cemerald insight



Journal of Service Management

Dynamics between social media engagement, firm-generated content, and live and time-shifted TV viewing Vijay Viswanathan, Edward C. Malthouse, Ewa Maslowska, Steven Hoornaert, Dirk Van den Poel,

Article information:

To cite this document:

Vijay Viswanathan, Edward C. Malthouse, Ewa Maslowska, Steven Hoornaert, Dirk Van den Poel, (2018) "Dynamics between social media engagement, firm-generated content, and live and time-shifted TV viewing", Journal of Service Management, Vol. 29 Issue: 3, pp.378-398, <u>https://doi.org/10.1108/JOSM-09-2016-0241</u> Permanent link to this document:

https://doi.org/10.1108/JOSM-09-2016-0241

Downloaded on: 25 June 2018, At: 11:57 (PT) References: this document contains references to 82 other documents. To copy this document: permissions@emeraldinsight.com The fulltext of this document has been downloaded 126 times since 2018*

Users who downloaded this article also downloaded:

(2018),"Actor engagement valence: Conceptual foundations, propositions and research directions", Journal of Service Management, Vol. 29 Iss 3 pp. 491-516 https://doi.org/10.1108/JOSM-08-2016-0235

(2018),"Engagement within a service system: a fuzzy set analysis in a higher education setting", Journal of Service Management, Vol. 29 Iss 3 pp. 422-442 https://doi.org/10.1108/JOSM-08-2016-0232

Access to this document was granted through an Emerald subscription provided by emerald-srm:275112 []

For Authors

If you would like to write for this, or any other Emerald publication, then please use our Emerald for Authors service information about how to choose which publication to write for and submission guidelines are available for all. Please visit www.emeraldinsight.com/authors for more information.

About Emerald www.emeraldinsight.com

Emerald is a global publisher linking research and practice to the benefit of society. The company manages a portfolio of more than 290 journals and over 2,350 books and book series volumes, as well as providing an extensive range of online products and additional customer resources and services.

Emerald is both COUNTER 4 and TRANSFER compliant. The organization is a partner of the Committee on Publication Ethics (COPE) and also works with Portico and the LOCKSS initiative for digital archive preservation.

*Related content and download information correct at time of download.

JOSM 29,3

378

Received 6 September 2016 Revised 17 February 2017 13 June 2017 Accepted 6 March 2018

Dynamics between social media engagement, firm-generated content, and live and time-shifted TV viewing

Vijay Viswanathan and Edward C. Malthouse Department of Integrated Marketing Communications, Medill School, Northwestern University, Evanston, Illinois, USA

Ewa Maslowska

Amsterdam School of Communication Research (ASCoR), University of Amsterdam, Amsterdam, The Netherlands, and Steven Hoornaert and Dirk Van den Poel Department of Marketing, Ghent University, Ghent, Belgium

Abstract

Purpose – The purpose of this paper is to study consumer engagement as a dynamic, iterative process in the context of TV shows. A theoretical framework involving the central constructs of brand actions, customer engagement behaviors (CEBs), and consumption is proposed. Brand actions of TV shows include advertising and firm-generated content (FGC) on social media. CEBs include volume, sentiment, and richness of user-generated content (UGC) on social media. Consumption comprises live and time-shifted TV viewing. **Design/mathcodology/approach**. The authors study 31 new TV shows introduced in 2015 Consistent

Design/methodology/approach – The authors study 31 new TV shows introduced in 2015. Consistent with the ecosystem framework, a simultaneous system of equations approach is adopted to analyze data from a US Cable TV provider, Kantar Media, and Twitter.

Findings – The findings show that advertising efforts initiated by the TV show have a positive effect on time-shifted viewing, but a negative effect on live viewing; tweets posted by the TV show (FGC) have a negative effect on time-shifted viewing, but no effect on live viewing; and negative sentiment from tweets posted by viewers (UGC) reduces time-shifted viewing, but increases live viewing.

Originality/value – Content creators and TV networks are faced with the daunting challenge of retaining their audiences in a media-fragmented world. Whereas most studies on engagement have focused on static firm-customer relationships, this study examines engagement from a dynamic, multi-agent perspective by studying interrelationships among brand actions, CEBs, and consumption over time. Accordingly, this study can help brands to quantify the effectiveness of their engagement efforts in terms of encouraging CEBs and eliciting specific TV consumption behaviors.

Keywords Social media, Customer engagement, User-generated content, Firm-generated content,

Service-dominant logic, TV shows, Time-shifted viewing

Paper type Research paper

Introduction

Customer engagement (CE) is gaining traction among marketing practitioners and academics, who have increasingly begun to acknowledge its potential to affect purchase and consumption decisions, in addition to related outcomes such as loyalty (e.g. Aksoy *et al.*, 2016; van Doorn *et al.*, 2010). Engagement is often described as a process in which customers partake in co-creative interactions with a firm. For example, Brodie *et al.* (2011) define CE as "A psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g. a brand) in focal service relationships." Due to its interactive and value-co-creative nature, CE is of particular interest in the customer-relationship management and service contexts (Hollebeek, 2011). While research over the last decade has provided numerous valuable insights regarding the nature of engagement and its relevance to firms, we still have much to learn. Most extant work has focused on defining and



Journal of Service Management Vol. 29 No. 3, 2018 pp. 378-398 © Emerald Publishing Limited 1757-5818 DOI 10.1108/JOSM-09-2016-0241 measuring engagement, and relied mostly on cross-sectional surveys (e.g. Algesheimer *et al.*, 2005; Calder *et al.*, 2009; Hollebeek *et al.*, 2014). Brodie *et al.* (2011) astutely theorize that engagement is a dynamic, iterative process, but few studies to date have isolated the components of this process, or developed longitudinal designs to empirically analyze how these components influence one another over time. Elucidation of these issues has the potential to provide crucial theoretical and practical insights regarding how actions carried out by a brand and by its customers influence one another as well as marketplace outcomes such as purchase and consumption behaviors. These issues become even more pressing in light of the development of digital technologies, such as social media, which, on the one hand, provide platforms where brands, customers, and other actors can interact with one another, and, on the other hand, provide firms with a means of tracking and analyzing these interactions. Such data can enable brands to leverage their understanding of customers' needs and preferences, and allow them to adjust their activities in real time to stimulate CE and value creation (Kunz *et al.*, 2017).

The current paper seeks to address these issues in a fast-changing context in which CE, and especially loyalty, are particularly salient, namely, the media and entertainment industry. This industry is characterized by a highly dynamic environment whose ecosystem is currently undergoing disruptive changes. Rapid advances in digital technologies have led to the fragmentation of media outlets and platforms, changing the way content is delivered to consumers. Content creators are no longer solely dependent on satellite and cable providers to distribute their content and can offer direct access through streaming services (e.g. Netflix, HBO GO, Hulu, Amazon Prime) or their own platforms (e.g. Disney Movies Anywhere). This means that consumers have a growing number of content options, which they can access whenever they wish, increasing the competition for their attention. Consequently, it is becoming more difficult for media organizations – a term we use to refer collectively to content creators (such as studios) and content distributors (e.g. networks and cable channels) – to attract and retain audiences.

In addition to altering viewers' content consumption behavior, digital technologies and social media platforms have provided consumers with new opportunities to engage with that content and with other viewers, even during the act of consumption. Viewers connect with other viewers to discuss storylines or character developments, exchange trivia, speculate on what will happen next, comment on something that just happened, or any number of other activities around the content. Thus, instead of consuming content passively, they are active participants who talk about their experience with the show, often in real time. Viewers who concurrently watch a TV show and share their experiences on Twitter, an activity known as live tweeting, report that they feel connected to a wider audience (McPherson *et al.*, 2012; Schirra *et al.*, 2014). Initial research suggests that viewers who desire such an experience are likely to prefer to view TV programs at the time they are broadcast (referred to herein as "live viewing") rather than to record them and watch them later ("time-shifted viewing") (Benton and Hill, 2012; Lovett and Staelin, 2016). Notably, such social participation has been shown to be associated with future media consumption (Hollebeek, Malthouse, and Block, 2016; Hollebeek, Srivastava, and Chen, 2016; Mersey *et al.*, 2010).

In an attempt to keep up with these trends, media organizations have begun to proactively seek out consumer engagement by initiating interactions with their audiences on social media platforms (e.g. via Facebook and Twitter accounts; Nielsen, 2014). Shows can release trailers for a future episode to prompt discussions and speculation among loyal fans. *The Walking Dead*, for example, created a mobile app that allows fans to take a picture of themselves, apply picture-editing functionality to turn themselves into a zombie, and share this photo with friends. In some cases, organizations initiate discussion threads on social media, thereby involving the audience in the co-creation of social media content. For example, several days after airing an episode set in a roller-derby, the show *Bones* asked

consumers on its Twitter account to tweet suggestions for their own roller-derby names. Collectively, these contact points can create higher engagement with the show.

According to the service-dominant (S-D) logic, brand-related interactions such as those observed on social media – which take place not only within consumer-brand dyads but also across networks of interconnected consumers (and other stakeholders) - facilitate experiences that lead to value co-creation (Vargo and Lusch, 2008). The value that is created depends on the quality of those experiences (Fyrberg and Jüriado, 2009). The availability of detailed firm-generated content (FGC) and user-generated content (UGC) on social media offers a unique opportunity to observe those customer-brand experiences, and to attempt to decode how they relate to value creation (as measured, e.g. in terms of consumption). In this paper, we take advantage of this opportunity to propose and empirically examine a theoretical framework that explains how engagement develops as a dynamic, iterative process in the context of TV viewing. Our model comprises three key components: consumer-generated interactions with brands on social media, brand actions (namely, advertising and social media posts), and consumption behaviors. To test the framework, we analyze TV show viewing records from the set-top boxes of a US-based cable operator with more than 1.5 million monthly subscribers, obtained over nine months; Kantar Media data measuring TV show advertising efforts; and messages posted by the TV show (FGC) and by viewers (UGC) on Twitter. We study how the three components of our framework influence one another over time.

