Social TV Content and Television Consumption

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ABSTRACT

The television viewing landscape has undergone significant technological changes in recent years with the increase in digital video recorder (DVR) usage and the prevalence of social media activity commenting on television programs ("social TV"). Using data provided by a social media monitoring firm that has partnered with Nielsen to measure social TV activity, coupled with live and time-shifted viewing data for a television season, the authors investigate how the content of social media chatter about television programs affects the size of the total viewing audience and when viewing occurs. Drawing on narrative transportation theory, the authors demonstrate that the effect of social TV posts varies based on their content. General posts containing emotional reactions to the program positively impact the fraction of devices that engage in live viewing. Posts mentioning actors in the programs have a larger impact on live viewing. The authors discuss the implications of the research for advertisers and television networks.

Keywords: social TV activity, television viewing, DVR, panel data VAR-X

Statement of Intended Contribution

The television viewing landscape has evolved with the addition of technologies such as digital video recorders providing viewers with more control over when they watch television programs. The emergence of "social TV," social media activity relating to television programs, allows viewers to discuss their opinions with a broader network of individuals. Despite the technological advances in the market place, little empirical research has investigated the interplay between social TV activity and television consumption.

We empirically investigate the extent to which social media activity affects the total size of a television program's audience and when the television consumption occurs, allowing us to identify the drivers of live and time-shifted viewing. Because time-shifted TV can lead to more avoided commercials for advertisers and more non-monetized ad exposures for networks, the amount and timing of delayed viewing is of interests to both parties.

Our research contributes to the limited research exploring television consumption through time-shifted DVR viewing. Much of the research focuses on live viewing audiences. Secondly, unlike much extant research that uses holistic measures of volume or sentiment, we distinguish among social TV posts based on the content of the post enabling us to make statements about the influence of different types of social TV posts. Thirdly, we utilize a panel data VAR-X to address endogeneity concerns among TV and social TV. A key takeaway for practitioners is that not all social media posts are equivalent in their impact on television viewing behavior. We highlight that within social media's influence, different types of content affect viewing differently. These insights are helpful for networks seeking to increase viewership or encourage more live viewing. As advertising rates are linked to program ratings, networks and content creators may benefit from leveraging social media as a mechanism for promoting programs.

INTRODUCTION

The television viewing landscape has undergone significant technological changes in recent years. Notably, the introduction of time-shifted viewing technology (e.g., DVRs) and streaming services (e.g., Netflix, Hulu) provides consumers with the ability to decide when they will view television programs. For example, penetration of the digital video recorder (DVR) has increased from approximately 20% in 2005 to 50% in 2015 (eMarketer 2006; Nielsen 2015a). In addition to DVRs (e.g., Wilbur 2008a; Bronnenberg et al. 2010), streaming video platforms (e.g., Schweidel and Moe 2016) also facilitate time-shifted viewing. In contrast to live "appointment viewing" of programs based on the schedule set by television networks, viewers can now choose when they will view programs. This activity has raised concerns about the extent of advertising avoidance (e.g., Story 2007) and ultimately the effectiveness of television advertising (e.g., Wilbur 2008b). Despite the increased penetration of DVRs and use of streaming video platforms, there is a gap in our knowledge of the factors that affect consumers' decisions to engage in live and time-shifted television viewing.

Given the increased prevalence of time-shifted viewing, the television industry has adapted how the television ratings currency is calculated to include DVR viewing. Nielsen's C3 (C7) ratings combine the commercial-audience ratings of live viewing with DVR viewing that occurs within three (seven) days after the program airs. According to Nielsen, DVR playback can increase some program audiences by 40% and 73% when time-shifted viewing on the same day, and within three days of the live airing, respectively, are taken into account (e.g., Steinberg 2007). Some television shows might even see their ratings double with the inclusion of 7-day DVR playback. For example, one popular show's audience increased from almost 900,000 viewers (live and same-day DVR viewing) to 1.69 million viewers with the inclusion of DVR playback within seven days (Stelter 2013).

Television networks stand to benefit from time-shifted viewing occurring earlier, as C3 ratings have become the default currency for national television networks (Friedman 2012). Under C3 ratings, normal-speed time-shifted viewing that occurs beyond three days after the program initially airs is not included in the calculation of the total audience size, and networks are not compensated for the viewers reached by advertising. In addition to the impact that time-shifted viewing has on television networks, time-shifted viewing may also adversely affect marketers. When marketers air advertisements in programs that attract significant amounts of time-shifted viewing, some viewers may not be exposed to an advertisement until several days after its live airing. Understanding the factors that contribute to time-shifted viewing may yield important insights for advertisers, such as particular programs in which they should avoid placing highly time-sensitive advertisements (e.g., “one day sale Saturday’).

Beyond providing viewers with more control over when they consume television content, DVRs also allow viewers to skip (zip) through commercials. Previous research has documented advertising skip rates during time-shifted viewing of 68% (Pearson and Barwise 2007) and 60-70% (Bronnenberg et al. 2010). However, as more viewers time-shift programs, greater numbers of ads will be seen at normal speed with varying delays since live airing. With firms expecting to spend more than $70 billion annually on television advertising by 2017 (eMarketer 2016), the proliferation of time-shifted viewing that facilitates advertising avoidance and delays poses a significant concern for both marketers and networks.

A second way in which television viewing has evolved involves increased social media activities related to television viewing. Many participants in a recent global survey reported that they wanted to remain current with shows so that they could participate in social media conversations (Nielsen 2015b). Early research on online word-of-mouth (WOM) investigated the link between online conversations and television ratings (e.g., Godes and Mayzlin 2004; Gong et al. 2014). While prior research has examined the relationship between social TV activity and live viewing, particularly in light of the increased penetration of DVRs, little is known about the link between social TV activities and time-shifted viewing. For programs that generate a high volume of social TV activity, viewers may be more prone to engage in live viewing than time-shifted viewing to avoid spoilers (Johnson and Rosenbaum 2015; Leavitt and Christenfeld 2013) and experience a sense of community with other viewers (e.g., Cohen and Lancaster 2014).

An important limitation of much extant research is the use of holistic metrics such as volume and sentiment to capture online WOM activity (e.g., Godes and Mayzlin 2004; Liu 2006; Chevalier and Mayzlin 2006; Tirunillai and Tellis 2012; Gong et al. 2014; Schweidel and Moe 2014; Fossen and Schweidel 2017). While these measures may provide a summary of the volume and tone of the conversation occurring online, they fail to consider the content of the social media posts. One notable exception to this is work by Liu et al. (2016). In addition to the volume and sentiment of Twitter activity, the authors also derive measures related to the content of the posts. The authors apply principal components analysis to n-grams and identify content relating to the timeliness of viewing ("tonight," "can't wait," and "watch"), the viewing environment ("bed" and "home"), season premieres ("season," "start" and "premiere") and season finales ("excited," "finale" and "love"). They show that the content of social media posts provides information distinct from volume and sentiment metrics when predicting television ratings.

Beyond the contextual aspects surrounding viewing behavior identified by Liu et al. (2016), the content of social TV activity also contains viewers' reactions to the program content itself. A television viewer may have a positive reaction that is expressed on Twitter. But, does that reaction focus on the program? A specific character in the program? Or the actor who portrays that character? To the best of our knowledge, research has yet to conduct a broad investigation across television programs that explores how reactions focusing on such elements may differentially affect viewing behavior. From a managerial perspective, such insights would be helpful as they would provide guidance into the types of social TV conversations that networks and content creators should seek to foster among viewers. This is the goal of the current research.

To accomplish this, we collect data from ComScore's TV Essentials database. Key to our research interests, this database distinguishes between viewing that occurs live and time-shifted. We pair this with social media data collected by Canvs, which receives Twitter data on television viewing behavior from Nielsen, making the data the same as that which comprises the Nielsen Twitter TV ratings. Using these data sources, we examine the extent to which the total size of an episode's television viewing audience and the timing of the viewing is affected by the content of social TV posts. In contrast to previous studies, we do not find evidence to suggest that social TV activity affects the total size of the viewing audience. Rather, we find that certain types of social TV posts -- in particular posts about the actors in the program -- affect the share of viewing that occurs live compared to time-shifted.

Our research contributes to the literature in two key ways. First, we distinguish among social TV posts based on the content of the post. While Liu et al. (2016) incorporate content-based measures arising from their analysis of the unstructured data, we make use of data from Nielsen that Canvs has categorized into different types of social TV posts. This categorization has been adopted by television networks including CBS, NBC and Fox.[1] It enables us to make

[1] https://variety.com/2019/digital/news/cbs-canvs-artificial-intelligence-tv-emotional-response-1203142779/

general statements about how different types of social TV posts affect television viewing, which in turn can inform the social media strategy employed by networks and content creators. Second, we contribute to the prior research on television consumption. Though there has been extensive work in the marketing literature that focuses on live television viewing (e.g., Rust and Alpert 1984; Shachar and Emerson 2000; Wilbur 2008b; Schweidel and Kent 2010), limited research has explored consumption through time-shifted viewing (e.g., Wilbur 2008a; Bronnenberg et al. 2010). We empirically investigate the extent to which social media activity affects not only the total size of a television program's audience, but also when the television consumption occurs, allowing us to identify the drivers of live and time-shifted viewing. Because time-shifted TV can lead to more avoided commercials for advertisers, and more non-monetized ad exposures beyond the C3 or C7 payment window for networks, the amount and timing of delayed show viewing affects the interests of the critical participants in the television business

In the next section, we review the related literature. We then describe the data used in our analysis. We present our modeling approach and empirical findings, and then discuss the managerial implications.

RELATED RESEARCH

We begin by providing a brief review of the empirical literature that has investigated television-viewing behavior and social TV activity. We then discuss narrative transportation theory on which we draw to provide a theoretical foundation for this research. While our data do not allow us to engage in testing particular behavioral theories, we draw on the narrative transportation literature to motivate our analysis.

Television Viewing Behavior

To understand television viewers' behavior, researchers have investigated viewers' choices among alternative programs. That is, for a given set of programs that a viewer may watch at a particular point in time, researchers have investigated those factors that drive the utility associated with viewers' choosing different programs (e.g., Rust and Alpert 1984). Subsequent research extended the core choice modeling framework by incorporating viewer segments (e.g., Rust et al. 1992) and program characteristics (e.g., Shachar and Emerson 2000). Building on previous research, Wilbur (2008b) develops a two-sided model that considers both viewer and advertiser demand. Wilbur (2008b) conducts a counterfactual experiment to investigate the impact of advertising avoidance technology on advertising revenue, suggesting that increased penetration of advertising avoidance technology could adversely affect advertising revenue. While much of the television viewing literature investigates viewers' choice of programs, the focus of research to date has been on live tuning (e.g., Wilbur 2008a), limiting our understanding of increasingly common time-shifted viewing behavior.

While live viewing was reported to account for approximately 80% of television consumption in 2008, it has declined sharply to approximately 50% in the 2015-2016 television season (Crupi 2016). Given increased DVR penetration and usage, networks and content creators have an interest in understanding those factors that drive live viewership. By leveraging a unique dataset that includes both live and time-shifted viewing over the course of a winter television season, we investigate the impact of social TV activity on both the total audience size and when television viewing occurs.

Social Media Activity and Television Viewing

Like research on program choice, research investigating the link between television viewing behavior and social TV activity has focused primarily on live viewing. Seminal work by Godes and Mayzlin (2004) explores the impact of online WOM on future television show ratings. The authors consider new television shows that aired during the 1999-2000 season, during which time both DVR use and social TV activity were in their infancy. While the authors do not find support for the volume of online conversations driving future television ratings, they do find that online conversations occurring across a broader range of newsgroups are associated with higher future television ratings. Recent research by Liu et al. (2016) explore content within Twitter posts, demonstrating that both the content and volume of Twitter messages are predictors of television ratings and highlight the importance of exploring the content of social media activity. To the best of our knowledge, our research is among the first investigations to examine the impact of social TV activity by taking into account the focus (i.e., character, actor, etc.) of social media posts, which offers actionable insights for both advertisers and networks.

