Distribution Agreement

Measuring Consumers' Emotional Engagement via Firm and User Generated Content on Social Media

By

Buffy Mosley
Doctor of Philosophy

Business

____
David Schweidel, Ph.D.
Advisor

____
Panagiotis Adamopoulos, Ph.D.
Committee Member

____
Michelle Andrews, Ph.D.
Committee Member

____
Ryan Hamilton, Ph.D.
Committee Member

Accepted:

____
Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

____
Date

Measuring Consumers' Emotional Engagement via Firm and User Generated Content on Social Media

By

Buffy Mosley
M.B.A, Georgia State University, 2013

Advisor: David Schweidel, Ph.D.

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2020

Abstract

Measuring Consumers' Emotional Engagement via Firm and User Generated Content on Social Media

By Buffy Mosley

Brands have begun to embrace social media and develop branded social media pages to disseminate content and engage with consumers. Using the content of social media posts, this research explores the influence of emotionality of user-generated content (UGC) and firm-generated content (FGC) on marketing outcomes.

The first essay explores user-generated textual content surrounding brand crisis events to understand how the event affects consumers' perceptions of the brand. Consumers' language before and after distinct events is assessed to evaluate the effect of the event on the emotionality of their posts. The extent to which consumers have interacted with the brand's Facebook page prior to the event and the strength of the brand are incorporated into the analysis. Results show that brands experience a significant increase in negative emotional content after brand crises, but that brand familiarity and strength mitigate this shift. Comments from consumers who have engaged with the brand prior to the event include less negative language than comments from consumers posting on the brand's page for the first time after the event.

The second essay extends beyond the emotionality of textual content to consider the emotionality of visual content. I investigate the individual and combined effects of the emotionality of both text and visual components of firm-generated content (FGC) on consumer engagement within branded Facebook posts. Results show that the extent to which the two elements are (in)congruent can influence the number of consumer comments to firm-generated content and their emotional valence. Results indicate that a moderate mismatch between the emotional valence of the text and visual content can increase engagement for FGC. Conversely, results show that a complete mismatch between the emotional valence of text and visual elements decreases consumer engagement. Notably, brand personality mitigates this effect.

Finally, the third essay examines the effect of emotionality of social WOM on marketing outcomes external to the social WOM domain – television consumption. Using narrative transportation as a conceptual framework, social TV activity is segmented along two dimensions: emotional valence (positive and negative) and content focus (fiction and nonfiction). I find evidence that heterogeneity among the types of social TV activity influences television consumption differently.

Measuring Consumers' Emotional Engagement via Firm and User Generated Content on Social Media

By

Buffy Mosley
M.B.A, Georgia State University, 2013

Advisor: David Schweidel, Ph.D. Marketing

A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy
in Business
2020

Table of Contents

List of Tables

List of Figures

List of Appendices

INTRODUCTION

Given the proliferation of social media use, research in social media and online word of mouth (WOM) has grown over the years. Researchers have demonstrated that WOM can influence firm performance indicators such as sales (Liu 2006), television ratings (Godes and Mayzlin 2004), stock market performance (Tirunillai and Tellis 2014), and product adoption (Trusov et al. 2009). Others have investigated posting behavior of users (Moe and Schweidel 2012) and network effects within social media (Goldenberg et al. 2012). Social media WOM has become an important part of brand equity in terms of helping to build awareness, increase sales, and understand consumers' sentiments towards brands. Considering the influence of social media WOM on market performance, it is crucial for brands to understand how social media can be used to enhance marketing strategies.

Social media provides consumers with a platform on which to voice their opinions of brands while providing brands with information about consumers. Following brand crisis events such as product recalls or social/product failures, social media can become inundated with millions of emotional comments about the incident. For example, many commenters suggested Nike be boycotted following its recent launch of its 30th anniversary marketing campaign featuring controversial athlete Colin Kaepernick (Ladd 2018). However, in the days following the event, Nike's online sales grew by more than 30% (Berr 2012). Conversely, a recent marketing campaign by Pepsi featuring Kendall Jenner resulted in the brand cancelling the advertisement and issuing a formal apology within 24 hours due to the backlash on social media (Zipkin 2017). Similarly, cancelled television shows have been renewed due to an overwhelming show of support from viewers' emotionally charged social media posts. Given the consequences of social media WOM, what can brands learn from the emotionality of consumers' social media activity? Chapter 1 of my research examines the emotionality of user-generated textual content on social media surrounding brand crisis events. Chapter 2 extends beyond the emotionality of textual content to provide a method for measuring the emotionality of visual elements. Chapter 2 investigates the (mis)alignment between the emotionality of textual and visual content to determine how it influences consumer engagement and subsequent emotional responses. Chapter 3 explores how the emotionality of user-generated (social TV) content can influence marketing outcomes such as television ratings.

Chapter 1 investigates the emotionality of social media comments before a brand crisis event compared to the emotionality of comments after the event to assess the impact of the crisis on consumers' perceptions. Previous social media literature has analyzed consumer perceptions using social media content (e.g. Culotta and Cutler 2016; Tirunillai and Tellis 2014; Schweidel and Moe 2014; Netzer et al. 2012; Lee and Bradlow 2011). However, these works do not account for heterogeneity among respondent population. In my first chapter, I use an event study approach to understand how consumers' perceptions of brands shift after a major brand crisis. Using data collected via Facebook's API, I employ text analysis to capture the emotions expressed in over 120,000 user comments on the brand pages before and after critical events. I account for user heterogeneity by making a distinction between users who had engaged with the brand prior to the event and those who posted after the event for the first time. I incorporate a measure of brand strength to assess how brand strength may moderate the emotionality of consumer responses.

Results show that users who have engaged with the brand on Facebook (both before and after the event) express less negative emotion – particularly less anger – after the event compared to those who only comment on the brand's Facebook page after the event. These findings highlight the importance of understanding the composition of the social media contributor base in the wake of a brand crisis, as not all consumers will react to the crisis in the same way.

Chapter 2 examines firm-generated content on social media to determine how brands can create content that influences consumer engagement and the emotionality of subsequent comments to the brand's post. Chapter 2 extends beyond textual content to explore the use of images, specifically faces within images, to determine how the text and visual content elements of firm-generated content drive consumer engagement. The proliferation of social media platforms such as Instagram, Pinterest and Snapchat, which are dominated by images, presents an unknown area in our understanding of online WOM. This is an area of vast potential for firms and marketers, yet our knowledge of the effects of image content is limited. Using facial expressions within visual content to capture emotional valence of images, I analyze the individual and combined effects of textual and visual components of firm-generated content on consumer engagement. The results suggest that a complete mismatch between the emotional valence of text and imagery within firm-generated content can decrease consumer engagement and that brand personality can moderate this negative effect. This knowledge contributes to the advancement of marketing by (1) addressing the gap in the research related to the impact of images within online WOM; (2) demonstrating a method to capture emotional valence using faces that can be utilized by marketing managers with relative ease; and (3) extending the knowledge of print advertising to a digital media context.

Chapter 3 examines social media activity relating to television programs. The television viewing landscape has undergone significant technological changes in recent years with the increase in digital video recorder (DVR) use 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, I investigate how the content of social media chatter about television programs affects the size of the total viewing audience and the times that viewing occurs.

I analyze 55 scripted television programs that aired in the winter 2017 season and collect tuning data corresponding to 684 individual episodes airing for the first time. TV viewing data is paired with minute-by-minute data on social TV activity occurring on Twitter pertaining to a given television program. Drawing on narrative transportation theory, I segment social TV activity along two dimensions: emotional valence (positive, negative) and content focus (fiction, non-fiction). I find evidence that heterogeneity among the types of social TV activity influences TV consumption differently. Positive emotionally valenced posts about the fictional elements of the program (e.g. characters in the program) positively impact total viewership and the fraction of devices that engage in earlier time-shifted DVR viewing. Positive emotionally valenced posts about nonfictional elements (e.g. actors) have a negative impact on total viewership, while negative emotionally valenced nonfictional posts have a positive impact on the fraction of live views compared to DVR time-shifted views. These results provide insight for networks and content creators crafting digital marketing strategies.

Collectively, my research enhances the understanding of the emotionality of social media activity, and to the knowledge of online firestorms and social TV activity. Additionally, this research contributes to our understanding of how the emotionality of user-generated content offers a more nuanced view of consumers' multifaceted responses. Given this knowledge, there is no "one size fits all" solution when developing digital content, and marketers should consider brand attributes when crafting digital marketing campaigns.

Chapter 1

Emotionality of User Generated Content: Outrage or Indifference? The Moderating Roles of Brand Familiarity and Strength on Social Media Content Emotionality Following Brand Crises

INTRODUCTION

#BoycottNike and #BurnItNow were among the top trending social media handles after Nike launched its 30th anniversary marketing campaign featuring controversial athlete Colin Kaepernick (Ladd 2018). Social media was inundated with millions of comments about the Nike brand after the polarizing campaign launch, with some suggesting that Nike be boycotted and others supporting the brand's decision (Dudharejia 2018). In the days following the launch, Nike stock price fluctuated, online sales grew by more than 30% and some suggested the brand was in crisis as a result of the campaign (Berr 2018). Similarly, Pepsi's launch of its campaign featuring Kendall Jenner generated a significant amount of social media buzz resulting in the company retracting the advertisement and issuing an apology within 24 hours (Zipkin 2017). Anecdotally, marketers have suggested that Nike's ad campaign was a calculated risk and that the brand could withstand any criticism it received (Pearl 2018). Others suggested that the ad campaign was consistent with Nike's brand perception among target consumers (Pearl 2018). Marketers recognize that consumer attitudes and brand evaluations are critical ingredients of brand equity (Keller 1993). Damaging information about brands can have severe consequences for brands, as rebuilding trust is difficult (Nooteboom et al. 1997).

Social media provides consumers with a platform from which to voice their opinions of brands. Researchers have shown that online word of mouth (WOM) can influence sales (e.g. Kumar et al. 2016, Chevalier and Mayzlin 2006, Liu 2006, Moe and Trusov 2011), television ratings (e.g. Godes and Mayzlin 2004) and product adoption (e.g. Trusov et al. 2009). Given the documented influence of online WOM on market performance, it is critical for brands to monitor consumers' social media posts to gauge how perceptions may be shifting. An increasing stream of social media literature explores consumer perceptions using social media (e.g. Culotta and Cutler 2016; Tirunillai and Tellis 2014; Schweidel and Moe 2014; Netzer et al. 2012; Lee and Bradlow 2011). Brand crises, such as product recalls (e.g. Cleeren et al. 2013; Borah and Tellis 2016) and product or social failures (e.g. Hansen et al. 2018), may arise suddenly and affect the way in which consumers interact with the brand on social media.

In light of the considerable volume of social media posts surrounding such brand-related events, what can brands hope to learn from consumers' social media activity? While popular social media listening platforms report volume and the average sentiment over time, such metrics fail to distinguish among contributors. Despite the increasing research utilizing social media, limited work decomposes the aggregated measures into contributions from different segments of the social media contributor base. That is, heterogeneity among the social media contributor base (e.g. Winer and Fader 2016) is typically ignored. As a result, even if brands observe fluctuations in volume or sentiment, they are limited in their ability to discern if such fluctuations warrant concern. In the cases of Nike and Pepsi mentioned earlier, did consumers who had previously engaged with the brand differ from those who were posting on the brand's Facebook page for the first time? Assessing how different groups of consumers react to brand-related events, whether they be positive or negative, is critical information as brands seek to engage with these groups over time.

In this research, an event study approach is employed to understand how consumers respond to brands on social media in the wake of major brand-related events. Using data collected via Facebook's API, we employ text analysis to capture the emotions expressed in over 120,000 user comments on the brand pages before and after critical events. With access to data on consumer comments from the time the brands created their Facebook pages, we distinguish between users who had engaged with the brand prior to the event and those who post after the event for the first time. Drawing on the brand equity literature, we also examine how brand strength may moderate emotionality of consumers' social media posts following brand crises.

Results indicate that both brand strength and consumers' brand familiarity (as inferred from their prior interaction with the brand's Facebook page) impact the emotionality expressed in Facebook comments. We find that consumer posts on brands' Facebook pages are more negative, marked by higher levels of comments containing anger and a significant decrease in posts containing joy, after brand crises. However, the increase in negativity is mitigated by consumers' past interactions with the brand on Facebook, resulting in less negativity in the posts from these consumers compared to their posts from before the brand crisis. This indicates the importance of brands considering the composition of their contributors when determining how best to react to online comments in the wake of a brand crisis, as not all consumers will react to the crisis in the same way. We also find that brand strength moderates the way in which consumers react to a brand crisis. Following a brand crisis, the comments posted to the Facebook pages of strong brands contain less anger and more joy compared to the comments posted to the pages of weaker brands, suggesting that brand strength can aid a brand in times of crisis.

The remainder of this article is structured as follows. We review the literature related to the social media word of mouth and brand crisis. We then discuss how consumers' familiarity with a brand and brand strength may moderate the effects of a brand crisis on consumers' brand-related social media activity. Next, the data used in the analysis id discussed along with model free evidence supporting the difference in emotionality before and after an event. We present our empirical analysis and discuss the findings. Lastly, we discuss the managerial implications and limitations of our research.

RELATED LITERATURE

Our research explores the emotions that consumers express in social media posts to understand how brand crisis events may shift consumer perceptions. Drawing on the brand equity literature, we incorporate measures such as consumers' familiarity with the brand and brand strength to investigate the degree to which firms can insulate themselves from the consequences of a brand crisis. Our work draws on three streams of literature: social media, brand crises, and brand familiarity and strength. First, we provide a review of social media literature highlighting research that focuses on emotions, then review the literature related to brand crises and negative publicity resulting from brand crises. Lastly, we detail the anticipated moderating impact of overall brand strength and familiarity on how consumers react to brand crises.

Emotionality in Social Media Posts

Given the proliferation of social media use, research in social media and online WOM has grown over the years. Researchers have shown that WOM can influence firm performance indicators such as sales (Chevalier and Mayzlin 2006; Liu 2006; Moe and Trusov 2011), television ratings (Godes and Mayzlin 2004), stock market performance (Tirunillai and Tellis 2014), and product adoption (Trusov et al. 2009). Others have investigated posting behavior of users (Moe and Schweidel 2012; Godes and Silva 2012; Toubia and Stephen 2013) and network effects within social media (Mayzlin and Yoga 2012; Watts and Dodds 2007; Trusov et al. 2010; Goldenberg et al. 2012).

A growing stream of research using social media data focuses on capturing consumer perceptions from digital text. Lee and Bradlow (2011) use online product reviews to derive market structure based on consumer perceptions. Similarly, Netzer et al. (2012) use consumer online forums and text mining techniques to derive market structure using consumer co-mentions of brands. They propose a method of verifying consumer brand perceptions. Tirunillai and Tellis (2014) use Latent Dirichelet Allocation (LDA) to capture brand quality perceptions over time. Schweidel and Moe (2014) demonstrate that social media data can be used to derive a measure of brand health, demonstrating the importance of accounting for the variation in comments that exist across social media venues. Arvidsson and Caliandro (2016) extend the notion of brand communities (Muniz and O'Guinn 2001) to the social media space by introducing the notion of brand publics that facilitate brand-related conversations among consumers. Packard et al. (2018) examine pronoun use by firm agents and find that agents' use of "we" rather than "I" increases customer satisfaction and purchasing. Humphreys and Wang (2018) provide a roadmap for the use of automated text analysis to aid in consumer research, and Berger et al. (2020) discuss the opportunities that text analysis provides for marketing academics trained in various disciplines to find common ground.

In addition to the content of social media posts, research has also focused on the valence of social media posts. Chevalier and Mayzlin (2006) show that negative reviews have greater impact than positive reviews. Similarly, Luo (2007) find that consumer complaints have a negative impact on firm's stock market performance. Shin et al. (2010) find that positive and negative buzz are leading indicators of price fluctuations. While valence offers a convenient summary, it can be a coarse operationalization of consumers' multifaceted attitudes.

To alleviate this concern, researchers have begun using more granular measures of emotionality to provide increased nuance to their analysis. Earlier work in consumer behavior and psychology produced an extensive body of literature examining the influence of emotions on consumer judgement and behavior (Pham 2004; Cohen et al 2008; Forgas 1995; William and

Aaker 2002). Researchers showed that opposing emotional valences, positive (e.g. happiness) vs. negative (e.g. sadness), have different impacts on consumer's cognition. A phenomenon known as affect congruency suggests that consumers' evaluative judgements are congruent with their current affect resulting in positive (negative) evaluations when consumers engage in positive (negative) affect (Forgas 1995; Pham 1998). This has been found to apply to different product categories (Gorn et al. 1993), brand extension evaluations (Yeung and Wyer 2005), advertisements (Murry and Dacin 1996), and consumption choices (Pham 1998). Research has also explored specific emotions of the same valence and found that different emotions of the same valence (e.g. anger and sadness) can result in different outcomes (Lerner et. al 2004). Several studies have revealed variations in cognitive processing among different emotional states. For example, sadness offers systematic cognitive processing while anger and joy favor heuristic information processing (Corson and Verrier 2007). Joy, disgust, anger and surprise have implications for customer satisfaction (Westbrook and Oliver 1991). Anger has been linked to a desire for punitive damages, retaliation, negative word of mouth, and optimistic judgments while fear induces greater risk aversion and pessimistic judgments (Gregoire and Fisher 2008; Schawrtz 2000).

More recently, researchers have examined the two dimensions of emotions: arousal (high and low) and valence (positive and negative). Heath et al. (2001) explored emotionality in the context of the urban legend and found that content which aroused emotions (particularly emotions related to interest, surprise, joy and disgust) was more popular. Berger and Milkman (2012) examine which type of emotion gets shared more and find evidence that emotional content indicative of high arousal (awe, anger, and anxiety) is shared more. Berger (2011) examines high emotional arousal (amusement and anxiety) and high physical arousal and find that physiological arousal drives information transmission. Ludwig et. al (2013) find a strong positive effect of higher levels of affective content in consumer reviews on conversion rates. Yin et al. (2014) finds that online reviews with more anger are perceived to be more helpful.

The analysis of the emotionality of consumers' social media posts in the wake of a brand crisis may offer brands a method to assess consumers' responses to the situation. We explore the specific emotions that are expressed in social media responses from consumers at the time of brand-related crises. Consistent with prior research, in addition to examining the effect of the brand crises on positive and negative emotions, we also examine high-arousal emotions of positive and negative valence (e.g. anger, disgust, joy[1] and surprise).

Brand Crises

Brand crises resulting from adverse events can have serious repercussions for the brand in terms of how it is viewed by consumers. A brand crisis is defined as "an event that threatens a corporate's reputation and therefore its future" which includes accidental, intentional, and uncontrollable events (Lerbinger 2012). Brand crises have received attention among marketers and practitioners as the consequences impact firms' financial performance (Chen et al. 2009; Cleeren et al. 2008; van Heerde et al. 2007), brand equity (Ahluwalia 2000; Dawar and Pillutla 2000), advertising effectiveness (Cleeren et al. 2013), and ultimately consumer buying decisions. Researchers have also investigated the various characteristics of brand crises such as blame attribution, firm response, and negative publicity. Blame literature explores how consumers attribute blame in light of product harm crisis and how firms should respond (Yin et al. 2016; Lei et al. 2012). Other researchers have examined how firms should respond in brand crisis and the conditions under which firms should accept blame and apologize (Dawar and Pilluutla 2000).

Negative publicity arising from brand crises has been explored extensively. The negativity effect, whereby consumers weigh negative information more heavily than positive information, can affect consumers' perceptions of the brand (Aaker and Keller 1990; Lane and Jacobson 1995). Researchers have shown that extremely negative information is considered more diagnostic and interesting (Herr et al. 1991). Negative publicity can also damage brand equity, credibility, and reduce consumer product evaluations (Lei et al. 2008). The implications of negative publicity have been explored in various contexts. Chevalier and Mayzlin (2006) show that negative online book reviews influence subsequent sales and Chen et al. (2009) show that negative third-party reviews impact stock returns. We expect that the negative publicity from a brand crisis will manifest as an increase in the negative emotions expressed by consumers in their brand-related social media posts.

Recent research has also probed how brand crises emerge in digital media. Pfeffer et al. (2014) define online firestorms as an abrupt increase in primarily negative messages toward a brand. The authors highlight the potential for large volumes of messages to disseminate rapidly on digital media platforms, suggesting that this type of brand crisis is important to marketers. Hansen et al. (2018) investigate social media firestorms specifically and find both short- and long-term effects of social media firestorms on consumer's brand perceptions, emphasizing that strong heterogeneity exists across firms. Borah and Tellis (2016) argue that social media are a vital part of the product recall process and find evidence of a spillover effect of negative chatter about a brand onto other brands in the same product category. Hsu and Lawrence (2016) investigate product recall announcements' impact on stock performance to find that product recalls have a negative impact on the firm and that volume and valence of online WOM intensifies this negative effect. They find that strong brand equity mitigates the negative impact of the volume and valence of online WOM. Herhausen et al (2019) use a top-down approach to examine the negative emotions within consumer posts on social media and offer mediation strategies to help brands prevent online firestorms.

In this research, we move beyond emotional valence to investigate high arousal emotions (e.g. joy, anger, disgust, surprise) that consumers express in their social media posts following brand-related crises. To the best of our knowledge, this research is among the first to consider the effect of a consumer's familiarity with the brand as a potential moderator of how consumers react to a brand crisis, thereby considering the role of poster heterogeneity and the composition of the contributor base in the context of brand crises. Our approach enables us to distinguish how a brand's "core" audience and neophyte social media posters for a brand differ, which may affect the brand's strategy for responding to the crisis.

Brand Familiarity and Strength

Given the negative consequences of brand crises, scholars have shown that brand familiarity and brand strength can moderate consumer perceptions of a brand crisis. Despite the pervasiveness of the negativity effect, a disproportionate weighting of negative information compared to equally positive information, researchers have discovered boundary conditions that attenuate or moderate the negativity effect in the marketplace. Ahluwalia et al. (2000) find that a consumer's brand commitment moderates the negativity effect, with loyal consumers discounting disconfirmatory information and engaging in biased information processing. Dawar and Pillutla (2000) also show that selective processing by different customer segments can influence responses to brand crises. Consumers with positive expectations of the firm (loyal customers vs. potential customers) may insulate the brand in a crisis events as they may counter-argue negative news about the firm to buffer cognitive dissonance. Consumers with existing brand loyalty may exhibit more sympathy for the brand and become brand advocates (Feldman and Lynch 1988). Others have shown that prior brand attitudes can lead to consistency-based information processing (Chaiken et al. 1996). Ahluwalia (2000) suggests that familiarity with the brand can attenuate the negativity effect of a brand crisis. Consumers who are familiar with the brand may perceive negative information as less diagnostic and put more weight on positive information, while consumers unfamiliar with the brand may regard negative information more heavily. Consistent with the negativity effect, less-attached consumers are more likely to consider negative information in their judgment and emotional response (Schnalz and Orth 2012).

In addition to an individual's familiarity with the brand, other factors associated with the brand's equity may influence how consumers respond to the brand crisis events. Brand strength has been conceptualized in terms of consumer mindset metrics, financial measures, firm performance metrics or a combination of both (Aaker 1997, Keller 1993). Among the benefits that strong brands accrue are increased market share and benefits from price premiums (e.g. Park and Srinivasan 1994), increased leverage for product extensions (Aaker and Keller 1990; Morrin 1999), higher quality perceptions (Dodds et al. 1991), and product evaluations (Leclerc et al. 1994; Brown and Dacin 1997). In addition to these advantages, Dawar and Pillutla (2000) report that strong brands with positive consumer expectations are more resilient to brand crises.

We regard brand strength as "the differential effect that brand knowledge has on consumer responses" (Keller 1993). Keller (1998) suggest that consumers are more willing to process brand communications favorably for strong brands. To the extent that a brand's communication efforts are regarded more favorably and effectively, we contend that consumers may be predisposed to respond more positively to adverse events facing strong brands. To measure brand strength, we use Young and Rubicam's Brand Asset Valuator, which draws on two categories to capture overall brand strength: energized differentiation and customer relevance (Lovett et al. 2014). This view of brand strength captures the brand's perceived strength among consumers. We expect that brand strength affects consumers' brand-related posts, with social media posts from stronger brands having lower levels of negative emotions.

In this research, we account for variation that exists across brands with regard to their brand strength. We also take into account a social media user's familiarity with a given brand, recognizing the heterogeneity that may exist among contributors (e.g. Zhong and Schweidel 2020). We anticipate that users who have posted previously on the brand's Facebook page will express fewer negatively valenced emotions and more positively valenced emotions following a brand crisis compared to those users who have not previously interacted with the brand on Facebook. In addition to brand familiarity moderating the content emotionality following a brand crisis, we also anticipate that brand strength will moderate content emotionality, with posts for stronger brands containing fewer negatively valenced emotions and more positively valenced emotions.

METHODOLOGY

We employ an event study methodology that has been widely used in marketing literature (Elberse 2007; Agrawal and Kamakura 1995; Tellis and Johnson 2007; Lane and Jacboson 1995). In our analysis, we draw comparisons between the emotionality of consumers' brand-related social media posts before and after a brand crisis. We assume that emotions expressed prior to the event are reflective of consumers' brand perceptions prior to the event, while emotions expressed after the event are indicative of post-crisis perceptions. This empirical analysis examines ten firms across five product categories. Table 1 details the events included in this analysis.

Table 1. Events Studied in the Analysis

Brand	Category	Event Description	Date
Chick-fil-a	Food & Dining	Baptist Press published article where Chick fil a CEO states he supports traditional marriages	July 19, 2012
Delta Airlines	Travel Services	A global computer outage at Delta headquarters in Atlanta lead to hundreds of canceled flights.	Aug 08, 2016
Nike	Sports Apparel	Nike launched a new line of Hijabs for Muslim women in the sports arena sparking controversial consumer responses.	March 8, 2017
Nordstrom's	Department Store	Nordstrom's announced that the company would no longer provide Ivanka Trump's clothing line sparking politically charged consumer responses.	February 2, 2017
Southwest Airlines	Travel Services	A technology glitch (faulty router) caused a system wide outage resulting in thousands of cancelled flights.	Jul 20, 2016
Starbucks	Food & Dining	Starbucks consumer post viral video regarding Starbucks new red cup design sparking controversial consumer responses.	Nov 10, 2015
Taco Bell	Food & Dining	Taco Bell faced claims and legal suit for allegations that its seasoned beef used in food products was only 35% beef.	Jan 25, 2011
Target	Department Store	Target allows customers and employees to use restroom of their choice.	Aug 17, 2016
United Airlines	Travel Services	A man refused to give up his seat on an overbooked United Airlines flight and was forcibly removed from the fight. Other passengers recorded the incident and uploaded it to social media.	Apr 10, 2017
Volkswagen	Automobile	The EPA accused Volkswagen of using software in diesel cars to deceive emission test. Volkswagen recalled more than 480k cars in the U.S. and faced fines up to $18 billion.	Sept 18, 2015

The event date as the date when the firm makes the announcement. In the case of Starbucks and United Airlines, we use the date the video was uploaded to social media. We reviewed major media outlets for announcements, as well as the firm's website and social media accounts, to identify the event date. To validate that the proper event date was selected, we confirm that user comments related to the event occurred after the identified event date.[2]

Similar to Chen et al. (2009), we compare emotionality of social media content during a calibration window (the period over which we obtain the baseline emotionality of consumers' posts to social media) to emotionality of content during a test window (the period after the event during which we assess the change in the emotionality of consumers' posts). We use a 10-day window, beginning our calibration window 10 days prior to event and ending our test window 10 days after the event. As brand crises do not occur frequently, we do not risk any potentially confounding events in our event window.[3]

Table 2 provides illustrative Facebook comments before and after the brand crisis events.

Table 2. Facebook Comments on Brand Pages

Brands	Before Event Comment	After Event Comment
Chick-fil-a	Just went and got my free sandwich. I painted an old t-shirt to look like a cow. My Chic-fil-A was crowded, but then again it always is. There were lots of moo moo cows there too, too cute!	Wonder if the ones on here bashing CFA have gone and bashed the Boy Scouts for their beliefs as well. Guess I need to go and see This is a major company that has stated they do not believe that all people should have equal rights. That's the problem. If they said this about your own race, sexuality or religion you would understand
Delta Airlines	Well said. Delta taking care of their customers and planes.	Ruined my children's first trip to Disney world! They were in tears! Wait time for help 6 hours! Where's my voucher for my over 5 hour delay from DC to Cleveland on Friday? That was awful. You gotta do something for me atleast.
Nike	PLEASE NIKE, I NEED HELP WITH MY SHOES, IM A Partial amputee .. I LOVE NIKE I NEED INSOLES THAT WILL HOLD UP AND BE HANDICAP FRIENDLY...PLEASE HELP PLEASE HELP PLEASE HELP. Thank you ???? Richard Francis...rfrancis13167@gmail.com	So proud, Nike. We used to buy from a different shoe company with VERY different values. Our family is now ALL NIKE. Not only do we believe in your message, but your products just happen to be great Guess I bought my last pair of Nikes.
Nordstrom's	Marshall Parker you should do it! Nevermind I just realized you shaved lmao	boycott nordstrom for removing ivanka trump merchandise LOVE the poodle -- HATE your politics!!
Southwest Airlines	An airline with a heart. Flying LEO'S to the memorial services for fallen angels is a class act and greatly appreciated by this retired cop.	southwest just give em a break...they are a great airline and computers don't always work! Just sayin'! Been stuck in Vegas now for 2 days thanks southwest
Starbucks	Caffe Verona is my favorite!!!!!	Haters gonna hate ????...Eggnog latte,can't wait to have one!?? #lovestarbucks #goldcardmember I love the people who serve my Starbucks, my coffee... The cup I could care less about! Gimme Creme Bre all year!
Taco Bell	Volcano $5 Box=FREAKIN' AWESOME!	I love Taco Bell! My colon doesn't, but who cares what he thinks? He's a jerk! I'm never eating there again you r sooooo disgusting in sooo many ways

Target	Please change your security guards uniforms back to the old dark blue one. Me and my family felt much safer with the guards wearing the police looking uniform.	What do you intend to do about keeping men out of the dressing rooms that I send my 11yr old daughter into? Target is still putting confused men as a priority over it's female customers. Letting men use women's dressing rooms is beyond stupid.
United Airlines	They understand dogs but one thing United doesn't understand is customer care and that is why I will never fly United again.	The CEO should resign. Point blank. Just fly southwest where they beat their competitors and not their passengers
Volkswagen	GRC beetles have an almost inhuman launch. I bet it could outlaunch a Zonda.	Well I guess nobody will ever read this replay but I need to share my thoughts. In the past 10 years I have owned 6 VW. One was a 05 Jetta TDI. I still have 2 at this time but when these are gone.... I will never buy any VW in the rest of my life.... you have lied to us and I can't forgive... good luck with your crusade... you will need it Will never leave VW , by far the most iconic trademark .

