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Gerard J. Tellis, Deborah J. MacInnis, Seshadri Tirunillai, and
Yanwei Zhang

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What Drives Sharing of Online Digital Content?

The Case of YouTube Video Ads on Social Media

Gerard J. Tellis, Deborah J. MacInnis, Seshadri Tirunillai and Yanwei Zhang¹

Abstract

The authors test six theoretically-derived hypotheses about ad characteristics that influence digital sharing. Two completely independent field studies test these hypotheses using over 11 measures of emotions and over 60 ad characteristics. The results are consistent with our theory and robust across studies. Information-focused content has a significantly negative effect on sharing. However, information-focused content positively affects sharing in risky contexts. Positive emotions of amusement, excitement, inspiration, and warmth positively affect sharing. These positive emotions are created by the use of drama (plot and characters) and characteristics, such as babies, animals, celebrities, and surprise. Sharing is greatest when ad length is moderate (1.2 and 1.7 minutes). Early (versus late) placement of the brand name hurts sharing. Ironically, factors that significantly enhance sharing are rarely used by marketers, whereas those that hurt sharing are used extensively. A third study shows that the drivers of viral videos predict sharing fairly well in an entirely independent sample. A fourth study shows the importance of viral videos by their abnormal returns on stock prices.

Keywords: Virality, shares, networks, ad content cues, video ads, YouTube

Gerard J. Tellis (tellis@marshall.usc.edu) is Professor, Director of the Center for Global Innovation and Neely Chair of American Enterprise at the Marshall School of Business, University of Southern California. Deborah J. MacInnis (macinnis@usc.edu) is the Charles L. and Ramona I. Hilliard Professor of Business Administration and Professor of Marketing at the Marshall School of Business, University of Southern California. Seshadri Tirunillai is Assistant Professor at the Bauer College of Business, University of Houston. Yanwei (Wayne) Zhang (actuary_zhang@hotmail.com) is Data Scientist, Uber Technologies Inc. This study benefited from a grant of MSI and from a grant of Don Murray to the USC Marshall Center for Global Innovation.

Introduction

A unique feature about online communities and digital content is that consumers can share what they like with others. Sharing can *exponentially* impact the total number of views of digital content and the extent to which it goes viral. We define virality on the web as achieving a large number of views in a short time period due to sharing. Virality is maximized to the extent that content viewed by one consumer is shared with others in (the same or different) social networks. The *degree of virality* is intrinsically dependent on the *degree of content sharing* (Tucker 2015). Moreover, an individual who shares content is vested in that content. As such, the individual reveals enhanced commitment to the content and processes it in ways that go beyond merely viewing it. Sharing has become vitally important in the current environment because it can reach vast audiences in a short period of time at low cost. Thus, a primary motive for posting online content is to have it shared. But what drives online sharing?

The current study advances prior research on sharing online content in several important ways. First, *we examine the real-world behavior of people who have actually shared ads across multiple media*. We examine actual sharing as opposed to motivations for or intentions to share (which prior studies have examined (see Table 1)) given the potential discrepancies between motivations and intentions on the one hand and actual behavior on the other (e.g., Fishbein and Ajzen 2011). Some studies have described the characteristics of ads that have already achieved viral status in the marketplace (e.g., Dobeles et al 2007; Dafonte-Gomez 2014). Yet studying ads that have already gone viral limits the ability to understand what creates *variability* in sharing. In contrast, our study examines the drivers of ad sharing (measured continuously), both those that are highly shared and those not shared. Moreover, and different from some prior research, we emphasize ads (as opposed to other types of communications like WOM or online reviews). We do so because marketers have a strong interest in consumers' involvement with and sharing of their ads. Moreover, factors that influence ad sharing might differ when one examines sharing of ads versus sharing of non-commercial content. Specifically, commercial messages may activate persuasion knowledge (Friestad and Wright 1994), such that consumers are aware of and defend against

the sellers' motives to influence them. Furthermore, we also examine sharing behavior across the four major media (Facebook, LinkedIn, Twitter and Google+). This gives us the opportunity to assess the generalizability of the findings by media and to determine if certain factors that influence sharing vary by media. Prior studies (e.g., Stephen et al 2015, and Nelson-Field et al 2013) have examined shares in only one social medium (Facebook).

