot$), and logit($\eta_\cdot$) with diffuse normal priors. We assume that the variances for the normal distributions follow diffuse inverse gamma priors. Using three independent chain runs, the above equations are estimated from 20,000 iterations for each chain following a burn-in of 10,000 iterations. Our inferences are based on the remaining 10,000 draws from each of the three chains. 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.

Model Comparison

To assess the importance of accounting for both the individual-level direct and spillover effects of scandal-related brand publicity, we compare our proposed model to a series of alternative models in Table 21. Deviance information criterion (DIC) for the system of equations, a likelihood-based measure that penalizes more complex model specifications, and the mean absolute error (MAE) are used to compare our proposed model to these alternative specifications. Lower DIC and MAE indicate better model fit.

The baseline model accounts solely for the control variables and the halo effect of the scandal on the sentiment expressed about all players. The next model builds on the baseline model and further accounts for the brand-level short- and long-term direct effects of being linked to the scandal by the news media. The third model incorporates spillover effects, but assumes that the direct and spillover effects are homogeneous ($\beta_{\cdot}$ and $\theta_{\cdot}$ are not specific to player *i*). Finally, we incorporate heterogeneity in $\beta_{i\cdot}$ and $\theta_{i\cdot}$, which is the proposed model.

The DICs and MAEs in Table 21 highlight the importance of accounting for not only the brand-level direct effects but also for the potential brand-level spillover effects from scandal-related brand publicity on consumer sentiment toward the brand.

Specifically, the results indicate that accounting for direct effects improves fit substantially compared to the baseline model. Additionally, we find that accounting for both individual-level direct and spillover effects (the proposed model) further improves model fit; thus, we proceed to detail the parameter estimates for our proposed model in the following section.

Table 21: Model Comparison

Model	*DIC*	*MAE Estimate (SD)*
Baseline	-58848	.1227 (.0002)
Baseline + Individual-Level Direct Effects of the Scandal	-65069	.1154 (.0002)
Baseline + Direct and Spillover Effects of the Scandal (No Heterogeneity)	-59076	.1225 (.0002)
Baseline + Individual-Level Direct and Spillover Effects of the Scandal (Proposed Model)	-66290	.1150 (.0002)

Results

Parameter Estimates

Posterior means for the control parameter estimates are presented in Table 22, and estimates of the effects of the scandal-related brand publicity on player sentiment are presented in Table 23. Before turning our attention to the individual-specific direct and spillover effects of the publicity, we highlight a few key results below. First, the mean of the player-specific intercepts of social media sentiment is positive, and its 95% credible interval excludes zero. The posterior means for the individual-specific player intercept (α_i) are presented in Figure 12. Only 5 of the 410 players have negative intercept estimates, and this short list includes Alex Rodriguez and Bartolo Colon, both of whom are included in our focal list of players publicly linked to the Biogenesis scandal.

Table 22: Impact of Control Measures on Social Media Sentiment

Control Parameter	*Description*	*Mean*	*(SD)*
Special Events	All-Star events	.008	(.007)
	World Baseball Classic (WBC)	-.001	(.003)
Player Characteristics	Injury (placed on disabled list)	**-.065**	**(.013)**
	Major award winner	.018	(.013)
	Pitcher	.001	(.006)
	Previous PED suspension	-.024	(.021)
	Salary (in millions)	**.002**	**(.001)**
Team Characteristics	Game day	**-.009**	**(.002)**
	Game won	**-.016**	**(.002)**
	Games behind division leader	**-.001**	**(.000)**
	Metro size (in millions)	.000	(.000)
	Run differential	-.000	(.000)
	Team payroll (in millions)	*-.000*	*(.000)*
	Winning/losing streak	**.004**	**(.000)**

Note: Bold values indicate that the 95% credible interval does not contain zero, and italicized values indicates that the 90% credible interval does not contain zero.