DATA

Social media data is collected from Facebook brand pages for 10 brands: Chick-fil-a, Delta Airlines, Nike, Nordstrom's, Southwest Airlines, Starbucks, Taco Bell, Target, United Airlines and Volkswagen. For each brand, the Facebook graph API[4] is used to download all available activities made by a brand, such as posts and all user comments on posts. The data includes all activity from the day that the brand's page was created on Facebook through January 1, 2018. Events in the data set for these 10 brands range from January 2011 to April 2017. For each comment, the date of the post, time of the post, text of the post, and user ID associated with the individual who posted the comment is captured. User-specific identifiers allow for identification of users who engage with the brand both before and after the incident.[5]

The text of user comments is analyzed using a computational text-mining tool, Linguistic Inquiry and Word Count (LIWC), used in prior literature to capture valence and emotionality of text (Pennebaker et al. 2015). The NRC emotion lexicon is used to assess the presence of positively and negatively valenced words, as well as high-arousal emotions (anger, disgust, joy and surprise) (Mohammad et al. 2013). For each social media comment, we use LIWC to tabulate the proportion of words in the comment that correspond to positively and negatively valenced words, as well as the four specific emotions. Table 3 provides summary statistics, by brand, for the data.

Table 3. Summary Statistics of Facebook Comments by Brand

Brand	Positive	Negative	Anger	Disgust	Joy	Surprise	Comments Before Event	Comments After Event
Chick Fil A	6.13	3.77	1.97	1.84	3.6	1.05	253	1,092
Delta Airlines	4.81	2.11	0.74	0.85	2.6	1.27	911	7,849
Nike	3.57	2.79	1.35	1.17	2.22	0.82	142	1,644
Nordstrom	5.6	3.14	1.16	1.65	3.91	1.61	9,454	13,462
Southwest Airlines	4.43	2.56	0.97	0.8	2.2	1.08	984	9,429
Starbucks	7.49	1.76	0.72	0.77	6.14	1.47	880	1,620
Taco Bell	4.71	3.09	2.29	1.38	3.05	1.66	5,715	4,650
Target	5.04	3.03	0.98	0.94	2.26	1.1	217	1,411
United Airlines	6.18	5.67	2.55	2.48	1.55	1.34	419	59,239
Volkswagen	4.79	3.32	1.38	1.41	3.16	1.01	226	9,397
Overall	5.60	4.18	1.87	1.84	2.46	1.35	19,201	109,793

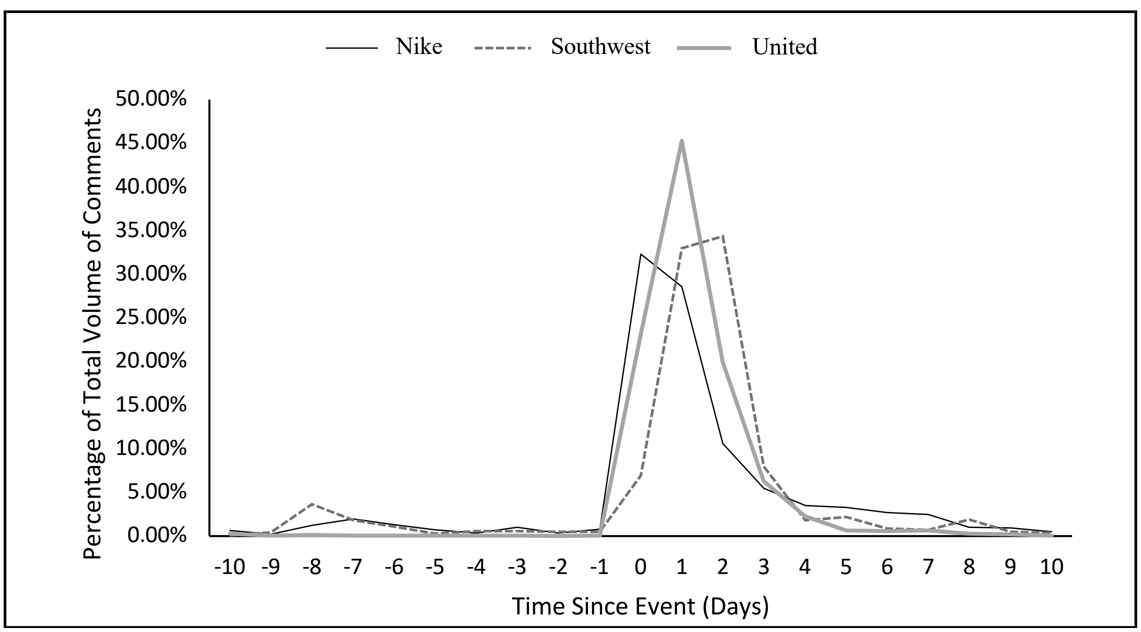
Table 4 provides additional summary statistics relating to the time at which users contributed social media comments. Within the dataset, users post an average of 1.1 comments. Approximately 85% of comments to the brand's page occur after the brand crisis. Approximately 0.90% of Facebook brand crisis comments were contributed by individuals who interacted with the brand both before and after the brand crisis. Within the data we find that brands may respond to consumers' comments within Facebook and account for these brands using an indicator variable at the comment level where 1 denotes comments made to brands who respond to consumers within the 10-day after period.

Table 4. Frequency Table for Category Variables

Variable	Percentage
Weekdays (Mon-Fri)	84.60
Weekend (Sat & Sun)	15.40
Morning (5am – 11:59am)	14.05
Afternoon (12pm – 6:59pm)	28.08
Night (7pm – 4:59am)	57.87
Brand Comment = 1	75.82
After brand crisis	85.11

As an illustration, in Figure 1 we present the fraction of user comments we observe during the observation window for Nike, Southwest, and United Airlines before and after the brand crisis. Figure 1 reveals a substantial increase in user posts beginning with the day of the brand crisis. Across brands, there is an increase in comments on the brand's Facebook page after the brand crisis event, suggesting that consumers may be using Facebook as a platform to express their opinions on the brand crisis.

Figure 1. Volume of Comment for Select Brands

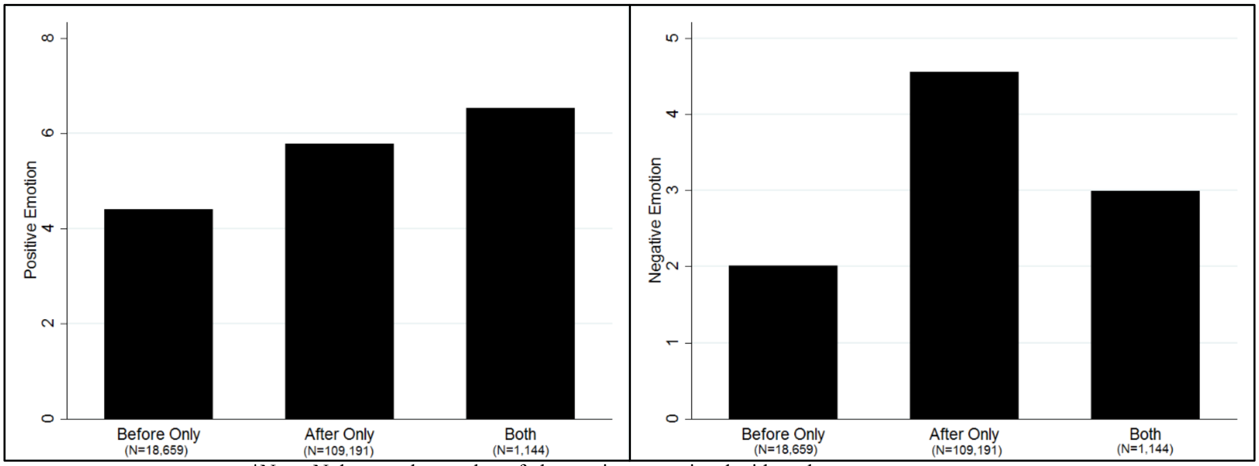


To measure brand strength, we rely on the BAV dataset provided by Lovett et al. (2014). The authors dataset includes 136 measures of brand characteristics for top U.S. brands. Brand strength is measured on a continuous scale and comprises consumers' responses to questions relating to energized differentiation and brand relevance.[6] The data was collected from a variety of sources that include a survey of 4,768 subjects between September – October 2010, a quarterly survey of 17,000 individuals conducted by Young and Rubicam between 2008 and 2010, and secondary data from Interbrand and the American Customer Satisfaction Index (ACSI).[7] Appendix A provides details on the brand strength metric for the brands in our data.

Model-Free Evidence

To explore differences among consumers' posts, based on the extent to which they interacted with the brand on social media prior to the brand crisis, we divide social media contributors into three groups: (1) those who only interact with the brand prior to the brand crisis, (2) those who only interact with the brand after the brand crisis, and (3) those who interact with the brand both before and after. Figure 2 shows the average proportion of positively and negatively valenced emotional content across the three groups. Those who comment both before and after the brand crisis are more positive than those who only comment before or after the crisis. Following a brand crisis, those who only comment in the wake of the incident are more negative than those who have interacted with the brand previously. This provides preliminary evidence that brand familiarity may insulate a brand from shifts in perceptions following a brand crisis.

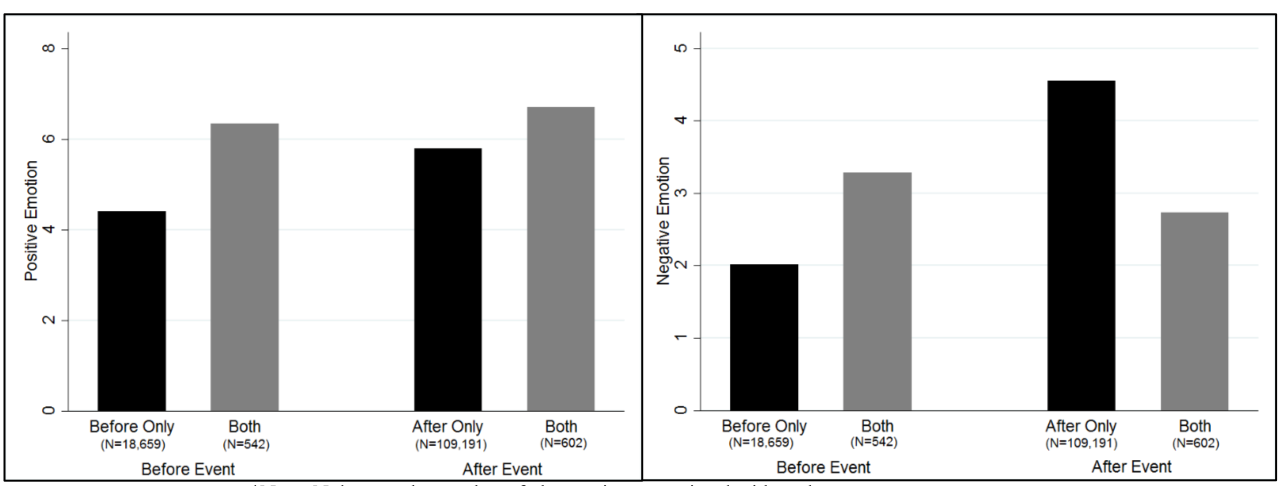
Figure 2. Average Positively and Negatively Valenced Emotion Across Commenter Segments



*Note: N denotes the number of observations associated with each commenter segment

For those commenters who post both before and after the brand crisis, we distinguish between their posts based on whether the posts occurred before or after the incident. Figure 3 shows that the use of positively valenced emotions increases slightly after the crisis, while the use of negatively valenced emotions decreases slightly. This would be consistent with those who are familiar with the brand coming to the brand's defense following a brand crisis.

Figure 3. Average Positive and Negative Emotion Before and After Event by Commenter Segment



*Note: N denotes the number of observations associated with each commenter segment

MODEL

To examine the impact of brand familiarity and strength on the emotionality of social media posts following a brand crisis, we conduct a comment-level analysis by estimating the following linear regression:

(2)

$$Emotion_{jc} = \alpha_0 + \lambda * After_c + \delta * BeforeCmtCount_c + \varphi * AfterCmtCount_c$$
$$+\vartheta * BrandStrength_{b(c)} + \gamma_1 * BeforeCmtCount_c * AfterCmtCount_c$$
$$+ \gamma_2 * After_c * BrandStrength_{b(c)} + \gamma_3 * After_c * BeforeCmtCount_c + \beta * X_c + \mu_{i(c)} + \varepsilon_{jc}$$

where, *j* = 1, …, 6 indexes the dependent variables (positively valenced emotions, negatively valenced emotions, anger, disgust, joy, surprise), *i* = 1, …, N indexes the distinct commenters (N=110,586), b=1,…,10 indexes brands and *c* = 1, …, C indexes comments in our dataset (C=128,650). We estimate linear regressions with six different dependent measures, using the same set of predictor variables to determine how brand strength and familiarity impact the effect of brand crises on the emotionality expressed in consumers' social media posts. The independent variable $After_c$ is an indicator variable such that $After_c = 1$ denotes that the comment was posted after the brand crisis for the brand associated with comment *c* and is equal to 0 otherwise. We account for brand strength using $BrandStrength_{b(c)}$, where the subscript denotes the brand *b* (b=1,…,10) associated with comment *c*. The interaction term $After_c * BrandStrength_{b(c)}$ allows use to assess the extent to which brand strength moderates the impact of the brand crisis on comment emotionality.

The term $BeforeCmtCount_c$ is the number of comments posted on the brand's Facebook page prior to comment *c* by the individual who contributed comment *c*, before the brand crisis for the brand mentioned in comment c. Similarly, $AfterCmtCount_c$ captures the number of comments posted on the brand's Facebook page prior to comment *c* by the individual who contributed comment *c*, after the brand crisis for the brand mentioned in comment c. Our primary interest is in the interaction term $BeforeCmtCount_c * After_c$, which captures the extent to which brand familiarity (operationalized via *BeforeCmtCount*) moderates the impact of the brand crisis on content emotionality. We also include the interaction $BeforeCmtCount_c * AfterCmtCount_c$ to assess the extent to which those who interact frequently with the brand both before and after the brand crisis may differ from those who primarily interacted with the brand before or after the crisis.

X_c denotes a vector of control variables. It includes $TimeSinceEvent_c$, which captures time trend relative to the event date and takes on values between -10,…,10. It also includes $NegEmoPrior_c$ and $PosEmoPrior_c$, which account for the valenced emotions expressed in comment c-1. In addition to valence, we include the number of comments ($VolumeComments_c$) that appear before comment c. $BrandCmmt_{b(c)}$ is an indicator variable such that $BrandCmmt_{b(c)} = 1$ if brand *b* responds to user comments during the event window and is equal to 0 otherwise. Temporal factors are included to control for the day of week and time of day at which comment *c* was posted. The indicator variable $Weekend_c = 1$ if the comment was posted on Saturday and Sunday. The variable $Morning_c = 1$ if comment c was posted between 5:00 AM-11:59 AM, and $Afternoon_c = 1$ if it was posted between 12:00 PM-6:59 PM. We allow for individual random effects, $\mu_{i(c)}$, to capture unobserved heterogeneity that may exist across commenters. Finally, ε_{jc} denotes the idiosyncratic error term. We estimate the regressions with robust standard errors.

RESULTS

Our analysis seeks to determine the extent to which brand strength and a consumer's familiarity with the brand moderate the emotionality of his/her reaction to brand crises. The results from our analysis are presented in Table 5.

Table 5. Model Results

	(1) Positive	(2) Negative	(3) Anger	(4) Disgust	(5) Joy	(6) Surprise
After	-1.67**	3.89**	4.43**	-0.29	-5.88**	0.93**
	(0.51)	(0.35)	(0.27)	(0.25)	(0.43)	(0.24)
Before Cmt Count	0.43**	0.10*	0.34**	-0.09*	0.18	0.10**
	(0.12)	(0.05)	(0.09)	(0.04)	(0.10)	(0.04)
After Cmt Count	-0.11**	0.09	0.03	-0.09**	-0.07**	0.04
	(0.03)	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)
Before Cmt Count X After Cmt Count	0.53	-0.06	-0.03	-0.03	-0.02	0.06
	(0.53)	(0.07)	(0.05)	(0.06)	(0.14)	(0.08)
Before Cmt Count X After	-0.80	-0.35*	-0.40**	0.08	-0.01	-0.15
	(0.72)	(0.14)	(0.13)	(0.11)	(0.32)	(0.12)
Brand Strength	-1.85**	0.39	2.19**	-0.82**	-1.30**	0.85**
	(0.33)	(0.22)	(0.19)	(0.15)	(0.27)	(0.15)
Brand Strength X After	1.62**	-1.91**	-2.81**	0.07	2.72**	-0.74**
	(0.34)	(0.24)	(0.20)	(0.16)	(0.29)	(0.16)
Time Since Event	-0.01	-0.09**	-0.04**	-0.03**	0.12**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
NegEmoPrior	0.00	0.02**	0.01**	0.01**	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PosEmoPrior	0.02**	0.01	0.00	-0.00	0.01**	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Brand Cmt	1.29**	1.46**	0.72**	0.58**	0.67**	0.40**
	(0.11)	(0.08)	(0.04)	(0.05)	(0.09)	(0.06)
Volume of Cmts	-0.00	0.00**	0.00**	0.00**	-0.00**	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weekend (Sat or Sun)	-0.42**	-0.11	-0.41**	-0.03	-0.27**	-0.06
	(0.10)	(0.09)	(0.06)	(0.06)	(0.08)	(0.05)
Morning (5am-11:59am)	-0.04	0.24**	0.36**	0.15*	-0.08	0.07
	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.04)
Afternoon (12pm-6:59pm)	0.10	-0.09	0.07*	0.01	0.07	0.02
	(0.06)	(0.06)	(0.03)	(0.04)	(0.05)	(0.03)
Constant	6.63**	0.80*	-2.57**	2.49**	6.03**	-0.11
	(0.49)	(0.32)	(0.26)	(0.24)	(0.41)	(0.22)

= * p<0.05, ** p<0.01 Notes: Standard errors in parentheses. Night and Weekday are the baseline categories for time of day and day of week measures, respectively.

The control variables included in our analysis reveal the extent to which the timing of Facebook posts by brands can impact the emotionality of user comments. Content posted by users on weekends tends to contain lower levels of positively valenced emotions, anger and joy. In comparison to posts at night, content posted in the morning tends to contain higher levels of negatively valenced emotions, anger and disgust. As more time elapses from the brand crisis, we observe a general decrease in negatively valenced emotions, anger, and disgust, while the levels of joy and surprise increase. In addition to the time at which comments are posted, the sentiment of the immediately preceding comment is related to the emotionality expressed. Negative sentiment in the prior comment is associated with greater negatively valenced emotions. Similarly, positive sentiment in the prior comment is associate with more positively valenced emotions, joy and surprise. This suggest that posters may exhibit "bandwagon" effects where the negative (positive) nature of the previous comment increases the likelihood that the following comment may also be negative (positive) in nature (Moe and Schweidel 2012). Lastly, we consider whether the firm responds to consumers after the brand crisis. We find that a firm's decision to respond significantly increases the emotionality of users' comments.[8]

We next turn our attention to the emotionality of comments after the brand crisis as compared to before. Consistent with prior work, the coefficient for $After_c$ is significant and associated with an increase in overall negative emotional content. Results show an increase in content expressing both negative emotion and anger after the brand crises. Anger may increase as a result of consumers receiving disconfirmatory information that contrasts with their image of the brand. Brand crises may cause consumers to reevaluate their relationship with brands resulting in unfavorable sentiments when disconfirming information about the brand arises (Aaker et al. 2004).

In addition to an increase in negative emotions, there is a significant decrease in positive emotional content and consumers' use of language that expresses joy after brand crises. Coupled with consumers' increased use of language associated with surprise, these findings suggest that the event may have come as a shock to consumers. This is consistent with past research that has shown that a brand crisis can disconfirm dependability and trust perceptions of brands, weakening consumers' relationships (Gregoire and Fisher 2008; Aaker et al. 2004). These results suggest that the negative effect around brand crisis events influence consumer emotional perceptions of brands (Lei et al. 2008).

Next, we examine differences in emotionality related to consumers' familiarity with the brand. As consumers' previous interactions with the brand before the brand crisis increase, consumers are more prone to express more positively valenced emotions, joy and surprise, while they are less likely to express disgust. Interestingly, those who have interacted with the brand prior to the brand crisis are also more likely to express anger. One potential explanation for this finding is that consumers may use the brand's Facebook page as an avenue to voice complaints. As one would expect, those who interact with the brand multiple times following the brand crisis, as evidenced by the coefficient of *AfterCmtCount*, are less likely to express positively valenced emotions or joy. Rather, they are more likely to express negatively valenced emotions. However, results indicate that they are less likely to express disgust. This polarization is consistent with literature which has shown that online word of mouth can be populated with both extreme negative and positive consumer responses (Moe and Schweidel 2012).

Next, we consider how consumers' interactions with the brand prior to the crisis may moderate the extent to which they express emotionality in their posts after the brand crisis. Though we do not observe a significant interaction between the number of comments posted prior to the brand crisis and the number of comments posted after, we find that the interaction $After \times BeforeCmtCount$ is significant. As consumers interact more with the brand's Facebook page prior to the crisis, their posts after the crisis are expected to contain less negatively valenced emotions and less anger. This suggests that, after a brand crisis, consumers who have posted on the brand's page and are already familiar with the brand via social media use less emotionally charged language compared to consumers who are interacting with the brand for the first time on Facebook after the incident.

Taken together, these findings illustrate how consumers react to a brand crisis on social media. In addition to the decrease in joy and increase in surprise, anger and negatively valenced emotions, those users who have previously posted comments on the brand's Facebook page are expected to post with less anger compared to those who have not previously interacted with the brand. This suggests that there are systematic differences across commenters linked to prior interactions with the brand on social media. This is consistent with research that has shown that brand familiarity can help buffer brands in crises (Aaker 1990), as those who have interacted with the brand previously on social media may hold favorable brand associations in their memory.

To assess the extent to which brand strength may mitigate the effects of a brand crisis, we examine the interaction term $After \times BrandStrength$. Taking the main effect of brand strength and interaction into account, the coefficients reveal that consumers express higher levels of joy for strong brands after a crisis. In addition to experiencing higher levels of joy in comments posted after a brand crisis compared to weaker brands, comments posted to the Facebook pages of strong brands also contain lower amounts of negatively valanced emotions and anger following brand crises. This indicates that brand strength can insulate strong brands in the event of a brand crisis.

DISCUSSION

With the widespread use of social media, consumer opinions are quickly thrust into the mainstream, offering brands the opportunity to assess consumer perceptions. Consumer perceptions are critical components of brand equity and consequently marketing strategy. Our research aims to examine the impact of brand crises on the emotionality of the language that consumers express in social media comments following the brand-related events. We examine the emotionality of social media posts before an event compared to afterward to assess the impact of the brand-related event on consumers' perceptions of the brand. We incorporate measures of brand strength and familiarity to assess the extent to which they may mitigate (or exacerbate) the effects of a brand crisis on brand perceptions.

Our analysis offers insights for managers reacting to brand crises. The results highlight the importance of brands understanding the composition of the social media contributor base in the wake of a brand crisis. Ignoring the differences that exist in the contributor base in terms of consumers' prior familiarity with the brand overlooks a critical factor related to the emotions they express. Although we observe an increase in negative emotions after a brand crisis, we find that consumers who have interacted with the brand previously express fewer negative emotions toward the brand compared to those who only comment after the brand crisis. This suggests that those who have interacted with the brand previously on social media may hold more favorable brand associations or exhibit greater attachment to the brand that can result in higher positive emotionality towards the brand (Aaker and Biel 1993).

By distinguishing between those who are likely to be predisposed toward being more favorable and those who are likely to be more negative, brands can formulate their response to the brand crisis based on the perceptions of each group. Brands may encourage those who have engaged with the brand previously to comment in attempts to create a buffer from the more negative comments coming from those who have not interacted with the brand previously. Moreover, marketers and shareholders should be prudent in examining consumer response to brand crises with aggregated metrics as new commenters may produce a large volume of negative comments that overshadow the voice of consumers who have engaged with the brand previously and who may represent the brand's more loyal customers. In terms of the decisions brands must make following a crisis, it may be in the brand's interest to overweigh the feedback being provided by more loyal customers rather than ceding to the larger volume of consumers who are less engaged with the brand.

We contribute to the social media literature by demonstrating how it can be used to assess how different consumer segments respond to brand crises. Keller (2009) offers a customer-based brand equity model in which he highlights consumer emotional response regarding the brand as a vital component in modern day brand equity. The emotionality of consumers' social media posts offers insights that can aid marketers in developing and sustaining brand equity. In addition to considering broader categories of positively and negatively valenced emotions, we also examine how brand crises affect consumers' use of high arousal emotions such as joy, anger, disgust, and surprise. In deriving such measures from social media posts, brands can construct a multidimensional view of consumer's perceptions surrounding brand crises.

Recent literature has shown that consumer responses to brand crisis are heterogenous and that brands can benefit from adopting a more heterogenous response approach to diffusing potential online firestorms (Herhausen et al. 2019). An understanding of consumers' emotions around brand crises can aid firms in generating appropriate responses based on an individual's (or segment's) emotional state. The way in which a brand chooses to respond, such as by employing empathy or providing a detailed explanation, may vary depending on the specific emotions being expressed by different consumer groups. For example, some groups that exhibit joy and anger may tend to adopt heuristic-based processing that relies on prior knowledge, while other groups may express sadness and adopt systematic processing that relies more on new information than on prior knowledge (Schwarz 2000). A firm's response to these distinct groups must take into account not only the size of the group, but the importance of the group to the brand.

The presence of emotions in content may convey meaning beyond simply a positive or negative sentiment. For example, anger and disgust have been linked to blame attribution, with the presence of anger in response to a brand crisis indicating an assumption of blame toward the firm (Oliver 1993). Anger has also been linked to retaliation and the spread of negative word of mouth. Understanding consumers' emotional response could aid firms in seeking to mitigate the cascading effect of virality originating with angry consumers (Gregoire and Fisher 2008; Bougie et al. 2003). By monitoring the presence of content emotionality in the wake of brand crises, firms can potentially detect shifts in the degree to which consumers hold them responsible for the event. Such an assessment offers more value than a general measure of negative sentiment. Moreover, anger is associated with increased risk seeking and optimism. In contrast, fear is associated with risk aversion and pessimism (Schwarz 2000). It is not uncommon for stock prices to fluctuate in the time surrounding a brand crisis as risk perceptions oscillate. Future research may investigate the extent to which content emotionality on social media may provide insight into stock market performance as stakeholders reevaluate their decisions.

We show that brand strength can insulate the brand from negative social media buzz. Strong brands experience a significant increase in positive and joy emotional language after the brand crisis event and a significant decrease in negative and anger-related emotional content. Our findings suggest that consumers may be more forgiving for strong brands after transgressions. While much of the extant literature on product harm focuses on product recalls, our empirical analysis makes use of brand-related events including product failures, service failures and what some may consider ethical/moral failures. The broad base of events on which we draw demonstrates the effectiveness of brand strength at buffering a range of brand crises.

While our research offers additional insights for marketers in terms of managing a brand crisis, it is not without limitations. Though we draw on brand crises from ten different firms in five product categories, future research may assess if our findings generalize to other product or service categories. While we make use of data collected from Facebook brand pages, it would be worthwhile to examine content emotionality following brand crises on different social media platforms.

We do not incorporate information about the severity of the brand crises or types of brand crises into our empirical analysis. If objective information about the magnitude of the damage stemming from a brand crisis were available across different types of incidents, researchers could probe the potential limits of our findings. Another area that could offer useful insights would be incorporating the network structure of social media contributors. Doing so would allow for the identification of the influence that social connections have on content emotionality. Additionally, segmentation based on the intensity or content of prior interactions with the brand could be further probed to develop and identify more refined poster segments, which could be used by the firm when responding to a crisis. Lastly, the emotionality of a brand's response could be explored to determine what types of emotional response are better suited to certain types of brand crises.

Chapter 2

Emotionality of Firm Generated Content: The Effects of Facial and Text-Based Emotions on Social Media Engagement

INTRODUCTION

Social media has become an important part of brand equity in terms of helping to build awareness, increase sales, and understand consumers' sentiments towards brands. Firm spending on social media advertising increased more than 50% between 2013 and 2014 from roughly $11 billion to $18 billion (eMarketer 2015). Brands have begun to embrace social media and develop branded social media pages to disseminate content to consumers. Within social media, a brand may choose to create content that is more textually dense or include imagery that focuses on the brand or persons. Anecdotally, marketers assume that providing images with the text can help capture consumers' attention and help firms' content "get noticed." Despite the pervasive use of imagery in social media, the empirical marketing literature has focused on the text elements primarily, leaving a gap in our understanding of visual content. The rise in platforms such as Instagram and Pinterest suggests that imagery is a fundamental component of social media content, and that deriving approaches to analyze both text and visual elements is critical to informing our knowledge of social media engagement. How do the two elements influence consumer engagement? How do they influence the positive or negative nature of consumer responses? This research considers the influence of both text and imagery within firm-generated content (FGC) to provide insights into how the two elements jointly influence consumer engagement.