Second, *our findings provide advertisers with concrete and theory-based insight into about how ads should be designed so as to influence sharing.* Using three classic theories of persuasion, namely the Elaboration Likelihood Model (ELM; Petty and Cacioppo 1986; Petty et al 2004), transportation theory (Green and Brock 2000; Green, Brock and Kaufman 2004; Green 2004), and the persuasion knowledge model Friestad and Wright 1994), we predict which ad characteristics should influence sharing. We code over 60 ad factors that might influence sharing, considerably more characteristics than considered in other studies (see Table 1).

Third, some research has examined the role of emotional content (Akpinar and Berger 2017; Berger 2011; Berger and Milkman 2012; Dubois, Bonezzi and De Angelis 2016; Eckler and Bolls 2011; Stieglitz and Dan-Xuan 2013; Kim 2015) or experienced emotions (Dobele et al 2007; Nelson-Field et al 2013; Phelps et al 2004) on sharing or sharing intentions. Yet, the current study examines *which ad content characteristics evoke emotions.* Specifically, and consistent with our theory, *the most shared ads are not merely emotional; they unfold as dramas*, with highly likable characters and a plot. Ad sharing is also maximized when ads are at an appropriate length to engage the viewer and they do not make the brand prominent. Ironically, advertisers rarely use those factors that enhance sharing. Hence our findings have the potential to influence how marketers develop ads so that they have greater potential to become viral.

Fourth, *our findings are robust across ads, raters, and time.* In two independent empirical studies, we tracked a large number of online video ads from YouTube between November 25, 2013 and March 4, 2014 and between January 2014 and December 2016. From these samples of video ads, we drew a stratified random sample of 345 video ads in Study 1 and 512 ads in Study 2. The two studies used

completely different ads, coders, and time periods. Despite these differences, we find consistent results across the studies. A third study also validates our effects with cross sample prediction. Those theoretical characteristics found to be significant in the hypotheses also have relatively high predictive power. No prior study has shown the out of sample predictive power of drivers of sharing.

Finally, *we demonstrate that sharing marketer-generated video ads can significantly benefit firms*. Whereas some research examines the effects of sharing on persuasion, our results show that ad sharing can influence *abnormal stock market returns*. Numerous studies in marketing have shown abnormal returns are the ultimate measure of response and such returns are managerially relevant (Srinivasan and Hanssens 2009). As far as we are aware, no study has linked ad sharing to stock market returns. This information shows that shared video ads can drive up stock prices, perhaps because the buzz they generate makes people want to invest in the company.

The context of our study is online video ads that advertisers have uploaded to YouTube. YouTube ads can benefit marketers in myriad ways. First, such ads have high potential to enhance exposure and sharing, perhaps leading to virality. Unlike traditional ads, sharing creates fresh exposure, as the video reaches new viewers across other social media, such as Facebook, Twitter, LinkedIn, and Google+. Second, YouTube ads are highly cost efficient. Advertising exposure is free, as it is costless to place videos on YouTube (except for the cost of making and optionally promoting the video). Moreover, advertising through YouTube is unlimited. An advertiser can upload as many videos as it wishes at minimum cost. Third, there is almost no length restriction on YouTube ads. Advertisers can create long ads with rich content. Long ads can tell a story or portray a drama that can arouse strong emotions. Fourth, unlike other advertising methods, viewership is voluntary. The ad is viewed only if a viewer chooses to watch it. Indeed, if the brand does not purchase additional services, the exposure of the video ad is mostly limited to the channel subscribers. Sharing of the ad on social media can exponentially enhance ad exposure. For these reasons, YouTube also represents an appropriate context for understanding the characteristics of content that affect sharing. Finally, YouTube complements TV advertising in new and important ways. Marketers can publish ads on YouTube as a pretest before placing

them in paid TV channels. Conversely, marketers can use paid TV channels as a seed to gain wide viewership and potential sharing when uploaded on YouTube.