Second, compared to the other groups of control measures, we find that team characteristics have the most substantial impact on a player's daily social media sentiment. Specifically, our results indicate that being on a team with a winning streak improves a player's social media sentiment. We also discover that as the number of games a team is behind the division leader increases, indicative of poorer team performance, the social media sentiment of its players suffers. Furthermore, we observe that being a member of a team that played a game on a given day has a negative impact on a player's sentiment, as does being a member of team that wins a game on a given day. To explain this finding, recall that our sentiment measure is not market-specific;

thus, on game day for a specific team, social media sentiment about players on that team is likely impacted by fans of the opposing team, which may contribute to these negative effects. Also recall that Major League Baseball was facing the publicity of the Biogenesis scandal throughout the season, and research has shown that context, such as game day, may impact how salient the scandal is in the minds of consumers (Roehm and Tybout 2006), which may also explain these negative effects.

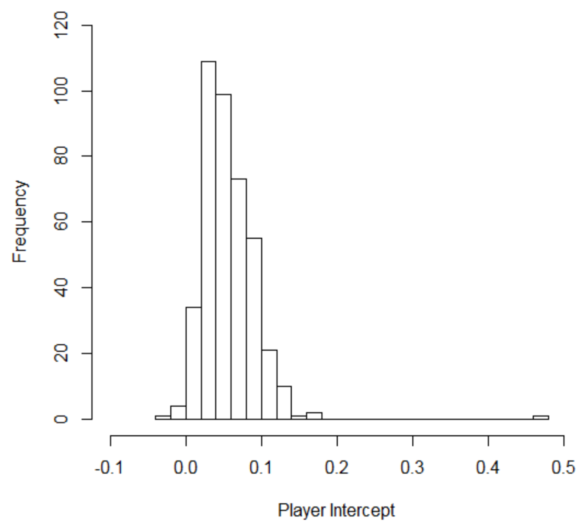
Table 23: Effects of Scandal-Related Publicity on Social Media Sentiment

Parameter	*Description*	*Mean Effect (SD)*		*Player Heterogeneity (SD)*	
$\bar{\alpha}$	Intercept	**.056**	**(.006)**	**.002**	**(.000)**
$\bar{\beta}_1$	Short-term direct effect	-.066	(.051)	**.048**	**(.019)**
$\bar{\beta}_2$	Long-term direct effect	-.001	(.029)	**.015**	**(.005)**
δ_1	Direct effects decay parameter	**.917**	**(.017)**	--	--
$\bar{\theta}_1$	Short-term spillover effect	.009	(.033)	**.033**	**(.007)**
$\bar{\theta}_2$	Long-term spillover effect	.064	(.040)	**.106**	**(.030)**
δ_2	Spillover effects decay parameter	**.993**	**(.001)**	--	--
σ_y	Variance	**.032**	**(.000)**	--	--

Note: Bold values indicate that the 95% credible interval does not contain zero, and italicized values indicates that the 90% credible interval does not contain zero.

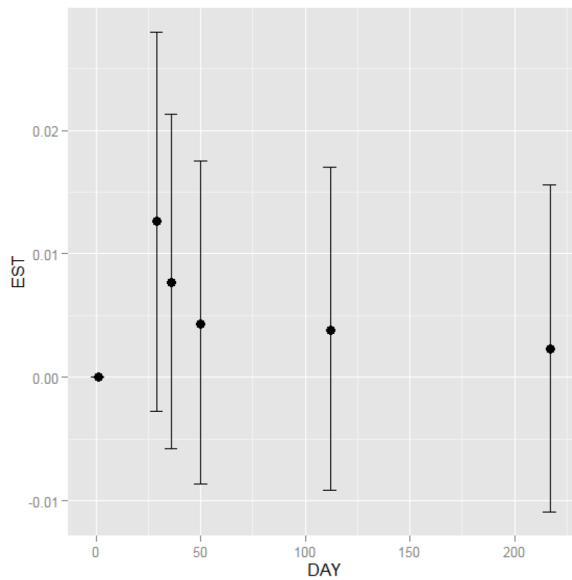
Third, in addition to controls for team characteristics, we find that two controls for player characteristics, salary and placement on the disabled list, impact a player's social media sentiment. We observe a positive relationship between a player's salary and his social media sentiment and find that placement on the disabled list, which indicates that a player has suffered an injury, has a detrimental impact on consumer sentiment toward that player. Fourth, it is worth noting that the daily decay parameters differ for the direct (δ_1) and spillover (δ_2) effects of the scandal-related brand publicity. After one week (four weeks), the direct effect of the publicity has diminished to 55% (9%) of its immediate impact. In contrast the spillover effect diminishes to 95% (82%) of its immediate impact after one week (four weeks). This suggests that the transition from short-term to long-term effects occurs more quickly for the direct effect of the scandal-related brand publicity compared to the spillover effect.