In an online context, Berger and Milkman (2012) showed that emotional textual content, specifically high-arousal text content, gets shared more. Others have shown that emotional textual reviews are considered more diagnostic and affective banner ads obtain higher click-through rates (Lohtia et al. 2003; Yin 2014). While this literature clarifies our understanding of how text drives consumer engagement, little is known about the influence of images on consumer engagement. In the content marketing domain, research has examined the effects of images in print advertisement. The advertising literature has shown that the use of pictorial elements and faces within advertisements can influence consumers' perceptions, attitudes towards the advertisement, and product evaluations (Pieters and Wedel 2004; Xiao and Ding 2014). Given the importance of pictorials and faces in print advertising, do these elements influence consumer behaviors in an online context? While research has examined the visual content of print advertising, limited work has been conducted on their effect on consumer engagement as a component of online WOM content.

This research explores the use of text and visual content to determine how emotionality within the two elements drives consumer engagement. In light of what the literature has shown about the effects of emotionality of text in an online context and the use of faces in print advertising, we explore the emotionality of FGC, drawing a distinction between the text and visual components. We explore how the emotional valence of FGC on Facebook influences consumer engagement, measured in terms of both the volume and valence of consumer comments. We leverage machine learning via Amazon's Rekognition facial recognition software to measure positive and negative emotional facial expression within images. We construct a measure of emotional valence for pictures using the emotions (happy, calm, sad, and angry) from facial expressions within the images. Utilizing text analysis, we measure emotional valence (positive/negative) of the text components of FGC. By measuring the emotional valence of text and image content, we show that the extent to which the two elements are (in)congruent influences the volume of comments and the emotional valence of comments.

Our analysis reveals that when the emotional valence of the text is incongruent with the emotional valence of visual elements, firm-generated posts experience fewer consumer comments. Alternatively, we find that a moderate mismatch between emotional valence of text and visual elements can significantly increase comment volume. Examining the potential moderating role of brand personality, results show that a mismatch in the emotional valence of text and visual elements can lead to higher consumer engagement for exciting brands, whereas sincere brands experience a decrease in consumer engagement. This suggests that there is not a single playbook that all brands can employ as to how to engage consumers with social media.

Additionally, the results suggest that contrary to anecdotal claims, adding an image to a firm's social media post, in some cases, can reduce the number of comments it receives if the two elements are incongruent. Lastly, in exploring the emotional valence within the content of consumer comments, results show that content congruence increases the amount of positive emotional language used within consumer comments for sincere brands. In contrast, a content mismatch increases the amount of positive emotional language used within comments for exciting brands. These findings have implications for marketing managers who develop digital and social media marketing strategies.

Given the significant financial and strategic emphasis placed on online engagement and social media, understanding how content influences the volume and content of consumer responses is beneficial. The approach we use to capture emotional valence of visual content can be useful in future research exploring the influence of images in the context of online word of mouth (WOM). We also extend the content marketing literature on the role of faces within print advertisement to a social media context. This analysis is among the first to explore the emotional valence of imagery within social media. Given recent findings of content emotionality's influence on consumer liking, clicking, and sharing behaviors (Berger and Milkman 2012; Lohtia et al. 2003; Agnieszka et al. 2018), images provide a rich data source that conveys emotion beyond the text components.

The remainder of this article is structured as follows. First, we discuss related literature and the intended contribution of our analysis. We then present the data and describe the measures used in the analysis. Lastly, we detail the analysis and present the results. We conclude with a discussion of the implications of our work for managers and researchers.

RELATED LITERATURE

Our study examines the impact of FGC on consumer engagement via the volume and emotionality of comments. We describe FGC using both textual and visual components and score the emotional valence of each element to evaluate the impact of congruent versus incongruent content. This research draws on three streams of literature: online WOM, content marketing, and brand personality. First, we discuss research of online WOM, focusing on articles related to content emotionality. Second, we discuss content marketing and the role of faces within advertisements. We then provide an overview of the literature related to (in)congruence and specify our expected outcomes when FGC is (in)congruent. Additionally, we briefly discuss brand personality and how it may moderate the way consumers respond to content (in)congruence.

Online WOM

Recent work by Kumar et al. (2013) suggests that brands embrace social media as it can potentially have a positive impact on sales, new customer acquisition, brand awareness, and consideration set formation (Kumar et al. 2013; Kumar et al. 2016; Goh et al. 2013; Sunghun et al. 2015). Research in social media and online WOM has shown that WOM can influence firm performance indicators such as sales (Chevalier and Mayzlin 2006; Liu 2006; Moe and Trusov 2011), consumers purchase decisions (Leskovec et al. 2007), television ratings (Godes and Mayzlin 2004), product adoption (Trusov et al. 2009), and stock market performance (Tirunillai and Tellis 2014). Others have investigated network effects within social media (Mayzlin and Yoganarasimhan 2012; Trusov et al. 2010) and posting behavior of users (Toubia and Stephen 2013; Moe and Schweidel 2012).

A wealth of literature has begun to employ text analysis techniques to derive meaning from the text of online WOM (e.g. Lee and Bradlow 2011; Tirunillai and Tellis 2014; Buschken and Allenby 2016). In regard to the valence of online WOM, researchers have shown that both positive and negative online WOM influence firms' price fluctuations (Shin et al. 2008). Others have demonstrated that the impact of negative valence content outweighs that of positive valence content (Chevalier and Mayzlin 2006; Luo 2007).

More recently, researchers have begun to investigate how content emotionality influences consumer engagement (e.g. likes, shares, or volume of comments). Literature has shown a link between high arousal emotionality and social transmission (Berger and Milkman 2012). A recent study by Agnieszka et al. (2018) found that the informative versus emotional appeal of FGC impacts consumer engagement. Tellis et al. (2019) examine digital advertisements in the context of YouTube and find that positive emotional content is shared more. The researchers find a negative relationship between sharing and informational content except in cases where informational ads were examined in a risky context (Tellis et al. 2019). Lee et al. (2018) find that including brand personality attributes (e.g. humor and emotion) in FGC positively influences consumer engagement while informative content (e.g. prices) is negatively associated with consumer engagement. Lohtia et al. (2003) find that emotional appeal in online banner ads leads to higher click through rates (CTR). Despite research into the emotional content of FGC and online WOM, limited work has investigated the role of visual content (Liu et al. 2017). To the best of our knowledge, our research is among the first to consider the emotional valence of visual content in social media.

Visual Elements of Content Marketing

Research has shown that verbal and visual information within advertisements have separate influences on consumers' brand attitudes and product evaluations (Rossiter and Percy 1983; Mitchell 1986; Pieters and Wedel 2004). Mitchell (1986) classified pictures as positive, neutral and negative, and found that affect-laden photographs influenced consumers' brand attitudes. The results suggested that images categorized as negative resulted in less favorable attitude than those categorized as positive or neutral. Pieters and Wedel (2004) use eye tracking and gaze duration to examine the surface size of pictorial, text and brand appearance in print advertisements and find that the pictorial elements capture the most attention. Similarly, Pieters et. al (2007) use bounding boxes to examine the size of design elements — brand, text, pictorial, price, and promotion — and find that surface size influences attention capture. Pieters et al. (2010) distinguish between visual and design complexity within advertisements and find that feature complexity is negatively associated with attention and attitude toward the ad, whereas design complexity is positively associated with attention and attitude toward the ad.

Recent advancements in machine learning have provided automated ways to analyze images. Liu et al. (2017) use deep neural networks to train image classifiers to predict brand attribute measures (e.g. rugged, glamorous, fun and healthy). Klostermann et al. (2018) use description tags of images via Google Cloud Vision API to cluster images based on contents (e.g. products) and context (e.g. scenery/situations). The authors suggest this method as means for brands to determine consumer's brand perceptions. Research leveraging automated approaches to process images in a social media context is in its nascency. Our research contributes to this emerging stream by incorporating the valence expressed in both textual and visual content. To the best of our knowledge, our work is among the first to examine how text and images jointly influence consumer engagement. By differentiating between certain visual attributes, we aim to provide insights into how visual elements within FGC influence the volume and emotional valence of consumer comments, and thus consumer engagement.

Relevant to the use of images in content marketing, research has also examined the impact of faces in visual elements of marketing content. Facial expressions provide additional non-verbal cues to the intent or meaning of communications. Researchers have found that attractiveness of models and persons in advertisements can influence product perceptions and consumer behaviors (e.g., Solomon et al. 1992; Bower and Landreth 2002;). Literature investigating faces has shown that faces can influence election results (Todorov et al. 2005) and trust perceptions (Gorn et al. 2008; Tanner and Maeng 2012). Small and Verrochi (2009) analyze faces within charity advertisements and find that sad faces elicit greater donations compared to happy or neutral faces. Xiao and Ding (2014) examine the effect of facial features in print advertising and find that faces have a substantial effect on consumer attitude towards the brand, advertisement and purchase decisions. Their results reveal that people showed preference towards certain facial traits in advertisements compared to others (e.g. attractiveness and trustworthiness) with some heterogeneity across individuals and product categories. Others have shown that emotional facial expressions capture attention in various settings (Lundqvist and Ohman 2005; Oatley and Jenkins 1996). As content emotionality has been found to drive online engagement, the emotionality expressed on the faces within FGC provides another avenue through which brands can communicate with consumers. Given the importance of faces in print advertising, we examine their impact within FGC on social media.

Content Matching Expectations

Consumer behavior and psychology literature provides insights into how (in)congruency influences consumers' perceptions. Some scholars suggest that congruent stimuli are perceived more favorably through schema-based positive affect transfer as compared to incongruent stimuli (Sujan 1985; Fish and Pavelchak 1986). Subsequent research found that positive affect transfer extended to situations where mild incongruence was present (Meyers-Levy and Tybout 1989). Mandler (1982) found that moderate incongruence, in contrast to completely congruent or incongruent, generated more favorable product evaluations. The author contends that the process of responding to incongruency is different than that required to process congruence, yielding more affective processing. Bosman (2006) explores the incongruence of ambient scent with the product category and finds that pleasant ambient scents that are congruent are more effective at increasing consumer product evaluations. Lee and Thorston (2008) investigate the impact of celebrity-product incongruence on purchase intentions to find that a moderate mismatch was better than either a complete mismatch or complete match. In some instances, extreme incongruity has been shown to decrease product evaluations as consumers work to reconcile the discrepancy. Moderate incongruity can be viewed as interesting and has been shown to elicit positive curiosity from the "unexpected-ness" of the information (Meyer-Levy et al. 1994; Mandler 1982).

Prior research has illustrated that pictorial and textual elements offer distinct influences on consumers' attitude, perception, and attention in the context of print advertisements. In this research, we investigate the joint impact of textual and visual elements within social media to determine how the two components drive consumer engagement. We focus on the emotional valence (positive and negative) of the text and facial images. To the extent that the emotional valence of the text conflicts with the emotional valence represented by faces within the image, we expect that (in)congruency effects may influence consumer engagement.

We consider positive (negative) valenced content paired with congruent positive (negative) valenced content to be indicative of a complete match. A complete match can occur in two ways: when both textual and visual content are positively valenced (e.g. positive valence text paired with a happy face) or when both textual and visual content are negatively valenced (e.g. negative valence text paired with an angry/sad face). We anticipate positive impacts of congruency on consumer engagement.

H1a: A complete match between textual and visual content within FGC will be associated with an increase in volume of comments.

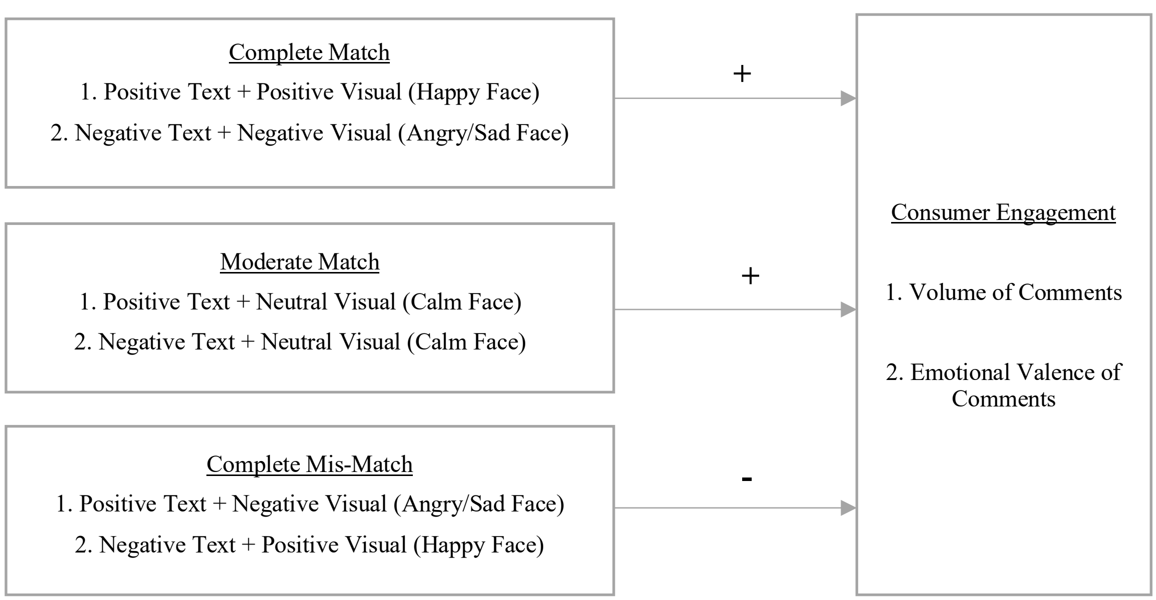
We consider positive (negative) valenced textual content combined with incongruent negative (positive) valenced visual content to be indicative of a complete mismatch. This incongruity can appear in two ways: positive valenced text content paired with negative valenced visual content (angry/sad face) or negative valenced text content paired with positive valenced visual content (happy face). We expect FGC containing a complete mismatch between visual and textual content to evoke unfavorable consumer responses (e.g. fewer comments). Greater distance between the emotional valence of the text and images may result in consumers extending more effort to reconcile the difference. This heightened cognitive processing may lead to consumers losing interest and/or fewer comments.

H1b: A complete mismatch between text and visual content within FGC will be associated with a decrease in volume of comments and positive emotionality of comments.

For the moderate match condition, we examine positive/negative valence emotion paired with neutral valenced content. This can occur when either positive or negative valenced text is paired with neutral visual content (calm face). Given the advantages of moderate incongruency, we expect that a moderate match between the emotional valence of the text and the image will evoke more favorable responses from consumers. When the distance between the emotional valence of the textual and visual element of a firm's post is moderate, we suspect that the content may be viewed as more interesting and arouse curiosity, leading to greater comments. Figure 4 denotes the content match pairs, congruency conditions and expected results.

H1c: A moderate match between textual and visual content within FGC to be associated with an increase in volume of comments.

Figure 4: Expected Influence of Content Match Pairs



Brand Personality

In addition to congruency between components of FGC we also examine how brand personality may moderate how consumers respond to in(congruency) in the firm's content. To the extent that certain brand personalities are more associated with incongruency than others, we contend that consumers may respond differently when presented with mismatched content from a particular type of brand.

Aaker (1997) defined brand personality as "the set of human characteristics associated with a brand." Brand personality has been used to capture the way consumers feel about brands along dimensions typically associated with a person. Aaker (1997) developed the Big Five brand personalities widely used in research (sincerity, excitement, competence, sophistication, and ruggedness). Scholars and marketers have suggested that brand personality is important in distinguishing a brand from competitors (Aaker 1997), building brand equity (Keller 1993), forming preferences for the brand (Biel 1993), influencing brand loyalty (Sung and Kim 2010), and facilitating consumer-brand relationships (Sung and Tinkham 2005).

In the marketplace, two brand personalities (sincere and exciting) make up most of the variation in brand personalities (Aaker 1997; Caprara et al. 2000). Sincere and exciting brand personalities are fundamental in the marketing landscape (Aaker et al. 2004). Prior research suggests that sincere brands are advantageous in fostering long-term consumer relationships as they are associated with traits such as honest, wholesome, down-to-earth, family-oriented, friendly, and sentimental, which have been linked to greater relationship strength (Aaker et al. 2004; Robbins et al. 2000). Brands such as Dove, Coca Cola, and Hallmark are associated with sincere personalities (Harvey 2017; Aaker 1997). Brands such as MTV and Virgin are considered to portray an exciting personality exhibiting traits such as daring, cool, young, unique, independent, and trendy (Aaker 1997). Researchers indicate that exciting brand personalities are advantageous in attracting young consumers, generating cultural vitality and generating interest (Harvey 2017; Altschiller 2000).

Prior literature supports the hypothesis that the interaction of brand personality and disconfirmatory actions by the firm may influence consumer brand relationships. Sudar and Noseworthy (2016) explore negative sensory disconfirmation (when touch disconfirms visual expectations) and brand personalities. They find that negative sensory disconfirmation by exciting brands can be perceived favorably, as consumers view the disconfirmation as more authentic of an exciting brand personality. In contrast, sensory confirmation is preferred for sincere brands (Sudar and Noseworthy 2016). In this analysis, we explore congruence between textual and visual elements within FGC on consumer engagement. We differentiate between sincere and exciting brand personalities to examine the moderating role that brand personalities play in consumers' responses to (in)congruence.

Aaker et al. (2004) suggest that consumers expect a degree of relationship disconfirmation and unpredictability with exciting brands and associate sincere brands with more dependable and consistent actions. We contend that content mismatch is more aligned with the exciting brand personality while consumers may expect content congruence with sincere brands. Incongruent content may be misaligned with consumer perceptions of the consistency of sincere brands. We anticipate that sincere brands may be viewed more unfavorably compared to exciting brands when there is a mismatch between the emotional valence of images and the valence of the brand's text. We expect that content mismatch from exciting brands may be viewed more favorably by consumers who expect a certain level of spontaneity and disconfirmation for exciting brands.

H2a: A content mismatch for sincere brands will be negatively associated with volume of comments.

H2b: A content mismatch for exciting brands will be positively associated with volume of comments.

In terms of emotional valence of consumer comments, we expect that a content match for sincere brands will evoke more positively valenced comments while content mismatch for exciting brands will evoke more positively valenced comments.

H3a: A content match for sincere brands will be associated with an increase in positive emotional comments from consumers.

H3b: A content mismatch for exciting brands will be associated with an increase in positive emotional comments from consumers.

DATA & MEASURES

We collect social media data from Facebook brand pages for 15 brands, presented in Table 6. We use the Facebook graph API to download all available activities made by a brand, such as posts (text and images) and all user comments for a given posts. The raw dataset includes all activity starting from the day the brand page was created on Facebook through October 31, 2018. Brands in our data started Facebook pages as early as January 2009 to February 2012, with Crest and Louis Vuitton being among the first to start Facebook pages and Colgate being the last. We analyze 23,605 Facebook post and aggregate over 2.38 million Facebook comments. Among brands, we find that Gucci has the largest number of brand posts and Nike the fewest. In terms of consumer comments, we see that Chanel garners the most comments of brands in our dataset, followed by Covergirl. Cosmetic brand L'Oreal has the least number of comments. In terms of product categories, we find that luxury brands have the most comments of all product categories while oral hygiene products have the least (Table 6). Similarly, luxury products have the most brand posts and oral hygiene products have the least.

Table 6: List of Brands in Analysis

Brand	Start Date	Product Category	Num. of Posts	Num. of Images	Num. of Comments
Adidas	2011-02-17	Sport Apparel	899	434	70,536
Chanel	2009-11-17	Luxury	1,462	837	494,693
Coach	2009-06-15	Luxury	1,795	1,123	124,922
Colgate	2012-02-15	Oral Hygiene	455	229	31,774
Covergirl	2009-06-22	Cosmetics	1,890	807	277,958
Crest	2009-01-01	Oral Hygiene	765	456	20,813
Estee Lauder	2009-06-24	Cosmetics	2,091	952	106,086
Gain	2010-02-11	Household Goods	1,258	432	138,853
Gucci	2009-01-17	Luxury	4,594	2,918	262,256
L'Oreal	2009-12-31	Cosmetics	903	618	10,401
Louis Vuitton	2009-01-01	Luxury	1,218	733	174,945
Maybelline	2009-07-15	Cosmetics	2,410	1,.83	249,702
New Balance	2009-12-14	Sports Apparel	2,262	1,281	50,506
Nike	2010-06-03	Sports Apparel	369	117	113,493
Tide	2010-06-03	Household Goods	1,234	434	257,471

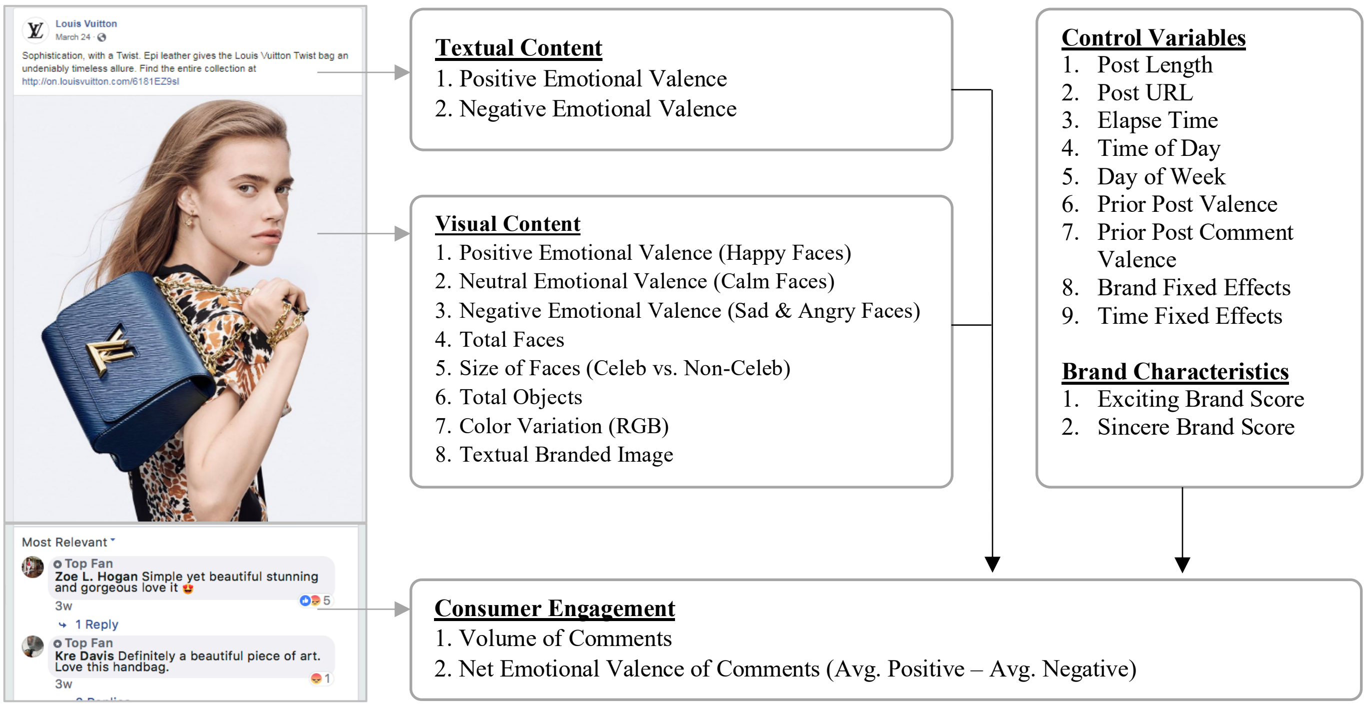
For each firm post we capture the date of the post, time, text, and images if any are used in the post. We also capture individual user comments in response to the brand's post. For each comment we capture the comment date, time, and the text of the comment. Figure 5 summarizes the measures used in the analysis. Table 7 details the description for the measure used in our analysis and data sources. We employ LIWC text analysis software to measure the emotional valence of the text and Amazon Rekognition API to analyze images. Each approach is described in subsequent paragraphs.

Table 7: Measures used in Analysis

Variable	Description	Source/Operationalization
Total Comments	Total number of comments a post receives	
Post Text Content		
Post Pos	Percetange of words in post that are associated with positive valence emotions	Text Analysis via NRC emotionality dictionary
PostNeg	Percetange of words in post that are associated with negative valence emotions	Text Analysis via NRC emotionality dictionary
Post Image Content		
TotalFaces	# of human faces in an image	Amazon Image API
NonCelebFaceSize	Percentage of image that contains non celebrity face(s)	Amazon Image API
CelebFaceSize	Percentage of image that contains celebrity face(s)	Amazon Image API
FacePos	Weighted percentage of image with a face containing positive emotion (happy face)	Amazon Image API
FaceNeg	Weighted percentage of image with a face containing negative emotion (angry or sad face)	Amazon Image API
FaceNeu	Weight percentage of image with a face containing neutral emotion (calm face)	Amazon Image API
TotalObjects	Number of objects types in image	Amazon Image API
Red	Average red channel among top 10 most prevalent colors within a given image	Google Image API*
Blue	Average blue channel among top 10 most prevalent colors within a given image	Google Image API*
Green	Average green channel among top 10 most prevalent colors within a given image	Google Image API*
TextualBrandedImage	Indicator that denotes if image contains brand name	Amazon Image API
User Comments Content		
CmmtPos	Average of expressed positive valence emotions among all comments for a given firm post	Text Analysis via NRC emotionality dictionary
CmmtNeg	Average of expressed negative valence emotions among all comments for a given firm post	Text Analysis via NRC emotionality dictionary
Net Emotional Valence	CmmtPos - CmmtNeg	
Brand Characteristics		
Exciting	Percentage of respondents who checked “energetic” as it relates to the brand	BAV Lovett et al. 2013 dataset
Sincere	Percentage of respondents who checked “authentic” as it relates to the brand	BAV Lovett et al. 2013 dataset
Controls		
Time of day		
Day of week		
Post Text Length		
Post URL		
Elapse Days between Post		
Sentiment Prior Post		
Comment Sentiment Prior Post		

* Google Image API is used to determine the dominate color variation within images as Amazon’s Image API (Rekogntion) does not offer this functionality.

Figure 5: Summary of Measures used in Analysis



Emotional Valence of Text and Comments

We analyze the text of user comments using Linguistic Inquiry and Word Count (LIWC), which has been used in prior literature to capture the emotional valence of text (Berger and Milkman 2012). It analyzes text by parsing through each comment one word at a time. Using the NRC emotion lexicon, LIWC processes each word within a comment by searching the dictionary file for a match and incrementing the appropriate emotional category (Pennebaker et al. 2007; Mohammad et al. 2013). We quantify emotional valence as the percentage of words within the comment associated with positive/negative emotion within the dictionary.

For each brand post, we capture the emotional valence (positive and negative) of the text element. Using the same approach, we capture the emotional valence for each user comment for a given post. We exclude comments that do not contain words as well as successive duplicate comments. We aggregate the emotional valence measures for comments by brand post such that we have total comments and the average emotionality (positive and negative) of comments for each brand post in our dataset. Table 8 shows the summary statistics of emotional valence measures in the dataset. Similar to prior literature, we find that on average brands score higher on positive related emotionality than negative content.

Table 8: Summary of Post and Comment Emotionality Measures

Variable	N	Mean	Std Dev.	Min	Mix
Post Positive	23,605	6.24	6.88	0.00	100.00
Post Negative	23,605	1.79	3.61	0.00	66.67
Comment Positive	23,605	8.59	8.49	0.00	100.00
Comment Negative	23,605	1.67	3.10	0.00	100.00
Post Word Count	23,605	28.25	36.02	0.00	3,176.00
Total Comments per Post	23,605	101.01	397.35	0.00	20,132.00

Image Data

In addition to the textual content of brand posts on Facebook, we analyze images posted in conjunction with the text. The data contains 12,710 images across 15 brands. We find that nearly 54% of FGC posts in our data contain an image, with some variation across product categories. For instance, luxury (62%) and oral hygiene (56%) brands include more pictures on average compared to other brands. Interestingly, cosmetic brands (49%) rank 4th of the 5 product categories in terms of percentage of post containing images. Table 9 provides a description of the number of images and the characteristics we examine in our analysis.

Table 9: Total Number of Measures by Product Category

Category	Post	Comments	Images	Face	Celebrity Face	Textual Branded Image
Cosmetics	7,294	644,147	3,560	1,519	692	960
Household	2,492	396,324	1,022	356	78	454
Luxury	9,069	1,056,816	5,611	3,007	1,593	609
Oral Hygiene	1,220	52,587	685	367	114	336
Sports Apparel	3,530	234,535	1,832	745	308	283
Total	23,605	2,384,409	12,710	5,994	2,785	2,642

Note: Face, Celebrity Face and Textual Branded Image denotes the number of images that contain a face, a celebrity face and the brand name, respectively.

There are several tools to analyze image content (Computer Vision System Toolbox via MATLAB, OpenCV, Deep Neural Networks) which have been explored in the computer information science field (Corke 2005; Liu et al. 2018; Klostermann et al. 2018). Cloud services such as Google Cloud, Amazon Rekognition and Microsoft Azure offer a computer vision API to aid with object detection and facial recognition. We utilize Amazon's Rekognition application to process image content. Given our focus on emotional facial expressions within images, Amazon's API provides a robust set of tools that can be used in a scalable means by researchers. Moreover, its identification of facial expressions provides more granular measures of facial expressions.

Our research examines the emotional valence of the text component of FGC in addition to the emotional valence of faces within visual components of firm-generated content. We categorize the affect within images as positive, negative and neutral valence via facial expressions within the image (Mitchell 1986). Using an image processing API, we determine the extent to which a face within a given image exemplifies positively valenced emotions (happy), negatively valenced emotions (angry and sad) and neutral emotional valence (calm). We also consider the size of the face compared to the overall size of the image in our investigation. Prior literature has found that surface size can influence visual attention (Pieters and Wedel 2004; Koch and Ullman 1985; Itti 2005). Larger surface size has been linked to greater "pop out," as it facilitates figure-ground segmentation which can lead to higher salience and attention (Itti 2005). Next, we describe the Amazon Rekognition API in detail and explain how we derive the image covariates.