The next sections describe the theoretical model and hypotheses, data, results, and discussion of the study. The paper ends with a discussion of the findings.

Sharing Digital Content: Background, Model and Hypotheses

We propose a theoretical model about why and how people share online ads (see Figure 1). This model, is grounded both in prior research on content sharing and in theory. Below we provide background information on sharing so as to review general findings around online sharing behavior. We then develop our theory-based hypotheses.

Background on Online Sharing Behavior

Sharing in Communities Around Mutual Interests. Over the last two decades, the internet has created a new world where communities form around mutual interests. Sharing content online complements the old world of communities formed by geography, race, gender, and nationality (Füller, Jawecki and Mühlbacher 2007; Tandy et al 2013; McWilliam 2000). The four most popular platforms for sharing online content are currently Facebook, Twitter, YouTube, and Google+. Communities on these platforms form in two ways. First, individuals sign up to websites, forums, and groups for which they have a focal interest. Second, individuals share information (digital content) with others. If the receiver likes the information, he or she may sign up to follow the source. In this way, communities arise based on self-selection through sharing. People follow those who share valuable content and disengage from those whose content lacks value. On the other hand, people share content that they think is important and will interest and increase the number of their followers. Some people are constantly on the lookout for content to share. Good sharers keep growing their audience while bad sharers lose their audience.

Motivation for Sharing. Research suggests that people often share online content for purposes of self-enhancement (e.g., Barasch and Berger 2014, Berger and Milkman 2012, Chiang and Hsiao 2015,

Dubois, Bonezzi and de Angelis 2016, Taylor et al. 2012, Hennig-Thurau et al. 2004, Lovett et al. 2013). We define self-enhancement as the basic human need to feel good about oneself in the eyes of others (de Angelis et al. 2012). One way to feel good about oneself is to share valuable content. Sharing such information signals to others that one is “in the know” (Muniz and Schau 2005) and that one is the carrier of interesting, engaging, valuable, or impactful content. This process of sharing is greatly facilitated by the growth of social media and the availability of communities for sharing as explained above.

Selectivity in Sharing. Consumers today live in a content-rich and time-poor environment. Consequently, people need to be discerning in what content they consume and share. Millions of pieces of content are generated each day. Each person who encounters each piece of content must judge whether to consume it or not and whether to share it or not. People do not want to spam their friends with ads. They risk reputational harm by sharing content that others do not find relevant, interesting, or compelling (Toubia and Stephens 2013). Hence, people often share only items that stand out from the noise. Very few pieces of content cross this threshold. If they do, content can be shared with one or many recipients, who can in turn share it with others in their social networks. The repetition of this process ultimately leads to outstanding material going “viral.”

What factors let content to go viral? That depends on the nature of the content. Since the content involved in this study represents ads (vs. other sharable content like non-commercial videos, reviews, etc.) we ground our predictions in widely accepted information processing theories of advertising, such as the ELM (Petty and Cacioppo 1986; Petty et al 2004), the persuasion knowledge model (Friestad and Wright 1994), and transportation theory (Green and Brock 2000; Green 2004).

Conceptual Model

Figure 1 represents the theoretical model that addresses what content factors enhance sharing. Figure 2 elaborates on Figure 1, showing the empirical variables used to capture the key constructs in Figure 1 and our hypotheses. Both figures portray three main content domains that drive sharing. If content has any hope of going viral, it must motivate sharing by providing value to others. Marketing communications theories suggest that there are two broad routes by which advertising content can provide value: by

providing information or by moving viewers emotionally (Tellis 2003; Petty and Cacioppo 1986; Deighton, Romer and McQueen 1989). Information-focused content contains facts, figures, and other pieces of information designed to characterize a product or service. Emotion-focused content represents the emotional evocativeness of the content (e.g., Edell and Burke 1987; Holbrook and Batra 1987). Ad characteristics are other ad executional elements under the control of marketers. Our interest here centers on those characteristics that engage the viewer through the use of drama. Such cues include use of a storyline or plot that unfolds over time, endearing characters, surprise, a length sufficient to support the storyline and late (vs. early) placement of brand name.