Figure 12: Posterior Means for the Player-specific Intercepts (α_i)



Finally, Figure 13 shows the league-wide halo effect of the Biogenesis Scandal on player sentiment ($MLBHalo_t$), which is comprised of a dummy variable to indicate the start of the scandal (posterior mean for γ_{15} = .03, SD = .02) and a component that accounts for number of players on the focal list (posterior mean for γ_{16} = -.01, SD = .01). We illustrate the mean and credible intervals for the days on which players enter the focal list. For each day in our sample, we find that the 95% credible interval for the effect of $MLBHalo_t$ contains zero, indicating that our data does not provide evidence of a league-wide impact of the scandal during our 10-month observation period. This finding is consistent with a *Forbes* report which speculated that the detrimental impact of the Biogenesis Scandal on the MLB would be minimal (Van Riper 2013). Though there is not an overall effect of the Biogenesis scandal on the sentiment toward all players, we next discuss the direct and spillover effects which vary from player to player.

Figure 13: League-wide Halo Effect of the Brand Scandal on Player Sentiment



Note: $MLBHalo_t$ only changes when a player enters the focal list. Thus, for visual simplicity, we only present the posterior mean and credible interval estimates for those days in which the size of the focal list changes.4.2 Direct Effects of the Brand Scandal

Direct Effects of the Brand Scandal

We begin our discussion of the direct impact of the scandal-related brand publicity by examining the short-term direct effects of being publicly linked to the Biogenesis scandal by the news media (β_{i1}). The posterior means of β_{i1} for the focal list players are presented in Table 24 and illustrate the damaging short-term impact of the scandal on the social media sentiment of the focal list players. Specifically, β_{i1} is negative for 18 of the 21

(86%) players on the focal list, and 7 players (33%) have negative short-term direct effects in which the 90% credible interval excludes zero. While we observe that the effect of being publicly linked to the Biogenesis scandal is predominantly damaging to the social media sentiment of focal list players in the short-term, the sentiment for one player on the focal list, Sergio Escalona, was positively impacted in the short-term (for which the 95% credible interval excludes zero). Escalona is a minor league player who, prior to the widespread dissemination of the Biogenesis scandal, was very rarely discussed in the news media. The positive short-term impact on his social media sentiment may be explained by recent research that has shown that lesser-known brands can benefit from negative publicity as it helps increase brand awareness (Berger et al. 2010).

Table 24 also presents the long-term direct effects of being publicly linked to the scandal on social media sentiment (β_{i2}). While the majority of β_{i2} estimates are negative (62%), the 95% credible intervals for each of these estimates contains zero with one exception, suggesting that being publicly associated with the scandal does not have a long-term impact on a focal player's social media sentiment across the 10-month period explored in our analysis. The one exception, Bartolo Colon, sees a positive long-term impact from the scandal. Colon, while linked to the scandal, was not suspended during the 2013 investigation. Fan speculation that Colon may have been wrongfully accused could explain why we find a positive long-term impact of the scandal.

Why do we not observe any negative long-term direct effects of being publicly linked to the scandal on social media sentiment? Aaker et al. (2004) show that while a negative brand event is damaging to consumer-brand relationships for sincere brands, exciting brands do not suffer as much and can even benefit from a transgression, a

Table 24: Posterior Means for the Short- and Long-term Direct Effects of the Brand Scandal on Social Media Sentiment