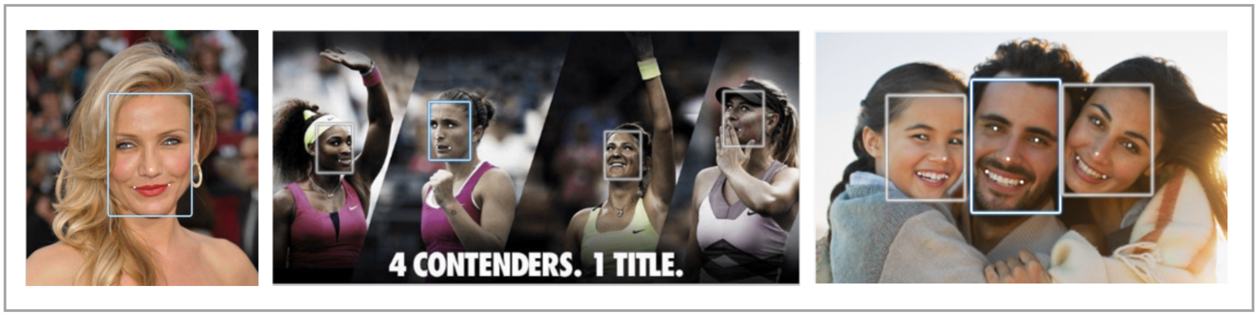
Number and Size of Faces. We examine the number of faces present in the image and the size of the faces as control measures. Using Amazon's facial recognition feature, we can determine the number of faces within a given photo and the relative size of the faces within an image. The API is designed to determine if there is a face within an image by looking for key facial features such as eyes, nose and mouth (Amazon 2019). In the affirmative, the facial detection application provides face details including a bounding box of the face, facial landmarks (e.g., coordinates of eye and mouth), emotions, sunglasses detection, and beard and mustache detection (Amazon 2019). The bounding box is a rectangle surrounding the face only. For each face, the API provides normalized width and height values of the bound box. Figure 6 provides examples of the bounding box functionality. We create two facial measures: a count of the number of faces that appear in an image and the fraction of the image that contains a face. The former allows us to control for multiple faces within an image and the latter allows us to control for the proportional size of the faces within a given image.

Using the bounding box width and height metrics, we calculate the fraction of the image occupied by each face and sum across all the faces within a given image to determine the total percentage of the image that contains a face. Specifically, we operationalize size of faces as:

$$NonCelebFaceSize_j = \sum_{i=1}^{F_j} Width_{ij} * Height_{ij} \tag{1}$$

where *j* denotes image j=1,…,12710, F_j denotes the total number of faces in image *j,* and $Width_{ij}$ and $Height_{ij}$ are normalized measures associated with face *i* in image j.

Figure 6: Facial Recognition Bounding Box



Celebrity Faces. We control for the number of celebrity faces within a given image and the size of the celebrity face in the photo. Prior literature has documented the positive effects of celebrity endorser on brand attitude, box office performance, and product sales. Given the positive impact of celebrity endorsers in prior research, we expect that having a celebrity face within a firm's social media post may influence consumer engagement.

Amazon's API uses a database of celebrity faces from a range of categories (e.g. sports, business, politics, and entertainment) along with facial recognition software to determine if the face within an image is a celebrity and an associated confidence measure (Amazon 2019). The software has the ability to match celebrity faces in a variety of settings and conditions such as makeup and alter egos (e.g. Johnny Depp dressed as Jack Sparrow from the film *Pirates of the Carribean*) (Amazon 2019). As with non-celebrity faces, we code for the number of celebrities faces in an image along with the fraction of the photo that contains a celebrity face.

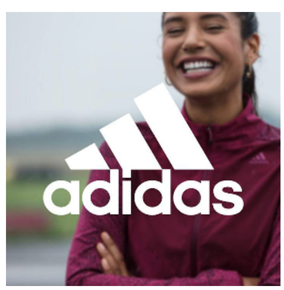
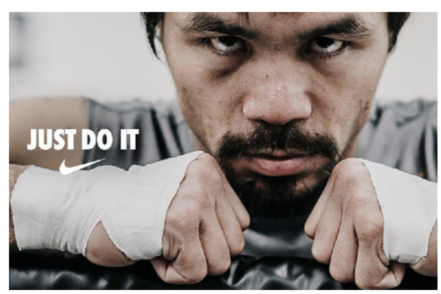
$$CelebFaceSize_j = \sum_{i=1}^{F_j} Width_{ij} * Height_{ij} \tag{1}$$

where j denotes image j=1,…,12710, F_j denotes the total number of celebrity faces in image j, and $Width_{ij}$ and $Height_{ij}$ are normalized measures associated with celebrity face i in image j.

Emotional Valence of the Face. Because an image can potentially convey many emotions, we operationalize emotionality as the fraction of the image that conveys a particular emotional valence. This fraction approach is similar to the text analysis approach which considers the fraction of words within a text corpus associated with a given emotion. To the extent that the faces may be the driving influence in determining the overall emotionality of the entire image, we suspect that our operationalization may provide conservative estimates.

Consistent with prior literature, we capture the positive, negative and neutral valance of images to determine how the different levels of emotional valence impact consumer engagement (Mitchell 1986). We capture emotion conveyed on faces across four emotional measures (happy, calm, sad, and angry) as an indication of the level of emotional valence represented within an image. We measure happy, sad, and angry as they denote positive and negative emotions, while calm represents a neutral emotion. We utilize Rekognition to rate each face across the four emotional measures. Using an internal algorithm, Rekognition determines the emotion (on a scale of 0-100) within faces detected for an image. Table 10 provides examples of Rekognition's facial emotionality measure for different images.

Table 10: Examples of Emotional Facial Expressions

	Example 1	**Example 2**	**Example 3**
Image			
Happy	14.08	94.20	0.93
Calm	71.72	0.06	9.98
Sad	2.47	0.23	3.46
Angry	1.86	1.37	81.05

* Values range from 0-100

For each emotion we calculate a weighted average of the emotion across the number of faces within the image accounting for facial size. For example, if there are two faces within an image, one that occupies 30% of the picture and another that occupies 10% of the picture, the emotionality on the face is weighted proportional to the size of the face such that the emotions on the face that occupies 30% of the picture is weighed higher than the emotions on the face that occupies 10%. Equation 2 denotes the derivation of the emotion measure for each photo in our analysis:

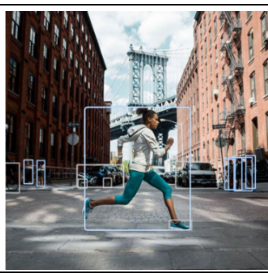
$$wEmotion_{je} = \sum_{i=1}^{F_j}(Width_{ij} * Height_{ij} * Emotion_{ije}) \quad (2)$$

where *j* denotes image j=1,…,12710, *e* denotes a given emotion (e=1,…,4) across the four emotions, F_j denotes the number or total faces within image *j*, $Width_{ij}$ denotes the width of face *i*, $Height_{ij}$ denotes the height of face *i*, and Emotion_{ije} indicates the emotional measure for face *i* in image *j* along emotional dimension *e*. Effectively, for each photo within our data that contains a face, we have a weighted measure for each emotionality (happy, calm, sad and angry) which provides a measure of the fraction of the image that contains emotional content related to the four emotions of consideration in our analysis. *FacePositive* represents the emotional measure for happy faces. *FaceNeutral* represents the emotional measure for calm faces. *FaceNegative* represents the emotional measure for both sad and angry faces.

Number of Objects. To control for the number of types of objects within an image we rely on object and scenery detection tools within Amazon's API. Rekognition's object detection uses deep learning to generate description tags that decipher the objects and scenery within a given image. The API can detect objects (e.g. tree, flower, table), events (e.g. graduation, wedding, party), and concepts (e.g. nature, evening, landscape) (Amazon 2019).

Recognizing the scenery and objects within images is a fundamentally challenging task within the image analysis domain. Drawing on prior research (Klosterman et al. 2018; Ho 2019; Girshick et al. 2016), we use object detection tags in conjunction with part of speech (POS) tagging, to identify descriptors tags that are nouns as nouns denote objects in linguistic text (Straka and Straková 2017). Table 11 provides examples of images, the corresponding tags produced by the API and the measure of the total number of object types.

Table 11: Examples of Object and Label Detection Results

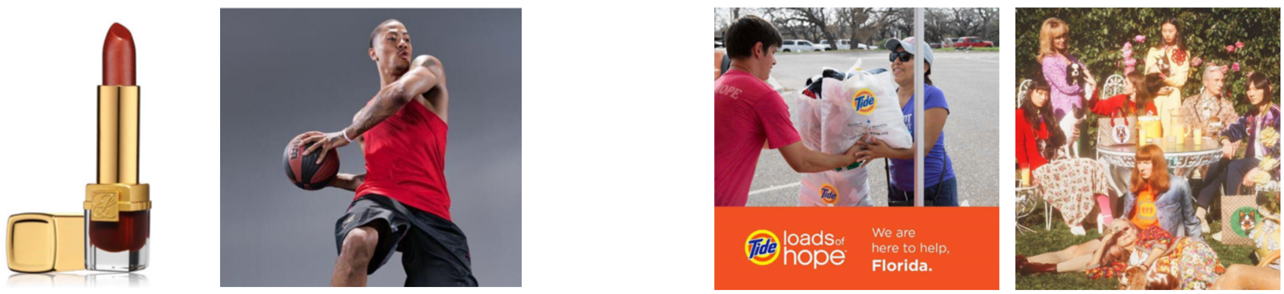
Image	Image Description Tags	Number of Objects
	**Person, Human, Apparel, Footwear, Shoe, Clothing, Pedestrian, Path, Building, Urban, Town, Metropolis, City, Shorts, Vehicle, Automobile, Transportation, Car, Road, Skin, Street, Tarmac, Asphalt, Bike, Bicycle, Downtown, Pavement, Sidewalk, Wheel, Machine, Pants, Sleeve, Office Building,** Architecture, **Flooring**, **Intersection, Walkway, Long Sleeve,** Walking, **Sport**, Working Out, **Exercise**, **Fitness**	43
	**Tool, Brush, Mascara, Cosmetics**	4

* Bold denotes labels that are categorized as nouns, plural nouns and proper nouns using parts of speech (POS) tagger.

We operationalize number of objects as the number of unique nouns associated with an image. This approach is consistent with approaches within the image analysis and offers a reasonable proxy for the number of object types within an image. Our approach offers a reasonable summary measure of the number of objects within an image based on sophisticated machine learning algorithms (Klosterman et al. 2018, Girshick et al. 2016). Figure 7 shows examples of images with low number of objects and high number of objects using our approach.

Figure 7: Example of Number of Object Types Measure

Low Number of Objects | High Number of Objects



Textual Branded Images. Advertising design strategy has urged firms to display the brand prominently on marketing materials. Some suggest that the presence of the brand logo or name helps garner interest among consumers and increases awareness. Amazon's API recognizes any text within an image and reports the textual content. As a control measure, we denote images that contain the brand's logo or name. To the extent that the brand logo contains the name of the brand or consistent lettering, we are able to parse the text within a given image to determine if it contains the brand's name. We construct an indicator variable denoting if the image contains the brand name. Figure 8 provides examples of instances where the brand name and/or logo can be identified. In cases such as Nike (e.g. Nike's swoosh), in which the branding/logo does not contain text, we are unable to indicate branded image. To this degree we suspect that our approach to identifying branded images will result in a conservative estimate of the influence of branded images on consumer engagement and emotionality.

Figure 8: Example of Branded Images in Data

Control Variables. We account for time of day, day of week, the emotional valence of the brand's prior post, the emotional valence of prior comments, post word count, and whether the post contains a URL. For time of day we denote 6:00 AM – 11:59 AM as morning, 12:00 PM – 5:59 PM as afternoon, 6:00 PM – 11:59 PM as evening and 12:00 AM – 5:59 AM as night (Kanuri et al. 2018). For day of the week, we distinguish between weekdays (Monday-Friday) and weekends (Saturday and Sunday). Prior post emotional valence captures the positive and negative emotional valence of the prior post by the brand to Facebook. Prior comment emotional valence is constructed as the average positive and negative emotional valence of comments from the previous post. We also include a measure of the amount of time (in days) that has elapsed since the brand's previous post. We incorporate a linear and quadratic term to allow for a non-linear effect of time since the last post.

EMPIRICAL ANALYSIS AND RESULTS

This analysis investigates two dependent measures: total comments a post receives and the net emotionality of consumer comments. For the former, we estimate a negative binomial regression based on equation (4). For the latter, we estimate a linear regression as the net emotionality takes on continuous values that may be either positive or negative. We model both total comments and net emotionality as a function of firm textual and visual content characteristics:

$$y_i = \alpha + \sum_{j=1}^{n} \beta_{1j} * \text{PostTextContent}_{ij} + \sum_{j=1}^{k} \beta_{2j} * \text{PostImageContent}_{ij} \\ \sum_{j=1}^{n} \beta_{3j} * \text{PriorPostTextContent}_{ij} + \sum_{j=1}^{p} \beta_{4j} * \text{PriorPostCommentSentiment}_{ij} \\ \sum_{j=1}^{k} \gamma_j * \text{ControlVariables}_{ij} + \varphi_b + \delta_y + \varepsilon_i \tag{4}$$

where y_i denotes the number of comments for post i, β_{1j} denotes a vector of coefficients of the post's text attributes (positive and negative emotionality), β_{2j} denotes a vector of coefficients of the image characteristics (FacePositive, FaceNeutral, FaceNegative, total number of faces, size of faces in image [celeb and non-celeb], number of objects, textual branded image), β_{3j} denotes a vector of coefficients for prior post's emotional valence (positive and negative emotion), β_{4j} denotes a vector of coefficients for prior comments' emotional valence (positive and negative), γ_j denotes a vector of coefficient for control variables (time of day, day of week, elapsed time, elapsed time^2, URL indicator, post length), and φ_b and δ_y denote brand-specific fixed effects and year fixed effects, respectively. Table 12 presents the full model results.

We begin our discussion of the results by first examining the influence of emotional valence of content on total comments. Next, we examine the influence of firm content characteristics on net emotional valence of consumer comments, offering insight into what content characteristics are indicative of positive or negative consumer responses.

Total Comments

We estimate three models: (1) a base model, (2) a model that incorporates two-way interaction between emotional valence of text and faces to examine the potential influence of content (in)congruency on consumer engagement, and (3) a model that also incorporates a 3-way interaction between visual emotional valence, text emotional valence and brand personality to examine how brand personality may moderate the effects of content (in)congruency. Comparing models 1 and 2, the likelihood ratio test is χ^2=38.4 (d.f.=6, *p*<.01), indicating a statistically significant interaction between text and visual emotional valence. Comparing models 2 and 3, the likelihood ratio test is χ^2=65.7 (d.f.=22,*p*<.01), indicating a significant 3-way interaction between brand personality, text-based emotional valence and visual emotional valence.

Base Model. From the base model, our results show that positive and negative emotionally valenced text has a positive impact on the number of comments for a firm post. For visual elements, we use the emotional facial expressions (happy, calm, sad and angry) within the image as a measure of the emotional valance for visual content. The significant and positive effect of *FacePos* suggests that happy faces within firm Facebook post are positively associated with total comments. Conversely, the significant negative coefficient estimates for *FaceNeu* and *FaceNeg* show that calm, angry and sad faces within images decrease volume of comments for a firm's post. We also find that exciting brands are associated with greater consumer comments. These results help to understand how the components of a firm-generated Facebook post individually influence the number of comments it receives.

We find a non-linear relationship between number of faces and volume of comments. The *TotalFaces* covariate is significant and positive while the quadratic term is significant and negative. The size of the face seems to only matter when it is a celebrity face, shown by the positive significant parameter estimates for *CelebFaceSize* covariate and lack of significance for the *NonCelebFaceSize* parameter. We find a negative correlation between number of objects and total comments, indicating that the more objects within an image the fewer comments it receives. This could be a result of consumer's attention being disjointed, causing the image to stand out less and leading to fewer comments. In controlling for color variation that exist within images, we find that the level of red channel within an image is positively associated with total comments. Given recent literature denoting time of day effect on consumer engagement (Kanuri et al. 2018; Gullo et al. 2018), we control for time of day the brand posted the content to Facebook. We find that compared to firm posts at night, firm posts in the morning garner more comments while firm posts in the afternoon garner significantly less comments. This suggests that firms should consider timing posts in the morning rather than the afternoon or night. Results show that FGC posted during the week (Mon-Fri) are associated with higher volume of comments. Other content measures such as word count and presence of a URL link are shown to significantly reduce the number of comments a firm's post receives.

Table 12: Result of Covariates on Total Comments

	Equations					
	(1)		(2)		(3)	
	Base Model		Text X Face		Text X Face X Personality	
	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
PostPos	0.003*	(0.001)	0.003*	(0.002)	0.011	(0.009)
PostNeg	0.019**	(0.003)	0.021**	(0.003)	-0.026	(0.020)
FacePos (Happy Face)	0.024**	(0.004)	0.025**	(0.006)	0.040	(0.064)
FaceNeu (Calm Face)	-0.018*	(0.008)	-0.024	(0.018)	-0.129	(0.167)
FaceNeg (Sad/Angry Face)	-0.013*	(0.005)	-0.003	(0.007)	-0.076	(0.053)
Sincere	0.023	(0.026)	0.024	(0.026)	0.021	(0.026)
Exciting	0.200**	(0.045)	0.200**	(0.045)	0.196**	(0.045)
PostPos x FacePos			0.000	(0.001)	0.010	(0.007)
PostPos x FaceNeu			-0.001	(0.002)	0.014	(0.019)
PostPos x FaceNeg			-0.001*	(0.001)	0.005	(0.005)
PostNeg x FacePos			-0.005**	(0.001)	0.016	(0.014)
PostNeg x FaceNeu			0.003*	(0.001)	-0.019	(0.035)
PostNeg x FaceNeg			-0.000	(0.001)	0.011	(0.009)
PostPos x Sincere					-0.000	(0.001)
PostNeg x Sincere					0.002	(0.002)
PostPos x Exciting					-0.001+	(0.000)
PostNeg x Exciting					0.003**	(0.001)
FacePos x Sincere					-0.000	(0.005)
FaceNeu x Sincere					0.006	(0.014)
FaceNeg x Sincere					0.007	(0.005)
FacePos x Exciting					-0.001	(0.004)
FaceNeu x Exciting					0.006	(0.012)
FaceNeg x Exciting					0.001	(0.004)
PostPos x FacePos x Sincere					-0.000	(0.001)
PostPos x FaceNeu x Sincere					-0.001	(0.002)
PostPos x FaceNeg x Sincere					-0.001*	(0.001)
PostNeg x FacePos x Sincere					-0.002*	(0.001)
PostNeg x FaceNeu x Sincere					0.003	(0.003)
PostNeg x FaceNeg x Sincere					-0.001	(0.001)
PostPos x FacePos x Exciting					-0.001**	(0.000)
PostPos x FaceNeu x Exciting					-0.000	(0.001)
PostPos x FaceNeg x Exciting					0.001*	(0.000)
PostNeg x FacePos x Exciting					-0.000	(0.002)
PostNeg x FaceNeu x Exciting					-0.001	(0.003)
PostNeg x FaceNeg x Exciting					-0.000	(0.000)
TotalFaces	0.050**	(0.008)	0.051**	(0.008)	0.051**	(0.008)
$TotalFaces^2$	-0.001**	(0.000)	-0.001**	(0.000)	-0.001**	(0.000)
NonCelebFaceSize	0.040	(0.238)	0.062	(0.241)	-0.032	(0.254)
CelebFaceSize	0.448*	(0.207)	0.583**	(0.218)	0.602**	(0.224)
TotalObjects	-0.022**	(0.002)	-0.022**	(0.002)	-0.023**	(0.002)
BrandedImage	0.005	(0.033)	0.008	(0.033)	0.007	(0.033)
RedColorChannel	0.003**	(0.001)	0.003**	(0.001)	0.004**	(0.001)
GreenColorChannel	-0.002	(0.001)	-0.002	(0.001)	-0.002	(0.001)
BlueColorChannel	-0.001	(0.001)	-0.000	(0.001)	-0.000	(0.001)
ElapseTimeDay	0.036**	(0.003)	0.035**	(0.003)	0.036**	(0.003)
$ElapseTimeDay^2$	-0.000**	(0.000)	-0.000**	(0.000)	-0.000**	(0.000)
Morning	0.238**	(0.057)	0.243**	(0.057)	0.244**	(0.057)

Afternoon	-0.095*	(0.041)	-0.092*	(0.041)	-0.094*	(0.041)
Evening	-0.075+	(0.041)	-0.068+	(0.041)	-0.064	(0.041)
Weekend	-0.056*	(0.027)	-0.056*	(0.027)	-0.073**	(0.027)
PostUrl	-0.298**	(0.023)	-0.299**	(0.023)	-0.289**	(0.023)
PostWC	-0.003**	(0.000)	-0.003**	(0.000)	-0.003**	(0.000)
L_PostPos	-0.001	(0.001)	-0.001	(0.001)	-0.001	(0.001)
L_PostNeg	0.004	(0.003)	0.004	(0.003)	0.004	(0.003)
L_cmtemo_postive	-0.005**	(0.001)	-0.005**	(0.001)	-0.005**	(0.001)
L_cmtemo_negative	0.012**	(0.004)	0.012**	(0.004)	0.012**	(0.004)
2010	0.498**	(0.084)	0.496**	(0.084)	0.494**	(0.084)
2011	0.798**	(0.082)	0.796**	(0.082)	0.796**	(0.082)
2012	0.849**	(0.082)	0.849**	(0.082)	0.850**	(0.082)
2013	0.880**	(0.082)	0.881**	(0.082)	0.886**	(0.082)
2014	0.555**	(0.084)	0.554**	(0.084)	0.555**	(0.084)
2015	0.784**	(0.085)	0.781**	(0.085)	0.750**	(0.085)
2016	0.358**	(0.084)	0.350**	(0.084)	0.353**	(0.084)
2017	0.276**	(0.083)	0.275**	(0.083)	0.277**	(0.083)
2018	0.143+	(0.082)	0.142+	(0.082)	0.145+	(0.082)
Chanel	3.258**	(0.384)	3.254**	(0.384)	3.253**	(0.384)
Coach	2.252**	(0.444)	2.250**	(0.444)	2.239**	(0.443)
Colgate	1.153**	(0.348)	1.148**	(0.348)	1.145**	(0.348)
Covergirl	1.930**	(0.318)	1.926**	(0.317)	1.930**	(0.317)
Crest	0.191	(0.337)	0.185	(0.337)	0.190	(0.336)
Estee Lauder	1.674**	(0.412)	1.671**	(0.412)	1.658**	(0.411)
Gain	1.796**	(0.323)	1.796**	(0.322)	1.797**	(0.322)
Gucci	1.796**	(0.430)	1.793**	(0.429)	1.797**	(0.429)
L'Oreal	-0.729**	(0.241)	-0.726**	(0.240)	-0.736**	(0.241)
Louis Vuitton	1.968**	(0.295)	1.964**	(0.294)	1.964**	(0.294)
Maybelline	1.838**	(0.354)	1.828**	(0.354)	1.821**	(0.353)
New Balance	-1.558**	(0.148)	-1.558**	(0.148)	-1.529**	(0.148)
Nike	1.001**	(0.111)	1.002**	(0.111)	1.063**	(0.112)
Tide	2.586**	(0.375)	2.583**	(0.374)	2.594**	(0.374)
_cons	0.784	(0.583)	0.773	(0.582)	0.809	(0.586)
lnalpha	0.764**	(0.008)	0.763**	(0.008)	0.761**	(0.008)
N	23589		23589		23589	
Parameters	55.000		61.000		83.000	
Log Likelihood	-118808.750		-118789.533		-118756.687	

**,*,+ denotes p<0.01, 0.05, 0.10 respectively. The baseline time of day is night, the baseline year is 2009, the baseline time of day is Weekdays (Mon-Fri), the baseline brand is Adidas.

Text and Imagery Interaction Effects. Model 2 incorporates the interaction between content elements, enabling us to draw inferences about the effects of a match vs. mismatch in textual and visual elements on consumer engagement. Consistent with the base model, we find that the main effects of positive and negatively valenced text is still positive and significant on volume of comments. For the visual content measures, we see that only positive (happy) faces remain significant and positive; we no longer find significant main effects for neutral (calm) or negative (angry/sad) emotionally valenced faces as the variation is now explained by interaction terms.

In examining the interaction terms, we find that positively valenced text paired with negatively valenced images decreases the total number of comments FGC receives. Similarly, negatively emotionally valence text paired with positively valenced visual stimuli is also negatively associated with total number of comments FGC receives. Taken together, our results support H1b, indicating that a mismatch between the text and visual elements of the brand's post decreases consumer engagement. Effectively, model 2 shows that angry and sad faces significantly lower consumer comments when paired with text that has positive emotional valence. Similarly, happy faces significantly decrease consumer comments when paired with negatively valenced text.

The interaction between negative valenced text and neutral visual imagery is positive and significant, suggesting that moderate incongruency between text and visual imagery is associated with greater consumer comments. Thus, we find support for H1c. This finding is consistent with prior literature that showed moderate incongruency could lead to favorable consumer responses. We do not find evidence to support H1a, that a complete match between emotional valence of text and visual content significantly influences consumer engagement. It could be that consumers expect text and images to match so when matching occurs in a social media context it doesn't elicit consumer action.

We find qualitatively similar results among control variables in the text and imagery interaction model as we did in the base model.

Text, Imagery and Brand Personality Interaction Effects. Model 3 allows us to test H3a and H3b by examining the interaction between content elements (visual and text) and brand personality measures. The 3-way interaction provides insights into how consumers' responses to (in)congruency between content elements may differ for certain brand personality types. In examining the model fit using log likelihood we find that Model 3 has better fit compared to Model 2 (χ^2=65.7,d.f.=22,p<.01), indicating that the inclusion of the 3-way interactions better fits the data.

Results from Table 12 show no significant main effects of emotional valence of text nor visual elements as the variation is now captured with interaction terms. Across all three models, we find a significant and positive effect for exciting brands on total number of comments for FGC. In examining the interactions with sincere brands, we find that content mismatch has a significant negative effect on total comments for FGC as evident by the negative parameter estimate for *PostPos x FaceNeg x Sincere* and *PostNeg x FacePos x Sincere* interaction terms. When positive emotionally valenced text is paired with negative valenced visual elements (e.g. angry/sad faces), we show a significant decrease in the number of comments for a sincere brand. Similarly, when negatively valenced text is paired with positive valenced visual elements (e.g. happy faces) we also find a significant decrease in volume of comments. These results suggest that consumers respond less favorable (e.g. fewer comments) to incongruences in FGC posted by sincere brands, supporting H2a.

In exploring the interactions with exciting brands (*PostPos x FaceNeg x Exciting*), we find that a mismatch between emotional valence of text and visual content has a significant positive impact on total comments. Specifically, results show that while positive valenced text paired with negative valenced imagery (angry/sad faces) decreases comments for sincere brands, there is a significant positive effect for exciting brands. Interestingly, we find that a complete match (*PostPos x FacePos x Exciting*) between emotional valence of text and visual content leads to a reduction in total comments for exciting brands. These findings suggest that consumers may respond more favorably to incongruences in FGC by exciting brands and may even expect a certain degree of incongruence from exciting brands. We find support for H2b.

In Model 3, we do not find evidence of a positive impact of moderate (in)congruence in visual and text content for either sincere or exciting brands. This may be a natural result of consumers more readily recognizing when FGC is either consistent or inconsistent with the brand personality. Among other control variables in the model, we find consistent results in the brand personality interaction model as we did in the base model.

Summary. The results from Models 1-3 suggest that imagery and text jointly affect the volume of consumer engagement with FGC. Our results reveal that both positive and negative emotionally valenced text content increases the volume of consumer engagement. Among visual elements, we find that happy faces increase consumer engagement while calm, sad, and angry faces reduce consumer engagement. When negatively valenced text is paired with positively valenced visual content (e.g. a happy face), FGC experiences a significant decrease in the number of comments. Similarly, positively valence text paired with negatively valence visual content (angry/sad faces), can also reduce the number of comments FGC receives. Our results show that brand personality moderates this negative effect. Our findings indicate that sincere brands experience lower consumer engagement with content incongruence. However, this negative effect is reversed for exciting brands, such that total comments increase with incongruence between text and visual content.

As a robustness check, an alternate model is estimated allowing for category fixed effects and includes brand's digital advertising spend as additional controls measures. (See Appendix C). Results are substantively similar.

Net Emotional Valence of Comments

Next, we examine the influence of text and visual content on emotionality expressed within consumer comments. Table 13 details the results of Models 1 – 3. A positive parameter estimate can be interpreted as an increase in positively valenced emotional consumer responses while a negative parameter estimate can be interpreted as a decrease in positive emotionally valenced consumer responses (e.g. an increase in negatively valenced consumer responses). As was the case for the volume of comments, in comparing Models 1 and 2 we see that the incorporation of the 2-way interaction between text and visual emotional valence improves model fit (χ^2=26.0, d.f.=6, p<.01). We also find that the addition of the 3-way interaction between text, visual and brand personality in Model 3 (compared to Model 2 which omits the 3-way interaction) improves model fit (χ^2=59.1, d.f.=22, p<.01).

The particular covariates of interest are the 3-way interaction terms between text, visual and brand personality, as they allow us to test H3a and H3b. Our results suggest that a match between emotional valence of text and visual elements is associated with an increase in net emotional valence for sincere brands as evidenced by the *PostPos x FacePos x Sincere* covariate. Coupled with the findings regarding the volume of comments, our results suggest that positively valenced text paired with happy faces may not increase the number of comments a post receives, but it does increase the amount of emotionally positive language within the content of consumer comments for sincere brands. Additionally, we find a marginally significant (p<0.1) positive effect of *PostNeg x FaceNeg x Sincere* on the net emotional valence of consumer responses. These results support H3a, suggesting that on average consumers may respond favorably when text and visual content from sincere brands are congruent. In looking at the interaction *PostNeg x FaceNeu x Sincere*, we see that the moderate mismatch between emotional valence of text and images is associated with an increase in the net emotional valence of responses from consumers for sincere brands. This is consistent with the sincere brand personality and the notion that consumers may respond more favorably to consistency from sincere brands and less favorably to inconsistency.