Theoretical underpinnings

Overview of the engagement ecosystem framework

The theoretical underpinnings of engagement are embedded in the domains of relationship marketing and S-D logic (Hollebeek, Malthouse, and Block, 2016; Hollebeek, Srivastava, and Chen, 2016). These theoretical perspectives see consumer behavior as "centered on customers' and/or other stakeholders' interactive experiences taking place in complex, co-creative environments" (Brodie *et al.*, 2013). In line with this view, a seminal paper by Brodie *et al.* (2011, p. 260) defines CE as:

A psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g. a brand) in focal service relationships. It occurs under a specific set of context dependent conditions generating differing CE levels; and exists as a dynamic, iterative process within service relationships that co-create value. CE plays a central role in a nomological network governing service relationships in which other relational concepts (e.g. involvement, loyalty) are antecedents and/or consequences in iterative CE processes. It is a multidimensional concept subject to a context- and/or stakeholder-specific expression of relevant cognitive, emotional and/or behavioral dimensions.

Though this definition is widely accepted among scholars, it requires certain clarifications. For example, though it suggests that engagement can manifest in "behavioral dimensions" (in addition to cognitive or emotional dimensions), it assumes that engagement is a "psychological state" rather than a behavioral construct. Yet, many engagement researchers have focused on the behavioral nature of engagement (e.g. Javornik and Mandelli, 2012; Vivek *et al.*, 2012); for example, Vivek *et al.* (2012) describe engagement in terms of intensity of participation in brand-related activities. A behavioral perspective emphasizes the active role of consumers in co-creating value (Kunz *et al.*, 2017). Moreover, given that a consumer's behaviors may be observable to others, this perspective provides opportunities to investigate the role of engagement in social-influence and social-learning processes. These aspects are particularly relevant in the era of social media and other interconnected environments (Lemon and Verhoef, 2016). Herein, in line with these studies, we focus on behavioral manifestations of engagement, and observe specific customer engagement

JOSM

29.3

behaviors (CEBs; van Doorn *et al.*, 2010) that are relevant to our context. We note, however, that this focus does not negate the psychological aspects of engagement. Indeed, several researchers have sought to clarify the relationships between psychological constructs related to engagement (such as involvement) and actual behavior (Harmeling *et al.*, 2017), and to use such insights to investigate antecedents and consequences of engagement (Pansari and Kumar, 2017).

Even more importantly, while there seems to be a broad consensus that, as suggested by Brodie *et al.* (2011), engagement is a "dynamic, iterative process," there has been little research to date on the specifics of this process. To our knowledge, Viswanathan et al. (2017) were the first to attempt to model the iterative process of CE empirically; their study used vector autoregressive models to investigate the relationships among engagement with mobile apps, purchases, and brand consumption. Maslowska et al. (2016) proposed the CE ecosystem, which is a conceptual model of engagement consisting of brand actions, other actors, customer-brand experience, shopping behaviors, brand consumption, and brand-dialogue behaviors. The elements of the ecosystem are assumed to interact continuously in a nonlinear fashion, creating value for both customers and the firm. Building on the work of Maslowska et al. (2016), we propose the framework shown in Figure 1, which reflects our focus on the behavioral manifestations of engagement in a social media environment in the context of TV consumption. Specifically, we see CE in the context of the TV industry as comprising three main elements; CEBs, brand actions, and consumption. CEBs are assumed to include consumers' social media behaviors that relate to TV consumption (UGC). Brand actions consist of a TV show's advertising and messages posted by the TV show on social media (FGC). Consumption consists of live and time-shifted TV show viewing. Our framework argues that there are intra- and interrelationships among these engagement elements. In what follows, we discuss each of these elements and outline our predictions regarding the influences that they are expected to have on one another.

CEBs

van Doorn *et al.* (2010, p. 253) define CEBs as "customers' behavioral manifestation toward a brand or firm, beyond purchase, resulting from motivational drivers." According to Verhoef *et al.* (2010) and van Doorn *et al.* (2010), CEBs consist of a vast array of activities (e.g. watching commercials, sharing posts on Facebook, liking tweets), excluding consumption behaviors. Notably, CEBs that take place in the context of social media are observable by others and thus have the potential to influence the consumption and



Figure 1. Conceptual model of engagement ecosystem

non-consumption behaviors of other consumers (Bijmolt *et al.*, 2010). This idea is in line with the S-D perspective, according to which value is created by interactions among multiple actors, in economic and social networks that extend beyond the customer-brand dyad (Jaakkola and Alexander, 2014; Vargo and Lusch, 2016). The experiences facilitated by these interactions produce value beyond that of the actual product/offering (Lusch and Vargo, 2006). Thus, our framework acknowledges that actors engaging in CEBs can, in turn, be co-creators of other customers' engagement. Notably, the value created by CEBs is not necessarily positive (Heinonen and Strandvik, 2009). Though CEB that gives rise to a positive experience can create positive value, a CEB that gives rise to a negative experience is likely to create negative value (Grönroos and Voima, 2013).

CEBs on social media can be characterized on the basis of three key properties: volume (e.g. number of tweets per week), sentiment (e.g. the proportion of positive or negative tweets), and interactivity, or richness (e.g. the extent to which posts contain photos, videos, URLs). Overall, each of these properties has been found to relate positively to various engagement- and firm-performance-related outcomes. In what follows, we explore how each of these properties is expected to influence the various components of the engagement ecosystem.

Effects of CEBs on consumption. In general, existing literature theorizes that CEBs have the potential to positively affect a brand's reputation and financial performance (e.g. van Doorn *et al.*, 2010). Indeed, studies in the context of integrated marketing communications (IMC) and CRM (e.g. Ngai *et al.*, 2015; Malthouse, Haenlein, Skiera, Wege, and Zhang, 2013) have shown that users' posts on social media can affect consumer attitudes and purchase behaviors, though Hollebeek *et al.* (2014) suggest that more empirical research is needed to establish such relationships.

More specifically, there are at least two main mechanisms by which CEBs have the potential to influence consumption. First, they create online word of mouth (WOM). The volume of WOM can signal product popularity (Liu, 2006; Park and Lee, 2008) and increase consumers' product awareness (Chen et al., 2004). It can also increase consumers' trust toward, and certainty in, the opinions expressed (Wang et al., 2015). Colliander and Dahlén (2011) highlighted the importance of the user-generated nature of such WOM: brand-related content that appears in blog posts purportedly written by consumers elicits more positive attitudes and stronger purchase intentions toward those brands compared with identical content in traditional online magazines. Goh et al. (2013) showed that the richness, valence, and volume of UGC (i.e. posts and comments) on a focal brand's page have a positive effect on consumption. Moreover, studies in the context of the movie industry have found that the volume of online WOM about a movie is positively associated with box office performance (e.g. Chevalier and Mayzlin, 2006; Chintagunta et al., 2010; Duan et al., 2008; Liu, 2006; Zhang and Dellarocas, 2006). Notably, Zhang and Dellarocas (2006) observed that box office revenues are primarily affected by WOM sentiment, and that WOM volume does not have an effect when sentiment is controlled for.

Second, the very act of engaging online with a brand has the potential to influence consumption (Oestreicher-Singer and Zalmanson, 2012). Gamboa and Gonçalves (2014) find that being a brand fan on Facebook is related to higher customer loyalty. Malthouse, Vandenbosch and Kim (2013) and Malthouse *et al.* (2016) looked into the effects of participation in a brand contest and showed that the amount of brand-related cognitive elaboration is associated with future consumption behaviors. Kawale *et al.* (2009), who studied online gaming, operationalized engagement as time spent in a game and used it to predict churn of gamers.

In light of these findings, we suggest that CEB volume, sentiment, and richness will have positive effects on the extent of TV consumption. In our analysis, we also examine the effects of CEBs on specific TV consumption behaviors, namely live TV viewing and time-shifted TV viewing.

29.3

JOSM

Effects of CEBs on other consumers' CEBs. Drawing from the WOM literature cited above, we suggest that CEB volume, sentiment, and richness can have a reinforcing effect not only on consumption but also on consumers' propensity to engage in CEBs. Regarding richness in particular, we note that CE in online brand communities is often motivated by a need for information (Brodie *et al.*, 2013) and/or entertainment (Muntinga *et al.*, 2011). Since tweets that are rich with visuals (e.g. photo/image, video) and text (e.g. URL) provide information that is more interesting and interactive, we can expect that greater levels of richness stimulate greater engagement. This notion is supported by the media richness theory (Daft and Lengel, 1986), which suggests that richer and more personal media are generally more effective than less rich media.

Effects of CEBs on brand actions. CEBs can directly affect the actions of the brands with which consumers engage. For example, brands are increasingly investing resources in webcare, defined as "the act of engaging in online interactions with consumers, by actively searching the web to address consumer feedback (e.g. questions, concerns and complaints)" (van Noort and Willemsen, 2011, p. 133). Indeed, many companies have social media teams devoted to posting content on social media in response to customers' questions and, in particular, to addressing negative comments. Firms can also react to CEBs with traditional marketing mix elements. Increasing advertising can delay negative CEBs' destructive impact on consumption, while decreasing advertising does not hurt consumption in the presence of positive CEBs (Mahajan *et al.*, 1984). The following section elaborates further on brand actions in the context of TV consumption.