Focal List Player	*Short-term Direct Effects* *Mean*	*(SD)*	*Long-term Direct Effects* *Mean*	*(SD)*
Antonio Bastardo	**-.18**	**(.08)**	-.04	(.04)
Ryan Braun	-.13	(.08)	-.01	(.04)
Everth Cabrera	-.03	(.07)	.01	(.04)
Melky Cabrera	*-.15*	*(.09)*	-.02	(.05)
Robinson Cano	-.02	(.07)	.03	(.04)
Cesar Carrillo	-.02	(.08)	-.04	(.05)
Francisco Cervelli	-.07	(.08)	.04	(.04)
Bartolo Colon	.03	(.09)	**.10**	**(.04)**
Nelson Cruz	**-.21**	**(.09)**	-.01	(.05)
Fautino de los Santos	-.02	(.08)	-.01	(.04)
Sergio Escalona	**.53**	**(.09)**	.02	(.04)
Gio Gonzalez	**-.32**	**(.10)**	*-.09*	*(.05)*
Yasmani Grandal	-.09	(.08)	-.02	(.04)
Fernando Martinez	-.03	(.08)	.01	(.04)
Jesus Montero	**-.20**	**(.08)**	.00	(.04)
Jordan Norberto	-.03	(.08)	-.00	(.04)
Jhonny Peralta	**-.18**	**(.08)**	-.05	(.04)
Cesar Puello	-.00	(.08)	.05	(.04)
Alex Rodriguez	-.13	(.09)	-.01	(.05)
Jordany Valdespin	.03	(.07)	-.01	(.04)
Danny Valencia	*-.14*	*(.08)*	-.00	(.05)

Note: Bold values indicate that the 95% credible interval does not contain zero, and italicized values indicates that the 90% credible interval does not contain zero.

finding that may also speak to Colon's positive β_{i2} estimate. Professional athletes are in the business of entertainment and are more likely to be classified as exciting rather than sincere brands. Thus, the exciting nature of athlete brands may offer an explanation as to why we do not see even more damaging impacts on consumer sentiment toward the scandalized brands in both the short- and long-term. Additionally, the actions undertaken by the MLB to hold accountable those players guilty of using PEDs supplied by the Biogenesis Clinic also may have impacted the long-term direct effects of the scandal.

Specifically, the existence of no substantial negative long-term direct impacts on social media sentiment may reflect a consumer perception that the suspensions issued by the MLB served as sufficient payment for the offenses of the focal list players.

Spillover Effects of the Brand Scandal

In addition to investigating the direct effects of being publicly linked to the Biogenesis scandal, we also examine the short- and long-term spillover effects from the scandal. Figure 14 presents the posterior means of the individual-specific short- and long-term spillover effects ($\theta_{i\cdot}$). We find both positive and negative individual-specific spillover estimates in which the 90% credible interval excludes zero, indicating that some players experience collateral construction from the scandal while others suffer collateral damage to their social media sentiment. In the short-term period following the scandal, 35 players (9%) have reputational spillover effects (θ_{i1}) in which the 90% credible interval excludes zero, and the majority of these estimates (54%) are positive. In the long-term period following the scandal, 104 players (25%) have reputational spillover effects (θ_{i2}) in which the 90% credible interval excludes zero. As in the short-term, the majority of these estimates (73%) are positive. These findings are consistent with research on competitive spillover that shows that disseminated brand information can spillover and significantly impact competitors (e.g., Janakiraman et al. 2009; Kalra et al. 2011; Roehm and Tybout 2006).

Brand Similarity and Spillover

Recall that we make use of three attributes (team, field position, and salary level) to operationalize brand similarity and estimate each attribute's weight (η_k). Our results indicate that a player's field position (posterior mean = .55, SD = .07) is the most important attribute dimension in defining similarity between player *i* and focal list players *j*. Position is followed in importance by player salary level (posterior mean = .28, SD = .06), which was defined in quartiles. Finally, we discover that team (posterior mean = .17, SD = .07) is the least important attribute dimension of the three in defining similarity between player *i* and focal list players *j*.