We predict that such information-focused content will generally not be shared. The reason is that such content tends to be dry and uninteresting, unless the context involves some degree of product, purchase, or social risk (hence the moderating role of risk in Figure 1). We predict that emotion-focused content will have a positive effect on sharing when it arouses positive (vs. negative) emotions. Finally, we predict that the use of drama, and cues that support its usage enhance sharing by enhancing the emotional evocativeness of the ad. Other cues (i.e., ads of moderate length and content that minimize the commercial of the ad) directly influence sharing. Moderately long ads minimize the time/content tension that underlies online content while still allowing sufficient time to build drama. Ads that minimize the commercial appearance of the ad directly affect sharing by making the ad look less like a marketer-generated communication.

Figure 1 is similar to and partly inspired by the framework of Lovett et al (2013). However, it differs from their framework in two ways. Their stimulus is the mention of a brand name in printed content. Our stimulus is the content itself. Social meaning of the brand name is relevant in their context, whereas the informational and emotional nature of the content is relevant in our context. Also, attributes of the brand name are relevant in their context, whereas attributes of the content (length of content and prominence of the brand) are relevant for us.

Hypotheses

Contingent Sharing of Information-Focused Content. Information-focused content is verbally rich. It typically contains arguments or factual descriptions from a narrator or voice-over about products, attributes, people, behaviors, and events. By virtue of its argumentative or factual focus, information can be dry, difficult to process, and uninteresting. Given its inherent dryness and the motivation required to process it, people may be reluctant to share informative content when the brand is familiar. In such cases, consumers have had personal experiences with the brand, or have observed others' use of it. Information about such items is boring to consumers because features and risks are known and the content fails to inform them about anything new. As such, processing of facts and information about the brand is limited (Petty and Cacioppo 1986). Moreover, people don't want to risk their reputation by sharing (not just boring, but also) ads that are clearly designed to persuade others by virtue of their product-focused content (Friestadt and Wright 1994). Consumers may be more open to such communications when the product is new and can address an unresolved consumption problem. This reasoning is also consistent with some prior work on the sales impact of TV advertising (e.g., Chandy et al 2001; MacInnis, Rao and Weiss 2002), though that work did not examine sharing as a dependent variable. The above reasoning suggests the following hypothesis.

H₁. In general, information-focused content has a negative effect on sharing.

Augmenting H₁, we predict that sharing information-focused content *does* enhance sharing in contexts characterized by risk (see Figure 1). According to the ELM (e.g., Petty and Cacioppo 1986; Petty et al 2004), a risky product enhances consumers' involvement in the ad and makes them more attuned to the credibility of the message arguments. Thus, we expect that in general, consumers will share factual information only when risk is high. We consider three types of risk (1) product risk, which may be high when products are new and unknown, (2) purchase risk, which is high when products are expensive, and (3) social risk, which may be high when the platform used for sharing is more professional and formalized (vs. used in less professional contexts).

Product Risk: New Offer (Product or Service). Prior research of offline ads finds that ads that use information focused appeals are most likely to impact behavior when markets are new (vs. mature; MacInnis et al 2002; Chandy et al. 2001). When buying a new product or service, product risk is high, as the consequences of product usage are unknown. In such instances, consumers often search for information that reduces usage uncertainties (Locander and Hermann 1979; Dowling and Staelin 1994). In these cases, information can provide compelling facts and arguments that describe new benefits or reduce risk perceptions associated with the new product (Petty et al 2004; Dens and De Pelsmacker 2010). Deeply processing such information can reduce the risk and uncertainty associated with new products.