Brand actions

Brands communicate with consumers using paid media, such as advertising, and owned media such as their websites, social media accounts, or YouTube channels (Corcoran, 2009; Stephen and Galak, 2012). While there is a long history of research on traditional advertising, research on owned media has only recently become popular. The brand actions we focus on herein are advertising and posts on social media via official Twitter accounts.

Effects of brand actions on consumption. For decades, brands have exposed consumers to ads on television, radio, billboards, print media, and the internet. Numerous studies have shown that these initiatives have a positive effect on brand consumption (e.g. Gopinath *et al.*, 2014; Onishi and Manchanda, 2012). The objective of most traditional advertising campaigns is to achieve maximum "reach" i.e., to communicate with as many potential consumers as possible in a cost-effective manner. Television networks typically advertise shows to viewers with the hope that they arouse interest and increase viewership. Lovett and Staelin (2016) show that these ads have a positive effect on both live and time-shifted viewing. Therefore, in line with previous work, we expect that advertising has a positive effect on TV consumption.

Some scholars suggest that reach does not necessarily translate into "marketing exchange," since consumers are often merely bystanders (rather than active participants) in the face of a brand's marketing actions (Hanna *et al.*, 2011; Stephen and Galak, 2012). In addition, while traditional media may be successful at attracting the attention of masses, it may not be able to evoke interest and sustain engagement with the brand. Conversely, the selectivity mechanism suggests that while the reach of social media content may not be as large as that of traditional advertising, it may pinpoint consumers who are actively interested in the focal brand (Malthouse *et al.*, 2016; Stephen and Galak, 2012), and who might therefore be more likely to act. A recent study by Kumar *et al.* (2016) shows that FGC on social media has a positive effect on customer spending (i.e. amount of dollars spent) and customer cross-buying (i.e. buying from multiple product categories). Specifically for TV viewing, Gong *et al.* (2015) show that exposure to FGC on social media can lead to a

77 percent increase in live viewing. Hence, it seems that a TV show's activities on social media should have a positive effect on consumption.

Effects of brand actions on CEBs. While brand efforts via paid and owned media should have a positive effect on consumption, they also foster CEBs on social media. These CEBs are often referred to as a form of earned media. Only a few studies to date have examined the effect of brand actions on CEBs. Some studies have found that advertising has a positive effect on CEB volume (Fossen and Schweidel, 2016; Gopinath *et al.*, 2014; Onishi and Manchanda, 2012) and CEB valence (Gopinath *et al.*, 2014).

Brands increasingly use hashtags in their ads as a call to action to prompt discussion on social media. According to recent research, including a call to action in an ad results in 2.6 times more online WOM for that ad (Fossen and Schweidel, 2016). Another recent article reveals that individuals who watch a TV commercial and subsequently engage on Twitter are more likely to have positive sentiment about the advertisement and the brand (Swant, 2016). We therefore hypothesize that brand actions have a positive effect on CEB volume and sentiment on social media.

Effects of a brand's actions on its other actions. A brand's decision to advertise on a certain medium may be based on past advertising efforts and the effectiveness of those efforts. The IMC perspective suggests that firms should coordinate their campaigns on different media. For instance, if a network wishes to share information about a TV show with its viewers, it should communicate this information using both traditional and owned media platforms. We therefore expect that traditional advertising should drive the brand's activities on social media and vice versa.

TV consumption

Including consumption (TV viewing) in the engagement ecosystem is paramount, because consumption ultimately relates to financial outcomes; these include ad revenues (particularly in the case of live as opposed to time-shifted viewing) or payments from multisystem operator (MSOs) subscription fees. Large audience sizes provide networks with bargaining power both to remain in the bundle and command a higher payment amount from the MSO. Thus, large audiences are generally in the financial interests of media organizations.

According to the S-D logic, value is created and perceived by the customer during the consumption process (Lusch and Vargo, 2006) and "occurs at the intersection of the offer and the customer over time: either in direct interaction or mediated by a good" (Lusch and Vargo, 2006, p. 284). While most studies examine consumption as an outcome, the engagement ecosystem (Figure 1) suggests that it can also influence CEBs and brand actions.

Effects of TV consumption on CEBs. The more people purchase and consume a product, the more they share their experiences with others. In our context, this means that as more consumers watch a show (i.e. TV consumption), more CEBs relating to the show are likely to be generated (e.g. posts about the TV show, users' sentiments, photos, and videos about the show). Indeed, Godes and Mayzlin (2004), for example, found that previous-period live viewing can drive current-period WOM volume. Hence, we expect TV consumption to have a positive effect on CEB volume, sentiment, and richness.

Effects of consumption on brand actions. Consumption of a product or service can also influence brand actions. For instance, a brand may decide to change its advertising efforts because of changes in consumption behaviors. In the TV industry, the prevalence of digital video recorders has added a layer of complexity to consumption, enabling consumers to decide whether to watch a show live or record the show and watch it later at their convenience (i.e. time-shifted viewing). When watching recorded content, viewers can skip

29.3

JOSM

ads and focus on the show. When live viewership goes down and time-shifted viewership goes up, firms may choose to increase their advertising on traditional and/or social media with the hope that more viewers watch the show live and the network is able to maximize its advertising revenues. We therefore posit that TV consumption affects brand actions.

Effects of live (time-shifted) consumption on time-shifted (live) consumption. Media organizations believe that a show with more time-shifted viewers has fewer live viewers (Bond and Garrahan, 2015; Nielsen, 2014). In other words, the industry believes that time-shifted viewing grows at the expense of live viewing. Empirical research, however, suggests that live and time-shifted viewers are distinct (Belo *et al.*, 2016; Lin, 1993; Wilbur, 2008). Belo *et al.* (2016) were the first to investigate the difference between live, time-shifted, and total viewing using set-top box data. In our analysis, we test whether live viewership has an effect on time-shifted viewership.

Research design

Data

Since this study examines the engagement ecosystem in the context of TV shows, we first used various websites and news sources to identify shows in the entertainment and drama genres that aired in the fall of 2015. We decided to focus on new shows and not new seasons of old shows for the following reasons in order to eliminate the possibility that any observed viewing and engagement behavior can explained by previous TV show brand actions, CEBs, or viewing. Taking into account this requirement, we obtained a sample of 31 new TV shows. Of the 31 shows considered for the analysis, 10 were canceled during or at the end of their season. The remaining 21 shows were renewed by their networks either for a new season or for the remainder of their season. Table I provides a description of the 31 shows used for the analysis, their Twitter handles, renewal status, and primary networks. As we can observe from the table, these shows were aired on 13 different channels. The unit of analysis is a TV show aired in a single week. A total of 206 observations were available for the analysis. After identifying the sample of 31 TV shows to be studied, we merged data from three different sources to operationalize the variables in the theoretical framework (Figure 1). We explain this process in detail below.

Operationalization of TV consumption. We used set-top box data provided by a US cable operator to develop the two measures of TV consumption – live TV viewing and timeshifted TV viewing. The cable provider operates primarily in Tier-2 markets in the southern, eastern, and western states of the USA and has over 1.5 million subscribers. Viewing data for a random sample of 191,222 set-top boxes from April 2015 to December 2015 were provided to us. The data consist of information on when a show was aired and whether the set-top box was tuned to the program at that time or not. The data also capture information on whether the set-top box was programmed to record the show when it was first aired and when it was viewed. If the set-top box was tuned to the program when it was first aired, we define it as live viewing. We note that we focus on first-time broadcasts and not on reruns, as it is difficult to determine whether the latter qualifies as live viewing or time-shifted viewing. If the set-top box was programmed to record the show and the show was viewed at least one day after the show was first aired, we define it as time-shifted viewing. We were therefore able to identify for each set-top box in our sample whether a TV show was viewed live, or time-shifted. For each TV show s, we then computed for every week t the total number of devices that were tuned in into the show live (NLive) and the total number of devices that recorded the show and watched it later (NTimeShifted).