Research examining the link between social media and television viewing has also focused on the impact of advertisements on social TV activity. Hill et al. (2012) examine social TV activity following advertisements in the Superbowl. The authors find that the extent of consumer engagement following an advertisement, as measured by the growth in followers, varies based on the extent to which social media was incorporated into the advertisement. They also report that the emotional content of the advertisement is correlated with the number of tweets following the advertisement. Fossen and Schweidel (2017) use data from a television season to explore the relationship between television advertising and online WOM, considering both program- and brand-related WOM. The authors find evidence of increased online WOM for

TV programs and brands following commercial advertisements, with the increase varying across product categories, advertisers, and television programs.

While research has established a link between social TV activity and live television viewing, we know little about the impact of social media activity on time-shifted viewing. Given networks' and marketers' interest in driving live viewing (e.g., Littleton 2014) and reaching viewers with advertisements, we investigate the extent to which social TV activity may affect the prevalence of time-shifted viewing.

Narrative Transportation Theory

Narrative transportation concepts can connect the content of show-related social media posts to live and delayed TV viewing actions. Gerrig (1993) introduced the term "narrative transportation," defined as "immersion into a text." Green and Brock (2000) explicate narrative transportation as losing oneself within a story and the extent to which viewers are absorbed in the story. Viewers who are engrossed in the narrative can be mentally transported, in the physiological sense, into the fictional world of the story (Green and Brock 2000). Green (2008) describes it as the idea that people are so immersed in the story that parts of the real world may become less accessible because the viewer is cognitively invested in the fictional world. Van Laer et al. (2014) state that narrative transportation occurs when the viewer experiences immersion in a world evoked by the narrative because of emotions towards the characters or plot. The authors contend that narrative transportation requires both an empathetic feeling towards the characters or plot and visual imagery (Van Laer et al. 2014).

Researchers argue that television programs allow viewers to repeatedly immerse themselves in narratives that simulate social interactions and allow viewers to become attached to characters, the environment, and situations (Cohen 2004). For example, it is not uncommon for viewers to identify with the protagonist in narratives (Oatley and Gholamain 1997) and become transported. Some works suggest viewers identify emotionally with characters and start to merge their identity with traits of the characters taking on the character's emotions in some instances (e.g., Oatley 1999).

Considering scripted television programs as stories, viewers can become transported in the narrative, having emotional responses and feeling immersed in the fictional world of the program. Social media provides a platform through which viewers can connect with each other and express their attitudes, opinions, and sentiment towards a particular program (Yvette and Na 2011). We contend that the focus of a viewer's tweets while consuming a television program provides an indication of their degree of narrative immersion within the program and the degree of immersion may influence timing of subsequent television consumption.

Consistent with narrative transportation theory, we differentiate among social TV posts based on their content. As elicitation of emotion is a necessary condition of narrative transportation (e.g., Green 2008; Escalas and Stern 2003), we distinguish between social TV posts that contain emotional reactions and those that do not contain emotional reactions. Among social TV posts with emotional reactions, we further segment the posts based on the focus of the post, distinguishing between posts that reference the fictional world of the story (i.e., characters of the program) and the non-fictional world (i.e., cast, guest stars, and producers).

By distinguishing among social TV posts in a manner consistent with narrative transportation theory, we consider the extent to which the timing of television viewing is affected by viewers' immersion in the program. For example, consider the following tweets:

General Tweet: “@RansomCBS… great TV show”

Talent Tweet: @CarloRota OMG you play the ‘bad guy’ just perfectly. Bravo! @RansomCBS”

Character Tweet: kate better not cheat on toby im gonna be so upset #ThisIsUs”

Viewers who participate in social media conversations focusing on characters, as illustrated by the character tweet, may be more engaged emotionally with the fictional elements of the narrative and feel higher levels of immersion with the program. In contrast, viewers who recognize non-fictional elements, such as the actors who portray the characters (as shown in the talent tweet), may not exhibit the same degree of immersion. They may still exhibit an emotional connection but acknowledge non-fictional elements. We contend that viewers who post general comments about the program (i.e., the general tweet), or reference the actors (talent) exhibit lower levels of immersion in the narrative compared to those who reference the characters.

Narrative transportation has been shown to elicit more affective processing resulting in positive impacts for the firm (e.g. positive consumers attitudes, ad attitudes and brand evaluations) while a lack of narrative transportation can lead to more critical thought processing resulting in negative impacts for the firm (Escales 2004; Phillips et al 2010). We contend that social TV activity offers a way to capture narrative immersion for a given program and that the degree of immersion in the narrative, as reflected in the content of social TV posts, affects consumers television consumption. We anticipate that social TV activity that is indicative of no/low narrative immersion will have negative impact on television viewing. We anticipate that social TV activity that contains emotional reactions that signify moderate levels of narrative immersion (e.g., general and talent tweets) will be linked to earlier program consumption (e.g., more live viewing). Social TV activity that signify a high degree of immersion (character related posts) may result in two opposing consumer behaviors. One possibility is that these programs will be more likely to be viewed live, which facilitates in-person or online conversation among viewers. Alternatively, viewers of such programs may prefer to engage in time-shifted viewing in order to control the viewing pace (e.g. pausing, rewinding) or to avoid interruptions to their experience, akin to immersed binge-watching viewers who respond less to distractions such as advertisements (e.g., Schweidel and Moe 2016). These competing effects on the timing of television viewing may result in social TV activity that exhibits a high degree of narrative transportation having a smaller (or no) impact on the timing of viewing compared to social TV activity exhibiting moderate levels of narrative transportation.

DATA

We collected data on 55 scripted television programs that aired in the winter 2017 season on the five broadcast networks (CBS, ABC, NBC, FOX and CW). We complement the tuning data with social TV activity from Canvs, a social media monitoring platform that has partnered with Nielsen and its Twitter TV ratings to measure social media activity for television programs. We next discuss the data sources in detail.

Television Tuning Data

Television viewing data was obtained from ComScore’s TV Essentials database, which collects live viewing and DVR tuning data from set-top boxes. The data contains the number of set-top boxes tuned to an episode of a program each second, averaged over 30-second intervals. As an example, for a program that airs from 8:00 – 8:30 PM, there are 60 30-second intervals. For each interval, we observe the start and end time and the number of set-top boxes tuned to the program that are engaged in live viewing. Those set-top boxes that engage in time-shifted viewing, which includes households that have paused live programming or recorded the program and are not viewing it live, our data contain the number of set-top boxes that are tuned to program, averaged into 30-second intervals based on the original airtime of the program. For example, for the program content airing in the interval 8:00:00 PM – 8:00:30 PM, our data include the number of set-top boxes that display that content live, as well as the number of set-top boxes that display that content up to 15 days later. The time-shifted viewing data only includes those set-top boxes for which playback occurs at regular speed and thus does not include those set-top boxes that are fast-forwarding through the content.

For the 55 scripted television programs that aired in the winter 2017 season, we collect tuning data corresponding to 684 individual episodes airing for the first time. More than 80% of the shows in the data set aired more than 10 episodes. *Reign* aired 16 episodes, making it the most aired show within the dataset. Table 1 summarizes the data by network.

<INSERT TABLE 1 ABOUT HERE>

Table 2 provides descriptive statistics of television tuning behavior, averaged across episodes. The DVR tuning data are recorded based on when content is viewed (same day as live programming, 1-3 days after live programming, and more than 3 days after live programming). Our data are collected from a total of 21,875,707 reporting set-top boxes. In Table 2, we report television ratings for live and time-shifted viewing, averaged across 30-second intervals of an episode and across all episodes. We see that the average live viewing audience is roughly 49.6% of total viewing for a given scripted show. On average, time-shifted viewing accounts for roughly 50.4% of total audience, with playback occurring same day, 1-3 day, and beyond three days after the live airing accounting for 13%, 27.9% and, 9.5% respectively. Table 2 shows that scripted programs experience a larger proportion of time-shifted viewing occurring within 1-3 days after the program airs.

<INSERT TABLE 2 ABOUT HERE>

While Table 2 provides an overall sense for the prevalence of time-shifted viewing, there is considerable heterogeneity in live vs. time-shifted viewing across television programs. We provide an illustration of how the tuning audience varies across episodes for two programs, *Ransom* and *This is Us* in Figure 1. For some programs, we observe that the live tuning audience has a higher share of the total tuning audience. In contrast, for other programs, we observe a larger share of time-shifted viewing. Figure 1 demonstrates the variation in tuning behavior between two shows; we see that DVR tuning for *This is Us* exceeds live tuning while the opposite is true for *Ransom*.

Taken together, Figure 1 and Tables 1 and 2 suggest considerable heterogeneity across episodes of television programs in terms of the prevalence of live and time-shifted tuning. Factors related to these differences may include air time, day of the week, program length, and the ordinal episode number (e.g., n^{th} episode of the season). Limited research addresses time-shifted (versus live) TV viewing. However, for the scripted shows that are the staple of the critical weeknight primetime network TV schedule grid, the delayed audience may on average be as large as the live audience.

< INSERT FIGURE 1 ABOUT HERE >

Social Media Activity Data

Using Canvs, we collect data on the volume of conversations occurring on Twitter pertaining to a given television program over time. Canvs receives its Twitter data through a partnership with Nielsen, which measures program-related Twitter activity for linear episode airings and on a 24/7 basis. The raw Twitter posts are then processed by Canvs to identify the focus of the content (characters, cast members, guest stars, producers) and emotional reactions. The majority of the social TV activity occurs the day of the episode, with most of the activity occurring during the live airing. As an illustration, Figure 2 shows the social TV activity over time for the program *This Is Us*. Consistent with a Nielsen study which found that a large share (68%) of weekly show-related Twitter activity occurred during the live airing (Nielsen 2014), the largest volume of social TV activity in our dataset occurs while the program is airing. We therefore focus our analysis on social TV activity occurring on Twitter during the live airing of an episode and investigate its impact on viewing of the next episode of the program.

< INSERT FIGURE 2 ABOUT HERE >

Using Canvs, we collect minute-by-minute social TV activity, which we then aggregate for each episode in our sample. The data provided by Canvs is processed through a proprietary text analysis algorithm to asses if a tweet contains words, phrases, or emoji icons associated with over 20 emotions, enabling us to distinguish those posts that contain emotional reactions from those that do not. Roughly 33% of all tweets associated with a particular program are categorized as emotional tweets while the remaining tweets are categorized as non-emotional. Second, for those tweets that have been categorized as containing an emotional reaction, Canvs categorizes the tweets based on the content of the post: cast member, character, guest star and executive producer. Web Appendix A shows the volume of each segment of social WOM for the TV show American Housewife as an example.

MODEL DEVELOPMENT

Endogenous Variables

Our analysis includes ten endogenous variables of interest; four measures pertaining to television viewing and six measures that capture social TV activity. For each episode, we collect the total number of tweets related to the program, the number of those tweets that are emotional and non-emotional, and the number of emotional tweets for each content topic category (general, cast, character, guest star, and producer). Table 3 reports descriptive statistics for social media activity segments.

For television viewing variables, we decompose the observed data on live and time-shifted tuning behavior into the following components: (1) the size of the audience that tunes into episode *t* of program *i* (regardless of whether it is live or time-shifted), (2) the share of the episode *t* of program *i*'s total audience that engages in live viewing (relative to time-shifted viewing), and (3) the proximity to the live airdate with which time-shifted viewing of episode *t* of program *i* occurs (same day as live airing, 1-3 days after live, or more than three days after the live airing). We provide descriptive statistics of these variables in Table 3.

< INSERT TABLE 3 ABOUT HERE >

Control Variables

While our primary interest is in the impact of social TV activity on television viewing, we include additional independent variables in our analysis to account for potential sources of variation. We provide a description of these variables in Table 4. We provide the frequency distribution for the number of episodes by start time, program length and, day of week in Table 5.

< INSERT TABLE 4 ABOUT HERE >

< INSERT TABLE 5 ABOUT HERE >

VAR-X Model

We employ vector autoregression analysis (VAR) to investigate the dynamic relationship between social media activity and television viewing audience size. A concern for empirical analysis in the social media domain is potential endogeneity (e.g., Borah and Tellis 2016; Hewett et al. 2016). VAR models treat all variables in the system as endogenous while accounting for dynamic feedback effects which may exist between endogenous variables. With the VAR modeling approach, we can control for serial correlation and reverse causality (Granger and Newbold 1986) allowing us to draw conclusions about the interrelationship between social media posts and television consumption. General impulse response functions by VAR models provide forecast that are robust to causal ordering of endogenous covariates (Persaran and Shin 1998).