Figure 14: Short- (θ_{i1}) and Long-term (θ_{i2}) Spillover Effects of the Brand Scandal

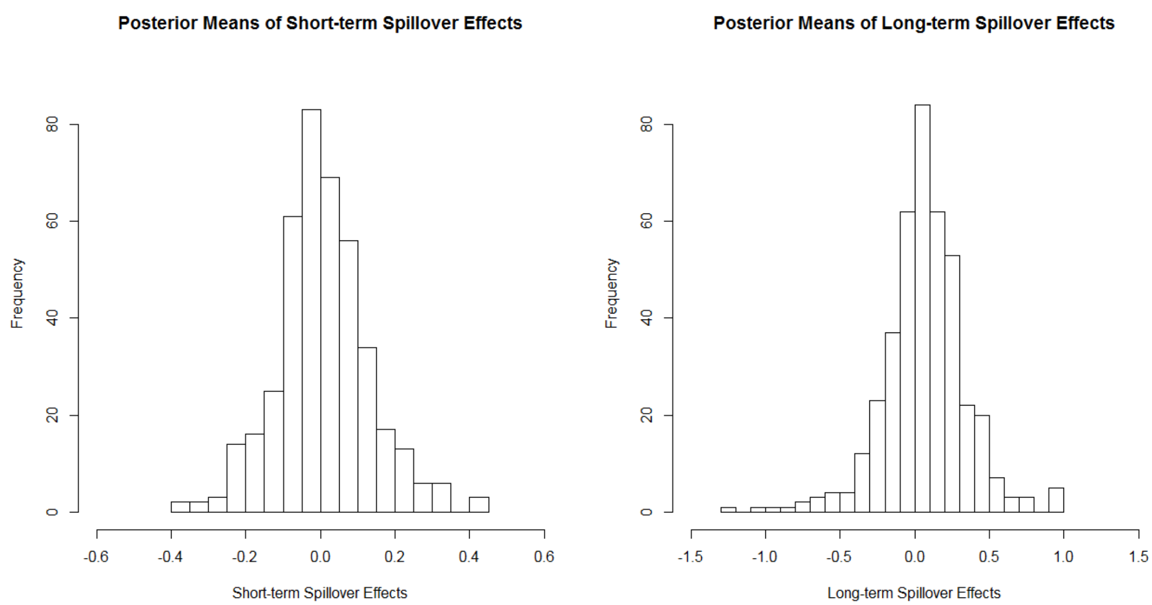
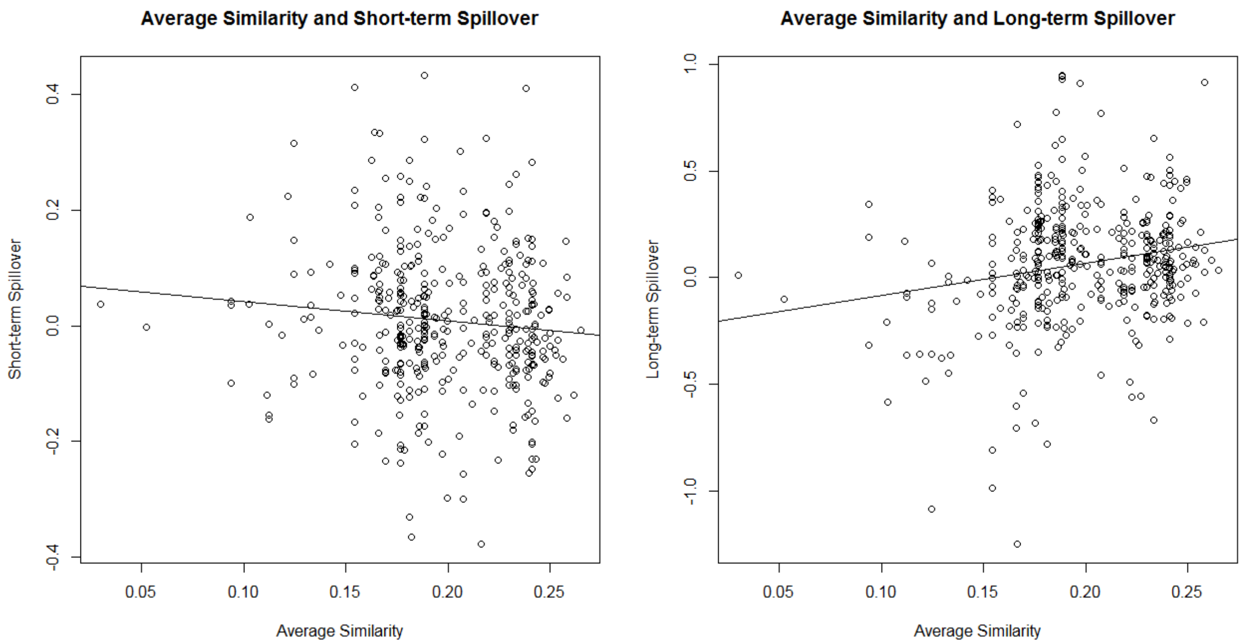