Notably, prior research has not examined sharing as the dependent variable in new vs. mature markets. Akpinar and Berger (2017) observed that information focused ads were not likely to be shared, however, they did not examine the moderating role of product newness to the market (or risk more generally). We predict that individuals may be motivated to share information with others when products are new. Sharing such information has the potential to offer value to recipients by reducing their product risk perceptions. Sharing also enhances the self by signaling that the sharer is “in the know” regarding new and untried products. We expect that the extent of positive sharing is directly related to the newness of the information. The above reasoning suggests the following hypothesis:

H_{2a}. For new offers (products or services), information-focused content has a positive effect on sharing (in contrast to its negative effect on sharing in general).

Purchase Risk: Information-focused content may also be important and shared when purchase risk is high, as would be the case with high-priced products. This is so for several reasons. First, a high-priced product or service triggers greater financial risk for consumers because a bad choice can create a significant economic loss. Second, a high-priced product or service triggers higher involvement in the choice process. In such contexts, consumers will be receptive and attentive to information about the product or service so as to minimize purchase risk (Murray 1991). High involvement choices typically

involve greater information processing (Petty and Cacioppo 2004). Therefore, content that contains information may be more carefully processed for high-priced products and services than for low-priced ones. Beyond thoughtfully processing this information (to reduce their own purchase risk), consumers may share such information with others to minimize *the recipient's* purchase risk. Doing so, places the sharer in the position of one who is concerned about the welfare of others, thus enhancing the self. As a result, we expect greater sharing of ads for high-priced (vs. low-priced) products and services. Thus,

H_{2b}. Information-focused content is more likely to be shared for high-priced products and services than for low-priced products and services.

Social Risk: We expect that the network on which content is shared could also moderate the link between information-focused content and sharing. The four major networks for sharing are Facebook, Twitter, Google+ and LinkedIn. Of these, LinkedIn stands apart from the other three because it is a professional network. We expect the behavior of consumers on LinkedIn to differ markedly from that on the other three networks. Sharing on the other three networks is likely to be informal and casual. However, because LinkedIn is a professional network primarily designed to secure jobs and advance careers, consumers are likely to be careful, thoughtful, and cautious on this network. Sharing content that is deemed unprofessional would generate significant social risk. Since LinkedIn is a professional network, content that is factual and informative is more likely to be shared on LinkedIn than on other networks. This line of reasoning suggests the following hypothesis.

H_{2c}. Information-focused content is more likely to be shared on LinkedIn than on Facebook, Twitter, and Google+.

Role of Emotions in Sharing

Emotion Valence. Emotion-focused content can arouse either positive or negative human emotions. Common positive emotions evoked by advertising include joy, love, warmth, amusement, excitement, and pride (Edell and Burke 1987; Holbrook and Batra 1987; Tellis 2003). Common negative emotions are

fear, sadness, shame, anger, and disgust. Outside of a sharing context, research shows that ads that induce positive emotions generally enhance attitudes toward the ad and brand (Edell and Burke 1987; Holbrook and Batra 1987), increase purchase intentions (Aaker et al 1986) and recall (Stayman and Batra 1991), reduce ad avoidance (Teixeira et al 2012), and affect sales (Chandy et al 2001; MacInnis et al 2002).

In terms of sharing online ad content, evidence suggests that ads that evoke positive emotions would be shared. Ekler and Bowles (2011) found that consumers had stronger intentions to forward ads that were positively vs. negatively or mixed in affective tone. Southgate et al (2010) found that sharing of ads was greater as the as the enjoyment of ads increased, however that research did not emphasize the specific emotions that influenced enjoyment. Nelson-Field, Riebe and Newstead (2013) examined commercial videos shared via Facebook, observing that ads that evoked high arousal emotions were most likely to be shared. However, that study did not examine what characteristics of ads induced these emotions. Berger and Milkman (2012; see also Berger 2011) also found that consumers were more likely to share emotionally arousing non-commercial content, but they did not look at sharing of commercial content. As noted earlier, commercial content and non-commercial content may be processed differently because they vary in the extent to which they activate persuasion knowledge (Friestad and Wright 1994).