Given our interest in understanding how social TV activity and television consumption are interrelated, we adopt the VAR-X approach used by Hewett et al. (2016). Specifically, we use a panel data VAR-X model which enables us to capture lagged and contemporaneous effects of endogenous variables while controlling for exogenous factors. Given the nature of the data and the number of endogenous variables, we use a panel VAR-X with homogenous response parameters across television programs with program specific fixed effects. Fixed effects account for unobservable panel specific heterogeneity. This approach allows us to pool data across television shows while permitting heterogeneity among programs and maximizing the number of observations. Our time series panels consist of 55 programs across an average of 12.45 episodes, allowing us to formulate general conclusions about how social media activity influences television ratings and timing of television consumption.

We transform the television viewing variables from fractions to continuous measures. *TotalView* represents the fraction of set-top boxes (including both live and time-shifted) tuned in to a given episode, averaged across the 30-second intervals that comprise the episode. *LiveView* is the fraction of set-top boxes tuned into the episode that engage in live viewing for a given episode. We apply a logit transformation to the fraction $TotalView_{it}$ and $LiveView_{it}$.

$$Y_{1it} = \log\left(\frac{TotalView_{it}}{1-TotalView_{it}}\right) \quad (1)$$

$$Y_{2it} = \log\left(\frac{LiveView_{it}}{1-LiveView_{it}}\right) \quad (2)$$

In a similar fashion, we transform our measures of time-shifted viewing. We define $DVRSameDay_{it}$ and $DVRUpto3_{it}$ in terms of Y_{3it} and Y_{4it} as follows:

$$DVRSameDay_{it} = \frac{\exp(Y_{3it})}{1+\exp(Y_{3it})+\exp(Y_{4it})} \quad (3)$$

$$DVRUpto3_{it} = \frac{\exp(Y_{4it})}{1+\exp(Y_{3it})+\exp(Y_{4it})} \quad (4)$$

where Y_{3it} reflects the prevalence of same-day time-shifted viewing relative to time-shifted viewing more than three days after the live airing, and Y_{4it} reflects the prevalence of time-shifted viewing occurring 1-3 days after the live airing relative to time-shifted viewing occurring more than three days after the live airdate. The fraction of devices that engage in time-shifted viewing beyond three days after the live airdate can then be written as:

$$DVRBeyond3_{it} = 1 - DVRSameDay_{it} - DVRUpto3_{it} = \frac{1}{1+\exp(Y_{3it})+\exp(Y_{4it})} \quad (5)$$

Dividing equations (3) and (4) by equation (5) and taking the logarithm, Y_{3it} and Y_{4it} can be expressed as (e.g., Schweidel and Kent 2010):

$$Y_{3it} = \log\left(\frac{DVRSameDay_{it}}{1 - DVRSameDay_{it} - DVRUpto3_{it}}\right) \quad (6)$$

$$Y_{4it} = \log\left(\frac{DVRUpto3_{it}}{1 - DVRSameDay_{it} - DVRUpto3_{it}}\right) \quad (7)$$

VAR-X Test

We begin our empirical analysis by determining whether the endogenous variables entering the model are stationary or evolving. Details of the augmented Dickey-Fuller panel unit root test results are provided in Web Appendix B. All variables (total views,live views, same day DVR viewing, 1-3 day DVR viewing, noemo, general, character, talent, guest, and production) are time trend stationary and enter the model in levels. Next, we test our system of variables for cointegration using the Johansen Fisher panel test for cointegration. Based on the results we determine that there is no cointegration among the variables in the system permitting the use of a VAR model in contrast to a vector error correction model (VECM) (See Web Appendix B). We select the optimal lag order based on minimizing the Bayesian Information Criterion (BIC) (See Web Appendix B).

We specify a first order panel data VAR-X model given by Equation 8.

$$\begin{bmatrix} Y_{1i,t} \\ Y_{2i,t} \\ Y_{3i,t} \\ Y_{4i,t} \\ NonEmo\ WOM_{i,t} \\ Genral\ WOM_{i,t} \\ Character\ WOM_{i,t} \\ Talent\ WOM_{i,t} \\ Guest\ WOM_{i,t} \\ Production\ WOM_{i,t} \end{bmatrix} = \begin{bmatrix} \mu_{1,0} + \sum_{i=1}^{P-1} \mu_{1,i} S_i \\ \mu_{2,0} + \sum_{i=1}^{P-1} \mu_{2,i} S_i \\ \mu_{3,0} + \sum_{i=1}^{P-1} \mu_{3,i} S_i \\ \mu_{4,0} + \sum_{i=1}^{P-1} \mu_{4,i} S_i \\ \mu_{5,0} + \sum_{i=1}^{P-1} \mu_{5,i} S_i \\ \mu_{6,0} + \sum_{i=1}^{P-1} \mu_{6,i} S_i \\ \mu_{7,0} + \sum_{i=1}^{P-1} \mu_{7,i} S_i \\ \mu_{8,0} + \sum_{i=1}^{P-1} \mu_{8,i} S_i \\ \mu_{9,0} + \sum_{i=1}^{P-1} \mu_{9,i} S_i \\ \mu_{10,0} + \sum_{i=1}^{P-1} \mu_{10,i} S_i \end{bmatrix} + \sum_{n=1}^{p} \begin{pmatrix} \varphi_{1,1}^{n} & \cdots & \varphi_{1,10}^{n} \\ \vdots & \ddots & \vdots \\ \varphi_{10,1}^{n} & \cdots & \varphi_{10,10}^{n} \end{pmatrix} \begin{bmatrix} Y_{1i,t-1} \\ Y_{2i,t-1} \\ Y_{3i,t-1} \\ Y_{4i,t-1} \\ NonEmo\ WOM_{i,t-1} \\ Genral\ WOM_{i,t-1} \\ Character\ WOM_{i,t-1} \\ Talent\ WOM_{i,t-1} \\ Guest\ WOM_{i,t-1} \\ Production\ WOM_{i,t-1} \end{bmatrix} +$$

$$\begin{pmatrix} \lambda_{1,1} & \cdots & \lambda_{1,10} \\ \vdots & \ddots & \vdots \\ \lambda_{10,1} & \cdots & \lambda_{10,10} \end{pmatrix} \begin{bmatrix} x_{1i,t} \\ x_{2i,t} \\ x_{3i,t} \\ x_{4i,t} \\ x_{5i,t} \\ x_{6i,t} \\ x_{7i,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,i,t} \\ \varepsilon_{2,i,t} \\ \varepsilon_{3,i,t} \\ \varepsilon_{4,i,t} \\ \varepsilon_{5,i,t} \\ \varepsilon_{6,i,t} \\ \varepsilon_{7,i,t} \\ \varepsilon_{8,i,t} \\ \varepsilon_{9,i,t} \\ \varepsilon_{10,i,t} \end{bmatrix} \tag{8}$$

where i = 1, …, P (=55) television programs and t = 1, …, T (=16) episode level observations for a total of 684 observations. Intercepts are represented by $\mu_{1,0}\ldots\ \mu_{10,0}$. Indicator variables are used to denote the program specific fixed effect where S_i = 1 for program P and 0 otherwise.

The dynamic relationship between endogenous variables is captured by matrix $\varphi_{j,f}^{n}$. The diagonal terms represent the direct effect of endogenous variables while the off-diagonal terms indicate the indirect effects among endogenous variables. Contemporaneous effects are captured in the error terms $\varepsilon_{1,i,t}\ldots\ \varepsilon_{10,i,t}$ ~ N(0, σ), where σ is a 10 x 10 covariance matrix. The exogenous vector X contains our control variables – program length, weekday, four start time dummy variables, and a deterministic episode trend to capture any omitted time-varying effects.

RESULTS

The results section is structured as follows. We first discuss the results of the Granger causality tests. We then present the results from the VAR-X model and discuss the relationship between social TV activity and television viewing behavior. We follow with an exploration of the endogenous relationship among television viewing covariates and among social TV activity covariates.

Granger Causality Test

The Granger causality tests allow us to examine the interrelationship between the endogenous variables by accessing which variable Granger causes another. Our model consists of 10 endogenous variables that can potentially influence one another resulting in 10 x 9 potential causal relationships between one endogenous variable and another endogenous variable; there are 10 x 1 relationships between an endogenous variable and itself. Results show that roughly 30% of causal paths among endogenous variables are significant at the 10% significance level, suggesting that a dynamic model is appropriate (See Web Appendix C).

In terms of the impact of social activity on television viewing, we find that non-emotional social activity, talent-related and general emotional social activity Granger-cause live television viewing. In terms of television viewing impact on social TV activity, we find that time-shifted viewing and live viewing Granger-cause non-emotional and general program chatter. While Granger causality tests provide insights into the ordering of the casual relationship between social media activity and TV viewing, the model results from the panel data VAR-X provides detail into the magnitude and direction of the relationship.

Relationship Between Social TV Activity and Television Viewing

Some reports have suggested that aggregate measures of social TV activity can reflect audience interest in the show and influence ratings (Goel 2015). We examine the effects of social media activity on television consumption behavior, namely the impact of the social TV activity during a program's previous episode on the current episode.

We present notable results of the panel data VAR-X model using general impulse response functions (IRFs). Full model parameter estimates are available in Appendix D. IRFs forecast are robust and represent the dynamic impact of a one standard deviation shock in one variable on other endogenous variables in the system (Persaran and Shin 1998). For the 10 endogenous variables there exist a total of 100 IRF graphs. Our research examines the relationship between social TV activity and the timing of television program consumption. We explore the extent to which the relationship between social TV activity and television consumption varies based on the content focus of the social TV posts. To this end, there are 6 x 4 (social TV post types x television viewing measures) that capture this relationship. We summarize our notable findings in Figure 3. First, we discuss the interrelationship between social TV activity and television consumption. Next, we discuss the impact of television viewing on subsequent television viewing. We then explore the dynamics of how social activity drives subsequent social activity to provide more context in understanding the role of social TV activity.

General Tweets. Of the tweets containing emotional reactions, we find evidence to suggest that general posts about the program are associated with variation in viewing behavior. In particular, increased levels of general social media posts about the previous episode have a significant and positive direct impact on fraction of devices that engage in live viewing compared to time-shifted DVR viewing. Figure 4 details the IRF of a one standard deviation shock in general emotional tweets on television viewing behavior. General tweets are shown to have an overall positive correlation with greater live viewing (Figure 4 A) and less time-shifted DVR viewing (Figure 4 B and C). General tweets can help to create buzz about a program and heighten live audiences. A significant positive feedback loop exists between live views and general social TV activity (Figure 3), suggesting a reciprocal relationship where by live viewing increases subsequent general emotional chatter related to the program and general emotional social TV activity increases live views for subsequent episodes. Additionally, we find that same day DVR viewing from the previous episode is associated with more general social media post for the next episode while 1-3 day DVR viewing of the previous episode is associated with lower levels of general social media activity in the next episode. This suggest that among time shifted viewing, earlier DVR consumption is associated with greater levels of moderately immersed social TV activity for the next episode while later DVR consumption is associated with lower levels of moderately immersed social TV activity.

Talent Tweets. Similar to general posts, we also find that increased levels of social TV activity mentioning members of the cast are associated with more live viewing and less time-shifted viewing. Figure 4 shows the IRF for a one standard deviation shock in talent related posts. Talent related tweets in the previous episode have a significant and positive association with greater live viewing in the next episode (Figure 4 D). Interestingly, the coefficient for the impact of social media posts related to the actors in a program is nearly twice as large as the coefficient for general social media posts about the program, indicating that posts that mention the talent have a larger impact on earlier television consumption behavior (Figure 3). Even among social TV posts that contain emotional reactions, our results suggest that the impact of social TV activity on television viewing behavior depends on the focus of the content and that certain types of conversations exert more influence than others. This implies that talent-related tweets during one episode can boost live ratings of subsequent episodes, which may be beneficial for networks and content creators who are focused on driving live viewership.