Figure 15 shows the relationship between player *i*'s average similarity across our estimation window to focal list players *j* and short-term spillover. The negative relationship suggests that we are more likely to observe negative reputation spillover, or collateral damage, in social media sentiment in the short-term for those human brands that are more similar to those publicly named in the brand scandal. Figure 15 also shows the relationship between average similarity and long-term spillover. Interestingly, we find that the relationship is positive, indicating that players who are more similar to those publicly linked to the scandal are more likely to experience positive reputational spillover or collateral construction effects on their social media sentiment in the long-term period following the scandal. While the negative direct effects of the scandal-related brand publicity fade over time, we observe a shift from collateral damage to collateral construction with regards to the spillover effects. Based on the estimates for δ_1 and δ_2, we see that the negative direct effects of being linked to the Biogenesis scandal fade more rapidly than the transition from collateral damage to construction occurs for players similar to those linked to the scandal. This suggests that reputational spillover stemming from publicity may play out over a longer time horizon than the immediate fallout from such publicity.

Why do we observe this shift in brand scandal spillover effects from collateral damage to collateral construction? While our research is not intended to identify the underlying psychological mechanism, one potential explanation for this reversal may relate to changes in public perceptions of brand guilt over time. As noted in our discussion of the empirical context, the Biogenesis scandal evolved in such a way that more than six months passed between the initial report publicizing the scandal and the MLB's final sanctions for those found guilty. When the scandal broke, new players were being linked to Biogenesis nearly every week, and true culpability was unclear. As such, consumers may have painted players similar to those publicly named in the Biogenesis scandal with the same brush. The MLB suspensions may have helped to reveal true player accountability in the Biogenesis scandal, exonerating those who may have previously been deemed as guilty by association, thereby contributing to collateral construction in social media sentiment in the long-term.

Figure 15: Relationship between Average Player Similarity and Spillover Effects



While our research is the first to examine the evolution of spillover effects from brand publicity over time, current investigations of competitive spillover are consistent with this line of reasoning. Votolato and Unnava (2006) show that negative spillover from a parent to host brand following a negative brand event involving the parent brand does not occur if the host brand is not perceived to be culpable. Furthermore, in their investigation of competitive spillover, Roehm and Tybout (2006) postulate that when a scandal is perceived as unique to the brand at fault, detrimental scandal side-effects are more likely to be isolated to the scandalized brand, and positive spillover to competitors may be possible. These findings provide support for our interpretation that the shift in scandal-generated reputational spillover effects from collateral damage in the short-term to collateral construction in the long-term may relate to changes in consumer perceptions of brand guilt over time.

Conclusion

Brand information disseminated through publicity, WOM, and other earned media is playing an increasingly important role in influencing consumer perceptions about brands. Yet, research on how such publicized brand information influences the customer-brand relationship over time has been limited. We extend research on publicity, brand transgressions, and spillover effects by investigating how being publicly linked to a brand scandal affects the perceptions of brands over time. Specifically, we explore the evolution of both brand-level direct and spillover effects of scandal-related brand publicity on the consumer-brand relationship.

Using the highly publicized Biogenesis PED scandal in Major League Baseball as our context, we present a modeling approach to investigate both the direct and reputational spillover effects from disseminated brand information using the sentiment of social media conversations about a brand. We find that the social media sentiment for human brands publicly linked to the scandal suffers a decline in the short-term, but this decline does not persist in the long-term throughout our 10-month estimation window. Additionally, we find evidence of both positive and negative reputational spillover to brands not publicly associated with the scandal. While research on advertising interference has shown that advertising and other forms of paid media can create competitive spillover (e.g., Danaher et al. 2008), our results show that publicity and earned media are also capable of generating spillover effects. Exploring how paid versus earned media differ in producing spillover may be a fruitful area of future research.