Operationalization of CEBs. We collected social media messages about each TV show on Twitter between April and December 2015. Twitter is the dominant outlet for discussing TV shows, given its public accessibility, instantaneous nature, and rich media options

29,3	TV shows	Twitter handle	Status	Network
	Agent X	AgentXTNT	Canceled	TNT
	Ash vs Evil Dead	AshvsEvilDead	Renewed	STRZ
	Benders	BendersIFC	Canceled	IFC
	Best Time Ever With Neil Patrick Harris	BestTimeEver	Canceled	NBC
000	Blindspot	NBCBlindspot	Renewed	NBC
386	Blunt Talk	BluntTalk_STARZ	Renewed	STRZ
	Chicago Med	NBCChicagoMed	Renewed	NBC
	Code Black	CodeBlackCBS	Renewed	CBS
	Crazy Ex-Girlfriend	CW_CrazyXGF	Renewed	The CW
	Dr Ken	DrKenABC	Renewed	ABC
	Fear The Walking Dead	FearTWD	Renewed	AMC
	Gigi Does It	GigiDoesIt	Canceled	IFC
	Grandfathered	Grandfathered	Renewed	Fox
	Kevin From Work	KevinFromWorkTV	Canceled	ABCF
	Knock Knock Live	KnockKnockFox	Canceled	Fox
	Life in Pieces	LifeinPiecesCBS	Renewed	CBS
	Limitless	LimitlessCBS	Renewed	CBS
	Mr. Robinson	NBCMrRobinson	Canceled	NBC
	Public Morals	PublicMoralsTNT	Canceled	TNT
	Quantico	QuanticoTV	Renewed	ABC
	Rosewood	RosewoodFox	Renewed	Fox
	Sex&Drugs&Rock&Roll	SDRR	Renewed	FX
	Supergirl	SupergirlCBS ^a	Renewed	CBS
	Superstore	NBCSuperstore	Renewed	NBC
	The Bastard Executioner	TheBastardEx	Canceled	FX
	The Carmichael Show	CarmichaelShow	Renewed	NBC
	The Grinder	TheGrinderFox	Renewed	Fox
	The Jim Gaffigan Show	GaffiganShow	Renewed	TVL
	The Magicians	MagiciansSyfy	Renewed	SYFY
	The Muppets	TheMuppetsABC	Renewed	ABC
Table I.	Wicked City	WickedCityABC	Canceled	ABC
Description of sample of TV shows	Notes: ^a Supergirl's Twitter handle was cl May 2016 of its move from CBS to The CW	hanged to @thecwsupergirl	following the anne	ouncement in

(Roy, 2014; Schirra *et al.*, 2014; Wohn and Na, 2011). We first identified the official Twitter account corresponding to each TV show, either through a link on the TV show's (or network's) website, or from a manual search on Twitter followed by a verification of the account's authenticity (e.g. verified by Twitter, contained words such as "official" or "real," or included a reference to the show's official website).

We then collected user-generated Twitter messages that referred to each show. Specifically, we collected messages that mentioned the Twitter handle of a show in the data set (e.g. @Grandfathered for the Fox sitcom *Grandfathered*). We used this approach and did not simply collect tweets mentioning the names of the shows (even if those names were labeled by hashtags (#), which are used on Twitter to mark a tweet's topic) in order to avoid the problem of words that have different meanings in different contexts (i.e. polysemy). For example, a tweet with the hashtag "#grandfathered" could be related to the show *Grandfathered*, or to a person who is sharing with his followers that he is going to be a grandfather. Each message's author, text, media (photo, video, or URL), and date of publication were extracted using Twitter's Advanced Search.

We followed a standard natural language processing approach to prepare each messages for further text analysis (Feldman and Sanger, 2007). First, numbers, redundant spaces, special characters, hashtags, user mentions, and URLs were deleted. Next, contractions and abbreviations were transformed to their original form (e.g. "can't" to "cannot," "workin" to "working") and possessive suffixes were removed (e.g. "Ben's" to "Ben"). Finally, three or more identical consecutive characters were reduced to one (e.g. "amaaazing" to "amazing") and stop words were eliminated from the text.

After text cleaning, a probabilistic part-of-speech tagger called TreeTagger (Schmid, 1994a, b) was used to stem the words (e.g. usage, using, used transform to their root form use). Words that were not recognized at first were checked for spelling errors using an automated spellchecker (Rinker, 2013) and run again through TreeTagger. Finally, we calculated the Levenshtein similarity index between the suggestion of the spellchecker and the original word to ensure sufficient accuracy of the suggestion. This index is one of the most commonly used methods to compute word similarity, and its value ranges from 0 (very low similarity) to 1 (very high similarity). The original word in the tweet was only replaced by the spellchecker's suggestion if the index was above 0.80. This threshold value is between 0.70 (weak similarity) and 0.90 (strict similarity) and can be considered sufficiently conservative given the 140-character message restriction on Twitter and the common occurrence of spelling errors in social media conversations (Pang *et al.*, 2015).

Emoticons are common on social media and convey facial expressions or emotions using a limited number of characters. The emoticons included in the message were transformed to text based on their underlying meaning: :-), :), =), :'-), :') were coded as happy; :-D, :D, xD, =D as laugh; :-(, :(as sad; ;-(, :(as sad wink; :-II > :(as angry; :-'(:'(as cry; :-p :p as playful; ;) ;-); D as wink; and < 3 as heart. In this way, the meaning of an emoticon is captured in the sentiment score of the message along with its text.

After these steps, each word was matched to a sentiment dictionary (Warriner *et al.*, 2013) to determine the extent to which the message containing that word was positive or negative. The nine-point Likert scale of the sentiment dictionary was centered around 5 to facilitate computation. This resulted in a modified scale ranging from -4 (unhappy, calm, in control) over 0 (neutral) to +4 (very happy, excited, controlled). In cases of an all-caps word (e.g. "HAPPY"), the sentiment score corresponding to that word was doubled to reflect the added emphasis intended by the author. In cases in which a word was preceded by a negation (e.g. "not happy," "no mercy"), the sign of the word's sentiment score was reversed (e.g. -3 to +3). Each word's sentiment score was then multiplied by the number of times it occurs in the message to arrive at the message's overall sentiment score.

For each TV show s in our sample, we computed for every week t the mean positive sentiment score (Positive tweets) and mean negative sentiment score (Negative tweets). We also calculated the total number of tweets from viewers each week (NTweetViewers) as a measure of tweet volume. Finally, we operationalized tweet richness (Richness) as the sum of the number of URLs, hashtags, Twitter user mentions, exclamation marks, question marks, number of words, embedded links, photos, and videos. Our attempt to separate richness into visual media (photos and videos) and text (everything else) was scuttled, since the two measures were highly correlated.

Operationalization of brand actions. We obtained information on the advertising efforts of our sample of TV shows from Kantar Media, which tracks the advertising expenditure and placements for brands and services across various media platforms such as television, radio, print, outdoor, and internet. To measure advertising (Advertising), we calculated the total number of ad placements across all media platforms (TV, print, radio, or internet) in each week *t* for each TV show *s*. We evaluated placements rather than dollar values of advertising investments because different networks might charge different rates for airing commercials, such that dollar investments might not be an accurate way of comparing advertising efforts across TV shows. To measure the volume of brand actions on owned media, we calculated the total number of tweets generated by the TV show's Twitter handle (NTweetShow).

JOSM Descriptive statistics and estimation methodology

The descriptive statistics for the variables mentioned above are in Table II. We can observe that, while there is sufficient variation in all the variables, some of the variables are right-skewed. We therefore log-transform NLive, NTimeShifted, Advertising, NTweetShow, and NTweetViewers before including them in the model. Since the minimum value for all the variables in the model is 0, we add a small value of 0.01 before computing the log transformations.

The theoretical framework assumes that TV show brand actions, CEBs, and consumption are interrelated. Accordingly, we consider the measures of brand actions (Advertising, NTweetShow) and consumption (NLive, NTimeShifted) as endogenous. We also consider the number of tweets from viewers (NTweetViewers) as an endogenous variable. However, we consider sentiment and richness as exogenous, since these variables are largely driven by the content of the TV show, about which we lack information.

We assume that all dependent variables except Advertising are affected by other endogenous and exogenous variables in the same time period *t*. However, since decisions on advertising efforts have to be made in advance, we assume that this variable is affected by endogenous and exogenous variables from the previous week t-1. We do not consider lags beyond this period since the network can easily use its own channel to air commercials for the show. For instance, NBC can evaluate TV consumption and CEBs for a TV show, say *Chicago Med*, in week t-1 before deciding the extent of its advertising efforts for the show in the following week *t*. Consequently, we use linear simultaneous systems of equation approach for the estimation with the following specification:

$$\begin{split} \log{(Y_{1st})} &= \alpha_1 + \beta_{11} \log{(Y_{2st})} + \beta_{12} \log{(Y_{3s,t})} + \beta_{13} \log{(Y_{4s,t})} + \beta_{14} \log{(Y_{5s,t})} \\ &+ \beta_{15} X_{1s,t} + \beta_{16} X_{2s,t} + \beta_{17} X_{3s,t} + \beta_{18} w_s \\ \log{(Y_{2st})} &= \alpha_2 + \beta_{21} \log{(Y_{1st})} + \beta_{22} \log{(Y_{3s,t})} + \beta_{23} \log{(Y_{4s,t})} + \beta_{24} \log{(Y_{5s,t})} \\ &+ \beta_{25} X_{1s,t} + \beta_{26} X_{2s,t} + \beta_{27} X_{3s,t} + \beta_{28} w_s \\ \log{(Y_{3st})} &= \alpha_3 + \beta_{31} \log{(Y_{1st})} + \beta_{32} \log{(Y_{2s,t})} + \beta_{33} \log{(Y_{4s,t})} + \beta_{34} \log{(Y_{5s,t})} \\ &+ \beta_{35} X_{1s,t} + \beta_{36} X_{2s,t} + \beta_{37} X_{3s,t} + \beta_{38} w_s \\ \log{(Y_{4st})} &= \alpha_4 + \beta_{41} \log{(Y_{1st})} + \beta_{42} \log{(Y_{2s,t})} + \beta_{43} \log{(Y_{3s,t})} + \beta_{44} \log{(Y_{5s,t})} \\ &+ \beta_{45} X_{1s,t} + \beta_{46} X_{2s,t} + \beta_{47} X_{3s,t} + \beta_{48} w_s \\ \log{(Y_{5st})} &= \alpha_5 + \beta_{51} \log{(Y_{1s,t-1})} + \beta_{52} \log{(Y_{2s,t-1})} + \beta_{53} \log{(Y_{3s,t-1})} \\ &+ \beta_{54} \log{(Y_{4s,t-1})} + \beta_{55} X_{1s,t-1} + \beta_{56} X_{2s,t-1} + \beta_{57} X_{3s,t-1} + \beta_{58} w_s \end{split}$$

where Y_1 is the logarithm of the number of devices tuned in into the TV show live – log (NLive); Y_2 the logarithm of the number of devices that recorded the TV show and watched it

Variable	Description	Mean	SD
NLive (Y_1)	The number of devices tuned in into the TV show live	3.335.60	3.240.72
NTimeShifted (Y_2)	The number of devices that recorded the TV show and watched it later	2.861.13	3.079.91
Advertising (Y_5)	The number of placements of TV, print, radio, and internet ads	29.80	149.50
NTweetShow (Y_4)	The number of tweets posted by the TV show	63.14	65.88
NTweetViewers (Y_3)	The number of tweets posted by viewers	1,139.20	1,693.29
Positive tweets (X_1)	Overall mean positive sentiment score	10.04	1.82
Negative tweets (X_2)	Overall mean negative sentiment score	1.26	0.60
Richness (X_3)	Number of tweets containing photos, videos, URLs, hashtags,	1,437.56	1,766.06
	exclamation marks, etc.		