For exciting brands, we find one notable significant interaction, *PostNeg x FacePos x Exciting*, which is associated with an increase in the net emotional valence of consumer comments. Thus, we find support for H3b, revealing that content mismatch for exciting brands is associated with more positive emotional comments. This is consistent with our prior results showing that incongruence from exciting brands is associated with greater number of comments. Taken together, the results from net emotionality and total comments suggest that for exciting brands, a mismatch between emotional valence of text and images can lead to greater total comments and greater positively valenced consumer responses.

Other covariates such as textual branded image, positively valenced text, total objects and positive emotionality of comments from the firm's prior post are also associated with increase in positively valenced emotionality of consumer responses. This suggest that while textual branded image do not increase total number of comments, the presence of the brand name/logo does help to foster positive consumer responses.

Table 13: Result of Covariates Impact on Net Emotional Sentiment of Consumer Comments

	Equations					
	(1)		(2)		(3)	
	Base Model		Text X Face		Text X Face X Personality	
	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
PostPos	0.111**	(0.008)	0.112**	(0.009)	0.373**	(0.055)
PostNeg	-0.070**	(0.016)	-0.065**	(0.016)	-0.042	(0.113)
FacePos (Happy Face)	0.017	(0.023)	-0.008	(0.033)	0.384	(0.244)
FaceNeu (Calm Face)	-0.146*	(0.059)	0.120	(0.100)	-1.094	(0.835)
FaceNeg (Sad/Angry Face)	-0.002	(0.030)	-0.023	(0.038)	-0.074	(0.277)
Sincere	-0.067	(0.150)	-0.062	(0.150)	0.016	(0.152)
Exciting	0.244	(0.233)	0.238	(0.233)	0.306	(0.233)
PostPos x FacePos			0.002	(0.002)	-0.059*	(0.023)
PostPos x FaceNeu			-0.010	(0.009)	-0.053	(0.074)
PostPos x FaceNeg			0.000	(0.003)	0.014	(0.025)
PostNeg x FacePos			0.004	(0.006)	-0.102+	(0.060)
PostNeg x FaceNeu			-0.053**	(0.011)	0.430**	(0.161)
PostNeg x FaceNeg			0.009*	(0.004)	-0.036	(0.034)
PostPos x Sincere					-0.021**	(0.005)
PostNeg x Sincere					-0.002	(0.010)
PostPos x Exciting					-0.006**	(0.002)
PostNeg x Exciting					-0.001	(0.005)
FacePos x Sincere					-0.032	(0.020)
FaceNeu x Sincere					0.135+	(0.074)
FaceNeg x Sincere					0.002	(0.026)
FacePos x Exciting					-0.006	(0.020)
FaceNeu x Exciting					-0.032	(0.051)
FaceNeg x Exciting					0.007	(0.018)
PostPos x FacePos x Sincere					0.006**	(0.002)
PostPos x FaceNeu x Sincere					0.001	(0.007)
PostPos x FaceNeg x Sincere					-0.001	(0.003)
PostNeg x FacePos x Sincere					0.003	(0.004)
PostNeg x FaceNeu x Sincere					-0.036*	(0.014)
PostNeg x FaceNeg x Sincere					0.006+	(0.003)
PostPos x FacePos x Exciting					-0.001	(0.002)
PostPos x FaceNeu x Exciting					0.006	(0.005)
PostPos x FaceNeg x Exciting					-0.000	(0.001)
PostNeg x FacePos x Exciting					0.011*	(0.006)
PostNeg x FaceNeu x Exciting					-0.015	(0.011)
PostNeg x FaceNeg x Exciting					-0.003	(0.002)
TotalFaces	-0.091+	(0.047)	-0.101*	(0.047)	-0.118*	(0.047)
$TotalFaces^2$	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
NonCelebFaceSize	0.740	(1.344)	0.201	(1.354)	0.257	(1.366)
CelebFaceSize	1.132	(1.175)	0.677	(1.179)	0.815	(1.186)
TotalObjects	0.049**	(0.011)	0.049**	(0.011)	0.049**	(0.011)
BrandedImage	0.456*	(0.191)	0.453*	(0.191)	0.440*	(0.191)
RedColorChannel	0.007	(0.004)	0.007	(0.004)	0.006	(0.004)
GreenColorChannel	0.005	(0.007)	0.005	(0.007)	0.005	(0.007)
BlueColorChannel	-0.009	(0.006)	-0.009	(0.006)	-0.008	(0.006)
ElapseTimeDay	-0.008	(0.012)	-0.008	(0.012)	-0.009	(0.012)

ElapseTimeDay^2	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Morning	0.392	(0.315)	0.391	(0.315)	0.368	(0.314)
Afternoon	0.014	(0.233)	0.009	(0.233)	-0.007	(0.233)
Evening	0.257	(0.238)	0.249	(0.238)	0.243	(0.238)
Weekend	0.078	(0.151)	0.075	(0.151)	0.075	(0.151)
PostUrl	0.148	(0.129)	0.147	(0.129)	0.157	(0.129)
PostWC	-0.004*	(0.002)	-0.004*	(0.002)	-0.004*	(0.002)
L_PostPos	-0.009	(0.008)	-0.009	(0.008)	-0.006	(0.008)
L_PostNeg	0.010	(0.016)	0.010	(0.016)	0.009	(0.016)
L_cmtemo_postive	0.063**	(0.007)	0.062**	(0.007)	0.063**	(0.007)
L_cmtemo_negative	0.008	(0.018)	0.008	(0.018)	0.005	(0.018)
2010	0.198	(0.487)	0.211	(0.487)	0.176	(0.487)
2011	-0.064	(0.473)	-0.050	(0.472)	-0.109	(0.472)
2012	-0.388	(0.477)	-0.366	(0.477)	-0.380	(0.477)
2013	-0.070	(0.478)	-0.059	(0.478)	-0.078	(0.477)
2014	-1.056*	(0.488)	-1.041*	(0.487)	-1.076*	(0.487)
2015	-1.310**	(0.488)	-1.290**	(0.488)	-1.310**	(0.488)
2016	-2.972**	(0.483)	-2.961**	(0.483)	-3.013**	(0.482)
2017	-4.574**	(0.477)	-4.561**	(0.477)	-4.595**	(0.477)
2018	-5.825**	(0.475)	-5.812**	(0.474)	-5.864**	(0.474)
Chanel	8.538**	(2.023)	8.479**	(2.022)	8.779**	(2.023)
Coach	8.578**	(2.278)	8.525**	(2.278)	8.905**	(2.277)
Colgate	3.969*	(1.789)	3.936*	(1.788)	4.137*	(1.788)
Covergirl	5.578**	(1.620)	5.534**	(1.619)	5.735**	(1.619)
Crest	3.130+	(1.742)	3.100+	(1.741)	3.285+	(1.741)
Estee Lauder	7.351**	(2.082)	7.299**	(2.081)	7.476**	(2.080)
Gain	7.196**	(1.632)	7.162**	(1.632)	7.284**	(1.631)
Gucci	7.192**	(2.228)	7.129**	(2.228)	7.525**	(2.228)
L'Oreal	5.391**	(1.206)	5.373**	(1.206)	5.472**	(1.210)
Louis Vuitton	7.159**	(1.598)	7.113**	(1.598)	7.331**	(1.597)
Maybelline	5.960**	(1.805)	5.899**	(1.805)	6.130**	(1.805)
New Balance	0.848	(0.791)	0.863	(0.791)	0.796	(0.792)
Nike	0.008	(0.620)	-0.019	(0.620)	-0.012	(0.621)
Tide	3.443+	(1.894)	3.394+	(1.894)	3.672+	(1.893)
_cons	0.351	(2.892)	0.369	(2.891)	-1.163	(2.915)
N	23589		23589		23589	
Log Likelihood	-84209.052		-84196.077		-84166.537	

**,*,+ denotes p<0.01, 0.05, 0.10 respectively. The baseline time of day is night, the baseline year is 2009, the baseline time of day is Weekdays (Mon-Fri), the baseline brand is Adidas.

DISCUSSION

FGC on social media platforms use a combination of textual and visual content. Much extant empirical research focuses more on the text of online WOM and less on the visual components. This study examines the individual and combined effects of textual and visual elements of firm-generated content on consumer engagement. We leverage machine learning via an image processing API to capture emotions using facial recognition software. Using the emotions from facial expressions, we construct a measure of emotional valence of images. We employ text analysis to construct a measure of emotional valence of the textual component within firm-generated content. By measuring the emotional valence of both text and visual elements, we show that the extent to which the two elements are (in)congruent can influence the number of comments a social media post receives and the emotional valence of consumer comments. Our method can be replicated by researchers and marketers with relative ease to assist with understanding how pictorial elements influence consumer responses in online WOM.

This research adds to the nascent social media research that incorporates image analysis. Given the proliferation of social media platforms such as Instagram, Pinterest and Snapchat which are dominated with images, this is an area of potential for firms and marketers. To the best of our knowledge, this research is among the first to examine the influence of both text and visual content (specifically faces) within a social media context. Additionally, we offer an approach for measuring the emotional valence within images utilizing facial recognition tools. Given the burgeoning literature related to consumers' emotional responses to brands and the influence of emotionality on social media engagement, images offer another dimension on which brands can convey emotionality.

Our results offer content marketing insights for digital marketers. Contrary to what conventional practitioners may believe, adding images to social media posts can potentially reduce consumer engagement in cases where there is a complete mismatch between the text and visual content. For example, our results suggest that pairing positively valenced text with negatively valenced visual content (angry/sad faces) can lead to a decrease in number of comments while a moderate mismatch leads to increases in number of comments. For marketers focused on increasing consumer engagement, our findings inform content marketing strategies and provide concrete insights into how to craft digital media content.

Our research suggests that the decision to match or mismatch should be informed by brand attributes and that brand personality can influence how consumers respond to FGC. There is no "one size fits all" approach to social media marketing strategy; what works for one brand may not work for another brand, and marketers should be cognizant of this when implementing digital media strategies. We find that for sincere brands, consumer engagement is negatively associated with a mismatch between textual and visual content components, but exciting brands experience a significant increase in user comments when the text and visual content is mismatched. We also show that consumers' net emotional response to FGC from sincere brands is significantly more positive when there is a match between text and visual content and significantly more negative when there is a content mismatch. For exciting brands, consumers' net emotional responses are more positive when there is a mismatch between text and visual elements.

Our research is not without limitations. As image analysis is a developing stream of literature there are numerous ways to measure various elements within images. We offer one approach, but others can work to develop alternatives. With innovations in machine learning and deep learning other approaches currently exist, and new tools are being built that may offer additional methods to analyze image content. While we measure emotions based on facial expressions, one direction to pursue would be to leverage the combination of text and images to infer the emotions associated with other objects in images. Another avenue for future researchers to consider is the extent to which color variation may arouse emotions. Similarly, there may be other ways to measure color variation than the way it is operationalized within this analysis.

Our research employs Facebook posts from a limited number of product categories. Future research may investigate if our findings generalize to other product categories and across other social media platforms, such as Instagram and Twitter. While we determine emotional facial expressions using happy, sad, angry and calm, researchers may also explore identifying other emotions and the degree of arousal in an image. While we make use of field data to investigate the impact of content (in)congruence in FGC on online consumer engagement, future research in a laboratory setting may allow one to identify the boundary conditions of our findings. While we investigate how content characteristics drive consumer engagement, future studies should also seek to move beyond understanding drivers of online WOM to identify how content affects metrics such as website traffic and sales (e.g., Akpinar and Berger 2017; Fossen and Schweidel 2019).

Chapter 3
Emotionality of Social TV Content and Television Consumption

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 its impact 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 fictional elements of the program (e.g. characters in the program) or non-fictional elements of the program (e.g. the actor who portrays that character)? Moreover, does the emotionality of the post play a role? Do posts containing negative emotional responses pertaining to fictional elements have the same effect as a negative emotional post pertaining to fictional elements of the television program? 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. Consistent with prior literature (Mayzlin and Godes 2004), we find evidence that social TV activity affects the total size of the viewing and timing of television program consumption, however its effects are not homogenous. In segmenting social TV activity based on the emotionality and the focus of the content of the post, we find evidence that heterogeneity among the types of social TV activity influences TV consumption differently. Social TV activity is segmented along two dimensions: emotionality (positive and negative) and content (fiction, non-fiction). We find that certain types of social TV posts — in particular positive posts about fictional elements in the program (e.g. characters) — affect the total viewing audience size and earlier time-shifted DVR consumption. Our results show that social TV activity expressing positive emotion about non-fictional elements of the television program (e.g. actors) has an adverse impact on total viewership. We find that social TV activity expressing negative emotion about non-fictional elements of the television program affects the share of devices that engage in live-viewing compared to time-shifted DVR viewing.

Our research contributes to the literature in three key ways. First, we distinguish among social TV posts based on the content of the post. We extend prior research (Mayzlin and Godes 2004) by segmenting social TV activity based on the content of the post to find that allowing heterogeneity among social TV activity provides varying consequences on viewership. 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 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

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

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. Third, we add to the growing literature stream examining how emotionality of social media content influences marketing outcomes. We examine social TV activity containing high arousal positive and negative valenced content to show that emotionality and arousal influence television viewership.

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, 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 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 and its emotional valence (positive and negative), 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. Within online WOM emotionality has been linked to sharing of information, we know little about how emotionality of social media activity may influence information dissemination and subsequent television viewing. This analysis explores social media activity along two dimensions (content focus and emotional valence) to examine its influence on live and time-shifted DVR viewing. Table 14 provides a summary of seminal research in the marketing literature pertaining to this analysis. 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.

Table 14: Contribution of Research

	TV Viewing Behavior	Time-shifted DVR Viewing	Online Buzz	Emotionality of Online Buzz
Rust and Alpert (1984)	✓			
Rust et al.(1992)	✓			
Shachar & Emerson (2000)	✓			
Pearson & Barwise (2007)	✓	✓		
Downey (2007)	✓	✓		
Wilbur (2008a)	✓			
Wilbur (2008b)	✓	✓		
Godes and Mayzlin (2004)	✓		✓	
Berger (2011)			✓	✓
Berger & Milkman (2012)			✓	✓
Hill et al. (2012)	✓		✓	
Liu et al. (2016)	✓		✓	
Fossen and Schweidel (2017)	✓		✓	
Current Analysis	✓	✓	✓	✓

Building on dimensions of narrative transportation theory, we segment social TV activity along two dimensions: emotional valence (positive/negative) and content focus (fiction/nonfiction). First, we detail narrative transportation theory and how we expect it to apply in the television viewing context. Next, we detail literature pertaining to emotionality of online content to provide background on the influences of emotionality and the particular emotions of interest in this analysis.

Narrative Transportation Theory

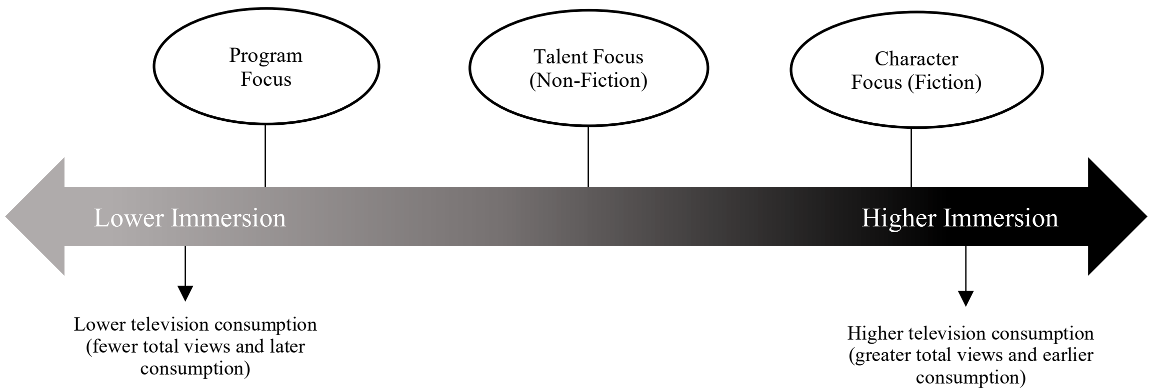
Narrative transportation concepts can connect the content of show-related social media posts to live and delayed TV viewing actions. Gerrig (1993) introduced the term "narrative transportation," defined as "immersion into a text." Green and Brock (2000) explicate narrative transportation as losing oneself 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). 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 connect with each other and express their attitudes, opinions, and sentiment towards a particular program (Yvette and Na 2011), providing networks with consumers' reaction to a particular program. Social TV activity provides insights into overall audience interest in a given television program (Goel 2015). We contend that social TV activity can provide a proxy measure of how immersed viewers are in a television program. Moreover, viewer's engagement with the narrative can serve as an indication of the audience interest, overall quality of the narrative, and the program's ability to resonate with viewers.

Researchers agree that narrative immersion requires both an emotional response to the narrative (Laer et al. 2014) and an emphasis on fictional rather than non-fictional elements (Green and Brock 2000; Green 2008). Using this framework, we examine emotional social TV activity associated with a given program. We segment social TV activity along two dimensions: emotional valence (positive/negative) and content focus (fiction/nonfiction).

In terms of content focus, we differentiate between content that is focused on fictional elements (characters), non-fictional elements (talent), and program-related posts. We define talent as posts mentioning the real-world actors who portray characters in the program. Posts that mention the program but do not reference fictional or nonfictional elements are categorized as program-related. Viewers who participate in social media conversations focusing on characters 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, may exhibit a lesser degree of immersion. Viewers who make broad comments about the program irrespective of the character or talent may be even less immersed in the narrative. We propose that posts that are focused on fictional elements (e.g. character focus) indicate a greater level of narrative immersion compared to posts that focus on non-fictional elements (e.g. talent focus) or program-related posts. Using the focus of the content of social TV activity, networks can get a proxy measure of how immersed viewers are with the narrative. Figure 9 illustrates the continuum of narrative immersion and how different types of social TV post align with immersion levels.

Figure 9: Narrative Immersion Conceptual Framework



We expect that social TV activity focused on fictional elements (character-related posts) will be associated positively with television consumption (e.g. greater total views and earlier consumption), as these posts indicate a higher degree of narrative immersion with the program. Regarding timing of consumption (e.g. live vs. time-shifted viewing), fictional character-related posts may result in two different 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). Consequently, we expect that social TV activity relating to fictional elements will have positive consequences for earlier program consumption (e.g. greater live viewing and earlier DVR time-shifted consumption)

We expect posts focused on non-fictional elements (talent-related posts) to be indicative of a lower level of immersion with the program and consequently exhibit a lower (potentially negative) impact on total viewership compared to social activity indicative of higher levels of immersion. We contend that the lower level of immersion will result in unfavorable consequences for television consumption (e.g. fewer total views, and later consumption). Program-related posts exhibit the least amount of narrative immersion and are expected to have little influence (potentially negative) on television consumption compared to talent- and character-related social TV activity.

Emotionality of Online WOM

In addition to the content focus of social TV activity we examine the emotional valence of the posts. A burgeoning stream of literature within marketing investigates the emotionality of online WOM. In this analysis we examine the emotional valence of social TV activity in addition to the content focus of tweets. Given that narrative immersion requires an emotional response to the narrative (Laer et al. 2014), we consider the emotionality of social TV posts associated with a given program. To determine which emotions to examine, we rely on the expanding literature relating to emotionality within online WOM. Berger (2011) examines high emotional arousal (amusement and anxiety) and high physical arousal and find that physiological arousal drives information transmission. Berger and Milkman (2012) find that both positive (awe) and negative (anger and anxiety) high-arousal content are shared more, resulting in greater virality compared to low-arousal emotions (sadness). Yin et al. (2014) examine emotionality of online reviews and find that content with more anger is perceived to be more helpful. Ludwig et al. (2013) find that higher levels of affective content in consumer reviews increase conversion rates.

In this analysis we examine emotional tweets related to television programs. Specifically, we analyze positive valenced emotion (admiration) and negative valence emotions (anger and anxiety). We focus on this subset of emotions as they have been previously documented within the marketing literature in the context of online WOM (Berger and Milkman 2012; Berger 2011; Yin et al 2014). Berger and Milkman (2012) suggest that awe is “characterized by a feeling of admiration." Keltner and Haidt (2003) likens awe to someone overcoming adversity. McDougall (1910) likens awe to being in the presence of someone you extremely admire. Additionally, anger and anxiety are considered universal emotions (Ekman et al. 1982). Appendix A provides the formal definitions for emotions within the analysis and Table 16 provides examples of social TV post and their classification. Because the aforementioned emotions have been linked to activation, we expect that they will a positive effect on television viewership despite opposing valence (Ekman et al 1928; Berger 2011; Berger and Milkman 2012).

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 include 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 the 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 15 summarizes the data by network.

Table 15: Number of Shows and Average Number of Episodes by Network

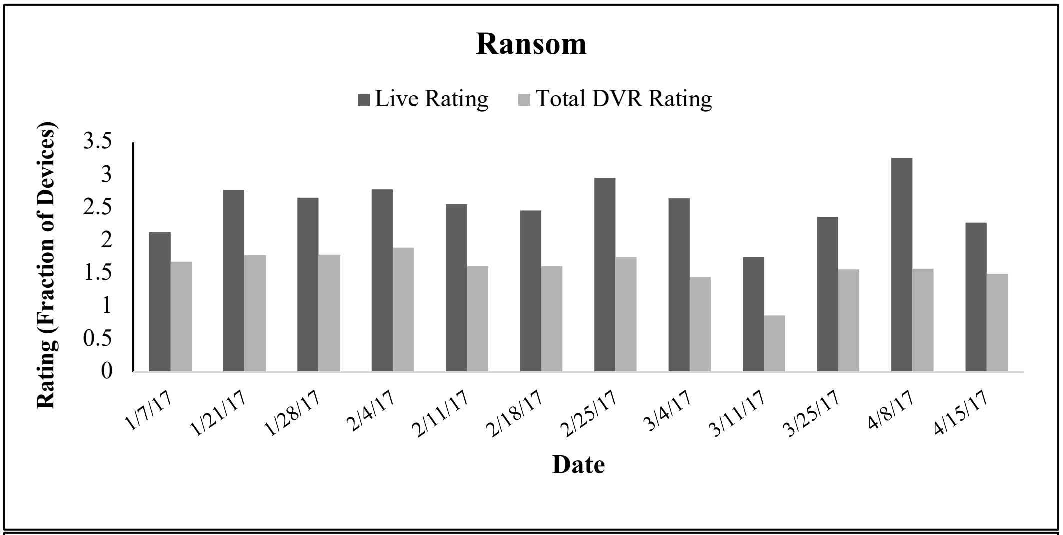
Network	Number of Shows	Average # of Episodes (s.d.)
ABC	8	12.13 (2.11)
CBS	21	13.14 (1.12)
CW	2	14.50 (1.50)
FOX	10	11.60 (1.50)
NBC	14	11.79 (2.37)

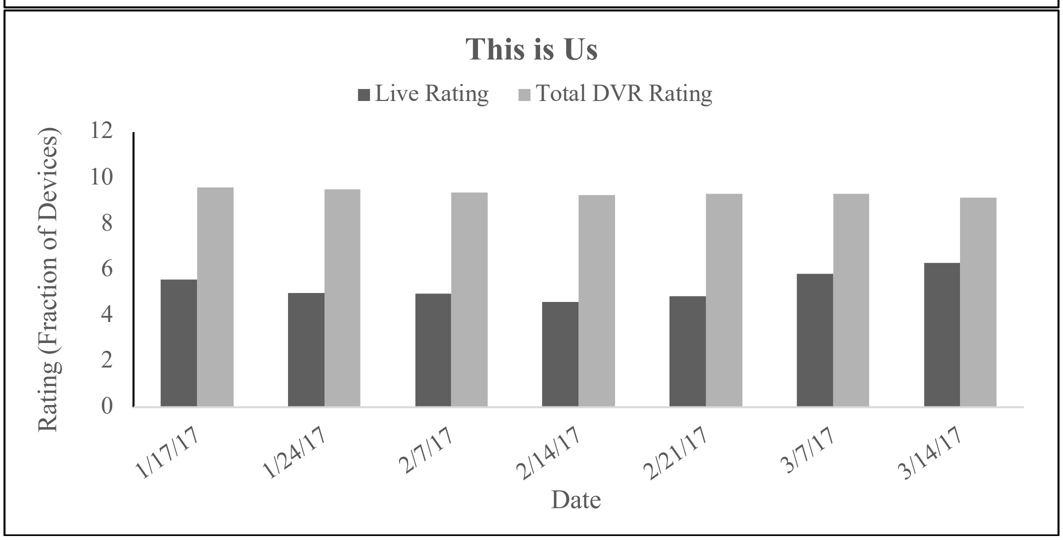
Table 17 provides descriptive statistics of television tuning behavior, averaged across episodes. The DVR tuning data are recorded based on when content is viewed (within 3 days after live programming and more than 3 days after live programming). Our data are collected from a total of 21,875,707 reporting set-top boxes. In Table 17, 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 57.8% of total viewing for a given scripted show. On average, time-shifted viewing accounts for roughly 42.2% of total audience, with playback occurring within 3 days of the live airing and beyond 3 days accounting for 31.4% and 10.8% respectively. Table 17 shows that scripted programs experience a larger proportion of time-shifted viewing occurring within 3 days after the program airs.

While Table 17 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 10. 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 10 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 10 and Tables 15 and 17 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.

Figure 10: Live and Time-Shifted Viewing

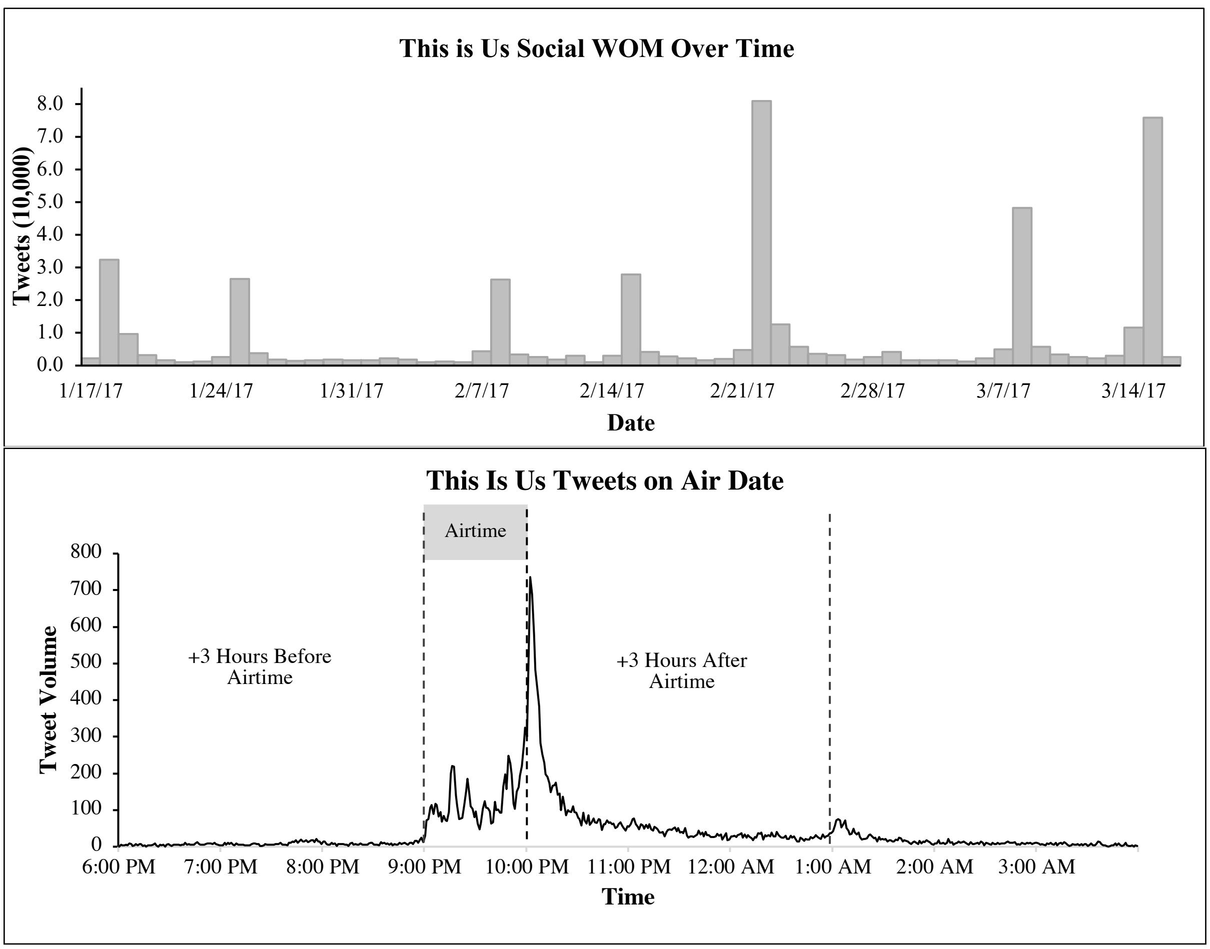




Social Media Activity Data

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 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 11 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 within a 3-hour window before and after the live airing to capture any build-up and post-show social TV activity. We investigate the impact on viewing of the next episode of the program.

Figure 11: Social Activity for This is Us



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 specific emotions. This enables us to distinguish between posts that contain positive and negative valenced emotional reactions. Appendix D shows how Canvs defines the emotions of interest in our analysis. Canvs relies on text analysis algorithms and Pultchik's wheel of emotions, which identifies 8 basic human emotions and 3 degrees of intensity to assess the emotionality of each tweet (Canvs 2020; Plutchik 1910). The reliability of the Canvs classification was validated using LIWC text analysis, which supported accuracy in positive/negative classification. LIWC has been used widely in the literature as a method for measuring positive and negative emotional valence (Berger and Milkman 2012; Ludwig et al. 2014). For those tweets that have been categorized as containing an emotional reaction, Canvs categorizes the tweets based on the content of the post: character, talent (actors) and program. Table 16 provides examples of tweets and corresponding classification while Table 17 provides summary statistics for social WOM variables. Appendix E shows the volume of each segment of social WOM for the TV show *American Housewife* as an example.