We also discover that the relationship between player similarity and short-term spillover is negative, indicating largely short-term collateral damage effects to social media sentiment for players who are similar to those involved in the scandal. Interestingly, we observe the opposite association in the long-term in which the relationship between player similarity and spillover is found to be positive. This suggests that players that are more similar to those publicly associated with the scandal predominantly experience positive reputational spillover to their social media sentiment in the long-term. One potential explanation for the shift from collateral damage in the short-term to collateral construction in the long-term could relate to changes in consumer perceptions of brand culpability over time. While testing the psychological mechanism at work is beyond the scope of this research, we believe it to be an area that warrants future work.

While the empirical context of our research focuses on scandal-related publicity in the human brand context, our modeling framework is generalizable to traditional brand settings and can be used to estimate spillover effects from positive or negative publicity. Additionally, our approach is not limited to feature matching constructions of brand similarity and is flexible to alternative methods of measuring brand similarity such as perceptual mapping. Our framework can also be used with other dependent variables, which could allow brand managers to investigate the direct or indirect effects of brand publicity on marketing outcomes such as sales, stock prices, or advertising elasticities.

Our research has further managerial implications for brand managers administering brands that are directly or indirectly linked to a scandal. First, brand managers may make use of the social media conversations about their brand to assess in real time the direct or potential spillover effects of a brand transgression or brand-related publicity. This approach could serve as a diagnostic tool to help brand managers gauge the health of the consumer-brand relationship following direct or indirect involvement in a brand event or scandal.

Second, we do not observe long-term negative impacts from the brand scandal on social media sentiment toward human brands directly linked to the transgression. This may encourage talent or brand managers working with celebrity endorsers to adopt a less aggressive approach toward long-term damage control when overseeing crisis management for a scandalized human brand. Further research can explore how issuing a denial or apology in response to being publicly linked to a brand transgression (e.g., Roehm and Brady 2007) impacts the short- and long-term direct effects of a brand scandal on the consumer-brand relationship. It may also be beneficial for future research to investigate how the direct effects of a brand scandal vary over time in a non-human brand context. Consumers may be more forgiving to human brands given the exciting nature of their brand type (Aaker et al. 2004), and less-exciting product or service brands may see negative effects of the scandal persist in the long-term.

Finally, as we show, scandal-related brand publicity has an impact beyond the brands involved in the transgression, and this spillover can have substantially different effects in the short- and long-term periods following the scandal. Our findings advise brand managers to be aware that the spillover effects from an ally or competitor's transgression can vary over time. Managers looking to take advantage of another brand's involvement in a scandal may want to be wary of doing so in the short-term period immediately following the transgression if their brand is similar to those publicly linked to the transgression.

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Appendix 1: Descriptive Statistics – Impact of Additional Brand, Ad, and Program Characteristics on Online WOM

	Change in Brand WOM		Change in Program WOM	
Brand and Ad Characteristics	Mean	(SD)	Mean	(SD)
Ad break position				
First ad break in program	80%	(296%)	0%	(125%)
Last ad break in program	89%	(754%)	7%	(54%)
Ads on other networks	101%	(800%)	3%	(48%)
Brand sign-offs				
Auditory brand sign off	141%	(1873%)	2%	(69%)
Visual brand sign-off	91%	(1296%)	4%	(75%)
Half-hour break	190%	(3326%)	5%	(53%)
Twitter account				
Brand does not have Twitter account	95%	(892%)	6%	(53%)
Brand has Twitter account	111%	(1504%)	4%	(76%)
Program Characteristics	Mean	(SD)	Mean	(SD)
Fall finale	70%	(309%)	5%	(46%)
Program length				
30 minute programs	91%	(545%)	-2%	(50%)
60 minute programs	106%	(1670%)	8%	(83%)
120 minute programs	143%	(495%)	-6%	(27%)
Program ratings				
Below average (<1.85)	50%	(206%)	5%	(47%)
Above average (>1.85)	180%	(2099%)	3%	(96%)
Season premiere	267%	(3863%)	10%	(42%)