388

29.3

Table II. Descriptive statistic later – log(NTimeShifted); Y_3 the logarithm of the number of tweets posted by viewers – log (NTweetViewers); Y_4 the logarithm of the number of tweets posted by the TV show – log (NTweetShow); Y_5 the logarithm of the number of placements of TV, print, radio, and internet ads – log(Advertising); X_1 overall mean positive sentiment score – Positive tweets; X_2 overall mean negative sentiment score – Negative tweets; X_3 number of tweets containing photos, videos, URLs, hashtags, exclamation marks, etc. – Richness; and w a weekly trend variable starting from the first week the show was aired and $u_i \sim N(0, \Sigma)$ for TV show s in week w. Y_i , i = 1, 2, 3, 4, 5 are the endogenous variables and X_j , j = 1, 2, 3 are the exogenous variables.

Results

In this section, we summarize the results from the simultaneous systems of equations; subsequently, in the Discussion section, we highlight the main findings and explain their significance. Model fit statistics suggest that each equation in the system is significant. The results from the estimation are in Table III and illustrated in Figure 2, where the width of a line is proportional to the t statistic, green indicates a positive effect, and red a negative effect.

$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(1) log (NLive)	(2) log (NTimeShifted)	Dependent variabl (3) log (NTweetViewers)	es (4) log (NTweetShow)	(5) log (Advertising)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	log(NLive)		0.8420*** (0.0474) 17760	-0.0702^{***} (0.0221) -3.170	0.0762 (0.0494) 1.540	0.1349 (0.1880) 0.720
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	log(NTimeShifted)	0.8355*** (0.0471) 17.760	11.100	0.1730*** (0.0200) 8.650	-0.2307^{***} (0.0480) -4.800	$\begin{array}{c} 0.0039 \\ (0.1421) \\ 0.030 \end{array}$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	log(NTweetViewers)	-0.6096^{***} (0.1926) -3.160	1.5181*** (0.1756) 8.650	0.000	1.9214*** (0.0996) 19.290	0.0065 (0.3323) 0.020
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	log(NTweetShow)	0.1381 (0.0888) 1.550	-0.4186^{***} (0.0870) -4.810	0.3961*** (0.0205) 19.280	10.200	-0.2566 (0.2101) -1.220
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	log(Advertising)	-0.0655^{**} (0.0297) -2.210	0.0865^{***} (0.0298) 2.910	-0.0228^{**} (0.0101) -2.260	0.0105 (0.0223)	-1.220
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Positive tweets	0.0201 (0.0726) 0.280	-0.1238^{*} (0.0722) -1.720	-2.200 0.1371*** (0.0223) 6.160	-0.2669^{***} (0.0519) -5.140	-0.2726^{*} (0.1634) -1.670
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Negative tweets	0.5045** (0.2153) 2 340	-0.8327^{***} (0.2135) -3.900	0.4467*** (0.0688) 6 500	-0.9493^{***} (0.1527) -6.220	-1.070 -1.0732^{**} (0.4791) -2.240
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Richness	0.0003* (0.0002) 1.840	-0.0006^{***} (0.0001) -4.250	0.0005*** (0.0000) 12 260	-0.220 -0.0008^{***} (0.0001) -7.420	0.0008*** (0.0002)
1930 -1560 2120 -2490 -33000	t	0.0281^{*} (0.0146) 1.930	-0.0230 (0.0148) -1.560	0.0105** (0.0050) 2120	-0.0272^{**} (0.0109) -2.490	-0.1054^{***} (0.0319) -3.3000
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Intercept	3.3237*** (0.7702) 4.320	-3.7541^{***} (0.7824) -4.800	1.4604*** (0.2442) 5.980	-2.430 -2.2449^{***} (0.5768) -3.890	1.5223 (1.4984) <i>1.020</i>

Notes: The reported values are parameter estimates. The standard errors are in parentheses. The *t*-statistics simultaneous system of equations of equations p = 0.01; p = 0.05; p = 0.01

Table III. Results from



For predicting the size of the live audience, we find that the size of the time-shifted audience has a significant positive effect, whereas advertising efforts have a significant negative effect (Equation (1) in Table III). We also find that the volume of tweets from viewers has a small but significant negative effect on the size of the live audience. The level of negative sentiment about a show has a positive effect on the size of the live audience. The effects of other variables such as the number of tweets generated by the TV show's Twitter account, positive sentiment, richness, and time trend are not statistically significant.

In predicting the size of the time-shifted audience, we find that a large live audience has a significant positive effect (Equation (2) in Table III). Advertising efforts of the TV show also have a significant positive effect. The number of tweets generated by the TV show and the level of negative sentiment about the show have a significant negative effect. The number of tweets with rich content has a negative effect on the size of the time-shifted audience. The effects of positive sentiment and time trend are not statistically significant.

For the number of viewer-generated tweets for a TV show in a week, we find that as the size of the live audience increases, the number of tweets from viewers decreases (Equation (3) in Table III). However, the size of the time-shifted audience has a positive effect. Larger advertising efforts have a negative effect on the number of viewer-generated tweets. However, the number of tweets generated by the TV show, positive and negative sentiment levels, and the number of tweets containing rich content all have significant positive effects. The number of tweets from viewers also increases with time.

With respect to the number of tweets generated by the TV show, we find that the size of the time-shifted audience has a significant negative effect (Equation (4) in Table III). While the effect of the number of viewer-generated tweets is positive, the effects of positive sentiment, negative sentiment, richness, and time trend are all negative and significant. The size of the live audience and the advertising efforts of the TV show do not have a significant effect.

Finally, for the advertising efforts of the TV show, we find that negative sentiment and time trend both have negative effects (Equation (5) in Table III). However, richness has a positive effect. The effects of other variables, such as the size of the live audience, size of the time-shifted audience, the number of viewer-generated tweets, the number of tweets generated by the TV show, and positive sentiment about the show are not significant.

Discussion

Live and time-shifted viewing are distinct

Summarizing the results, we find that the sizes of the live and time-shifted audiences positively affect each other. This observation is in line with previous research that suggests that people who watch a show live are distinct from those who record and watch it later (Belo *et al.*, 2016; Lin, 1993; Wilbur, 2008). While a negative relationship between these two variables would imply that a TV show has either a live or time-shifted audience, these results show that a TV show can have both. We therefore confirm the findings of Belo *et al.* (2016), who concluded that time-shifted viewing increases the "size of the TV pie" without hurting live viewing. Furthermore, the positive interrelationships suggest that as more people watch a show live, they arouse the interest of those who record and watch the show later, and vice versa. We discuss the implications of this result below.

The unintended effects of advertising

We find that advertising efforts of the TV show decrease the size of the live audience, but increase the size of the time-shifted audience. This indicates that advertising is not beneficial for all modes of TV consumption. Investigating the roles of paid, owned, and earned media on TV consumption, Lovett and Staelin (2016) showed that advertising is more effective than owned or earned media for arousing show awareness, but not for creating interest. Evidently, if consumers are aware of a show but not interested in it, exposure to more advertising will not change their behavior. In fact, it can result in negative effects such as ad wear-out (Naik *et al.*, 1998) or ad avoidance (Wilbur, 2008). This can explain why, after controlling for brand actions and CEBs, more advertising results in more time-shifted viewing and in less live viewing.

The novelty of the TV shows we study can also explain the observed effects. Most research on time-shifted viewing suggests that consumers use time-shifting to postpone consumption (e.g. scheduling conflict) or enhance the viewing process (e.g. skipping ads) (Hub Entertainment Research, 2015). This enhanced control over the consumption process can decrease the risk and costs that consumers perceive to be associated with adopting a new TV show and, as a result, stimulate trial. This can explain why advertising has a positive effect on time-shifted viewing (i.e. stimulate trial), but a negative effect on live viewing, where such control is not available. Taken together, our results suggest that advertising reminds consumers to watch the show[1], in line with Lovett and Staelin (2016), but that they subsequently do so in a time-shifted manner. In our view, these results typify the changing world of media and entertainment consumption. Notably, as discussed above, media organizations are increasingly expressing concern that viewers are switching from live to time-shifted viewing (Bond and Garrahan, 2015; Nielsen, 2014); our results suggest that large-scale advertising efforts intended to counteract this trend might actually exacerbate it.