< INSERT FIGURE 4 ABOUT HERE >

Non-Emotional Tweets. In contrast to general and talent related post that increase live viewing of the next episode, we find a negative impact of non-emotional social TV activity on live viewing of the next episode. Figure 4 shows the IRF for a one standard deviation shock in non-emotional post on television viewing patterns. Notice that an increase in non-emotional social TV activity in the previous episode has a negative impact the number of viewers who engage in live viewing of the next episode. Figure 4 H and I show that non-emotional tweets are linked to less live viewing, thereby increasing the amount of time-shifted DVR viewing. Assuming non-emotional posts are indicative of a lower degree or lack of narrative transportation, the negative influence of non-emotional posts is consistent with prior literature which has found that lack of narrative transportation can lead to higher levels of critical thought and negative impacts on ad attitudes and brand evaluations (Escalas 2004). We also find a statistically significant feedback loop between non-emotional posts and the fraction of devices that consume programs live vs. time-shifted DVR. While non-emotional social activity negatively impacts live views of the subsequent episode, live viewing has a positive influence on the amount of non-emotional posts for the next episode. Intuitively, larger live viewing audiences suggest that more viewers are consuming the program which can lead to greater buzz about the program.

Character Tweets. Although we do not find that character tweets have a statistically significant impact on television viewing audience size, the impulse response function of a one standard deviation shock in character tweets is positively correlated with total viewership, live viewing and time-shifted DVR viewing (Figure 5). Among the different types of social TV activity, character tweets show positive correlations with both live views and time-shifted viewing (Figure 5 A, B and C) in contrast to talent and general tweets which are significantly associated with heightened live viewing and negatively associated with time-shifted DVR viewing. High narrative immersion can lead to greater live views for a segment of viewers or greater earlier time-shifted viewing to allow control of viewing pace, facilitating zipping/zapping commercials or, rewind functionality. It is possible that there exists heterogeneity among the influence of social TV activity related to high narrative immersion and the competing effects lead to non-significant findings.

< INSERT FIGURE 5 ABOUT HERE >

Summary. In terms of social TV activity on television viewing, we find that social TV activity indicative of no/low narrative transportation (non-emotional posts) is associated with a decrease in live viewing and greater time-shifted viewing for the next episode. Social TV activity indicative of moderate levels of narrative transportation (general and talent posts) are associated with greater live viewing and less time-shifted viewing for the next episode. While we find evidence that social TV activity indicative of higher levels of narrative transportation (character posts) has a positive directional link to increase live and time-shifted viewership, we do not find that character-related social TV activity is statistically significant. Though this finding may appear somewhat counterintuitive, it may arise because high levels of narrative immersion could result in either a desire to control the viewing environment through time-shifted viewing or a desire to consume content live.

Additionally, we find evidence that the impact of social TV activity on television viewing is not equivalent for all categories. The parameter coefficient estimates from the panel data VAR-X for non-emotional, general and talent related post are -0.02, 0.08, and 0.15 respectively. We observe that the impact of emotional talent-related tweets on live views is nearly double that of general emotional comments suggesting that talent related tweets offer greater impact. Such insights can be used by networks seeking to encourage more live viewing of their programs, as their social media strategy to promote the show should focus more on the cast than on the characters themselves.

Television Viewing on Subsequent Television Viewing

Among television viewing variables we obtain the impact of the viewing behavior of a program's previous episode on the current episode. Our model includes four television viewing covariates resulting in 4 x 3 possible bivariate effects of one covariate on another and 4 x 1 univariate own effects of a variable with itself. We present the notable results of television viewing on subsequent television viewing in Figure 3 and use general impulse response functions (IRFs) to provide further detail.

In terms of own effects, results show that three of the endogenous covariates exhibit significant own effects. In particular, we find a significant positive feedback effect where higher levels of total viewership in the previous episode are associated with more total viewership in the next episode (Figure 3). Similarly, we find a significant positive feedback loop where higher levels of live viewing in the previous episode are associated with more live viewing in the subsequent episode; and more same-day time-shifted viewing in the previous episode is associated with more same-day time-shifted viewing for the next period. We also observe that live viewing and total viewing do not influence other viewership covariates.

Moving to the bivariate relationships, we find evidence that time-shifted viewing significantly impacts other viewership (e.g., total views and live viewership for the next episode). Specifically, we find that 1-3 day DVR consumption has a statistically significant and positive association with total views a program receives in the next episode (Figure 6 A). This finding is understandable given the prevailing downward trend in live viewing audiences (50% in 2016 compared to 80% in 2008) and the significant increases in total viewership for a given program after considering DVR viewership (Steinberg 2007; Crupi 2016). These findings suggest that time-shifted viewing, in contrast to live viewing, can contribute to increased total viewership for a given program.

< INSERT FIGURE 6 ABOUT HERE >

Another finding that supports the influence of time-shifted viewing on other viewership is the impact of same-day DVR viewing on subsequent viewing patterns. Results from the IRF of a one standard deviation shock in same-day DVR viewing, shows that an increase in share of devices engaged in live viewing and 1-3 day time-shifted DVR viewing for the following episode (Figure 6 B and C). It is worth noting that same-day DVR consumption from the previous episode influences three of our four television viewing variables suggesting that, among the television viewing covariates, same-day DVR can be a critical in driving subsequent live viewing and time-shifted viewing, and consequently total viewership. Given the complexities of ad avoidance in “near live” show consumption, same day viewing may be associated with lower levels of ad zipping than later DVR viewing (see Story, 2007). Additionally, Figure 6B shows that the effect of same-day DVR viewing on live viewing for the next episode persists for two periods before returning to baseline in contrast to one period. These finding suggest that networks may consider strategically embracing time-shifted viewing as a way to grow total program viewership and live viewing. Methods to strategically utilize advertising blocks within DVR technology may be an area of interest for networks and programs.

Summary. In exploring the relationship between television viewing on subsequent television viewing our results reveal positive own effects for live views, total views and same day DVR views. Among notable bivariate relationships we find that higher 1-3 day time-shifted viewing in the current period is correlated with greater total viewership in the next period. Our results show that greater same day DVR viewing is associated with greater live views for the next episode. Collectively, these findings suggest that time-shifted viewing significantly influences other television audience size in contrast to live viewership.

Social Activity on Subsequent Social Activity

To further our understanding of how social TV activity contributes to its own proliferation through positive and negative feedback loops, we next explore the relationships among different types of social TV activity. In the present research we examine the extent to which the relationship between social TV activity and television consumption varies based on the content of the social TV posts. We find evidence that non-emotional, talent and general comments about the program influences television viewings patterns and explore the dynamics of how these social activities influence one another. Figure 3 details the most pertinent and notable findings. Of the three endogenous variables that influence television viewing audiences (non-emotional, general and talent) we examine how social TV activity during the previous episode influences social activity in the current episode. There exist 3 x 2 bivariate relationships and 3 x 1 univariate relationships. Next, we present notable relationships and the corresponding IRFs.

In terms of univariate effects, we find that non-emotional tweets have a significant and positive feedback effect with subsequent non-emotional tweets in the next period while general emotional tweet have a significant and negative own effect with general emotional tweets in the next period. The IRFs for a one standard deviation shock in general social TV activity shows a decrease in non-emotional related posts for the next period that stabilizes by the second period (Figure 7 A). Similarly, our results show that an increase in talent related post also decreases the amount of non-emotional posts (Figure 7 B). These results suggest that emotional posts in the current period reduces the amount of non-emotional social TV activity in the next period.

< INSERT FIGURE 7 ABOUT HERE >

Interestingly, although we find that preceding emotional tweets reduce the amount of non-emotional post, we find that non-emotional tweets in the previous period generates higher emotional social TV activity in the current period. Specifically, higher non-emotional chatter is correlated with higher general social TV activity about the program (Figure 7 C). This could suggest that non-emotional post could be general buzz about the program building generating interest and eliciting emotional responses from viewers in the next period. Together this implies that non-emotional tweets drive emotional tweets but not the other way around.

DISCUSSION

The ways in which viewers consume television programming has changed in recent years, providing viewers with more control over when they watch programs and more broad venues to discuss TV programs. Yet, despite the shift in consumers' behaviors, there is surprisingly little empirical research into the interplay between social media activity and time-shifted television consumption. Combining live and time-shifted tuning data with program-related Twitter activity, we empirically investigate the impact of social TV activity on both the size of the program audience and when viewing occurs. Extending the findings of previous literature (e.g., Mayzlin and Godes 2004), we find that higher levels of social TV activity are associated with larger live audiences. Moreover, our analysis suggests that it is not simply the volume of social media activity that matters, but also the content of that activity. We find that posts containing emotional reactions about a program or mention the actors in the cast have a positive impact on the proportion of devices that engage in live viewing of the next episode. As social media posts mentioning the cast are indicative of a higher level of immersion in the program, consistent with narrative transportation theory, these posts have a larger impact on viewing behavior compared to general emotional posts. We also discover a negative direct association between non-emotional social TV activity and live television viewing behavior; yet, non-emotional social TV activity has a positive impact on other influential segments of social TV activity (general tweets).

One of the key takeaways for practitioners from our research is that not all social media posts are equivalent in their impact on television viewing behavior. We highlight that within social media's influence on television viewing, different types of content affect different aspects of viewing. Talent-related posts have the largest impact on the share of devices that engage in live viewing as opposed to time-shifted viewing.

These results have implications for networks and content creators, as well as advertisers. DVR viewing that occurs the same day and within the first few days of an episode's live airdate are incorporated into television ratings. Our findings suggest that a social media strategy that encourages conversations about the actors in television programs is more effective than the one which seeks to encourage general social media posts about television programs. As advertising rates are linked to program ratings, networks may benefit from leveraging social media as a mechanism for promoting their programs. Considering the documented positive attitudinal effects of narrative immersion on brand and advertisement evaluations, advertisers can benefit from knowing which programs have social TV activity that is marked by higher levels of narrative immersion (Escalas 2004). Advertisers can use different ad strategies in programs with higher volumes of social TV activity indicative of high immersion. For example, an advertisement containing celebrity endorsers who are members of the program's cast could garner more positive attitudes towards the brand/product when airing within the program.

The composition of social TV posts may serve as an important signal for advertisers in choosing among programs. For example, advertisers with time-sensitive messages such as commercials for the release of a new movie or upcoming promotions that expire within a few days may benefit from choosing programs that have higher levels of emotional social TV activity that is program-related or cast-related in contrast to character-related. Based on the social TV activity from the prior episode, these programs are likely to have higher levels of live viewing during the next episode. Moreover, as advertising avoidance is more prevalent the later viewing occurs relative to the live airdate (Story 2007), such programs may also contribute to the messages reaching a larger audience. Conversely, advertisers whose messages are not time sensitive may opt to place advertisements in programs that experience more time-shifted viewing, as advertising in these programs may come at a lower cost. For example, when ads are purchased under the C3 payment system, normal-speed ad views only four or five days after live airing may be free to the advertiser, and many ad messages are basic brand builders with content that does not degrade in four or even eight days.

Our findings illustrate the potential value of social media to the television industry as networks grapple with viewers having more control over the timing of their viewing experience. However, our research is not without its limitations. While this research examines the content of social TV posts, there are other components of a social media strategy that warrant consideration. For example, it may be useful to differentially examine the impact of firm- vs. user-generated content on marketing outcomes of interest. Doing so could inform us of the relative potency of organic posts, as well as the potential limitations of firms' social media strategies. Additionally, while this research examines emotional vs. non-emotional post and focus on the topic of emotional content, other researchers can explore the distinction of different types of emotional responses and the potential differential impact on television viewing audiences.

Our analysis is conducted using aggregate-level measures of live and time-shifted viewing. If sales data from advertisers were available, one could examine how the timing of program consumption relates to advertising effectiveness (e.g., Bronnenberg et al. 2010). Device-level data would also allow for a more detailed analysis of television viewing behavior, including identifying those devices or households that are more prone to engage in live vs. time-shifted viewing. As service providers experiment with targeted television advertising, such information could prove useful as a means of identifying those devices and/or programs that offer advertisers the highest likelihood of reaching viewers with their messages. Device-level data would also be particularly useful to marketers if combined with web browsing and online purchasing data from the same households (e.g., Joo et al. 2013; Liaukonyte et al. 2015). Doing so would also enable an assessment of advertising's effectiveness when viewers are exposed to marketing messages during accelerated playback of previously recorded video content (e.g., Brasel and Gips 2008).