Table 16: Examples of Tweets and Classification

	Positive (admiration)	**Negative (anger and anxiety)**
Fiction Tweets (Character)	Kate is a badass! #ThisIsUs Kate is such a badass when she's in her element. #ThisIsUs Like the new dynamic with Kate. She is badass, and owns it! Crossing my fingers for Toby #ThisIsUs	howard and raj should have ended up together im bitter #ThisIsUs I'm mad at Rebecca 😡 Ok Jack, your making me nervous. #ThinkSmart #ThisIsUs @NBCThisisUs 🙄
Non-Fiction Tweets (Talent)	@nataliemartinez is one bad ass cop! She's tough, but also has brains and beauty 😍😍😍 @i_am_othello @RansomCBS you're a bad dude!! I found the show Reign and I'm obsessed. I'm pretty sure @AdelaideKane is the prettiest woman ever playing the most bad ass character ever	@MiloVentimiglia I was nervous the entire episode! @TheMandyMoore HOW DARE YOU??!! @thisisus @sterlingkb1 nervous!!!
Program Tweets	no lie. this show #APB is badass. Omg why did it have to end lmao man that's a bad ass show now another bad ass show !!!! — watching APB FOX	Anxiously awaiting @NBCThisisUs I'm soo nervous to watch #ThisIsUs

MODEL DEVELOPMENT

Endogenous Variables

Our analysis includes seven endogenous variables of interest: three measures pertaining to television viewing and four 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 exhibit a specific emotional valence (positive/negative), and the number of tweets for each content topic category (character, talent, and program) for a given emotion. We aggregate social TV activity into six measures: positive valence character, negative valence character, positive valence talent, negative valence talent, positive valence program, and negative valence program. Table 17 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 (within 3 days of the live airing). We provide descriptive statistics of these variables in Table 17.

Table 17. Endogenous Variables

Variables	Description	Average	Std. Dev.	Min	Max
$TotalView_{it}$	Share of total views for program *i* given by episode *t*	0.080	0.019	0.011	0.338
$LiveView_{it}$	Fraction of $TotalView_{it}$ that occurs live for episode *t* of program *i*	0.578	0.088	0.394	0.845
$DVRViews_{it}$	Fraction of DVR viewing for episode *t* of program *i* that occurs between within 3 days after the live airing	0.749	0.039	0.654	0.903
$PosCharacter_{it}$	Positive valenced social media activity for episode *t* of program *i* that is related to the fictional characters in the program	3.532	12.168	0.000	164.000
$NegCharacter_{it}$	Negative valenced social media activity for episode *t* of program *i* that is related to the fictional characters in the program	6.567	19.320	0.000	333.000
$PosTalent_{it}$	Positive valenced social media activity for episode *t* of program *i* that is related to the nonfictional actors and guest stars of the program	1.475	4.217	1.475	56.000
$NegTalent_{it}$	Negative valenced social media activity for episode *t* of program *i* that is related to the nonfictional actors and guest stars of the program	1.728	4.979	1.728	77.000
$PosProgram_{it}$	Positive valenced social media activity for episode *t* of program *i* that is related to the program	2.089	5.676	0.000	59.000
$NegProgram_{it}$	Negative valenced social media activity for episode *t* of program *i* that is related to the program	16.365	70.090	0.000	1465.000

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 18. We provide the frequency distribution for the number of episodes by start time, program length, and day of week in Table 19.

Table 18. 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
ProgValAnger_{it}	fraction of words in IMDB.org and Wikipedia episode description that are associated with anger using LIWC text analysis method
$\text{ProgValAnticipation}_{itt}$	fraction of words in IMDB.org and Wikipedia episode description that are associated with anticipation using LIWC text analysis method
ProgValJoy_{it}	fraction of words in IMDB.org and Wikipedia episode description that are associated with joy using LIWC text analysis method
$\text{ProgValSadness}_{it}$	fraction of words in IMDB.org and Wikipedia episode description that are associated with sadness using LIWC text analysis method
Month	Month in which the episode aired (Jan, Feb, March, May, June)
Finale	Indicator variable where 1 denotes finale episode

Table 19. Frequency Table of Control Variables

Variable	Frequency (%)	Variable	Frequency (%)
Time of Day		Program Length	
8:00	26.8	30 Minutes	36.1
8:30	12.1	>30 Minutes	63.9
9:00	36.8	Day of Week	
9:30	6.9	Weekday	85.8
10:00	17.4	Weekend	14.2
Finale	8.2		

VAR-X Model

We employ vector autoregression analysis (VAR) to investigate the dynamic relationship between social media activity and television viewing audience size. 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 forecasts 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. In a similar fashion, we transform our measures of time-shifted viewing. We define $DVRViews_{it}$ to reflect the prevalence of time-shifted viewing occurring within 3 days of the live airing relative to time-shifted viewing occurring more than 3 days after the live airdate. A log transformation is used for all continuous endogenous variables, allowing for interpretations of parameter estimates that show short-term and long-term elasticities.

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 Appendix F. All variables (total views, live views, DVR viewing up to 3 days after live airing, positive fiction, negative fiction, positive nonfiction, and negative nonfiction) 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 Appendix F). We select the optimal lag order based on minimizing the Bayesian Information Criterion (BIC). (See Appendix F.)

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

$$\begin{bmatrix} TotalViews_{i,t} \\ LiveViews_{i,t} \\ DVRViews_{i,t} \\ PosCharacter_{i,t} \\ NegCharacter_{i,t} \\ PosTalent_{i,t} \\ NegTalent_{i,t} \\ PosProgram_{i,t} \\ NegProgram_{i,t} \end{bmatrix} = \begin{bmatrix} \mu_{1,0} + \sum_{i=1}^{P-1} \mu_{1,i} S_i \\ \mu_{2,0} + \sum_{i=1}^{P-1} \mu_{2,i} S_i \\ \mu_{3,0} + \sum_{i=1}^{P-1} \mu_{3,i} S_i \\ \mu_{4,0} + \sum_{i=1}^{P-1} \mu_{4,i} S_i \\ \mu_{5,0} + \sum_{i=1}^{P-1} \mu_{5,i} S_i \\ \mu_{6,0} + \sum_{i=1}^{P-1} \mu_{6,i} S_i \\ \mu_{7,0} + \sum_{i=1}^{P-1} \mu_{7,i} S_i \\ \mu_{8,0} + \sum_{i=1}^{P-1} \mu_{8,i} S_i \\ \mu_{9,0} + \sum_{i=1}^{P-1} \mu_{9,i} S_i \end{bmatrix} + \sum_{n=1}^{p} \begin{pmatrix} \varphi_{1,1}^{n} & \cdots & \varphi_{1,9}^{n} \\ \vdots & \ddots & \vdots \\ \varphi_{9,1}^{n} & \cdots & \varphi_{9,9}^{n} \end{pmatrix} \begin{bmatrix} TotalViews_{i,t-1} \\ LiveViews_{i,t-1} \\ DVRViews_{i,t-1} \\ PosCharacter_{i,t-1} \\ NegCharacter_{i,t-1} \\ PosTalent_{i,t-1} \\ NegTalent_{i,t-1} \\ PosProgram_{i,t-1} \\ NegProgram_{i,t-1} \end{bmatrix} +$$

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

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 $\mu_{1,0} \ldots \mu_{7,0}$. 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 $\varepsilon_{1,i,t} \ldots \varepsilon_{7,i,t}$ ~ N(0, σ), where σ is a 9 x 9 covariance matrix. The exogenous vector X contains our control variables – program length, weekday, four start-time dummy variables, month, 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 9 endogenous variables that can potentially influence one another, resulting in 9 x 8 potential causal relationships between one endogenous variable and another endogenous variable; there are 9 x 1 relationships between an endogenous variable and itself. Results show that roughly 17% of causal paths among endogenous variables are significant at the 10% significance level, suggesting that a dynamic model is appropriate (See Appendix G).

In terms of the impact of social activity on television viewing, we find that positive valenced character Granger-cause total views and DVR viewing while positive valenced talent social activity Granger-cause total television viewing. Negative valenced talent Granger-cause live views. While Granger causality tests provide insights into the ordering of the causal relationship between social media activity and TV viewing, the model results from the panel data VAR-X provide detail into the magnitude and direction of the relationship.

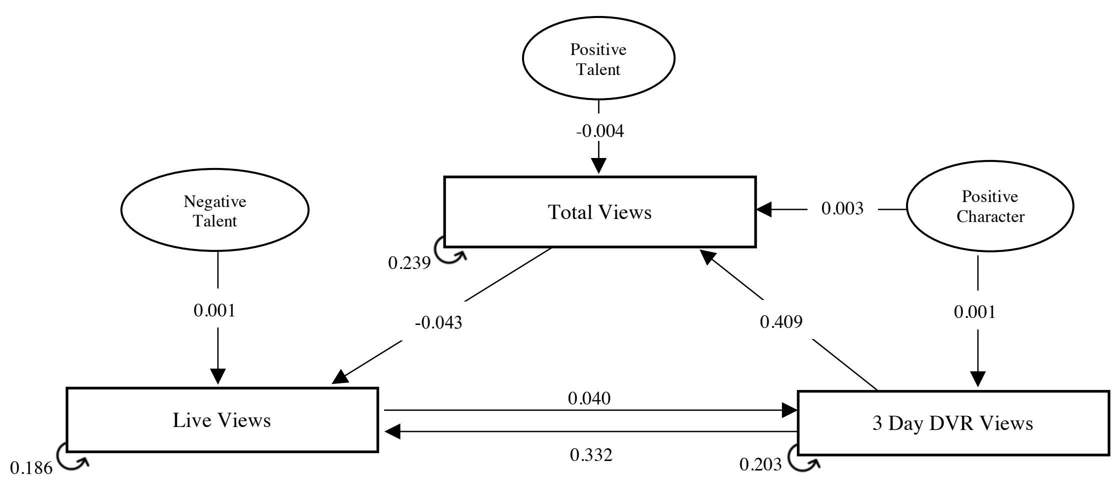
Relationship Between Social TV Activity and Television Viewing

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 consumption of 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 H. 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). The model imposes a Cholesky decomposition which allocates temporal priority to the ordering of endogenous variables in the model. Interpreting general IRFs allows us to examine the robustness of our effects.

For the 9 endogenous variables there exist a total of 81 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 and emotional valence of the social TV posts. To this end, there are 6 x 3 relationships (social TV post types x television viewing measures) that capture this relationship. We summarize our notable findings in Figure 12. First, we discuss the interrelationship between social TV activity and television consumption. Next, we briefly discuss the impact of television viewing on subsequent television viewing.

Figure 12: Summary of Notable Significant Findings Between Social TV Activity and Television Viewing

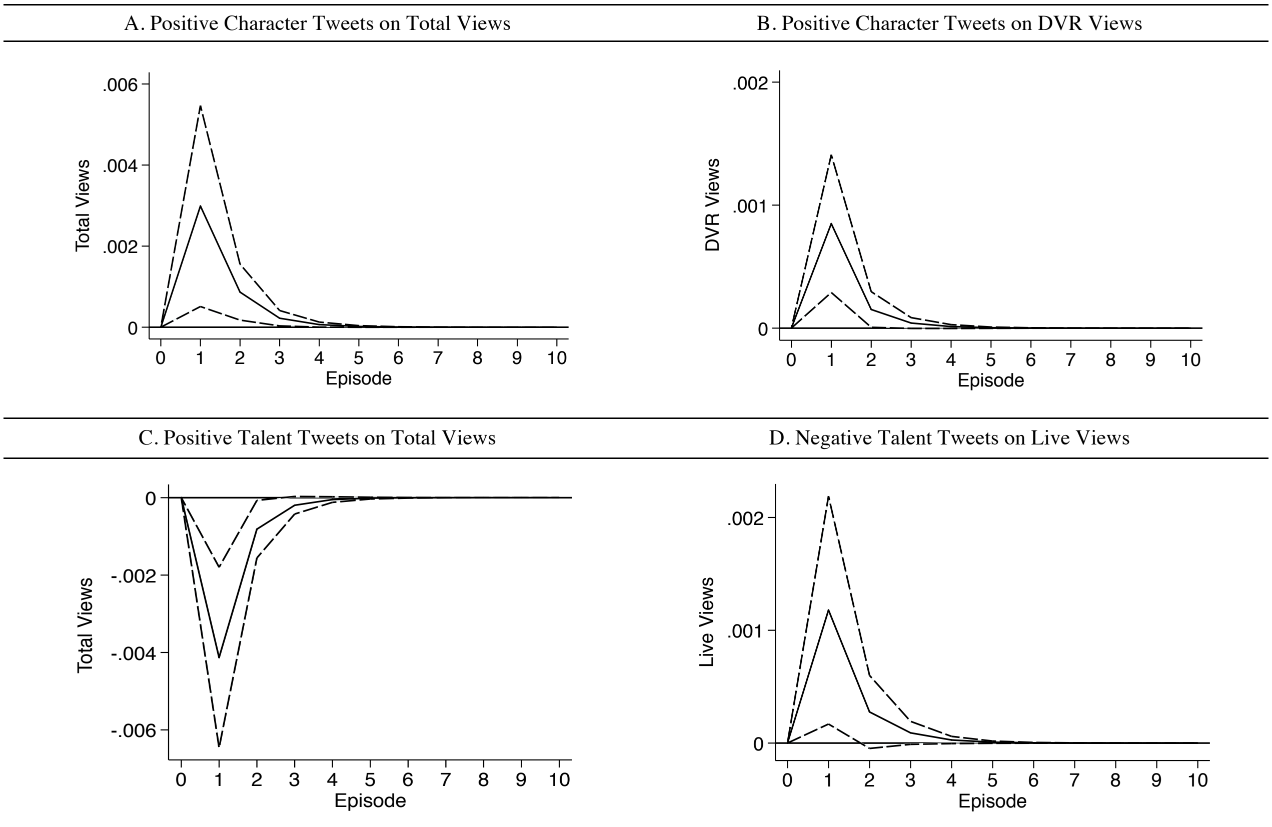


Note: Numbers represent the parameter coefficient estimates from the VAR-X model with p<0.10 significance levels. Ellipses denote social activity segments; boxes represent television viewing measures. Arrows reflect the direction of causal relationships indicated in the full VAR-X results. Full model results are available in Appendix H.

Character Tweets. We find evidence to suggest that posts about fictional elements of the program (e.g. characters) are associated with variation in viewing behavior. In particular, increased levels of positive character social media posts about the previous episode have a significant and positive direct impact on total views for the current episode. Figure 13 details the IRF of a one standard deviation shock in positive character tweets on television viewing behavior. The resulting IRF's (Figure 13 A) show that a shock in positive valenced character tweets increases total views for the next episode. This finding implies that posts that express positive emotion for fictional characters within the television programs are positively associated with greater total audience size. Assuming that posts pertaining to fictional elements indicate a higher level of narrative immersion, this finding supports the notion that higher immersion translates to more total television views for a program.

Additionally, we find evidence of a significant increase in earlier television consumption. Specifically, we find that tweets expressing positive emotion for characters are positively associated with a higher fraction of DVR playback occurring within 3 days of the live airing (Figure 13 B). Our results suggest that programs with higher levels of narrative immersion (as indicated by the volume of fictional social TV activity) also experience earlier DVR consumption, however we do not find a significant effect on fraction of live views. This suggests that shows that experience higher immersion may result in viewers preferring to watch via DVR rather than live. DVR viewing provides viewers with more control over the viewing experiences with the ability to zip (zap) through commercials, pause, and rewind (fast-forward) parts of the program.

Figure 13: GIRFs for the Impact of Talent-Related Tweets on Timing of Television Viewing



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

Talent Tweets. In contrast to positively valenced fiction related post, positively valenced nonfiction posts (e.g. talent) are associated with a decrease total viewership for the subsequent episode. This implies that social TV activity expressing positive emotion towards the actors within a television series reduces the total views for the next episode. Figure 13 C shows the IRF for a one standard deviation shock in positively valenced nonfiction posts. Assuming nonfiction related posts are indicative of a lower degree of narrative immersion, the negative influence of nonfiction related posts is consistent with prior literature which has found that a lack of narrative transportation can have negative consequences (Escalas 2004). If viewers are expressing positive emotions toward the talent before, during, or after viewing the program — rather than toward the characters — this may be an indication that the narrative did not resonate in a way that connected them to the fictional elements. Further, this could signal that the quality of the narrative is such that a notable attribute of the program is the talent being more noteworthy than the fictional elements.

Results suggests that negatively valenced emotional tweets about the talent are associated with earlier television consumption. Particularly, results show a significant and positive association between negatively valenced talent-related tweets and a larger fraction of devices viewing live compared to time-shifted DVR viewing. Counter to our expectation, this association between negative non-fiction related tweets is positive rather than negative. This may be a result of consumers' expressions of anxiety or anger toward the talent in the program. Research has shown that high arousal negative emotions (e.g. anger and anxiety) are linked to greater virality (Berger and Milkman 2012). Tweets that express anxiety and anger about nonfiction elements may have a higher propensity to be shared. This may help build anticipation for the program or increase awareness, resulting in a higher fraction of live views.

Program Tweets. Although we do not find that program-related social TV activity has a statistically significant impact on television viewing audiences, this null effect offers guidance to networks crafting social media engagement strategies. Our null finding suggests that generic program chatter that does not reference fiction or nonfiction elements of the program does not statistically drive television consumption. Networks can benefit more by fostering conversation pertaining to either fictional or nonfictional elements.

Interestingly, 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. More precisely, we find that positively valence tweets pertaining to characters have a positive impact on total views while positively valenced tweets pertaining to the talent have a negative impact on total viewership for the subsequent episode. This implies that nonfiction-related tweets during one episode can reduce total ratings of subsequent episodes, while fiction related tweets can increase total ratings. Such insights can be used by networks seeking to encourage more viewership of their programs, as their social media strategy to promote the show should focus more on the characters than on the actors themselves. Further, positively valenced character-related posts drive earlier DVR viewing, which may be beneficial for networks and content creators who are focused on driving earlier time-shifted DVR viewership.

Summary. Broadly, our results show that positive and negative valenced social TV activity has a significant impact on television consumption. We find that social TV activity indicative of higher levels of narrative transportation (positive valenced fiction-related posts) is associated with higher total views and earlier time-shifted viewing for the next episode. Social TV activity indicative of lower levels of narrative transportation (positive valenced nonfiction-related posts) are associated with decreases in total viewership for the next episode. We find evidence that negatively valenced social TV activity pertaining to nonfiction elements can significantly increase the fraction of live views a program receives. Program-related social TV activity is indicative of the lowest level of narrative immersion (compared to talent and character-related tweets), and we find that there is no significant influence of this segment on television consumption.

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 positive character, negative talent, and positive talent are 0.003, 0.001, and -0.004, respectively. We observe that the impact of positive character posts is nearly three times the effect of negatively valenced talent-related tweets. We also find that positively valenced posts focusing on talent have the greatest coefficient magnitude, however the effect is negative. This suggest that the negative effect of focusing on nonfictional elements may outweigh the positive effect of focusing on fictitious elements. This can be helpful to networks seeking to encourage more viewership of their programs, as their social media strategy to promote the show should focus more on the characters than on the actors themselves. Additionally, networks can employ this classification method as a means to capture how immersed viewers are in television programs when making the decision to cancel or renew certain programs.

Impact of 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 three television viewing covariates, resulting in 3 x 2 possible bivariate effects of one covariate on another and 3 x 1 univariate own effects of a variable with itself. In terms of own effects, results show that each of the three endogenous TV viewing covariates exhibit significant positive own effects. Moving to bivariate relationships, we find evidence that time-shifted viewing significantly impacts other viewership (e.g. total views and live viewership for the next episode). 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.

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 consumer behavior, 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 show that posts containing positive emotional reactions that mention the fictional characters in the program have a positive impact on total viewership for the next episode and a positive impact on the proportion of devices that engage in earlier DVR consumption of the next episode. As social media posts mentioning the character 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 posts about the program. We also discover a negative direct association between positive valenced emotional reactions to nonfictional (actors and guest stars) elements of the program and total views for the subsequent episode. Nonfictional-related posts may be indicative of a lower level of narrative immersion in the program and, consequently, are negatively associated with total views. Interestingly, we find that negative valence emotional posts focusing on nonfictional elements are positively associated with the share of devices that engage in live viewing as opposed to time-shifted viewing. This suggests that anger and anxiety towards non-fictional elements impact live viewing positively.

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. Positive valence cast-related posts have the largest magnitude effect on total views, however its effect is negative. Positive valenced character-related posts have the second largest magnitude effect on total views, suggesting that character-related posts may be more desirable than talent related posts in terms of total viewership. With respect to greater live viewing, negatively valenced posts about the talent are advantageous, while positively valenced posts about characters help to drive earlier DVR consumption.

These results have implications for networks and content creators, as well as advertisers. DVR viewing that occurs 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 fictional character in television programs is more effective than one which seeks to encourage broad 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 aired 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 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. Additionally, 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. While this research examines emotional vs. non-emotional posts and focuses on the topic of emotional content, other researchers might explore the distinction of different types of emotional responses and their 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 advertisings' effectiveness when viewers are exposed to marketing messages during accelerated playback of previously recorded video content (e.g. Brasel and Gips 2008).

References

Aaker, D. A., & Keller, K. L. (1990). Consumer evaluations of brand extensions. *Journal of marketing*, *54*(1), 27-41.

Aaker, J., Fournier, S., & Brasel, S. A. (2004). When good brands do bad. *Journal of Consumer research*, *31*(1), 1-16.

Aaker, J. L. (1997). Dimensions of brand personality. *Journal of marketing research*, *34*(3), 347-356.

Aaker, D. A., & Biel, A. L. (1993). *Brand equity and advertising: An overview* (pp. 1-10). Hillsdale, NJ: Lawrence Erlbaum Associates.

Agrawal, J., & Kamakura, W. A. (1995). The economic worth of celebrity endorsers: An event study analysis. *Journal of marketing*, *59*(3), 56-62.

Ahluwalia, R., Burnkrant, R. E., & Unnava, H. R. (2000). Consumer response to negative publicity: The moderating role of commitment. *Journal of marketing research*, *37*(2), 203-214.

Akpinar, E., & Berger, J. (2017). Valuable virality. *Journal of Marketing Research*, *54*(2), 318-330.

Amazon (2019) Rekognition Developer Guide, retrieved from https://docs.aws.amazon.com/rekognition/latest/dg/rekognition-dg.pdf, Accessed date June 10, 2019

Arvidsson, A. & Caliandro, A. (2016). Brand public. *Journal of consumer research*, 42 (5)727-748.

Bayliss, A. P., Pellegrino, G. D., & Tipper, S. P. (2005). Sex differences in eye gaze and symbolic cueing of attention. *The Quarterly Journal of Experimental Psychology*, *58*(4), 631-650.

Berger, J., & Milkman, K. L. (2012). What makes online content viral?. *Journal of marketing research*, *49*(2), 192-205.

Berger, J. (2011). Arousal increases social transmission of information. *Psychological science*, *22*(7), 891-893.

Berger, J., Humphreys, A., Ludwig, S., Moe, W.W., Netzer, O. & Schweidel, D.A. (2020). Uniting the tribes: using text for marketing insight. *Journal of Marketing*, 84 (1), 1-25.

Berr, J. (2018). Nike Stock Price Reaches All-Time High After Colin Kaepernick ad, *CBS News*, accessed at https://www.cbsnews.com/news/nike-stock-price-reaches-all-time-high-despite-colin-kaepernick-ad-boycott

Borah, A., & Tellis, G. J. (2016). Halo (spillover) effects in social media: do product recalls of one brand hurt or help rival brands?. *Journal of Marketing Research*, *53*(2), 143-160.

Bougie, R., Pieters, R., & Zeelenberg, M. (2003). Angry customers don't come back, they get back: The experience and behavioral implications of anger and dissatisfaction in services. *Journal of the academy of marketing science*, *31*(4), 377-393.

Bower, A. B., & Landreth, S. (2001). Is beauty best? Highly versus normally attractive models in advertising. *Journal of advertising*, *30*(1), 1-12.

Büschken, J., & Allenby, G. M. (2016). Sentence-based text analysis for customer reviews. *Marketing Science*, *35*(6), 953-975.

Brasel, S. Adam, and James Gips (2008), "Breaking through fast-forwarding: Brand information and visual attention." *Journal of Marketing*, 72 (6), 31-48.

Bronnenberg, Bart J., Jean-Pierre Dubé, and Carl F. Mela (2010), "Do digital video recorders influence sales?." *Journal of Marketing Research*, 47 (6), 998-1010.

Brown, T. J., & Dacin, P. A. (1997). The company and the product: Corporate associations and consumer product responses. *Journal of marketing*, *61*(1), 68-84.

Canvs (2020), “How Can I Map Canvs Emotions to Other Academic Emotional Frameworks?,” *Canvs Help Manual*, http://help.canvs.ai/en/articles/1659237-how-can-i-map-canvs-emotions-to-other-academic-emotional-frameworks

Chaiken, S., Giner-Sorolla, R., & Chen, S. (1996). Beyond accuracy: Defense and impression motives in heuristic and systematic information processing.

Chen, Y., Ganesan, S., & Liu, Y. (2009). Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. *Journal of Marketing*, *73*(6), 214-226.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, *43*(3), 345-354.

Cleeren, K., Dekimpe, M. G., & Helsen, K. (2008). Weathering product-harm crises. *Journal of the Academy of Marketing Science*, *36*(2), 262-270.

Cleeren, K., Van Heerde, H. J., & Dekimpe, M. G. (2013). Rising from the ashes: How brands and categories can overcome product-harm crises. *Journal of Marketing*, *77*(2), 58-77.

Cohen, J. B., Pham, M. T., & Andrade, E. B. (2008). The nature and role of affect in consumer behavior. *Handbook of consumer psychology*, *4*, 297-348.

Cohen, Elizabeth L. and Alexander L. Lancaster (2014), “Individual differences in in-person and social media television coviewing: The role of emotional contagion, need to belong, and coviewing orientation,” *Cyberpsychology, Behavior, and Social Networking,* 17 (8), 512-518.

Cohen, Jonathan (2004), "Parasocial break-up from favorite television characters: The role of attachment styles and relationship intensity." *Journal of Social and Personal Relationships,* 21 (2), 187-202.

Coles, M. E., & Heimberg, R. G. (2005). Recognition bias for critical faces in social phobia: a replication and extension. *Behaviour research and therapy*, *43*(1), 109-120.

Corke, P. I. (2005). The Machine Vision Toolbox: a MATLAB toolbox for vision and vision-based control. *IEEE robotics & automation magazine*, *12*(4), 16-25.

Corson, Y., & Verrier, N. (2007). Emotions and false memories: Valence or arousal?. *Psychological Science*, *18*(3), 208-211.

Chintagunta, P. K., Gopinath, S., & 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*, *29*(5), 944-957.

Culotta, A., & Cutler, J. (2016). Mining brand perceptions from twitter social networks. *Marketing science*, *35*(3), 343-362.

Crupi, Anthony (2016), “By the Numbers: A Look Back at the 2015-2016 Broadcast Season,” *Advertising Age*, May 26, accessed at http://adage.com/article/media/numbers-a-back-2015-16-broadcast-season/304193/.

Dawar, N., & Pillutla, M. M. (2000). Impact of product-harm crises on brand equity: The moderating role of consumer expectations. *Journal of marketing research*, *37*(2), 215-226.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive marketing*, *21*(4), 23-45.

DeMarree, K. G., Wheeler, S. C., & Petty, R. E. (2005). Priming a new identity: self-monitoring moderates the effects of nonself primes on self-judgments and behavior. *Journal of Personality and Social Psychology*, *89*(5), 657.

De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of interactive marketing*, *26*(2), 83-91.

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of marketing research*, *28*(3), 307-319.

Dudharejia, M. (2018) Four Branding Lessons from Nike's Colin Kaeperick Ad, Entrepreneur, retrieved at: https://www.entrepreneur.com/article/321130

Elberse, A. (2007). The power of stars: Do star actors drive the success of movies?. *Journal of Marketing*, *71*(4), 102-120.

eMarketer (2015), "Social Network Ad Spending to Hit $23.68 Billion Worldwide in 2015," (April 2015), (accessed May 2019), available at [https://marketingland.com/emarketer-social-ad-spending-will-hit-23-68-billion-globally-this-year-125410]

eMarketer (2016), "By 2020, TV's share of ad spending will drop below one-third," March 8, accessed at http://www.emarketer.com/Article/Digital-Ad-Spending-Surpass-TV-Next-Year/1013671.

Escalas, Jennifer Edson (2004), "Imagine yourself in the product: Mental simulation, narrative transportation, and persuasion." *Journal of Advertising,* 33 (2),37-48.

Escalas, Jennifer Edson, and Barbara B. Stern (2003), "Sympathy and empathy: Emotional responses to advertising dramas." *Journal of Consumer Research,* 29 (4)

Feldman, J. M., & Lynch, J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of applied Psychology*, *73*(3), 421.
Forgas, J. P. (1995). Mood and judgment: the affect infusion model (AIM). *Psychological bulletin*, *117*(1), 39.

Fossen, B. L., & Schweidel, D. A. (2019). Social TV, Advertising, and Sales: Are Social Shows Good for Advertisers?. *Marketing Science*.

Fossen, Beth L., and David A. Schweidel (2016), "Television advertising and online word-of-mouth: An empirical investigation of social tv activity." *Marketing Science,* 36 (1)

Friedman, Wayne (2012), "Why TV Networks Want To Move From C3 to C7 Ratings," *MediaPost*, November 12, accessed at http://www.mediapost.com/publications/article/187080/why-tv-networks-want-to-move-from-c3-to-c7-ratings.html.

Gerrig, Richard J. (1993) "Experiencing narrative worlds: On the psychological activities of reading," *Yale University Press*

Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2016). Region-based convolutional networks for accurate object detection and segmentation. IEEE Transactions on
Pattern Analysis and Machine Intelligence, 38(1), 142–158.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing science*, *23*(4), 545-560.

Godes, D., & Silva, J. C. (2012). Sequential and temporal dynamics of online opinion. *Marketing Science*, *31*(3), 448-473.