The marginal effects of brand actions on social media

We find that the number of tweets generated by the show has no effect on the number of live viewers, but a negative effect on the number of time-shifted viewers. This result is in contrast to findings from previous research (Gong *et al.*, 2015; Kumar *et al.*, 2016), and suggests that more brand actions on social media do not necessarily result in more consumption. One explanation is that consumers who observe a TV show's actions on social media – many of whom are likely to follow the show's account – are already well aware of the show. Indeed, research suggests that people who reach out to brands on social media are already those who consume more and who are more engaged with the brand (Kumar *et al.*, 2016; Stephen and Galak, 2012). Therefore, more frequently reminding these consumers to watch the show will not result in more viewers.

Another explanation can be found in the type of content a TV show posts. Before the start of an episode, TV shows post trailers and promos, and after the show follow up with

memorable quotes, character developments, plot twists, or teasers for the next episode. Timeshifted viewers want to avoid these spoilers and will go online only after they have watched the show (Schirra *et al.*, 2014). Live viewers, on the other hand, may like these brand actions but favor CEBs more (Lovett and Staelin, 2016), which can explain why brand actions do not have an additional effect on viewership after controlling for CEBs. Finally, we find a significant positive effect of the number of tweets from the show on the number of tweets from viewers and vice versa, suggesting that both the TV show and its audience can stimulate engagement.

More CEBs can draw time-shifted viewers in, but wear live viewers out

We find that the number of tweets from viewers and the size of the live audience have negative effects on each other, whereas the number of tweets from viewers and the size of the time-shifted audience have positive effects on each other. The negative mutual effects of CEB volume and live TV viewing may suggest that the two activities are substitutes for each other – that is, a consumer who is watching TV in real time is not tweeting, and vice versa. For time-shifted viewing, this is not the case. Indeed, it is well known that viewers increasingly use multiple devices while watching TV. Time-shifted viewers can pause or rewind a show while watching, enabling them to more easily tweet about the show without missing out (Lin, 1993; Roy, 2014; Schirra *et al.*, 2014; Wilbur, 2008). Live viewing and tweeting, on the other hand, requires more attention from viewers, often at the expense of viewing itself (Schirra *et al.*, 2014). The positive mutual effects of CEBs and time-shifted viewing behavior, in turn, suggest that time-shifted viewers are motivated to tweet about their viewing experiences, and that CEBs have a positive WOM effect on audiences who prefer time-shifted viewing. Finally, the negative relationship between the size of the live audience and the number of CEBs may suggest that shows with smaller live audiences are more engaged.

Negative sentiment toward a TV show has a stronger impact on consumer behaviors than positive sentiment does. We find that negative sentiment increases the size of the live audience, but decreases the size of the time-shifted audience. From a uses-and-gratifications perspective, this observation suggests that live audiences are more sensation seeking. Controversies and negativity may motivate live viewers to stay engaged with the show – bad news is good TV. On the other hand, viewers who partake in time-shifted viewing are likely to value their time more and avoid TV shows that are not well received by others.

We also find that negative sentiment toward a TV show has a more pronounced effect on brand actions, CEBs, and consumption than positive sentiment. For instance, the effect of negative sentiment on the number of tweets from viewers is around 3.25 times stronger than the effect of positive sentiment. In other words, viewers are more likely to engage on Twitter when there is negative sentiment surrounding a show than when there is positive sentiment. Interestingly, the effect on brand actions is just the opposite. For instance, the Twitter account of a TV show produces about 3.5 times fewer tweets when there is negative sentiment surrounding a show than when there is positive sentiment. These observations have important managerial implications, which are discussed in the next section.

Finally, the results for richness in user-generated tweets reveal interesting insights. While the number of tweets from users increases with increased richness, the effect of richness on the number of tweets generated by the TV show is just the opposite. Moreover, tweet richness has a significant negative effect on the size of the time-shifted audience. A possible explanation for this is that when time-shifted viewers are exposed to rich content that provides information on the show, their interest in watching the TV show wanes. However, viewers who are interested in the show avoid rich content to avoid spoilers (e.g. show clips). Research has shown that avoiding spoilers is an important motivator for viewers to watch a show live (Benton and Hill, 2012). This result reinforces the point made earlier that time-shifted audiences value their time and avoid watching shows that fail to provide a novel and/or positive experience.

JOSM

29.3

392

Conclusion

The main objective of this study was to understand the dynamic interrelationships among CEBs, brand actions, and consumption. The context is the media industry, which is undergoing disruptive changes as new competitors, business models, and consumption behaviors emerge. Media organizations such as broadcast networks and cable channels are faced with the daunting challenge of retaining their audiences in a media-fragmented world. While most studies on engagement have focused on static dyadic relationships between customers and firms, this study examines engagement from a dynamic perspective, unpacking the mutual influences among multiple actors and behaviors. To our knowledge, this is the first study to examine how consumer-firm interactions affect consumption of TV. Our findings have the potential to assist managers in understanding the implications of their efforts to engage consumers, and to quantify the effectiveness of those efforts.

Theoretical implications

We believe that this study reveals at least three findings that are counterintuitive and challenge the broad consensus on how firms and consumers engage with each other. First, we find that advertising has unintended effects, with a positive effect on the size of the timeshifted audience, and a negative effect on the size of the live audience. These effects are presumed to be "unintended" because most new TV shows aim to maximize the size of the live audience, e.g. as a means of commanding higher rates for commercials aired during the show. In contrast, viewers who record shows and watch them later can skip advertisements, such that increasing the size of the time-shifted audience provides no benefit in terms of the capacity to charge advertisers a premium for air time. Our observations regarding the unintended effects of advertising suggest that networks should work to understand the viewing motivations of live viewers and determine how they differ from those of timeshifted viewers. Marketers can develop strategies that specifically target these different audiences to drive viewership, revenues, and profits.

A second finding is that a TV show's efforts to engage with its audience on Twitter may not have the desired positive effect on TV viewership. In particular, contrary to the findings of Gong *et al.* (2015), we observe that an increase in the volume of tweets posted by the TV show does little to increase the size of the live audience. In fact, these efforts may have a negative effect on the size of the time-shifted audience. We speculate that these effects may be related to the fact that tweets generated by a TV show are unlikely to create awareness among consumers (given that followers of a TV show's Twitter account are likely to be familiar with the show), while at the same time, the content of those tweets may satiate the curiosity of potential time-shifted viewers, diminishing their likelihood of viewing the show. Interestingly, however, the number of tweets generated by the TV show is positively related to the number of tweets generated by users, and vice versa. This observation indicates that networks can trigger CEBs by increasing their own brand actions. It should be noted, however, that the impact of CEBs on brand actions is 4.85 times larger than vice versa.

A third interesting and counterintuitive finding pertains to the effect of negative sentiment. While some studies on negative WOM suggest that negative reviews have negative consequences, such as diminished purchases (e.g. Kim *et al.*, 2016), this study provides further insights on how it affects different audiences in different ways. Live viewers seem to be intrigued by negative sentiment surrounding a show, whereas time-shifted viewers seem to be put off by it and avoid watching the show. These results may suggest that live viewers are motivated by sensationalism, whereas time-shifted viewers place higher value on their time. Practitioners armed with this understanding can develop suitable communication strategies to increase the size of the live and/or time-shifted audiences.

Our analysis further indicates that, when faced with negative sentiment, TV shows hesitate to respond on Twitter (and they even diminish their advertising efforts). This behavior is

JOSM
29,3inconsistent with commonly held beliefs on how brands should respond to a crisis (Copulsky,
2011). In the context of product purchases, a public apology in response to customer
complaints can have a positive effect on viewers of reviews (Kim *et al.*, 2016) and attenuate the
negative brand evaluations caused by negative reviews (van Noort and Willemsen, 2011).
In fact, TV shows are even reluctant to respond to positive sentiment that might be expressed
by viewers. Clearly, TV shows need a plan to not only leverage positive comments but also
respond to negative sentiment and controversies that might surround a show.

Limitations and future research

The study has some limitations. First, viewing data were collected from only one cable operator based in the USA and thus may be biased. Initial tests, such as comparing viewing habits of our sample with ratings reported in the media, suggest that viewing differences are small and hence alleviate these concerns to some extent.

In addition, while social media use is prevalent across the USA, we do not know the extent to which the viewers of the shows we analyzed participate in social media. Matching brand actions, CEBs, and viewing data at the level of a viewer would be ideal to unearth the true dynamic interrelationship, but such data are hard to acquire. For example, most TV viewing data are obtained at the level of a household and not an individual. Another limitation is that the results are based on the analysis of 31 entertainment or drama shows, all of which were introduced in 2015. Future work should include more shows and genres, and should evaluate the dynamics of CE over a longer period of time. It would also be interesting to leverage data such as ours to attempt to identify early signs of a show's future cancellation.

A potentially fruitful avenue for future research would be to explore the cognitive and emotional aspects of engagement (Brodie *et al.*, 2011; Hollebeek *et al.*, 2014). Calder *et al.* (2016) and Calder and Malthouse (2008) identified and measured various types of experiences that consumers have when consuming different TV programs – where an experience is defined as the consumer's thoughts and beliefs about how the TV show contributes to goals in his or her life. An important research question is whether the experiences that a show intends to elicit affect the various components of the engagement ecosystem (Figure 1), or moderate the relationships we observe. For example, is consumption of a show designed to create social interactions particularly likely to be associated with CEBs, and vice versa? The framework in Figure 1 could be extended to include such cognitive and emotional dimensions.