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Table 1: Number of shows and Average Number of Episodes by Network

Network	Number of Shows	Average # of Episodes (s.d.)
ABC	8	11.25 (2.11)
CBS	21	12.14 (1.12)
CW	2	13.50 (1.50)
FOX	10	10.60 (1.50)
NBC	14	10.79 (2.37)

Table 2. Percentage of Devices Engaged in Live and Time-Shifted Viewing

Category	Average (s.d.)	Min	Max
Live Viewing	3.41 (1.43)	0.46	7.96
Same Day DVR Viewing	0.89 (0.53)	0.14	3.86
1-3 Day DVR Viewing	1.92 (1.04)	0.36	6.14
Beyond 3 Day DVR Viewing	0.65 (0.38)	0.09	1.94

Table 3. Endogenous Variables

Variables	Description	Average (s.d.)
$TotalView_{it}$	Share of total views for program *i* given by episode *t*	0.07 (0.03)
$LiveView_{it}$	Fraction of $TotalView_{it}$ that occurs live for episode *t* of program *i*	0.51 (0.08)
$DVRSameDay_{it}$	Fraction of DVR viewing for episode *t* of program *i* that occurs on the same day as live airing	0.26 (0.04)
$DVRUpto3_{it}$	Fraction of DVR viewing for episode *t* of program *i* that occurs 1-3 days after live airing	0.56 (0.03)
$Non\text{-}Emo_{it}$	Social media activity for episode *t* of program *i* that is not emotionally driven	1,510.80 (2,570.14)
$General_{it}$	Social media activity for episode *t* of program *i* that is categorized as general	423.87 (764.02)
$Cast_{it}$	Social media activity for episode *t* of program *i* that is related to the cast (actors)	89.16 (141.13)
$Character_{it}$	Social media activity for episode *t* of program *i* that is related to the fictional characters	192.16 (365.59)
$Guest_{it}$	Social media activity for episode *t* of program *i* that is related to guest star appearances	18.23 (66.08)
$Production_{it}$	Social media activity for episode *t* of program *i* that is related to directors and producers	9.86 (30.03)

Table 4. Control Variables

Independent Variable	Description
$EpisodeTrend_{it}$	Control variable for the ordinal episode number (*t*) to account for trends in viewing behavior over the season
$ProgramLength_{i}$	Length of program
$Weekday_{it}$	Day the show airs (Mon-Fri vs. Saturday or Sunday)
$StartTime_{it}$	Episode start time, in 30 minute increments
Finale	Indicator variable where 1 denotes finale episode

Table 5. Frequency Table of Control Variables

Variable	Frequency (%)	Variable	Frequency (%)
Time of Day		Program Length	
8:00	32.5	30	36.02
8:30	7.7	>30	63.8
9:00	36.0	Day of Week	
9:30	6.0	Weekday	85.9
10:00	17.8	Weekend	14.1
Finale	7.9		

Figure 1: Live and Time-Shifted Viewing

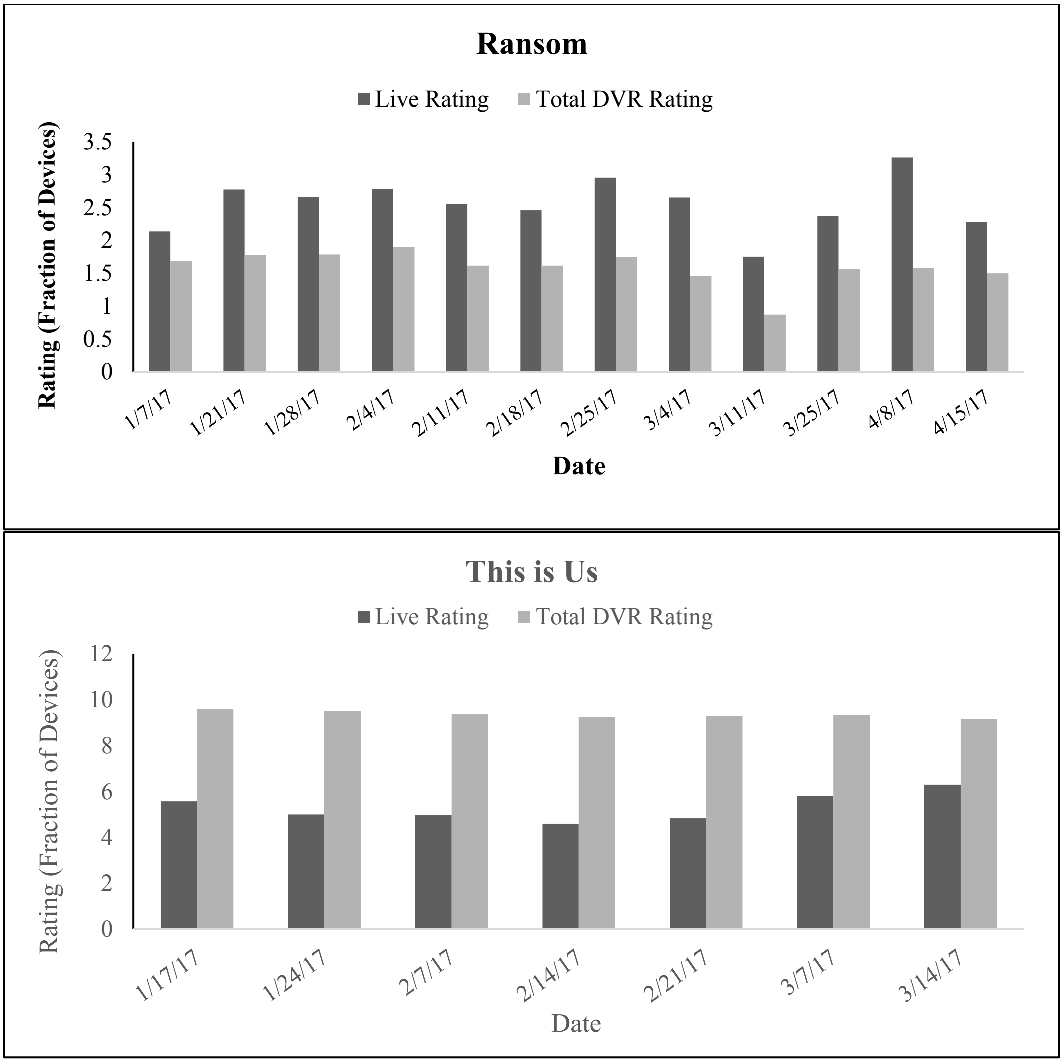
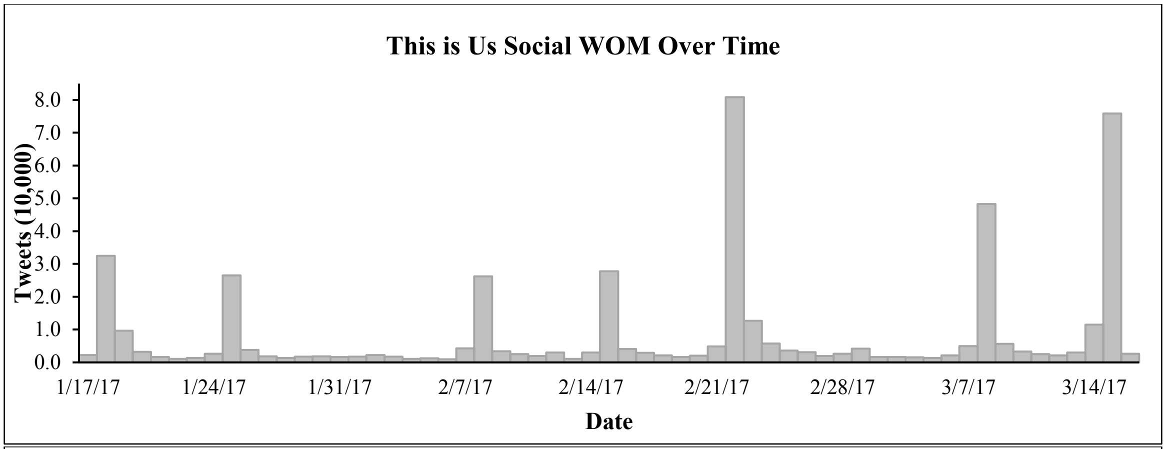


Figure 2: Social Activity for This is Us



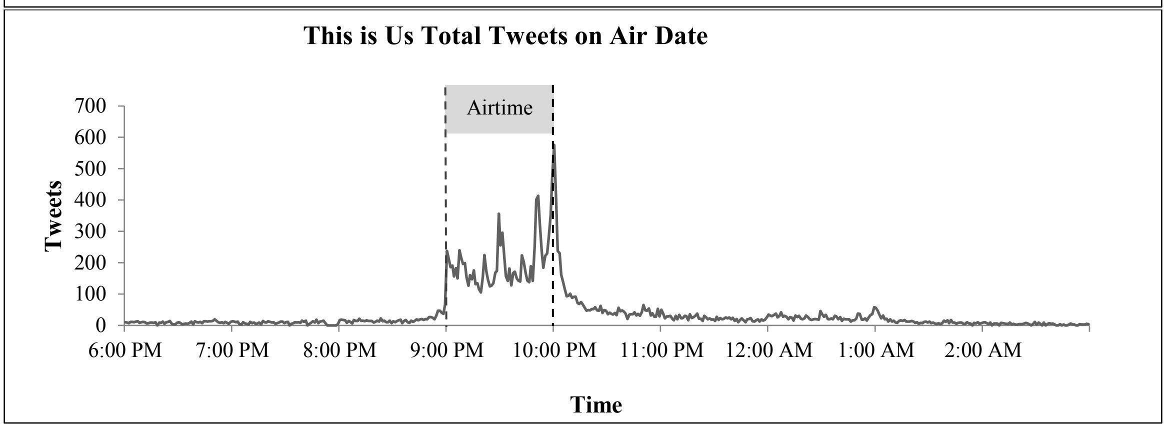
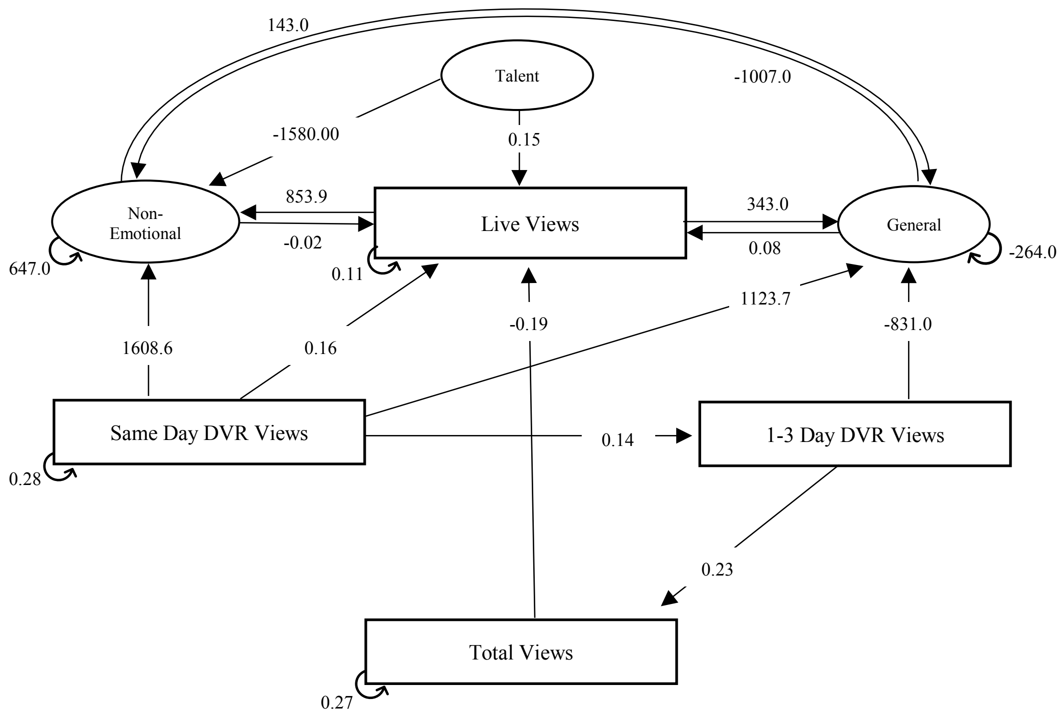


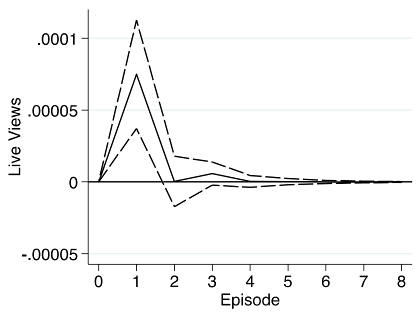
Figure 3: Summary of Notable Significant Findings Between Social TV Activity and Television Viewing



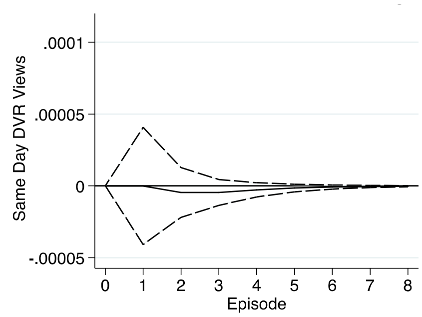
Note: Numbers represent the parameter coefficient estimates from the VAR-X model with $p<0.05$ significance levels. Ellipse denote social activity segments, boxes represent television viewing measures. Arrows reflect the direction of causal relationships indicated in the full VAR-X results. Full model results are available in Appendix A.