Goel, Vindu (2015), “Study of TV Viewers Backs Twitter’s Claims to be Barometer of Public Mood”, *The New York Times*, accessed at https://bits.blogs.nytimes.com/2015/03/08/twitter-chatter-reveals-what-we-like-to-watch/

Goh, K. Y., Heng, C. S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content. *Information Systems Research*, *24*(1), 88-107.

Goldenberg, J., Oestreicher-Singer, G., & Reichman, S. (2012). The quest for content: How user-generated links can facilitate online exploration. *Journal of Marketing Research*, *49*(4), 452-468.

Gong, Shiyang, Juanjuan Zhang, Ping Zhao and Xuping Jiang (2014), “Tweets and Sales,” working paper, accessed at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2461370.

Gorn, G. J., Jiang, Y., & Johar, G. V. (2008). Babyfaces, trait inferences, and company evaluations in a public relations crisis. *Journal of Consumer Research*, *35*(1), 36-49.

Gorn, G. J., Goldberg, M. E., & Basu, K. (1993). Mood, awareness, and product evaluation. *Journal of Consumer Psychology*, *2*(3), 237-256.

Granger, Clive William John, and Paul Newbold. *Forecasting economic time series*. Academic Press, 2014.

Grégoire, Y., & Fisher, R. J. (2008). Customer betrayal and retaliation: when your best customers become your worst enemies. *Journal of the Academy of Marketing Science*, *36*(2), 247-261.

Green, Melanie C., and Timothy C. Brock (2000), "The role of transportation in the persuasiveness of public narratives." *Journal of Personality and Social Psychology,* 79 (5)

Green, Melanie C. (2008), "Research Challenges: Research challenges in narrative persuasion." *Information Design Journal*, 16 (1), 47-52.

Gullo, K., Berger, J., Etkin, J., & Bollinger, B. (2018). Does time of day affect variety-seeking?. *Journal of Consumer Research*, *46*(1), 20-35.

Hansen, N., Kupfer, A. K., & Hennig-Thurau, T. (2018). Brand crises in the digital age: The short-and long-term effects of social media firestorms on consumers and brands. *International Journal of Research in Marketing*, *35*(4), 557-574.

Heath, C., Bell, C., & Sternberg, E. (2001). Emotional selection in memes: the case of urban legends. *Journal of personality and social psychology*, *81*(6), 1028.

Herhausen, D., Ludwig, S., Grewal, D., Wulf, J., & Schoegel, M. (2019). Detecting, preventing, and mitigating online firestorms in brand communities. *Journal of Marketing*, *83*(3), 1-21.

Herr, P. M., Kardes, F. R., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of consumer research*, *17*(4), 454-462.

Hewett, K., Rand, W., Rust, R. T., & Van Heerde, H. J. (2016). Brand buzz in the echoverse. *Journal of Marketing*, *80*(3), 1-24.

Hill, Shawndra, Aman Nalavade, and Adrian Benton (2012), "Social TV: Real-time social media response to TV advertising." *Proceedings of the Sixth International Workshop on Data Mining for Online Advertising and Internet Economy*. ACM.

Hsu, L., & Lawrence, B. (2016). The role of social media and brand equity during a product recall crisis: A shareholder value perspective. *International journal of research in Marketing*, *33*(1), 59-77.

Humphreys, A. & Wang, R.J-H. (2018). Automated text analysis for consumer research. *Journal of consumer research*. 44 (6), 1274-1306.

Itti, L., Rees, G., & Tsotsos, J. K. (Eds.). (2005). *Neurobiology of attention*. Elsevier.

Jenkins, J. M., & Oatley, K. (1996). Emotional episodes and emotionality through the life span. In *Handbook of emotion, adult development, and aging* (pp. 421-441). Academic Press.

Johnson, Benjamin K. and Judith E. Rosenbaum (2015), “Spoiler Alert: Consequences of Narrative Spoilers for Dimensions of Enjoyment, Appreciation, and Transportation,” *Communication Research*, 42 (8), 1068-1088.

Joo, Mingyu, Kenneth C. Wilbur, Bo Cowgill, and Yi Zhu (2013), "Television advertising and online search." *Management Science,* 60, no. 1, 56-73.

Joshi, A. M., & Hanssens, D. M. (2009). Movie advertising and the stock market valuation of studios: a case of “great expectations?”. *Marketing Science*, *28*(2), 239-250.

Kanuri, V. K., Chen, Y., & Sridhar, S. (2018). Scheduling Content on Social Media: Theory, Evidence, and Application. *Journal of Marketing*, *82*(6), 89-108.

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *Journal of marketing*, *57*(1), 1-22.

Keller, K.L. (1998) *Strategic Brand Management.* Upper Saddle River: Prentice Hall.

Keller, K. L. (2009). Building strong brands in a modern marketing communications environment. *Journal of marketing communications*, *15*(2-3), 139-155.

Keltner, D., & Haidt, J. (2003). Approaching awe, a moral, spiritual, and aesthetic emotion. *Cognition and emotion*, *17*(2), 297-314.

Kiffel, C., Campanella, S., & Bruyer, R. (2005). Categorical perception of faces and facial expressions: The age factor. *Experimental aging research*, *31*(2), 119-147.

Klostermann, J., Plumeyer, A., Böger, D., & Decker, R. (2018). Extracting brand information from social networks: Integrating image, text, and social tagging data. *International Journal of Research in Marketing*, *35*(4), 538-556.

Kumar, V., Bhaskaran, V., Mirchandani, R., & Shah, M. (2013). Practice prize winner—creating a measurable social media marketing strategy: increasing the value and ROI of intangibles and tangibles for hokey pokey. *Marketing Science*, *32*(2), 194-212.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing*, *80*(1), 7-25.

Ladd, B. (2018) Nike and Kapernick: Business 101, *Forbes*, accessed at: https://www.forbes.com/sites/brittainladd/2018/09/11/what-should-colin-kaepernick-do-next-become-a-police-officer-and-nike-should-design-the-uniform/#637ee88f28d8

Lane, V., & Jacobson, R. (1995). Stock market reactions to brand extension announcements: The effects of brand attitude and familiarity. *Journal of Marketing*, *59*(1), 63-77.

Lazarus, R. S. (1991). Cognition and motivation in emotion. *American psychologist*, *46*(4), 352.

Leavitt, J. D., & Christenfeld, N. J. S. (2013), "The fluency of spoilers: Why giving away endings improves stories," *Scientific Study of Literature,* 3 (1), 93-104.

Leclerc, F., Schmitt, B. H., & Dubé, L. (1994). Foreign branding and its effects on product perceptions and attitudes. *Journal of marketing Research*, *31*(2), 263-270.

Lee, D., Hosanagar, K., & Nair, H. S. (2018). Advertising content and consumer engagement on social media: Evidence from Facebook. *Management Science*, *64*(11), 5105-5131

Lee, T. Y., & Bradlow, E. T. (2011). Automated marketing research using online customer reviews. *Journal of Marketing Research*, *48*(5), 881-894.

Lee, J. G., & Thorson, E. (2008). The impact of celebrity–product incongruence on the effectiveness of product endorsement. *Journal of advertising research*, *48*(3), 433-449.

Leskovec, J., Adamic, L. A., & Huberman, B. A. (2007). The dynamics of viral marketing. *ACM Transactions on the Web (TWEB)*, *1*(1), 5.

Lei, J., Dawar, N., & Gürhan-Canli, Z. (2012). Base-rate information in consumer attributions of product-harm crises. *Journal of Marketing Research*, *49*(3), 336-348.

Lei, J., Dawar, N., & Lemmink, J. (2008). Negative spillover in brand portfolios: Exploring the antecedents of asymmetric effects. *Journal of marketing*, *72*(3), 111-123.

Lerbinger, O. (2012). *The crisis manager: Facing disasters, conflicts, and failures*. Routledge.
Lerner, J. S., Small, D. A., & Loewenstein, G. (2004). Heart strings and purse strings: Carryover effects of emotions on economic decisions. *Psychological science*, *15*(5), 337-341.

Liaukonyte, Jura, Thales Teixeira, and Kenneth C. Wilbur (2015),"Television advertising and online shopping." *Marketing Science,* 34 (3), 311-330.

Littleton, Cynthia (2014), “Networks Compete Against Themselves as Time-Shifted Viewing Spikes,” *Variety*, July 30, accessed at http://variety.com/2014/tv/awards/time-shifted-viewingshifts-competitive-landscape-1201271533/.

Liu, Yong (2006), "Word of mouth for movies: Its dynamics and impact on box office revenue." *Journal of Marketing* 74-89.

Liu, Xiao, Param Vir Singh and Kannan Srinivasan (2016), “A structured analysis of unstructured big data by leveraging cloud computing,” *Marketing Science,* 35 (3), 363-388.
McDougall, W. (1910). *An introduction to social psychology* (3rd ed.). Boston, MA: John W. Luce.

Liu, L., Dzyabura, D., & Mizik, N. (2018, June). Visual listening in: Extracting brand image portrayed on social media. In *Workshops at the Thirty-Second AAAI Conference on Artificial Intelligence*.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of marketing*, *70*(3), 74-89.

LoBue, V., & DeLoache, J. S. (2008). Detecting the snake in the grass: Attention to fear-relevant stimuli by adults and young children. *Psychological science*, *19*(3), 284-289.

Lohtia, R., Donthu, N., & Yaveroglu, I. (2007). Evaluating the efficiency of Internet banner advertisements. *Journal of Business Research*, *60*(4), 365-370.

Lovett, M., Peres, R., & Shachar, R. (2014). A data set of brands and their characteristics. *Marketing Science*, *33*(4), 609-617.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, *77*(1), 87-103.

Luo, X. (2007). Consumer negative voice and firm-idiosyncratic stock returns. *Journal of marketing*, *71*(3), 75-88.

Marsh, A. A., Ambady, N., & Kleck, R. E. (2005). The effects of fear and anger facial expressions on approach-and avoidance-related behaviors. *Emotion*, *5*(1), 119.

Mayzlin, D., & Yoganarasimhan, H. (2012). Link to success: How blogs build an audience by promoting rivals. *Management Science*, *58*(9), 1651-1668.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444-456.

Moe, W. W., & Schweidel, D. A. (2012). Online product opinions: Incidence, evaluation, and evolution. *Marketing Science*, *31*(3), 372-386.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444-456.

Morrin, M. (1999). The impact of brand extensions on parent brand memory structures and retrieval processes. *Journal of Marketing Research*, *36*(4), 517-525.

Murry Jr, J. P., & Dacin, P. A. (1996). Cognitive moderators of negative-emotion effects: Implications for understanding media context. *Journal of Consumer Research*, *22*(4), 439-447.

Muñiz, A.M. & O'Guinn, T. (2001). Brand Community, *Journal of Consumer Research*, 27 (4), 412–32.

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521-543.

Nielsen (2014) "From Live to 24/7: Extending Twitter TV Engagement Beyond the Live Airing", access at http://www.nielsen.com/us/en/insights/news/2014/from-live-to-24-7-extending-twitter-tv-engagement-beyond-the-live-airing.html

Nielsen (2015a) "TheTotal Audience Report Q3 2015", accessed at http://www.nielsen.com/content/dam/corporate/us/en/reports-downloads/2015-reports/total-audience-report-q3-2015.pdf

Nielsen (2015b), "Live TV + Social Media = Engaged Viewers", accessed at http://www.nielsen.com/us/en/insights/news/2015/live-tv-social-media-engaged-viewers.html

Nooteboom, B., Berger, H., & Noorderhaven, N. G. (1997). Effects of trust and governance on relational risk. *Academy of management journal*, *40*(2), 308-338.

Oatley, Keith (1999), "Why fiction may be twice as true as fact: Fiction as cognitive and emotional simulation." *Review of General Psychology* 3.2 101.

Oatley, Keith, and Mitra Gholamain (1997) "Emotions and identification: Connections between readers and fiction." *Emotion and the arts* 263-281.

Oliver, R. L. (1993). Cognitive, affective, and attribute bases of the satisfaction response. *Journal of consumer research*, *20*(3), 418-430.

Öhman, A., Flykt, A., & Esteves, F. (2001). Emotion drives attention: detecting the snake in the grass. *Journal of experimental psychology: general*, *130*(3), 466.

Packard, G., Moore, S. G., & McFerran, B. (2018). (I'm) Happy to Help (You): The Impact of Personal Pronoun Use in Customer–Firm Interactions. *Journal of Marketing Research*, *55*(4), 541-555.

Park, C. S., & Srinivasan, V. (1994). A survey-based method for measuring and understanding brand equity and its extendibility. *Journal of marketing research*, *31*(2), 271-288.

Pearl, D., (2018) Why Nike's 30th Anniversary Ad Featuring Colin Kaepernick Is a Worthwhile Risk On Labor Day, it debuted a spot with the former NFL player, *AdWeek,* accessed at: https://www.adweek.com/brand-marketing/why-nikes-30th-anniversary-ad-featuring-colin-kaepernick-is-a-worthwhile-risk-for-the-brand/

Persaran, H. Hashem, and Yongcheol Shin. "Generalized impulse response analysis in linear multivariate models." *Economics letters* 58.1 (1998): 17-29.

Pearson, Sarah and Patrick Barwise (2007), "PVRs and advertising exposure: a video ethnographic study," *International Journal of Internet Marketing and Advertising*, 4 (1)

Pennebaker, J.W., Boyd, R.L., Jordan, K. and Blackburn, K. (2015). *The development and psychometric properties of LIWC2015*.

Pfeffer, J., Zorbach, T., & Carley, K. M. (2014). Understanding online firestorms: Negative word-of-mouth dynamics in social media networks. *Journal of Marketing Communications*, *20*(1-2), 117-128.

Pham, M. T. (1998). Representativeness, relevance, and the use of feelings in decision making. *Journal of consumer research*, *25*(2), 144-159.

Pham, M. T. (2004). The logic of feeling. *Journal of Consumer Psychology*, *14*(4), 360-369.
Schwarz, N. (2000). Emotion, cognition, and decision making. *Cognition & Emotion*, *14*(4), 433-440.

Phillips, Barbara J., and Edward F. McQuarrie (2010) "Narrative and persuasion in fashion advertising." *Journal of Consumer Research*, 368-392.

Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing*, *68*(2), 36-50.

Pieters, R., Wedel, M., & Batra, R. (2010). The stopping power of advertising: Measures and effects of visual complexity. *Journal of Marketing*, *74*(5), 48-60.

Pieters, R., Wedel, M., & Zhang, J. (2007). Optimal feature advertising design under competitive clutter. *Management Science*, *53*(11), 1815-1828.

Rust, Roland T., and Mark I. Alpert (1984) "An audience flow model of television viewing choice." *Marketing Science*, 113-124.

Rust, Roland T., Wagner A. Kamakura and Mark I. Alpert (1992), "Viewer preference segmentation and viewing choice models for network television," *Journal of Advertising*, 21 (1),1-18.

Samochowiec, J., Wänke, M., & Fiedler, K. (2010). Political ideology at face value. *Social Psychological and Personality Science*, *1*(3), 206-213.

Shachar, Ron and John W. Emerson (2000), "Cast demographics, unobserved segments, and heterogeneous switching costs in a television viewing choice model," *Journal of Marketing Research*, 37 (2), 173-186.

Schweidel, David A. and Robert J. Kent (2010), "Predictors of the gap between program and commercial audiences: An investigation using live tuning data," *Journal of Marketing*, 74 (3), 18-33.

Schweidel, David A., and Wendy W. Moe (2016), "Binge watching and advertising." *Journal of Marketing*, 1-19.

Schweidel, D. A., & Moe, W. W. (2014). Listening in on social media: A joint model of sentiment and venue format choice. *Journal of Marketing Research*, *51*(4), 387-402.

Shin, H. S., Hanssens, D. M., & Gajula, B. (2011). Positive vs. negative online buzz as leading indicators of daily price fluctuation. *Anderson School of Business, UCLA. Unpublished Work*.

Solomon, M. R., Ashmore, R. D., & Longo, L. C. (1992). The beauty match-up hypothesis: Congruence between types of beauty and product images in advertising. *Journal of advertising*, *21*(4), 23-34.

Straka, M., & Straková, J. (2017, August). Tokenizing, POS tagging, lemmatizing and parsing UD 2.0 with UDPipe. In *Proceedings of the CoNLL 2017 Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies* (pp. 88-99).

Steinberg (2007), "DVR Ad Skipping Happens, But Not Always," *Advertising Age*, May 31, accessed at http://adage.com/article/media/dvr-ad-skipping/117023/.

Stelter, Brian (2013), “As DVRs Shift TV Habits, Ratings Calculations Follow”*, The New York Times*, October 6, accessed at http://www.nytimes.com/2013/10/07/business/media/dvrs-shift-tv-habits-and-ratings.html.

Story, Louise (2007), “Viewers Fast-Forwarding Past Ads? Not Always,” *The New York Times*, February 16, accessed at http://www.nytimes.com/2007/02/16/business/16commercials.html.

Tanner, R. J., & Maeng, A. (2012). A tiger and a president: Imperceptible celebrity facial cues influence trust and preference. *Journal of Consumer Research*, *39*(4), 769-783.

Tellis, G. J., MacInnis, D. J., Tirunillai, S., & Zhang, Y. (2019). What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence. *Journal of Marketing*, *83*(4), 1-20.

Tellis, G. J., & Johnson, J. (2007). The value of quality. *Marketing Science*, *26*(6), 758-773.

Tirunillai, Seshadri, and Gerard J. Tellis (2012), "Does chatter really matter? Dynamics of user-generated content and stock performance." *Marketing Science*, 31 (2), 198-215.

Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. image-related utility in social media: Why do people contribute content to twitter?. *Marketing Science*, *32*(3), 368-392.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of Marketing Research*, *51*(4), 463-479.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site. *Journal of marketing*, *73*(5), 90-102.

Trusov, M., Bodapati, A. V., & Bucklin, R. E. (2010). Determining influential users in internet social networks. *Journal of Marketing Research*, *47*(4), 643-658.

Tipples, J., Atkinson, A. P., & Young, A. W. (2002). The eyebrow frown: a salient social signal. *Emotion*, *2*(3), 288.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of Marketing Research*, *51*(4), 463-479.

Todorov, A., Mandisodza, A. N., Goren, A., & Hall, C. C. (2005). Inferences of competence from faces predict election outcomes. *Science*, *308*(5728), 1623-1626.

Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. image-related utility in social media: Why do people contribute content to twitter?. *Marketing Science*, *32*(3), 368-392.

Trusov, M., Bodapati, A. V., & Bucklin, R. E. (2010). Determining influential users in internet social networks. *Journal of Marketing Research*, *47*(4), 643-658.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site. *Journal of marketing*, *73*(5), 90-102.

Van Heerde, H., Helsen, K., & Dekimpe, M. G. (2007). The impact of a product-harm crisis on marketing effectiveness. *Marketing Science*, *26*(2), 230-245.

Van Laer, T., De Ruyter, K., Visconti, L. M., & Wetzels, M. (2013). The extended transportation-imagery model: A meta-analysis of the antecedents and consequences of consumers' narrative transportation. *Journal of Consumer research*, *40*(5), 797-817.

Watts, D. J., & Dodds, P. S. (2007). Influentials, networks, and public opinion formation. *Journal of consumer research*, *34*(4), 441-458.

Westbrook, R. A., & Oliver, R. L. (1991). The dimensionality of consumption emotion patterns and consumer satisfaction. *Journal of consumer research*, *18*(1), 84-91.

Wheeler, M. E., & Fiske, S. T. (2005). Controlling racial prejudice: Social-cognitive goals affect amygdala and stereotype activation. *Psychological Science*, *16*(1), 56-63.

Wilbur, Kenneth C. (2008a), "How the digital video recorder (DVR) changes traditional television advertising," *Journal of Advertising*, 37 (1), 143-149.

Wilbur, Kenneth C. (2008b), "A two-sided, empirical model of television advertising and viewing markets,"

Williams, M., Moss, S., Bradshaw, J., & Mattingley, J. (2005). Look at me, I'm smiling: Visual search for threatening and nonthreatening facial expressions. *Visual cognition*, *12*(1), 29-50.

Williams, P., & Aaker, J. L. (2002). Can mixed emotions peacefully coexist?. *Journal of Consumer Research*, *28*(4), 636-649.

Winer, R.S. & P.S. Fader (2016). Objective vs. Online Ratings: Are Low Correlations Unexpected and Does It Matter? A Commentary on de Langhe, Fernbach, and Lichtenstein. *Journal of consumer research*, 42 (6), 846-849.

Xiao, L., & Ding, M. (2014). Just the faces: Exploring the effects of facial features in print advertising. *Marketing Science*, *33*(3), 338-352.

Yeung, C. W., & Wyer Jr, R. S. (2005). Does loving a brand mean loving its products? The role of brand-elicited affect in brand extension evaluations. *Journal of Marketing Research*, *42*(4), 495-506.

Yin, D., Bond, S. D., & Zhang, H. (2014). Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. *MIS quarterly*, *38*(2), 539-560.

Yin, C. Y., Yu, H. Y., & Poon, P. (2016). Consumers' attributions and brand evaluations in product-harm crises: The role of implicit theories of personality. *Journal of Consumer Behaviour*, *15*(1), 87-95.

Zebrowitz, L. A. (2006). Finally, faces find favor. *Social Cognition*, *24*(5), 657-701.

Zhong, N. & Schweidel, D.A. Capturing changes in social media content: a multiple latent changepoint topic model. *Marketing Science*, forthcoming.

Zipkin, N. (2017) Pepsi Ignites Outrage with Kendal Jenner Ad, *Enterprepreneur.com*, accessed at: https://www.entrepreneur.com/article/292450

FOOTNOTES

[1] Joy shares conceptual space with other high-arousal emotions such as amusement (Lazarus 1991; Heath et al. 2001).

[2] In the case with Nike, a popular athlete is pictured with the new apparel one day prior to the official statement by Nike. To ensure consistent selection of event dates across brands and reliance on brand's dissemination of information, I use the date of the official statement by Nike as the event date. Robustness checks using the two different dates show that both dates produce similar results in our analysis.

[3] I conduct robustness checks in which I conduct our analysis with different event windows (5, 15, and 30 days) (Agrawal and Kamakura, 1995; Elberse 2007; Joshi and Hanssens 2009). Analyses using these alternative event windows yielded substantively similar results.

[4] https://developers.facebook.com/docs/graph-api/

[5] Changes to the API as of December 2017 no longer include a user ID for privacy concern. I therefore selected brand crises that occurred prior to this change for our empirical analysis.

[6] Appendix A details the specific survey questions and derivation of the brand strength measure.

[7] I rely on the responses from 2010, the most recent data available from Lovett et al. (2014), to operationalize brand strength for the brands in our study.

[8] To assess the robustness of our results, I vary the length of the event window by considering a 3-day and 5-day event window. These analyses yielded substantively similar results. As an alternative to a measure of brand strength, I estimated models using brand-specific fixed effects. I find that the effects of brand familiarity on content emotionality are substantively similar (See Appendix B).

Appendix A: Detail on Brand Strength Covariate

Variable	Values	Comments
Energized_Differentiation_C	0-1	Can be slightly > 1 because of population quota weighting. Average (Different_pct, Distinctive_pct, Unique_pct, Dynamic_pct, Innovative_pct)/100. Each of these components indicate the percentage of respondents who checked this attribute with respect to the brand.
Relevance_C	0-6	Average of scores for the question "How appropriate is BRAND for you personally?" (scale of 1-7) -1.
Brand_Strength_C	0-6	Energized_Differentiation_C*Relevance_C

Brand name	**Category**	**Energized_ Differentiation_C**	**Relevance_ C**	**Brand_ Strength_C**
Chick-Fil-A	Food and dining	0.491	2.958	1.454
Delta Airlines	Travel services	0.401	2.265	0.908
Nike	Clothing products	0.685	3.721	2.549
Nordstrom	Clothing products	0.558	2.396	1.336
Southwest Airlines	Travel services	0.547	2.415	1.322
Starbucks	Food and dining	0.681	2.779	1.892
Taco Bell	Food and dining	0.487	3.529	1.721
Target	Department Stores	0.488	4.462	2.179
United Airlines	Travel services	0.289	2.219	0.642
Volkswagen	Cars	0.630	1.935	1.220

Appendix B: Model Results with Brand Fixed Effects

	(1) Positive	(2) Negative	(3) Anger	(4) Disgust	(5) Joy	(6) Surprise
After	-1.32**	0.46*	0.36*	0.07	-1.23**	-0.45**
	(0.37)	(0.23)	(0.17)	(0.16)	(0.29)	(0.16)
Before Cmt Count	0.51**	0.05	0.27**	-0.12**	0.27**	0.11**
	(0.12)	(0.05)	(0.09)	(0.04)	(0.10)	(0.04)
After Cmt Count	-0.10**	0.05	0.01	-0.11**	-0.03	0.01
	(0.03)	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)
Before Cmt Count X After Cmt Count	0.54	-0.02	0.01	-0.02	-0.01	0.07
	(0.53)	(0.07)	(0.06)	(0.06)	(0.14)	(0.08)
Before Cmt Count X After	-0.89	-0.38**	-0.50**	0.11	-0.09	-0.28*
	(0.72)	(0.14)	(0.13)	(0.11)	(0.32)	(0.12)
Time Since Event	0.02	0.02	0.00	0.01	0.03*	0.03**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
NegEmoPrior	-0.00	0.02**	0.01*	0.01	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PosEmoPrior	0.01**	0.00	-0.00	-0.00	0.01*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Brand Cmt	3.69**	1.09**	0.27*	-0.28	1.41**	1.22**
	(0.35)	(0.21)	(0.13)	(0.15)	(0.27)	(0.16)
Volume of Cmts	-0.00**	-0.00**	-0.00	-0.00	-0.00**	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Weekend (Sat or Sun)	-0.42**	0.06	-0.32**	-0.01	-0.47**	-0.05
	(0.10)	(0.09)	(0.06)	(0.06)	(0.09)	(0.05)
Morning (5am-11:59am)	-0.01	0.27**	0.33**	0.17**	-0.06	0.05
	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.04)
Afternoon (12pm-6:59pm)	0.05	-0.03	0.12**	0.03	-0.03	0.04
	(0.06)	(0.06)	(0.03)	(0.04)	(0.05)	(0.03)
Delta Airlines	-1.14**	-1.68**	-1.26**	-0.99**	-0.87**	0.29**
	(0.26)	(0.23)	(0.12)	(0.18)	(0.21)	(0.11)
Nike	-2.32**	-0.99**	-0.66**	-0.67**	-1.18**	-0.09
	(0.34)	(0.32)	(0.18)	(0.22)	(0.27)	(0.14)
Nordstrom	-3.02**	-1.10**	-0.90**	0.05	-0.72*	-0.19
	(0.37)	(0.26)	(0.15)	(0.20)	(0.31)	(0.16)
Southwest Airlines	-4.78**	-2.19**	-1.25**	-0.75**	-2.42**	-0.94**
	(0.39)	(0.29)	(0.17)	(0.21)	(0.32)	(0.17)
Starbucks	-1.23**	-2.59**	-1.33**	-0.83**	1.55**	-0.37
	(0.46)	(0.29)	(0.17)	(0.22)	(0.39)	(0.20)
Taco Bell	-3.69**	-0.98**	0.28	-0.21	-1.47**	0.02
	(0.38)	(0.28)	(0.18)	(0.21)	(0.31)	(0.17)
Target	-1.00**	-0.78**	-0.97**	-0.91**	-1.28**	0.09
	(0.30)	(0.26)	(0.14)	(0.18)	(0.21)	(0.13)
United Airlines	-3.06**	1.01**	0.27	0.99**	-3.06**	-0.76**
	(0.39)	(0.30)	(0.17)	(0.23)	(0.32)	(0.17)
Volkswagen	-4.51**	-1.66**	-0.83**	-0.22	-1.49**	-1.23**
	(0.39)	(0.28)	(0.17)	(0.21)	(0.32)	(0.17)
Constant	7.11**	3.21**	1.56**	1.82**	4.52**	1.23**
	(0.38)	(0.26)	(0.18)	(0.20)	(0.31)	(0.16)

= * p<0.05, ** p<0.01 Notes: Standard errors in parentheses. Night and Weekday are the baseline categories for time of day and day of week measures respectively. Chick Fil A is the baseline brand.