To conclude, while the study suffers from certain limitation, it makes significant contributions to ongoing research on media consumption, especially regarding TV viewing. Moreover, the study lays a strong foundation for understanding the CE ecosystem.

Note

1. We thank the reviewer for this suggestion.

References

- Aksoy, L., Keiningham, T.L., Buoye, A. and Ball, J. (2016), "Relative value and customer choice in loan decisions: an application of the wallet allocation rule", *Journal of Creating Value*, Vol. 2 No. 1, pp. 92-108.
- Algesheimer, R., Dholakia, U.M. and Herrmann, A. (2005), "The social influence of brand community: evidence from European car clubs", *Journal of Marketing*, Vol. 69 No. 3, pp. 19-34.
- Belo, R., Ferreira, P., de Matos, M.G. and Reis, F. (2016), "The impact of time-shift television on TV viewership", working paper, Rotterdam School of Management, Erasmus University Rotterdam, Rotterdam, March 22.

- Benton, A. and Hill, S. (2012), "The spoiler effect: designing social TV content that promotes ongoing WOM", CIST in Conjunction with INFORMS, pp. 1-26, available at: https://faculty.wharton. upenn.edu/wp-content/uploads/2013/02/SpoilerEffect.pdf
- Bijmolt, T.H.A., Leeflang, P.S.H., Block, F., Eisenbeiss, M., Hardie, B.G.S., Lemmens, a. and Saffert, P. (2010), "Analytics for customer engagement", *Journal of Service Research*, Vol. 13 No. 3, pp. 341-356.
- Bond, S. and Garrahan, S. (2015), "Broadcaster fear falling revenues as viewers switch to on-demand TV", available at: www.ft.com/content/e46dc7a4-b843-11e4-86bb-00144feab7de (accessed August 31, 2016).
- Brodie, R.J., Hollebeek, L.D., Jurić, B. and Ilić, A. (2011), "Customer engagement: conceptual domain, fundamental propositions, and implications for research", *Journal of Service Research*, Vol. 14 No. 3, pp. 252-271.
- Brodie, R.J., Ilic, A., Juric, B. and Hollebeek, L. (2013), "Consumer engagement in a virtual brand community: an exploratory analysis", *Journal of Business Research*, Vol. 66 No. 1, pp. 105-114.
- Calder, B.J. and Malthouse, E.C. (2008), "Media engagement and advertising effectiveness", in Calder, B.J. (Ed.), Kellogg on Advertising and Media, Hoboken, NJ, pp. 1-36.
- Calder, B.J., Isaac, M.S. and Malthouse, E.C. (2016), "How to capture consumer experiences: a contextspecific approach to measuring engagement", *Journal of Advertising Research*, Vol. 56 No. 1, pp. 39-52.
- Calder, B.J., Malthouse, E.C. and Schaedel, U. (2009), "An experimental study of the relationship between online engagement and advertising effectiveness", *Journal of Interactive Marketing*, Vol. 23 No. 4, pp. 321-331.
- Chen, P.-Y., Wu, S. and Yoon, J. (2004), "The impact of online recommendations and consumer feedback on sales", *ICIS 2004 Proceedings*, p. 58.
- Chevalier, J.A. and Mayzlin, D. (2006), "The effect of word of mouth on sales: online book reviews", *Journal of Marketing Research*, Vol. 43 No. 3, pp. 345-354.
- Chintagunta, P.K., Gopinath, S. and Venkataraman, S. (2010), "The effects of online user reviews on movie box office performance: accounting for sequential rollout and aggregation across local markets", *Marketing Science*, Vol. 29 No. 5, pp. 944-957.
- Colliander, J. and Dahlén, M. (2011), "Following the fashionable friend: the power of social media", *Journal of Advertising Research*, Vol. 51 No. 1, pp. 313-320.
- Copulsky, J.R. (2011), Brand Resilience: Managing Risk and Recovery in a High-Speed World, Macmillan, New York, NY.
- Corcoran, S. (2009), "Defining earned, owned, and paid media", available at: http://blogs. forrester.com/interactive_marketing/2009/12/defining-earned-owned-and-paid-media.html (accessed August 31, 2016).
- Daft, R.L. and Lengel, R.H. (1986), "Organizational information requirements, media richness and structural design", *Management Science*, Vol. 32 No. 5, pp. 554-571.
- Duan, W., Gu, B. and Whinston, A.B. (2008), "The dynamics of online word-of-mouth and product sales – an empirical investigation of the movie industry", *Journal of Retailing*, Vol. 84 No. 2, pp. 233-242.
- Feldman, R. and Sanger, J. (2007), The Text Mining Handbook: Advanced Approaches in Analyzing Unstructured Data, Cambridge University Press, New York, NY.
- Fossen, B.L. and Schweidel, D.A. (2016), "Television advertising and online word-of-mouth: an empirical investigation of social TV activity", *Marketing Science*, Vol. 36 No. 1, pp. 105-123.
- Fyrberg, A. and Jüriado, R. (2009), "What about interaction? Networks and brands as integrators within service-dominant logic", *Journal of Service Management*, Vol. 20 No. 4, pp. 420-432.
- Gamboa, A.M. and Gonçalves, H.M. (2014), "Customer loyalty through social networks: lessons from Zara on Facebook", *Business Horizons*, Vol. 57 No. 6, pp. 709-717.
- Godes, D. and Mayzlin, D. (2004), "Using online conversations to study word-of-mouth communication", *Marketing Science*, Vol. 23 No. 4, pp. 545-560.

JOSM 29,3	Goh, KY., Heng, CS. and Lin, Z. (2013), "Social media brand community and consumer behavior: quantifying the relative impact of user-and marketer-generated content", <i>Information Systems Research</i> , Vol. 24 No. 1, pp. 88-107.
	Gong, S., Zhang, J., Zhao, P. and Jiang, X. (2015), "Tweeting increases product demand", working paper, School of Economics and Management, Tsinghua University, Beijing, January 7.
396	Gopinath, S., Thomas, J.S. and Krishnamurthi, L. (2014), "Investigating the relationship between the content of online word of mouth, advertising, and brand performance", <i>Marketing Science</i> , Vol. 33 No. 2, pp. 241-258.
	Grönroos, C. and Voima, P. (2013), "Critical service logic: making sense of value creation and co-creation", <i>Journal of the Academy of Marketing Science</i> , Vol. 41 No. 2, pp. 133-150.
	Hanna, R., Rohm, A. and Crittenden, V.L. (2011), "We're all connected: the power of the social media ecosystem", <i>Business Horizons</i> , Vol. 54 No. 3, pp. 265-273.
	Harmeling, C.M., Moffett, J.W., Arnold, M.J. and Carlson, B.D. (2017), "Toward a theory of customer engagement marketing", <i>Journal of the Academy of Marketing Science</i> , Vol. 45 No. 3, pp. 312-335.
	Heinonen, K. and Strandvik, T. (2009), "Monitoring value-in-use of e-service", Journal of Service Management, Vol. 20 No. 1, pp. 33-51.
	Hollebeek, L.D. (2011), "Demystifying customer brand engagement: exploring the loyalty nexus", <i>Journal of Marketing Management</i> , Vol. 27 Nos 7-8, pp. 7-8.
	Hollebeek, L.D., Glynn, M.S. and Brodie, R.J. (2014), "Consumer brand engagement in social media: conceptualization, scale development and validation", <i>Journal of Interactive Marketing</i> , Vol. 28 No. 2, pp. 149-165.
	Hollebeek, L.D., Malthouse, E.C. and Block, M.P. (2016), "Sounds of music: exploring consumers' musical engagement", <i>Journal of Consumer Marketing</i> , Vol. 33 No. 6, pp. 417-427.
	Hollebeek, L.D., Srivastava, R.K. and Chen, T.J. (2016), "SD logic–informed customer engagement: integrative framework, revised fundamental propositions, and application to CRM", <i>Journal of the</i> <i>Academy of Marketing Science</i> , pp. 1-25, available at: https://doi.org/10.1007/s11747-016-0494-5
	Hub Entertainment Research (2015), "Top reasons for time-shifting TV shows", available at: www.marketingcharts.com/television/as-tv-viewers-time-shift-whats-the-implication-for-ad- avoidance-51957/ (accessed October 12, 2016).
	Jaakkola, E. and Alexander, M. (2014), "The role of customer engagement behavior in value co-creation a service system perspective", <i>Journal of Service Research</i> , Vol. 17 No. 3, pp. 247-261.
	Javornik, A. and Mandelli, A. (2012), "Behavioral perspectives of customer engagement: an exploratory study of customer engagement with three Swiss FMCG brands", <i>Journal of Database Marketing & Customer Strategy Management</i> , Vol. 19 No. 4, pp. 300-310.

Downloaded by Ghent University Library At 11:57 25 June 2018 (PT)

Kawale, J., Pal, A. and Srivastava, J. (2009), "Churn prediction in MMORPGs: a social influence based approach", *Proceedings of 12th IEEE International Conference on Computational Science and Engineering*, Vol. 4, pp. 423-428.

Kim, S.J., Wang, R.J.H., Maslowska, E. and Malthouse, E.C. (2016), "Understanding a fury in your words': the effects of posting and viewing electronic negative word-of-mouth on purchase behaviors", *Computers in Human Behavior*, Vol. 54, pp. 511-521.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R. and Kannan, P.K. (2016), "From social to sale: the effects of firm generated content in social media on customer behavior", *Journal of Marketing*, Vol. 80 No. 1, pp. 7-25.