Figure 4: IRFs for the Impact of General and Talent Related Tweets on Timing of Television Viewing

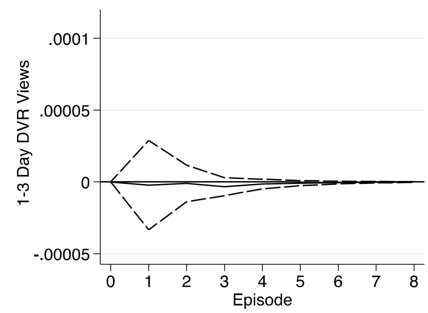
A. General Tweets on Live Views



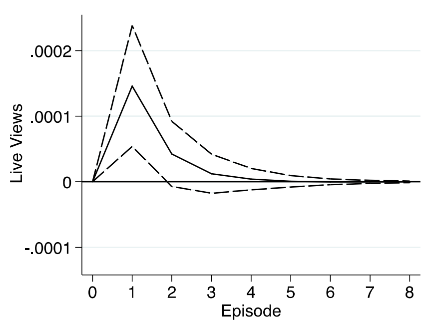
B. General Tweets on Same Day DVR Views



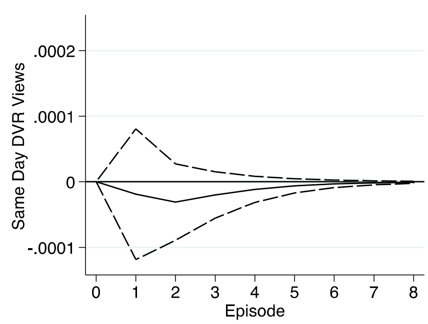
C. General Tweets on 1-3 Day DVR Views



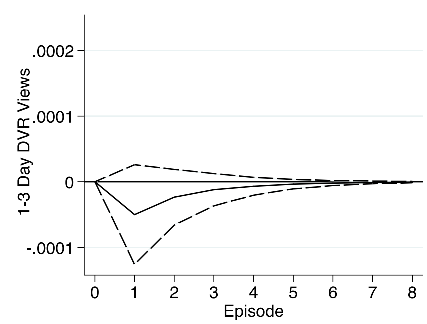
D. Talent Tweets on Live Views



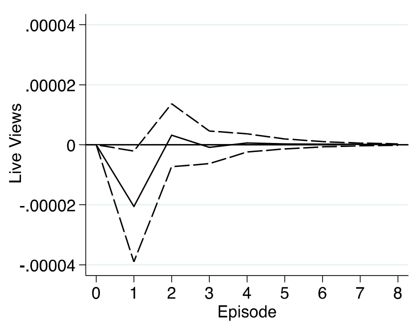
E. Talent Tweets on Same Day DVR Views



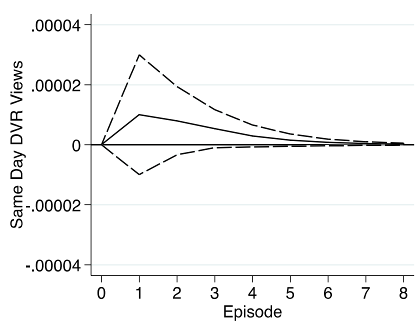
F. Talent Tweets on 1-3 Day DVR Views



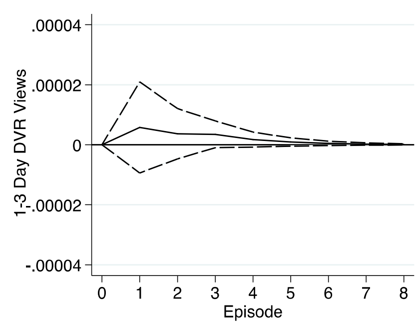
G. Non-Emotional Tweets on Live Views



H. Non-Emotional Tweets on Same Day DVR Views



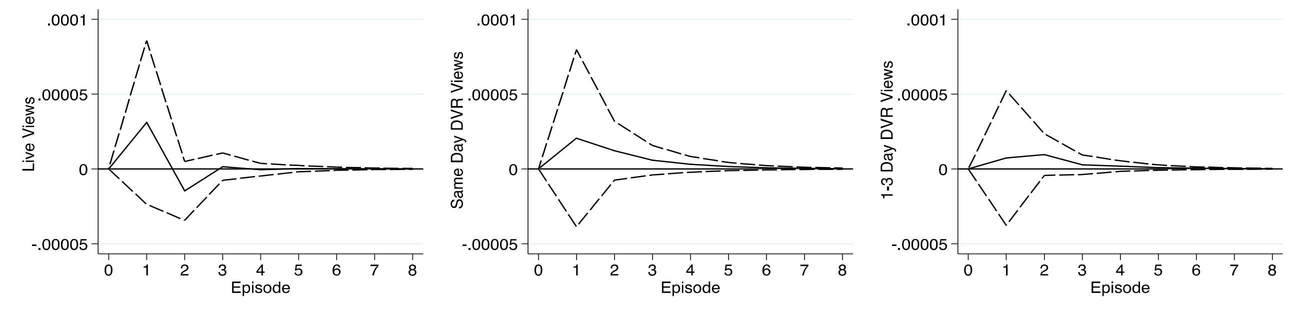
I. Non-Emotional Tweets on 1-3 Day DVR Views



Note: Solid line represents main effect and dashed line represents 90% confidence interval

Figure 5: IRFs for the Impact of Character Tweets on Television Viewing

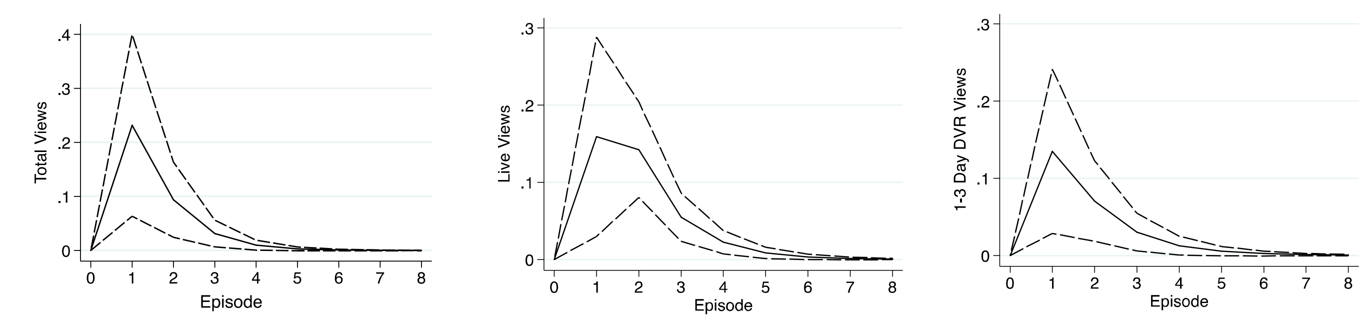
A. Character Tweets on Live Views | B. Character Tweets on Same Day DVR Views | C. Character Tweets on 1-3 Day DVR Views



Note: Solid line represents main effect and dashed line represents 90% confidence interval

Figure 6: IRFs for the Impact of Television Viewing on Television Viewing

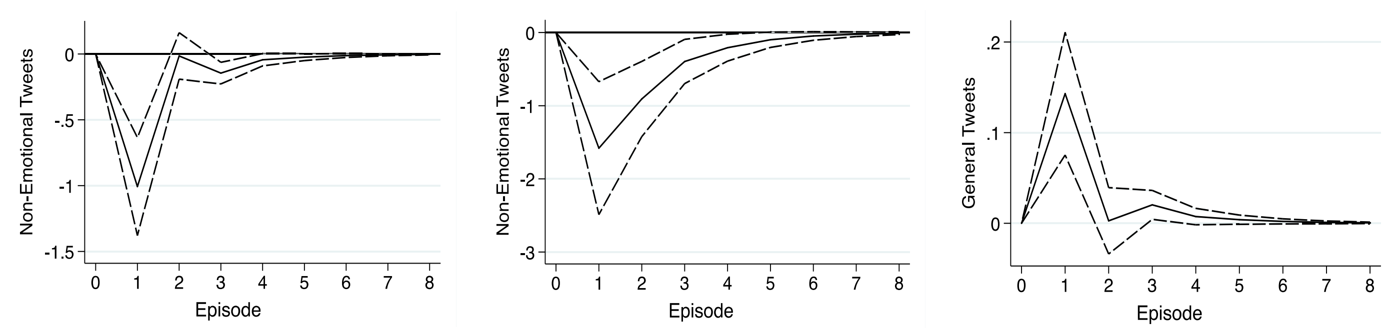
A. Impact of Shock in 1-3 Day DVR Views on Total Views | B. Impact of Shock in Same Day DVR Views on Live Views | C. Impact of Shock in Same Day DVR Views on 1-3 Day DVR



Note: Solid line represents main effect and dashed line represents 90% confidence interval

Figure 7: IRFs for the Impact of Social Activity on Social Activity

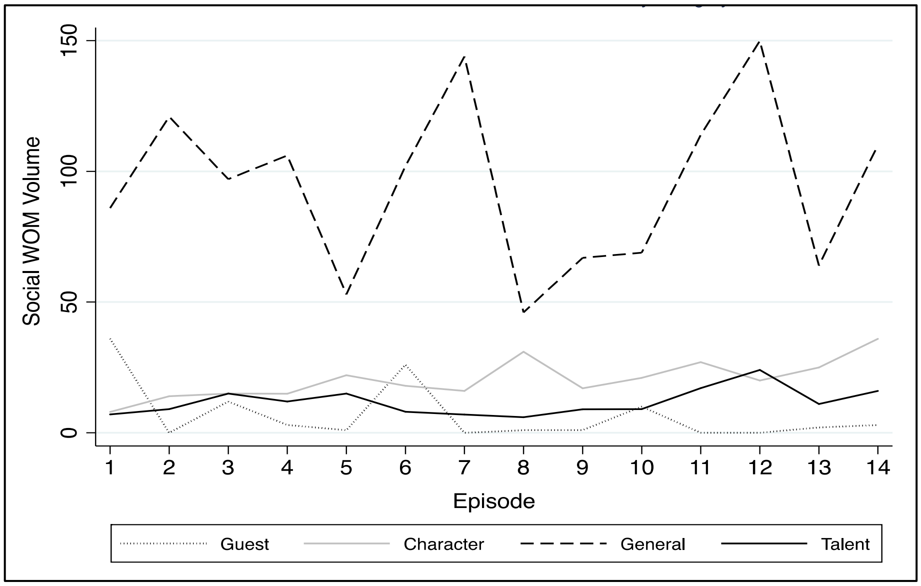
A. Impact of Shock in General Tweets on Non-Emotional Tweets | B. Impact of Shock in Talent Tweets on Non-Emotional Tweets | C. Impact of Shock in Non-Emotional Tweets on General Tweets



Note: Solid line represents main effect and dashed line represents 90% confidence interval