Appendix C. Robustness Check with Digital Ad Spend and Category Effects

Total Comment Model with Digital Advertising Spend

	Equations					
	(1)		(2)		(3)	
	Base Model		Text X Face		Text X Face X Personality	
PostPos	0.000	(0.002)	0.001	(0.002)	0.029**	(0.010)
PostNeg	0.019**	(0.003)	0.022**	(0.003)	-0.017	(0.021)
FacePos (Happy Face)	0.028**	(0.004)	0.028**	(0.007)	0.027	(0.075)
FaceNeu (Calm Face)	-0.037**	(0.008)	-0.046*	(0.019)	-0.141	(0.168)
FaceNeg (Sad/Angry Face)	-0.015*	(0.006)	-0.005	(0.007)	-0.144*	(0.056)
Sincere	0.552**	(0.011)	0.551**	(0.011)	0.565**	(0.013)
Exciting	-0.130**	(0.010)	-0.130**	(0.010)	-0.140**	(0.011)
PostPos X FacePos			0.001	(0.001)	0.008	(0.007)
PostPos X FaceNeu			-0.001	(0.002)	0.016	(0.018)
PostPos X FaceNeg			-0.001*	(0.001)	0.007	(0.006)
PostNeg X FacePos			-0.005**	(0.001)	0.015	(0.016)
PostNeg X FaceNeu			0.003*	(0.001)	-0.029	(0.037)
PostNeg X FaceNeg			-0.001	(0.001)	0.011	(0.010)
PostPos X Sincere					-0.003**	(0.001)
PostNeg X Sincere					0.000	(0.002)
PostPos X Exciting					-0.000	(0.000)
PostNeg X Exciting					0.005**	(0.001)
FacePos X Sincere					-0.001	(0.006)
FaceNeu X Sincere					0.008	(0.014)
FaceNeg X Sincere					0.015*	(0.006)
FacePos X Exciting					0.002	(0.005)
FaceNeu X Exciting					0.002	(0.013)
FaceNeg X Exciting					-0.001	(0.004)
PostPos X FacePos X Sincere					0.000	(0.001)
PostPos X FaceNeu X Sincere					-0.001	(0.002)
PostPos X FaceNeg X Sincere					**-0.002***	**(0.001)**
PostNeg X FacePos X Sincere					**-0.002+**	**(0.001)**
PostNeg X FaceNeu X Sincere					0.003	(0.003)
PostNeg X FaceNeg X Sincere					-0.001	(0.001)
PostPos X FacePos X Exciting					**-0.002****	**(0.001)**
PostPos X FaceNeu X Exciting					-0.000	(0.001)
PostPos X FaceNeg X Exciting					**0.001***	**(0.000)**
PostNeg X FacePos X Exciting					-0.001	(0.002)
PostNeg X FaceNeu X Exciting					-0.000	(0.003)
PostNeg X FaceNeg X Exciting					-0.000	(0.000)
TotalFaces	0.055**	(0.009)	0.056**	(0.009)	0.057**	(0.009)
$TotalFaces^2$	-0.001*	(0.000)	-0.001*	(0.000)	-0.001**	(0.000)
NonCelebFaceSize	0.153	(0.261)	0.191	(0.265)	0.168	(0.273)
CelebFaceSize	0.537*	(0.225)	0.687**	(0.235)	0.752**	(0.243)
TotalObjects	-0.023**	(0.002)	-0.023**	(0.002)	-0.025**	(0.002)
BrandedImage	0.025	(0.036)	0.026	(0.036)	0.022	(0.036)
RedColorChannel	0.005**	(0.001)	0.005**	(0.001)	0.005**	(0.001)
GreenColorChannel	-0.002	(0.001)	-0.002	(0.001)	-0.002	(0.001)
BlueColorChannel	-0.002	(0.001)	-0.002	(0.001)	-0.002	(0.001)
ElapseTimeDay	0.059**	(0.004)	0.059**	(0.004)	0.060**	(0.004)
$ElapseTimeDay^2$	-0.000**	(0.000)	-0.000**	(0.000)	-0.000**	(0.000)
Morning	-0.194**	(0.059)	-0.187**	(0.059)	-0.193**	(0.059)
Afternoon	-0.198**	(0.043)	-0.195**	(0.043)	-0.196**	(0.043)
Evening	-0.058	(0.044)	-0.053	(0.044)	-0.050	(0.044)

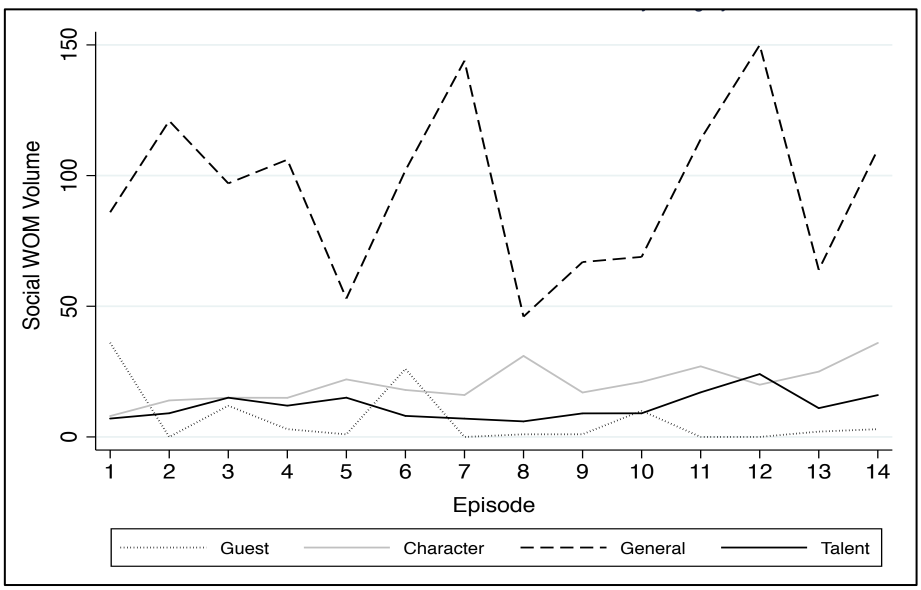
Weekend	-0.095**	(0.028)	-0.095**	(0.028)	-0.119**	(0.029)
PostUrl	-0.194**	(0.025)	-0.195**	(0.025)	-0.187**	(0.025)
PostWC	-0.005**	(0.000)	-0.005**	(0.000)	-0.005**	(0.000)
L_PostPos	-0.007**	(0.001)	-0.007**	(0.001)	-0.006**	(0.001)
L_PostNeg	0.001	(0.003)	0.001	(0.003)	0.002	(0.003)
L_cmtemo_postive	-0.003*	(0.001)	-0.003*	(0.001)	-0.003*	(0.001)
L_cmtemo_negative	0.010*	(0.004)	0.009*	(0.004)	0.011*	(0.004)
Digital Ad Spend	0.000**	(0.000)	0.000**	(0.000)	0.000**	(0.000)
2012	-0.044	(0.044)	-0.044	(0.044)	-0.039	(0.043)
2013	-0.071	(0.044)	-0.068	(0.044)	-0.054	(0.044)
2014	-0.551**	(0.049)	-0.550**	(0.049)	-0.544**	(0.049)
2015	-0.298**	(0.050)	-0.299**	(0.050)	-0.335**	(0.051)
2016	-0.684**	(0.050)	-0.686**	(0.050)	-0.681**	(0.050)
2017	-0.698**	(0.049)	-0.698**	(0.049)	-0.690**	(0.049)
2018	-1.040**	(0.050)	-1.040**	(0.050)	-1.021**	(0.050)
Cosmetics	-0.665**	(0.042)	-0.667**	(0.042)	-0.677**	(0.042)
Oral Hygiene	-2.055**	(0.062)	-2.060**	(0.062)	-2.068**	(0.062)
Sports Apparel	-0.535**	(0.105)	-0.532**	(0.105)	-0.511**	(0.106)
Luxury	-1.635**	(0.061)	-1.634**	(0.061)	-1.644**	(0.061)
_cons	0.863**	(0.112)	0.857**	(0.112)	0.769**	(0.134)
lnalpha	0.856**	(0.009)	0.855**	(0.009)	0.852**	(0.009)
N	20636		20636		20636	
k	44.000		50.000		72.000	
ll	-103732.347		-103715.694		-103672.426	

**,*,+ denotes p<0.01, 0.05, 0.10 respectively. The baseline time of day is night, the baseline year is 2009, the baseline time of day is Weekdays (Mon-Fri), the baseline category is Household Goods.

Appendix D: Classification Description for Canvs Emotion classification

Emotion	Description	Plutchik's Corresponding Emotion
Admiration	Contains emotional expression related to a person or object being formidably impressive, heroic in an action-oriented context, or otherwise tough and uncompromising.	Admiration
Anger	Contains emotional expression related to hostility and aggression.	Anger
Anxiety	Contains emotional expression related to stress and anxiety	Apprehension

Appendix E: Social WOM by segment for American Housewife Program



Appendix F: 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 = 12.42	
Variable	Statistic	p-value
TotalViews	212.29	0.0000
LiveViews	175.62	0.0001
DVR Views	212.79	0.0000
PosCharacter	170.47	0.0002
PosTalent	176.32	0.0001
PosProgram	218.33	0.0000
NegCharacter	191.28	0.0000
NegTalent	180.24	0.0000
NegProgram	264.66	0.0000

Table 2. Johansen Test for Cointegration

Maximum rank	Trace Statistic	Critical Value (5%)
0	2427.80	208.97
1	1949.84	170.8
2	1502.30	136.61
3	1079.99	104.94
4	772.88	77.74
5	480.45	54.64
6	313.83	34.55
7	160.69	18.17
8	48.32	3.74

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

Lag	Bayesian Information Criterion (BIC)
0	26.097
1	25.823*
2	26.776
3	27.960
4	29.399
5	30.794

Appendix G: Granger Causality Test

Response to	Total Views	Live Views	DVR Views	PosCharacter	PosTalent	PosProgram	NegCharacter	NegCharacter	NegTalent
Total Views	- -	5.624	0.392	0.638	**2.702**	0.229	1.448	0.044	**4.535**
Live Views	0.565	- -	**4.600**	**0.340**	0.193	2.386	0.039	1.594	0.134
DVR Views	**5.875**	**18.368**	- -	0.692	0.033	0.697	**4.196**	0.053	0.694
PosCharacter	**3.932**	0.111	**6.228**	- -	0.214	0.146	0.144	0.012	**2.932**
PosTalent	**8.473**	0.872	0.022	0.118	- -	1.488	0.849	1.714	0.024
PosProgram	0.374	0.350	0.018	**5.918**	0.418	- -	0.423	0.225	0.530
NegCharacter	0.080	0.106	0.553	0.026	0.000	0.001	- -	0.031	0.484
NegTalent	0.847	**3.683**	0.536	0.555	**6.153**	0.859	1.577	- -	0.190
NegProgram	0.588	0.118	0.002	2.089	0.029	0.855	0.462	0.071	- -

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 H: Full panel data VAR-X Model Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TotalViews	LiveView	DVRViews	PosCharcter	PosTalent	PosProgram	NegCharacter	NegTalent	NegProgram
Endogenous Variables									
L.TotalViews	0.239***	-0.043**	0.006	0.897	1.932	0.592	1.447	-0.260	-2.227**
	(0.041)	(0.018)	(0.009)	(1.123)	(1.175)	(1.237)	(1.202)	(1.235)	(1.046)
L.LiveView	-0.062	0.186***	0.040**	1.323	1.043	-3.860	0.478	-3.149	-0.772
	(0.082)	(0.036)	(0.019)	(2.269)	(2.374)	(2.499)	(2.429)	(2.494)	(2.112)
L.DVRViews	0.409**	0.322***	0.203***	-3.890	0.884	4.300	-10.254**	1.184	3.626
	(0.169)	(0.075)	(0.038)	(4.677)	(4.894)	(5.151)	(5.006)	(5.141)	(4.353)
L.PosCharcter	0.003**	0.000	0.001**	-0.050	0.020	-0.018	0.017	-0.005	0.067*
	(0.002)	(0.001)	(0.000)	(0.042)	(0.044)	(0.046)	(0.045)	(0.046)	(0.039)
L.PosTalent	-0.004***	0.001	-0.000	0.014	-0.023	0.053	0.039	0.057	-0.006
	(0.001)	(0.001)	(0.000)	(0.039)	(0.041)	(0.043)	(0.042)	(0.043)	(0.037)
L.PosProgram	0.001	-0.000	-0.000	0.088**	0.025	-0.030	0.025	0.019	0.025
	(0.001)	(0.001)	(0.000)	(0.036)	(0.038)	(0.040)	(0.039)	(0.040)	(0.034)
L.NegCharacter	-0.000	-0.000	-0.000	-0.006	-0.000	-0.001	-0.095**	0.007	0.025
	(0.001)	(0.001)	(0.000)	(0.038)	(0.040)	(0.042)	(0.041)	(0.042)	(0.036)
L.NegTalent	0.001	0.001*	0.000	0.028	0.099**	0.039	0.051	-0.006	-0.016
	(0.001)	(0.001)	(0.000)	(0.038)	(0.040)	(0.042)	(0.041)	(0.042)	(0.036)
L.NegProgram	0.001	-0.000	0.000	-0.062	-0.008	-0.043	-0.031	0.012	-0.139***
	(0.002)	(0.001)	(0.000)	(0.043)	(0.045)	(0.047)	(0.046)	(0.047)	(0.040)
Exogenous Variables									
Episode	-0.011***	-0.001	0.003***	0.086	0.174	0.121	0.108	0.006	-0.024
	(0.004)	(0.002)	(0.001)	(0.110)	(0.115)	(0.121)	(0.118)	(0.121)	(0.103)
Finale	-0.017	0.005	0.021***	1.170***	0.262	0.525	1.031**	0.976**	0.837**
	(0.016)	(0.007)	(0.004)	(0.446)	(0.467)	(0.491)	(0.477)	(0.490)	(0.415)
ProgValAnger	-0.001	0.000	0.000	0.045	0.072	0.185***	0.211***	0.130*	-0.055
	(0.002)	(0.001)	(0.001)	(0.065)	(0.068)	(0.071)	(0.069)	(0.071)	(0.060)
ProgValAnticipation	-0.001	0.001	-0.001**	0.123*	-0.018	-0.133*	0.054	-0.068	0.060
	(0.002)	(0.001)	(0.001)	(0.066)	(0.069)	(0.073)	(0.071)	(0.073)	(0.062)
ProgValJoy	-0.001	0.001	0.002***	-0.147*	-0.066	0.044	-0.023	0.088	-0.106
	(0.003)	(0.001)	(0.001)	(0.079)	(0.082)	(0.087)	(0.084)	(0.087)	(0.073)
ProgValSadness	-0.002	-0.001	-0.001	-0.044	-0.086	-0.078	-0.101	-0.101	-0.031
	(0.002)	(0.001)	(0.001)	(0.069)	(0.072)	(0.076)	(0.073)	(0.075)	(0.064)
m1	-0.062	0.028	0.064***	-2.629	-3.930	-0.164	1.186	-3.147	-0.697
	(0.084)	(0.037)	(0.019)	(2.313)	(2.420)	(2.547)	(2.475)	(2.542)	(2.153)
m2	-0.056	0.035	0.043**	-3.014	-3.950*	-0.011	0.536	-3.784	-1.291
	(0.076)	(0.034)	(0.017)	(2.109)	(2.207)	(2.323)	(2.258)	(2.318)	(1.963)
m3	-0.065	0.051	0.048***	-3.501*	-3.948*	-0.292	0.782	-3.717*	-1.740
	(0.070)	(0.031)	(0.016)	(1.949)	(2.040)	(2.147)	(2.086)	(2.143)	(1.814)
m4	-0.074	0.039	0.028*	-3.395*	-5.303***	-1.044	1.277	-3.511*	-2.176
	(0.066)	(0.030)	(0.015)	(1.840)	(1.925)	(2.027)	(1.970)	(2.023)	(1.713)
m5	-0.059	0.039	0.015	-4.020**	-5.461***	-0.744	0.594	-3.668*	-1.086
	(0.064)	(0.028)	(0.014)	(1.762)	(1.844)	(1.941)	(1.886)	(1.937)	(1.640)
p1	-0.002	0.028	0.014	-5.450**	1.387	3.879	-0.401	6.844**	-0.630
	(0.099)	(0.044)	(0.022)	(2.732)	(2.859)	(3.010)	(2.925)	(3.004)	(2.544)
t1	0.202***	0.020	-0.001	0.006	1.019	0.297	-0.475	-0.567	-0.221
	(0.044)	(0.020)	(0.010)	(1.219)	(1.276)	(1.343)	(1.305)	(1.340)	(1.135)
t2	0.141***	0.032	0.043***	-0.284	2.457*	1.702	-0.200	-2.964*	1.994
	(0.051)	(0.023)	(0.011)	(1.401)	(1.466)	(1.543)	(1.500)	(1.540)	(1.304)
t3	0.062*	-0.042***	-0.013	0.586	1.761*	0.304	0.523	0.647	1.324
	(0.035)	(0.016)	(0.008)	(0.973)	(1.018)	(1.071)	(1.041)	(1.069)	(0.905)
t4	-0.106**	-0.027	-0.001	-0.639	1.278	0.809	-0.123	-0.765	0.674
	(0.051)	(0.023)	(0.012)	(1.410)	(1.476)	(1.553)	(1.510)	(1.550)	(1.313)
wkend	-0.156**	0.106***	0.025*	-4.137**	-4.893***	-0.591	1.551	-2.034	-2.531
	(0.061)	(0.027)	(0.014)	(1.701)	(1.780)	(1.874)	(1.821)	(1.870)	(1.584)
ser1	0.165	0.113**	0.012	-8.334**	-6.160*	-0.512	1.046	6.606*	-2.713
	(0.121)	(0.054)	(0.027)	(3.344)	(3.499)	(3.683)	(3.580)	(3.676)	(3.113)
ser2	-0.490***	-0.254***	-0.047***	4.757**	-4.174**	2.692	9.426***	-0.175	6.297***
	(0.069)	(0.031)	(0.016)	(1.913)	(2.002)	(2.107)	(2.048)	(2.103)	(1.781)
ser3	-0.226*	0.006	-0.033	-7.292**	-6.536*	-0.908	2.485	8.564**	-2.577
	(0.122)	(0.054)	(0.027)	(3.371)	(3.527)	(3.713)	(3.608)	(3.706)	(3.138)
ser4	-0.104	-0.111***	-0.029**	2.336	-4.569**	2.681	5.217***	-2.631	2.913*
	(0.064)	(0.028)	(0.014)	(1.762)	(1.844)	(1.941)	(1.887)	(1.937)	(1.641)
ser5	0.021	0.075	-0.033	-7.000**	-5.324	0.179	6.632*	11.592***	4.066
	(0.121)	(0.054)	(0.027)	(3.351)	(3.506)	(3.690)	(3.587)	(3.683)	(3.119)
ser6	-0.212***	-0.096***	-0.077***	6.200***	1.009	-0.538	9.175***	0.430	5.779***
	(0.068)	(0.030)	(0.015)	(1.878)	(1.965)	(2.069)	(2.010)	(2.065)	(1.748)
ser7	0.003	-0.149***	0.038***	-0.455	-3.415**	-3.501**	6.887***	2.275	4.134***
	(0.054)	(0.024)	(0.012)	(1.503)	(1.573)	(1.655)	(1.609)	(1.652)	(1.399)
ser8	-0.011	-0.079***	-0.060***	0.362	-4.888***	-1.553	8.280***	0.251	5.619***
	(0.064)	(0.029)	(0.015)	(1.781)	(1.864)	(1.962)	(1.906)	(1.958)	(1.658)
ser9	-0.006	0.012	-0.028	-5.697*	-2.553	3.972	4.738	10.983***	3.375
	(0.119)	(0.053)	(0.027)	(3.309)	(3.463)	(3.645)	(3.542)	(3.638)	(3.081)

ser10	-0.122**	-0.019	-0.031**	-2.326	-6.525***	-1.965	3.082*	-2.303	1.702
	(0.062)	(0.027)	(0.014)	(1.705)	(1.784)	(1.877)	(1.825)	(1.874)	(1.587)
ser11	-0.134**	-0.169***	0.016	5.867***	-1.031	-0.979	11.522***	4.723***	7.195***
	(0.054)	(0.024)	(0.012)	(1.502)	(1.571)	(1.654)	(1.607)	(1.651)	(1.398)
ser12	0.082*	-0.089***	-0.032***	5.302***	3.381**	-0.819	2.994**	0.818	7.020***
	(0.047)	(0.021)	(0.011)	(1.295)	(1.355)	(1.427)	(1.387)	(1.424)	(1.206)
ser13	-0.202***	-0.117***	0.036**	-1.032	-6.366***	-0.818	8.469***	3.740*	4.651***
	(0.065)	(0.029)	(0.015)	(1.787)	(1.870)	(1.969)	(1.913)	(1.965)	(1.664)
ser14	-0.134**	-0.096***	-0.032**	0.553	-5.998***	-0.792	8.619***	2.661	6.459***
	(0.063)	(0.028)	(0.014)	(1.749)	(1.830)	(1.926)	(1.872)	(1.923)	(1.628)
ser15	-0.093	0.147***	0.024	-8.386**	-8.082**	-0.073	2.120	12.493***	-3.562
	(0.124)	(0.055)	(0.028)	(3.447)	(3.606)	(3.796)	(3.689)	(3.789)	(3.208)
ser16	0.068	-0.135***	-0.037***	1.839	-0.112	-0.044	3.230*	0.912	5.209***
	(0.057)	(0.025)	(0.013)	(1.570)	(1.643)	(1.730)	(1.681)	(1.726)	(1.462)
ser17	0.120*	0.048	-0.002	2.608	-6.261***	2.843	7.555***	-0.123	5.090***
	(0.067)	(0.030)	(0.015)	(1.859)	(1.945)	(2.048)	(1.990)	(2.044)	(1.731)
ser18	-0.191	0.188***	-0.005	-8.453***	-5.764*	0.531	2.660	5.121	-2.354
	(0.117)	(0.052)	(0.026)	(3.240)	(3.390)	(3.569)	(3.468)	(3.562)	(3.016)
ser19	-0.262***	-0.082***	0.022	1.007	-5.514***	0.976	9.223***	2.860	6.782***
	(0.068)	(0.030)	(0.015)	(1.883)	(1.970)	(2.074)	(2.015)	(2.070)	(1.753)
ser20	-0.159**	-0.047*	0.038***	3.465**	-3.331*	-0.683	7.854***	-2.056	1.991
	(0.063)	(0.028)	(0.014)	(1.749)	(1.830)	(1.926)	(1.872)	(1.922)	(1.628)
ser21	-0.181	0.035	0.034	-8.457**	-4.829	-0.283	0.767	7.010*	-1.888
	(0.119)	(0.053)	(0.027)	(3.301)	(3.454)	(3.636)	(3.533)	(3.629)	(3.073)
ser22	-0.140	0.009	0.037	-8.534**	-6.236*	-0.703	1.898	7.139*	-2.559
	(0.120)	(0.054)	(0.027)	(3.326)	(3.480)	(3.664)	(3.560)	(3.656)	(3.096)
ser23	-0.132**	-0.064**	-0.036**	5.968***	0.473	0.459	7.367***	2.678	5.703***
	(0.063)	(0.028)	(0.014)	(1.744)	(1.824)	(1.920)	(1.866)	(1.917)	(1.623)
ser24	0.026	-0.133***	-0.015	0.744	-1.934	0.760	8.391***	3.767*	5.307***
	(0.071)	(0.032)	(0.016)	(1.960)	(2.051)	(2.159)	(2.098)	(2.155)	(1.825)
ser25	0.025	0.074	0.028	-7.217**	-4.556	-0.928	1.203	6.977*	-4.183
	(0.122)	(0.054)	(0.028)	(3.375)	(3.532)	(3.718)	(3.613)	(3.710)	(3.142)
ser26	-0.075	-0.014	0.011	3.367*	-4.281**	1.123	6.096***	2.772	4.692***
	(0.068)	(0.030)	(0.015)	(1.884)	(1.971)	(2.075)	(2.016)	(2.070)	(1.753)
ser27	0.117**	-0.079***	0.015	4.829***	-1.829	-0.982	4.125***	1.760	3.645***
	(0.048)	(0.021)	(0.011)	(1.329)	(1.391)	(1.464)	(1.423)	(1.461)	(1.237)
ser28	-0.226*	0.080	-0.004	-8.113**	-6.780*	-1.420	1.046	8.480**	-6.723**
	(0.123)	(0.055)	(0.028)	(3.403)	(3.561)	(3.748)	(3.642)	(3.741)	(3.168)
ser29	-0.186	-0.085	-0.041	-7.934**	-4.035	-0.288	1.774	6.646*	-0.956
	(0.117)	(0.052)	(0.026)	(3.234)	(3.384)	(3.562)	(3.462)	(3.555)	(3.010)
ser30	-0.149	0.095*	0.060**	-8.973***	-5.463	1.840	1.501	5.160	-4.339
	(0.116)	(0.052)	(0.026)	(3.225)	(3.375)	(3.552)	(3.452)	(3.545)	(3.002)
ser31	-0.289***	-0.076***	-0.012	2.934	-4.435**	-3.399*	5.461***	3.447*	4.702***
	(0.066)	(0.030)	(0.015)	(1.836)	(1.921)	(2.022)	(1.965)	(2.018)	(1.709)
ser32	-0.063	-0.085***	-0.007	7.494***	0.668	-1.085	6.908***	2.903*	5.729***
	(0.052)	(0.023)	(0.012)	(1.432)	(1.499)	(1.578)	(1.533)	(1.574)	(1.333)
ser33	-0.076	-0.110***	-0.037***	1.335	-3.643**	-0.980	6.611***	1.262	2.001
	(0.050)	(0.022)	(0.011)	(1.392)	(1.457)	(1.534)	(1.490)	(1.531)	(1.296)
ser34	-0.170	0.049	-0.045*	-7.085**	-5.954*	1.545	6.401*	7.711**	4.603
	(0.120)	(0.053)	(0.027)	(3.323)	(3.477)	(3.660)	(3.557)	(3.653)	(3.093)
ser35	-0.007	-0.098***	-0.076***	10.718***	4.528**	3.848**	9.498***	7.104***	11.095***
	(0.061)	(0.027)	(0.014)	(1.693)	(1.771)	(1.864)	(1.812)	(1.861)	(1.576)
ser36	0.071	0.217***	-0.002	-7.513**	-4.191	-0.117	1.277	11.580***	0.789
	(0.124)	(0.055)	(0.028)	(3.423)	(3.581)	(3.770)	(3.664)	(3.762)	(3.186)
ser37	-0.074	-0.033	-0.022*	1.515	-2.399	-2.005	-0.009	1.348	1.128
	(0.056)	(0.025)	(0.013)	(1.556)	(1.629)	(1.714)	(1.666)	(1.711)	(1.449)
ser38	-0.255***	-0.155***	0.013	1.836	-5.107***	-0.908	8.739***	0.092	2.454
	(0.064)	(0.028)	(0.014)	(1.771)	(1.853)	(1.951)	(1.896)	(1.947)	(1.649)
ser39	-0.175***	-0.124***	0.010	-0.987	-1.850	-3.559*	4.658**	5.722***	5.635***
	(0.067)	(0.030)	(0.015)	(1.869)	(1.955)	(2.058)	(2.000)	(2.054)	(1.739)
ser40	-0.073	-0.104***	-0.024**	-0.964	-4.968***	-1.037	5.477***	-2.020	3.465***
	(0.051)	(0.023)	(0.011)	(1.407)	(1.473)	(1.550)	(1.507)	(1.547)	(1.310)
ser41	0.109*	-0.187***	-0.045***	10.513***	6.410***	5.336***	6.448***	7.057***	8.476***
	(0.060)	(0.027)	(0.014)	(1.658)	(1.735)	(1.826)	(1.774)	(1.822)	(1.543)
ser42	-0.096	-0.050*	-0.019	1.523	-4.623**	-0.747	6.870***	-3.089	3.803**
	(0.064)	(0.028)	(0.014)	(1.765)	(1.847)	(1.944)	(1.889)	(1.940)	(1.643)
ser43	0.005	-0.026	0.003	0.293	-6.183***	3.667*	11.504***	4.542**	7.579***
	(0.065)	(0.029)	(0.015)	(1.812)	(1.896)	(1.995)	(1.939)	(1.991)	(1.686)
ser44	-0.127	0.188***	0.053**	-8.869***	-1.838	-0.287	2.010	8.493**	-2.222
	(0.116)	(0.052)	(0.026)	(3.223)	(3.372)	(3.550)	(3.450)	(3.543)	(3.000)
ser45	-0.183	0.092*	0.027	-8.245**	-5.209	1.239	6.436*	7.669**	1.904
	(0.119)	(0.053)	(0.027)	(3.295)	(3.448)	(3.629)	(3.527)	(3.622)	(3.067)
ser46	0.150***	0.078***	-0.029**	5.056***	1.984	1.835	2.638*	1.344	4.071***
	(0.053)	(0.024)	(0.012)	(1.466)	(1.534)	(1.615)	(1.569)	(1.612)	(1.365)
ser47	-0.122*	-0.143***	-0.048***	6.750***	-3.455*	5.256***	10.527***	2.924	6.709***
	(0.066)	(0.030)	(0.015)	(1.840)	(1.926)	(2.027)	(1.970)	(2.023)	(1.713)
ser48	-0.249**	-0.115**	0.003	-7.220**	-4.684	-0.717	4.875	6.855*	3.898
	(0.119)	(0.053)	(0.027)	(3.288)	(3.441)	(3.622)	(3.520)	(3.615)	(3.061)

ser49	-0.107*	-0.264***	-0.040***	5.283***	0.181	3.076*	8.131***	3.190*	5.103***
	(0.058)	(0.026)	(0.013)	(1.593)	(1.667)	(1.755)	(1.705)	(1.751)	(1.483)
ser50	0.310***	-0.024	-0.026**	3.641**	-4.401***	1.046	4.153**	-2.060	5.947***
	(0.058)	(0.026)	(0.013)	(1.617)	(1.692)	(1.781)	(1.731)	(1.778)	(1.505)
ser51	-0.205*	0.164***	0.010	-7.751**	-5.929*	-0.464	1.978	10.651***	-5.204*
	(0.122)	(0.054)	(0.027)	(3.369)	(3.525)	(3.711)	(3.606)	(3.703)	(3.136)
ser52	-0.241*	-0.194***	-0.061**	-6.804**	-6.154*	-2.563	1.427	10.115***	-2.274
	(0.123)	(0.055)	(0.028)	(3.408)	(3.567)	(3.754)	(3.648)	(3.747)	(3.173)
ser53	0.370***	0.212***	0.006	-7.004**	-6.790*	0.859	3.864	7.858**	1.836
	(0.125)	(0.056)	(0.028)	(3.450)	(3.611)	(3.800)	(3.693)	(3.793)	(3.212)
ser54	0.206***	-0.215***	0.011	0.763	-7.866***	1.710	11.335***	5.798**	8.109***
	(0.075)	(0.034)	(0.017)	(2.083)	(2.180)	(2.295)	(2.230)	(2.290)	(1.939)
_cons	-1.675***	-0.480***	-0.254***	6.024	7.180	-6.491	-8.133*	-9.977**	-6.054
	(0.156)	(0.070)	(0.035)	(4.325)	(4.526)	(4.764)	(4.630)	(4.754)	(4.026)
Parms	81	81	81	81	81	81	81	81	81
RMSE	0.100	0.045	0.023	2.783	2.912	3.065	2.979	3.059	2.590
R-sq	0.761	0.922	0.827	0.603	0.460	0.464	0.574	0.442	0.635
chi2	2005.764	7479.354	3011.035	955.692	535.715	545.332	847.501	498.011	1096.154
P>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	683								
Log likelihood	=	-5772.387		AIC	=	20.67			
FPE	=	0.007783		HQIC	=	22.67			
Det(Sigma_ml)	=	0.0007566		SBIC	=	25.82			

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01