- Kunz, W., Aksoy, L., Bart, Y., Heinonen, K., Kabadayi, S., Ordenes, F. V. and Theodoulidis, B. (2017), "Customer engagement in a big data world", *Journal of Services Marketing*, Vol. 31 No. 2, pp. 161-171.
- Lemon, K.N. and Verhoef, P.C. (2016), "Understanding customer experience throughout the customer journey", *Journal of Marketing*, Vol. 80 No. 6, pp. 69-96.
- Lin, C.A. (1993), "Exploring the role of VCR use in the emerging home entertainment culture", Journalism & Mass Communication Quarterly, Vol. 70 No. 4, pp. 833-842.

- Liu, Y. (2006), "Word of mouth for movies: its dynamics and impact on box office revenue", Journal of Marketing, Vol. 70 No. 3, pp. 74-89.
- Lovett, M.J. and Staelin, R. (2016), "The role of paid, earned, and owned media in building entertainment brands: reminding, informing, and enhancing enjoyment", *Marketing Science*, Vol. 35 No. 1, pp. 142-157.
- Lusch, R.F. and Vargo, S.L. (2006), "Service-dominant logic: reactions, reflections and refinements", Marketing Theory, Vol. 6 No. 3, pp. 281-288.
- McPherson, K., Huotari, K., Cheng, F., Humphrey, D., Cheshire, C. and Brooks, A.L. (2012), "Glitter: a mixed-methods study of Twitter use during Glee broadcasts", *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work Companion*, pp. 167-170.
- Mahajan, V., Muller, E. and Roger, A.K. (1984), "Introduction strategy for new products with positive and negative word-of-mouth", *Management Science*, Vol. 30 No. 12, pp. 1389-1404.
- Malthouse, E.C., Vandenbosch, M. and Kim, SJ. (2013), "Social media engagement that drives purchase behavior", Advances in Advertising Research, Vol. IV, pp. 29-42.
- Malthouse, E.C., Calder, B.J., Kim, S.J. and Vandenbosch, M. (2016), "Evidence that user-generated content that produces engagement increases purchase behaviours", *Journal of Marketing Management*, Vol. 32 Nos 5-6, pp. 427-444.
- Malthouse, E.C., Haenlein, M., Skiera, B., Wege, E. and Zhang, M. (2013), "Managing customer relationships in the social media era: introducing the social CRM house", *Journal of Interactive Marketing*, Vol. 27 No. 4, pp. 270-280.
- Maslowska, E., Malthouse, E.C. and Collinger, T. (2016), "The customer engagement ecosystem", *Journal of Marketing Management*, Vol. 32 Nos 5-6, pp. 469-501.
- Mersey, R.D., Malthouse, E.C. and Calder, B.J. (2010), "Engagement with online media", Journal of Media Business Studies, Vol. 7 No. 2, pp. 39-56.
- Muntinga, D.G., Moorman, M. and Smit, E.G. (2011), "Introducing COBRA: exploring motivations for brand-related social media use", *International Journal of Advertising*, Vol. 30 No. 1, pp. 13-46, doi: 10.2501/IJA-30-1-013-046.
- Naik, P.A., Mantrala, M.K. and Sawyer, A.G. (1998), "Planning media schedules in the presence of dynamic advertising quality", *Marketing Science*, Vol. 17 No. 3, pp. 214-235.
- Ngai, E.W.T., Moon, K.K., Lam, S.S., Chin, E.S.K. and Tao, S.S.C. (2015), "Social media models, technologies, and applications", *Industrial Management & Data Systems*, Vol. 115 No. 5, pp. 769-802.
- Nielsen (2014), "The total audience report", available at: www.nielsen.com/content/dam/corporate/us/ en/reports-downloads/2014%20Reports/the-digital-consumer-report-feb-2014.pdf (accessed August 31, 2016).
- Oestreicher-Singer, G. and Zalmanson, L. (2012), "Content or community? A digital business strategy for content providers in the social age", available at: https://ssrn.com/abstract=1536768
- Onishi, H. and Manchanda, P. (2012), "Marketing activity, blogging and sales", International Journal of Research in Marketing, Vol. 29 No. 3, pp. 221-234.
- Pang, C., Sollie, A., Sijtsma, A., Hendriksen, D., Charbon, B., de Haan, M., de Boer, T., Kelpin, F., Jetten, J., van der Velde, J.K., Smidt, N., Sijmons, R., Hillege, H. and Swertz, M.A. (2015), "SORTA: a system for ontology-based re-coding and technical annotation of biomedical phenotype data", *Database*, Vol. 2015, pp. 1-13.
- Pansari, A. and Kumar, V. (2017), "Customer engagement: the construct, antecedents, and consequences", *Journal of the Academy of Marketing Science*, Vol. 45 No. 3, pp. 294-311.
- Park, D.H. and Lee, J. (2008), "eWOM overload and its effect on consumer behavioral intention depending on consumer involvement", *Electronic Commerce Research and Applications*, Vol. 7 No. 4, pp. 386-398.
- Rinker, T.W. (2013), QDAP: Quantitative Discourse Analysis Package. 2.2.5, University at Buffalo, Buffalo and New York, NY.

397

Live and

time-shifted

Roy, D. (2014), "K	ynote: Deb Roy, Twitter - MIPTV 2014", available at: www.youtube.com/watch?v
F_2IMAFI	a9w (accessed October 12, 2016).

- Schirra, S., Sun, H. and Bentley, F. (2014), "Together alone: motivations for live-tweeting a television series", *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems*, pp. 2441-2450.
- Schmid, H. (1994a), "TreeTagger a part-of-speech tagger for many languages", available at: www.cis. uni-muenchen.de/~schmid/tools/TreeTagger/ (accessed July 1, 2016).
- Schmid, H. (1994b), "Probabilistic part-of-speech tagging using decision trees", Proceedings of the International Conference on New Methods in Language Processing, pp. 44-49.
- Stephen, A.T. and Galak, J. (2012), "The effects of traditional and social earned media on sales: a study of a microlending marketplace", *Journal of Marketing Research*, Vol. 49 No. 5, pp. 624-639.
- Swant, M. (2016), "Emotionally driven programming could drive sales", available at: www.adweek. com/news/technology/infographic-tv-show-appeal-drives-ad-recall-twitter-study-says-170299 (accessed August 31, 2016).
- van Doorn, J., Lemon, K.N., Mittal, V., Nass, S., Pick, D., Pirner, P. and Verhoef, P.C. (2010), "Customer engagement behavior – theoretical foundations and research directions", *Journal of Service Research*, Vol. 13 No. 3, pp. 253-266.
- van Noort, G. and Willemsen, L.M. (2011), "Online damage control: the effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms", *Journal* of Interactive Marketing, Vol. 26 No. 3, pp. 131-140.
- Vargo, S.L. and Lusch, R.F. (2008), "Service-dominant logic: continuing the evolution", Journal of the Academy of Marketing Science, Vol. 36 No. 1, pp. 1-10.
- Vargo, S.L. and Lusch, R.F. (2016), "Institutions and axioms: an extension and update of service-dominant logic", *Journal of the Academy of Marketing Science*, Vol. 44 No. 1, pp. 5-23.
- Verhoef, P.C., Reinartz, W.J. and Krafft, M. (2010), "Customer engagement as a new perspective in customer management", *Journal of Service Research*, Vol. 13 No. 3, pp. 247-252.
- Viswanathan, V., Hollebeek, L., Malthouse, E., Maslowska, E., Kim, S.J. and Xie, W. (2017), "The dynamics of consumer engagement with mobile technologies", *Service Science*, Vol. 9 No. 1, pp. 36-49.
- Vivek, S.D., Beatty, S.E. and Morgan, R.M. (2012), "Customer engagement: exploring customer relationships beyond purchase", *Journal of Marketing Theory and Practice*, Vol. 20 No. 2, pp. 122-146.
- Wang, M., Lu, Q., Chi, R.T. and Shi, W. (2015), "How word-of-mouth moderates room price and hotel stars for online hotel booking an empirical investigation with Expedia data", *Journal of Electronic Commerce Research*, Vol. 16 No. 1, pp. 72-80.
- Warriner, A.B., Kuperman, V. and Brysbaert, M. (2013), "Norms of valence, arousal, and dominance for 13,915 English lemmas", *Behavior Research Methods*, Vol. 45 No. 4, pp. 1191-1207.
- Wilbur, K.C. (2008), "How the digital video recorder (DVR) changes traditional television advertising", Journal of Advertising, Vol. 37 No. 1, pp. 143-149.
- Wohn, Y.D. and Na, E.-K. (2011), "Tweeting about TV: sharing television viewing experiences via social media message streams", *First Monday*, Vol. 16 No. 3, pp. 1-15.
- Zhang, X. and Dellarocas, C. (2006), "The lord of the ratings: is a movie's fate is influenced by reviews?", Paper No. 117, ICIS 2006 Proceedings, pp. 1959-1978.

Corresponding author

Vijay Viswanathan can be contacted at: vijay-viswanathan@northwestern.edu

For instructions on how to order reprints of this article, please visit our website: www.emeraldgrouppublishing.com/licensing/reprints.htm Or contact us for further details: permissions@emeraldinsight.com

JOSM 29.3

This article has been cited by:

1. AlexanderMatthew, Matthew Alexander, JaakkolaElina, Elina Jaakkola, HollebeekLinda D., Linda D. Hollebeek. 2018. Beyond the dyadic: customer engagement in increasingly networked environments. *Journal of Service Management* **29**:3, 330-332. [Citation] [Full Text] [PDF]