Web Appendix

Appendix A: Social WOM by segment for American Housewife Program



Appendix B: Panel Data VAR-X Test Results

Table 1. ADF Panel Test for Unit Roots

Ho: All panels contain unit roots	Ha: Some panels are stationary	
Number of panels = 55	Avg. number of periods = 12.44	
Variable	Statistic	p-value
Y_1	221.6027	0.0000
Y_2	206.6825	0.0000
Y_3	175.1372	0.0001
Y_4	246.8374	0.0000
Non-Emotional	205.5409	0.0000
General	226.6623	0.0000
Character	256.1238	0.0000
Talent	181.8478	0.0000
Guest	349.9011	0.0000
Production	168.593	0.0003

Table 2. Johansen Test for Cointegration

Maximum rank	Trace Statistic	Critical Value (5%)
0	1170.9894	250.84
1	874.9831	208.97
2	609.4768	170.8
3	455.2812	136.61
4	346.4755	104.94
5	262.9583	77.74
6	187.9667	54.64
7	118.8403	34.55
8	64.681	18.17
9	30.1873	3.74

Table 3.: Optimal Lag Length in Var-X Model

Lag	Bayesian Information Criterion (BIC)
0	72.022
1	71.861*
2	72.477
3	72.906
4	73.597
5	74.437

Appendix C: Granger Causality Test

Granger Causality Test

Response to	Y_1	Y_2	Y_3	Y_4	NonEmo	General	Character	Talent	Guest	Production
Y_1 (Total Views)	- -	**0.00**	0.40	**0.06**	0.51	0.12	0.80	0.31	0.76	0.54
Y_2 (Live Viewing)	0.38	- -	0.30	0.75	**0.02**	**0.01**	0.50	0.83	0.49	0.81
Y_3 (Same Day DVR)	0.13	**0.04**	- -	**0.04**	**0.04**	**0.00**	0.94	0.31	0.26	0.88
Y_4 (1-3 Day DVR)	**0.02**	0.94	0.72	- -	0.29	**0.03**	0.73	0.50	0.41	0.53
NonEmo	0.71	0.07	0.41	0.53	- -	**0.00**	**0.00**	0.76	**0.00**	**0.00**
General	0.96	**0.00**	1.00	0.91	**0.00**	- -	**0.00**	0.74	**0.00**	**0.05**
Character	0.49	0.35	0.57	0.79	0.46	0.20	- -	**0.10**	**0.00**	**0.06**
Talent	0.90	**0.01**	0.75	0.28	**0.00**	0.78	**0.00**	- -	0.81	0.25
Guest	0.77	0.65	0.15	0.17	**0.00**	**0.00**	**0.00**	**0.02**	- -	0.11
Production	0.76	0.85	0.91	0.83	0.84	0.48	0.19	**0.01**	0.54	- -

Numbers represent the p-values. The null hypothesis assumes that the variable in the left most column does not Granger cause the variable in the top row. Bold denotes p-value at the <10% significance level

Appendix D: Full panel data VAR-X Model Results

	Equations									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	y1	y2	y3	y4	noemo	general	character	talent	guest	prod
Endogenous Variables										
L.y1	0.277**	-0.188**	-0.037	-0.0643	-272.3	-239.3	-21.40	36.35	5.315	3.474
	(0.040)	(0.041)	(0.045)	(0.034)	(412.5)	(153.5)	(83.60)	(35.73)	(17.16)	(5.623)
L.y2	-0.030	0.111**	0.039	0.009	853.9*	343.0**	47.91	-6.693	10.17	1.155
	(0.035)	(0.035)	(0.0387)	(0.0295)	(353.2)	(131.4)	(71.59)	(30.60)	(14.69)	(4.815)
L.y3	-0.117	0.159*	0.281**	0.135*	1608.6*	1123.7**	-11.36	68.09	-36.55	1.541
	(0.076)	(0.078)	(0.084)	(0.064)	(774.1)	(288.0)	(156.9)	(67.06)	(32.20)	(10.55)
L.y4	0.231*	-0.007	0.040	0.123	-1093.8	-831.0*	71.49	-61.03	35.28	-8.875
	(0.102)	(0.105)	(0.113)	(0.086)	(1031.9)	(383.9)	(209.1)	(89.39)	(42.92)	(14.07)
L.noemo	-0.004	-0.020***	0.010	0.006	647.000**	143.00**	167.000**	-2.880	28.400**	5.450**
	(0.011)	(0.011)	(0.012)	(0.009)	(111.000)	(41.200)	(22.400)	(9.590)	(4.610)	(1.510)
L.genr	-0.001	0.075**	0.000	-0.002	-1007.00**	-264.00**	-260.00**	6.480	-53.400**	-6.100*
	(0.022)	(0.023)	(0.025)	(0.019)	(227.000)	(84.300)	(45.900)	(19.600)	(9.420)	(3.090)
L.charc	0.022	0.031	0.021	0.007	-241.000	-158.000	-51.500	-46.300	-55.200**	-8.380
	(0.033)	(0.033)	(0.036)	(0.027)	(328.000)	(122.000)	(66.500)	(28.400)	(13.600)	(4.470)
L.tal	-0.007	0.146**	-0.019	-0.050	-1580.000**	58.100	-597.00**	58.300	5.400	-8.710
	(0.055)	(0.056)	(0.061)	(0.046)	(553.000)	(206.000)	(112.000)	(47.900)	(23.000)	(7.530)
L.guest	-0.027	0.042	-0.146	-0.105	-4771.000**	-1037.00**	-683.00**	-187.000*	-233.000**	20.300
	(0.091)	(0.093)	(0.101)	(0.077)	(918.000)	(342.000)	(186.000)	(79.600)	(38.200)	(12.500)
L.prod	0.076	-0.048	-0.031	-0.045	494.000	661.000	-669.000	616.000**	-64.900	-102.000**
	(0.249)	(0.255)	(0.276)	(0.210)	(2515.000)	(936.000)	(510.000)	(218.000)	(105.000)	(34.300)
Exogenous Variables										
episode	-0.011**	-0.0003	-0.003	-0.006**	-11.92	-6.992	2.653	-2.539	0.0709	-0.385
	(0.001)	(0.001)	(0.001)	(0.001)	(16.74)	(6.226)	(3.392)	(1.450)	(0.696)	(0.228)
finale	-0.002	-0.029	0.116**	0.088**	971.7**	340.7**	102.8**	78.35**	14.51*	11.56**
	(0.017)	(0.017)	(0.019)	(0.014)	(176.8)	(65.78)	(35.84)	(15.32)	(7.354)	(2.410)
p1	0.014	-0.0612	-0.067	-0.050	256.0	104.1	-36.41	-87.62	-27.84	2.423
	(0.110)	(0.113)	(0.122)	(0.092)	(1110.3)	(413.0)	(225.0)	(96.18)	(46.18)	(15.14)
t1	0.174**	0.0213	0.411**	0.137**	1300.3**	334.3*	92.25	86.37*	105.2**	10.90
	(0.045)	(0.046)	(0.050)	(0.038)	(458.2)	(170.4)	(92.85)	(39.69)	(19.05)	(6.245)
t2	0.074	-0.020	0.251**	0.128**	842.1	236.0	64.62	54.51	56.01*	5.693
	(0.053)	(0.055)	(0.059)	(0.045)	(544.1)	(202.4)	(110.3)	(47.13)	(22.63)	(7.417)
t3	0.027	-0.070*	0.132**	0.008	615.5	192.0	35.41	23.33	43.16**	2.732
	(0.032)	(0.033)	(0.036)	(0.027)	(332.0)	(123.5)	(67.28)	(28.76)	(13.81)	(4.526)
t4	-0.198**	-0.157**	-0.232**	-0.135**	259.6	27.97	14.95	25.44	22.37	1.419
	(0.047)	(0.048)	(0.052)	(0.039)	(475.7)	(176.9)	(96.40)	(41.20)	(19.78)	(6.484)
wknd	-0.0896	0.143*	0.020	-0.030	-1377.3*	-509.9*	-127.6	-93.70	-42.80	-4.945
	(0.064)	(0.066)	(0.0718)	(0.0547)	(655.1)	(243.7)	(132.8)	(56.75)	(27.25)	(8.931)
ser1	0.434**	0.270*	0.452**	0.134	-1302.0	-454.3	-38.10	-38.60	12.43	-10.48
	(0.132)	(0.135)	(0.146)	(0.111)	(1329.9)	(494.7)	(269.5)	(115.2)	(55.31)	(18.13)
ser2	0.0248	-0.668**	-0.274**	-0.375**	-707.8	-277.8	-141.0	-173.3*	-100.5**	-19.83
	(0.082)	(0.084)	(0.091)	(0.069)	(835.2)	(310.7)	(169.3)	(72.35)	(34.74)	(11.39)
ser3	0.192	-0.0157	0.118	-0.127	-1692.1	-626.6	-67.92	-61.20	-5.630	-13.71
	(0.137)	(0.140)	(0.152)	(0.116)	(1385.5)	(515.4)	(280.8)	(120.0)	(57.62)	(18.89)
ser4	-0.0259	-0.462**	-0.0366	-0.195**	332.6	92.43	-4.601	-68.76	16.32	6.699
	(0.0595)	(0.0609)	(0.0658)	(0.0501)	(600.5)	(223.4)	(121.7)	(52.02)	(24.98)	(8.186)
ser5	0.278*	0.0490	0.0894	-0.111	922.8	257.1	75.26	170.0	50.66	-12.60
	(0.125)	(0.127)	(0.138)	(0.105)	(1256.2)	(467.3)	(254.6)	(108.8)	(52.25)	(17.12)
ser6	0.214**	-0.288**	-0.382**	-0.422**	-420.8	-242.4	35.47	-170.9*	-85.96*	70.33**
	(0.0828)	(0.0847)	(0.0915)	(0.0697)	(835.2)	(310.7)	(169.3)	(72.35)	(34.74)	(11.39)
ser7	0.588**	-0.254**	0.134	0.197**	1136.6	434.8	72.59	96.09	7.860	-6.853
	(0.066)	(0.067)	(0.0734	(0.055)	(670.0)	(249.2)	(135.8)	(58.04)	(27.86)	(9.133)
ser8	-0.033	-0.355**	-0.198**	-0.228**	1882.6**	1015.0**	132.6	27.72	41.93	5.864
	(0.057)	(0.059)	(0.063)	(0.048)	(582.3)	(216.6)	(118.0)	(50.44)	(24.22)	(7.938)
ser9	-0.613**	-0.159	-0.305*	-0.460**	-1977.5	-790.9	-60.43	-35.63	-38.57	-17.91
	(0.137)	(0.141)	(0.152)	(0.116)	(1387.2)	(516.0)	(281.1)	(120.2)	(57.69)	(18.91)
ser10	0.688**	-0.0435	-0.0731	-0.158*	-323.6	40.38	-47.14	-121.1	-28.30	-10.02
	(0.075)	(0.077)	(0.084)	(0.063)	(766.2)	(285.0)	(155.3)	(66.37)	(31.86)	(10.44)
ser11	0.571**	-0.346**	0.111	0.086	3517.5**	1008.1**	318.1*	53.16	50.42	116.6**
	(0.068)	(0.070)	(0.076)	(0.057)	(694.1)	(258.2)	(140.7)	(60.12)	(28.87)	(9.461)
ser12	0.564**	-0.140*	-0.034	-0.050	1429.0*	491.8*	169.2	85.62	14.70	-0.785
	(0.056)	(0.058)	(0.062)	(0.047)	(572.2)	(212.9)	(116.0)	(49.57)	(23.80)	(7.800)
ser13	0.549**	-0.314**	0.165*	0.078	908.9	186.9	151.1	35.20	31.85	-11.09
	(0.072)	(0.074)	(0.080)	(0.061)	(733.3)	(272.8)	(148.6)	(63.53)	(30.50)	(9.997)

ser14	0.580**	-0.224**	-0.137	-0.158*	2094.7**	958.7**	47.72	-69.05	-3.572	-14.66
	(0.073)	(0.075)	(0.081)	(0.062)	(744.0)	(276.8)	(150.8)	(64.45)	(30.95)	(10.14)
ser15	0.073	0.395**	0.676**	0.319**	-1722.1	-906.1	-60.00	35.78	47.60	-5.330
	(0.127)	(0.130)	(0.141)	(0.107)	(1283.4)	(477.4)	(260.1)	(111.2)	(53.38)	(17.50)
ser16	0.243**	-0.189**	-0.0486	-0.009	1553.5*	679.4**	100.5	35.22	48.09	3.128
	(0.061)	(0.062)	(0.067)	(0.051)	(619.4)	(230.4)	(125.5)	(53.66)	(25.76)	(8.444)
ser17	-0.186**	-0.068	-0.140	-0.065	582.0	137.7	29.24	-42.78	-55.13	61.70**
	(0.071)	(0.073)	(0.079)	(0.060)	(721.1)	(268.3)	(146.1)	(62.47)	(29.99)	(9.830)
ser18	-0.015	0.345**	0.072	-0.120	-2006.3	-826.6	-90.82	-25.43	-11.02	-11.71
	(0.130)	(0.133)	(0.144)	(0.109)	(1311.1)	(487.7)	(265.7)	(113.6)	(54.53)	(17.87)
ser19	-0.031	-0.323**	-0.055	-0.045	370.0	269.3	-66.32	-109.5	-102.6**	-11.68
	(0.075)	(0.077)	(0.083)	(0.063)	(765.5)	(284.8)	(155.1)	(66.31)	(31.84)	(10.44)
ser20	0.535**	-0.131	0.148	0.122*	204.1	66.93	82.87	-103.7	22.48	43.28**
	(0.070)	(0.072)	(0.078)	(0.059)	(712.9)	(265.2)	(144.5)	(61.75)	(29.65)	(9.718)
ser21	0.364**	-0.009	0.180	-0.037	-2454.0	-929.7	-100.9	-112.7	-33.93	-20.04
	(0.138)	(0.141)	(0.153)	(0.116)	(1395.2)	(519.0)	(282.8)	(120.9)	(58.03)	(19.02)
ser22	0.291*	-0.039	0.109	0.023	-2408.7	-826.1	-119.0	-122.2	-61.53	-19.20
	(0.136)	(0.139)	(0.150)	(0.114)	(1371.4)	(510.2)	(277.9)	(118.8)	(57.04)	(18.69)
ser23	0.455**	-0.213**	-0.137	-0.178**	2437.1**	505.1	-24.72	229.2**	-40.33	-22.63*
	(0.072)	(0.074)	(0.080)	(0.061)	(733.3)	(272.8)	(148.6)	(63.52)	(30.50)	(9.997)
ser24	0.224**	-0.441**	-0.160	-0.200**	248.9	-52.17	141.7	74.87	-71.51*	-21.82
	(0.081)	(0.083)	(0.089)	(0.068)	(818.3)	(304.4)	(165.8)	(70.89)	(34.03)	(11.16)
ser25	0.502**	0.243	0.538**	0.241*	-982.6	-307.9	-37.48	-16.04	18.50	-6.860
	(0.132)	(0.135)	(0.146)	(0.111)	(1333.9)	(496.2)	(270.3)	(115.6)	(55.48)	(18.18)
ser26	0.195*	-0.098	-0.112	-0.094	-993.7	-391.1	12.85	-87.81	-77.72*	5.533
	(0.076)	(0.078)	(0.084)	(0.064)	(774.8)	(288.2)	(157.0)	(67.11)	(32.22)	(10.56)
ser27	0.517**	-0.149*	0.286**	0.148**	430.6	131.9	88.30	0.384	26.56	-2.581
	(0.058)	(0.059)	(0.064)	(0.049)	(587.3)	(218.5)	(119.0)	(50.88)	(24.43)	(8.006)
ser28	0.293*	0.201	0.320*	0.00144	-2317.7	-943.4	-107.8	-79.55	-11.72	-13.08
	(0.139)	(0.142)	(0.154)	(0.117)	(1400.9)	(521.1)	(283.9)	(121.4)	(58.26)	(19.10)
ser29	0.354**	-0.219	-0.058	-0.192	-610.2	-111.8	6.899	-35.32	9.411	-13.50
	(0.133)	(0.136)	(0.147)	(0.112)	(1342.8)	(499.5)	(272.1)	(116.3)	(55.85)	(18.31)
ser30	0.468**	0.065	0.521**	0.184	-1075.9	-463.0	-30.34	-24.96	44.47	-7.143
	(0.126)	(0.129)	(0.140)	(0.106)	(1273.2)	(473.6)	(258.0)	(110.3)	(52.95)	(17.36)
ser31	0.802**	-0.164	-0.0370	-0.166*	-737.2	-318.8	109.9	-83.94	-75.04*	-15.90
	(0.091)	(0.093)	(0.101)	(0.076)	(919.0)	(341.9)	(186.3)	(79.61)	(38.22)	(12.53)
ser32	0.590**	-0.080	0.0968	0.022	-208.4	-423.7	344.8*	13.06	6.920	-3.435
	(0.069)	(0.071)	(0.077)	(0.058)	(702.4)	(261.3)	(142.4)	(60.85)	(29.21)	(9.575)
ser33	0.582**	-0.134*	-0.136	-0.078	824.0	476.2*	31.90	-42.87	-1.962	-7.970
	(0.063)	(0.065)	(0.070)	(0.053)	(643.2)	(239.3)	(130.4)	(55.72)	(26.75)	(8.768)
ser34	-0.415**	-0.112	-0.246	-0.343**	-1948.9	-784.3	-56.04	-48.25	-25.43	-16.68
	(0.137)	(0.140)	(0.151)	(0.115)	(1378.6)	(512.9)	(279.4)	(119.4)	(57.34)	(18.79)
ser35	-0.103	-0.239**	-0.426**	-0.386**	5934.4**	1959.8**	1098.3**	279.7**	54.61	-15.51
	(0.077)	(0.079)	(0.085)	(0.065)	(780.8)	(290.5)	(158.2)	(67.64)	(32.47)	(10.64)
ser36	-0.400**	0.566**	0.257	-0.044	-2646.2	-1304.5*	-107.5	3.463	-16.22	-12.29
	(0.144)	(0.148)	(0.159)	(0.121)	(1454.8)	(541.2)	(294.8)	(126.0)	(60.51)	(19.83)
ser37	-0.138*	-0.042	-0.140*	-0.088	-1119.1	-402.6	-65.57	-79.75	-50.31	-8.038
	(0.062)	(0.063)	(0.068)	(0.052)	(627.5)	(233.4)	(127.2)	(54.36)	(26.10)	(8.554)
ser38	-0.972**	-0.669**	-0.208*	-0.142*	-221.8	-147.5	3.400	3.132	-30.37	-1.536
	(0.084)	(0.086)	(0.093)	(0.0713)	(854.2)	(317.8)	(173.1)	(74.00)	(35.53)	(11.64)
ser39	-0.349**	-0.454**	-0.242**	-0.134*	-588.8	-454.6	-31.00	113.8	-81.90**	-14.48
	(0.075)	(0.076)	(0.082)	(0.063)	(756.6)	(281.5)	(153.3)	(65.54)	(31.47)	(10.31)
ser40	0.486**	-0.195**	-0.032	-0.062	832.0	540.7*	70.49	-72.30	14.58	-6.301
	(0.060)	(0.061)	(0.066)	(0.051)	(610.8)	(227.2)	(123.8)	(52.91)	(25.40)	(8.326)
ser41	0.409**	-0.317**	-0.098	-0.054	3025.1**	1182.4**	171.3	169.8**	28.47	-5.549
	(0.063)	(0.065)	(0.070)	(0.053)	(644.6)	(239.8)	(130.6)	(55.84)	(26.81)	(8.787)
ser42	-0.426**	-0.290**	-0.297**	-0.125*	365.4	200.3	-7.586	-12.51	-22.50	-7.486
	(0.068)	(0.070)	(0.075)	(0.057)	(690.4)	(256.8)	(139.9)	(59.80)	(28.71)	(9.411)
ser43	0.062	-0.337**	-0.065	-0.085	11201.5**	3032.9**	670.5**	381.7**	78.37	-29.01*
	(0.100)	(0.102)	(0.111)	(0.084)	(1009.1)	(375.4)	(204.5)	(87.41)	(41.97)	(13.76)
ser44	0.177	0.391**	0.359*	0.127	-1928.5	-940.4	-59.36	31.29	-5.502	-9.796
	(0.130)	(0.133)	(0.144)	(0.110)	(1314.4)	(488.9)	(266.4)	(113.9)	(54.67)	(17.92)
ser45	-0.123	0.092	0.094	-0.064	-2483.3	-970.1	-111.7	-77.85	-51.13	-17.00
	(0.134)	(0.138)	(0.149)	(0.113)	(1356.3)	(504.6)	(274.9)	(117.5)	(56.41)	(18.49)
ser46	0.305**	0.215**	0.0191	-0.0983	-1.419	-86.36	-33.61	-1.525	-4.086	-9.397
	(0.059)	(0.061)	(0.066)	(0.050)	(602.4)	(224.1)	(122.1)	(52.19)	(25.06)	(8.212)
ser47	-0.800**	-0.646**	-0.408**	-0.345**	2630.1**	980.3**	554.0**	40.03	-28.99	-2.085
	(0.088)	(0.0905	(0.097)	(0.074)	(892.2)	(331.9)	(180.8)	(77.29)	(37.11)	(12.16)
ser48	0.862**	-0.224	0.0183	-0.137	-1544.1	-423.4	-53.12	-144.9	-60.78	-23.17
	(0.146)	(0.149)	(0.161)	(0.123)	(1470.9)	(547.2)	(298.1)	(127.4)	(61.17)	(20.05)

ser49	0.457**	-0.500**	-0.205**	-0.146**	1781.1**	778.0**	66.14	19.02	-14.35	-5.360
	(0.064)	(0.066)	(0.071)	(0.054)	(653.3)	(243.0)	(132.4)	(56.59)	(27.17)	(8.906)
ser50	0.115	-0.0904	-0.0891	-0.104*	383.5	234.6	-36.66	-73.55	-6.266	-8.291
	(0.060)	(0.062)	(0.067)	(0.051)	(611.3)	(227.4)	(123.9)	(52.95)	(25.42)	(8.333)
ser51	0.315*	0.483**	0.632**	0.197	-1678.7	-874.3	-25.49	31.00	44.30	-7.635
	(0.128)	(0.131)	(0.141)	(0.108)	(1288.7)	(479.4)	(261.2)	(111.6)	(53.60)	(17.57)
ser52	-0.115	-0.552**	0.159	-0.134	-346.2	-236.5	24.62	39.32	40.40	-6.810
	(0.127)	(0.130)	(0.141)	(0.107)	(1283.1)	(477.3)	(260.0)	(111.2)	(53.37)	(17.49)
ser53	-0.059	0.474**	0.487**	0.109	-1843.0	-774.3	-66.41	-22.53	26.83	-9.061
	(0.137)	(0.140)	(0.152)	(0.115)	(1383.2)	(514.5)	(280.3)	(119.8)	(57.53)	(18.85)
ser54	0.878**	-0.618**	0.0104	-0.0207	8618.0**	3385.4**	1486.3**	427.2**	-24.48	24.30
	(0.100)	(0.102)	(0.111)	(0.084)	(1009.3)	(375.5)	(204.5)	(87.43)	(41.98)	(13.76)
_cons	-2.354**	-0.373*	-0.0879	0.835**	443.4	114.1	-101.8	256.5	-26.10	26.03
	(0.165)	(0.169)	(0.183)	(0.139)	(1665.8)	(619.7)	(337.6)	(144.3)	(69.28)	(22.71)
Parms	73	73	73	73	73	73	73	73	73	73
RMSE	0.133	0.128	0.138	0.106	1211.890	448.064	237.140	104.606	56.222	21.105
R-sq	0.950	0.881	0.854	0.779	0.839	0.759	0.728	0.577	0.371	0.613
chi2	12952.190	5045.647	3991.660	2399.906	3551.688	2155.767	1826.462	930.064	402.408	1080.616
P>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	684									
Log likelihood	=	-22617.56		AIC	=	68.368				
FPE	=	2.35E+17		HQIC	=	70.240				
Det(Sigma_ml)	=	2.75E+16		SBIC	=	73.206				

Standard errors in parentheses. Social WOM variables (Noemo, General, Character, Talent, Guest, Prod) have been transformed x 1000. * p<0.05, ** p<0.01, *** p<0.10