We anticipate that people are more likely to share content that arouses positive (versus negative) emotions for two reasons. First, a natural tendency towards benevolence leads most people to pass on content that generates positive rather than negative emotions. As an example, on websites, positive reviews outnumber negative reviews by two to one (Godes and Mayzlin 2004; Tirunillai and Tellis 2012). Second, an important goal of sharing is self-enhancement, which is to feel good about oneself in the eyes of others. Self-enhancement is more likely to occur when one shares content that arouses others' positive emotions versus negative ones. Content that arouses negative emotions may be disconcerting to receivers, making senders less likely to share it. Conversely, people are likely to be happy with content that arouses positive emotions and feel positively towards the person who shared that content. The above reasoning suggests the following hypothesis:

H₃. Content that arouses positive (vs. negative) emotions has a positive effect on sharing.

Ad Characteristics that Drive Emotions. Emotion-focused content is typically triggered by content that use drama as opposed to narration (Deighton, Romer and McQueen 1989). Narration uses a third party (an author or voice over) who describes aspects of the item. Drama includes plot and characters. Dramatization increases to the extent that any piece of content uses elements of a drama, including plot, characters, and surprise. Increasing use of these key components of dramas is predicted to enhance the extent to which content is emotionally evocative and shared, as explained next.

The use of drama is likely to arouse more intense emotions than information-focused content, for three reasons (Tellis 2003). First, ads depicted as dramas are easier to process than is information. Transportation theory (Green and Brock 2000) suggests that individuals naturally gravitate to stories as a form of transmission of cultural information. Stories are relayed through drama. Because dramas uses characters interacting in a plot, it requires less effort to process than information. The viewer enjoys the characters and is drawn into the plot with limited effort.

Second, ads containing drama are engaging. Transportation theory (Green and Brock 2000; Green 2004) suggests that stories with characters can transport the reader into the story by evoking empathy and mental imagery. The characters and suspense draw the viewer into the plot, transporting them into the lives and experiences of the characters (Brock and Green 2000). The viewer can become immersed in the plot and can empathically experience the emotions played out by the characters (Deighton, Romer and McQueen 1989; Escalas and Stern 2003). These processes make viewers feel like they are experiencing the story from the characters' perspective. As such, drama has great potential to create strong emotions. By virtue of their story-telling nature, such ads have the potential to evoke emotions like pride and hope (Aaker and Williams 1998; Cavanaugh et al 2015), feelings of warmth, joy and love (Aaker et al 1986; Aaker et al 1988; Cavanaugh et al 2015). They might also provide a humorous story that creates amusement and/or induces excitement (Eisend 2009). Viewers likely assume that others will find such ads emotionally evocative as well. Viewers likely assume that others will be so engaged and will thus share the content (Nelson Field 2013) and/or Eckler and Bolls 2011).

Third, dramas are inherently enjoyable because the storyline keeps the viewer glued to the unfolding plot until the surprising resolution. The greater the surprise, the greater the enjoyment, and hence the more likely the content will be shared. In sum, drama increases engagement and emotional arousal with decreasing effort so that it increases sharing of content. Chen and Lee (2014) suggest that ads rated as high in transportation enhance sharing intentions. However, their study did not examine actual shares.

A plot is a sequence of events that creates increasing suspense or tension until it reaches a climax followed by a surprising resolution (Tellis 2003). The plot is effective to the extent that the sequence of events flows smoothly, is increasingly captivating, and has an internal unexpected solution from the role of characters (surprise). The more the plot evokes surprise, the higher the interest, engagement, and emotional arousal of the viewer. The resolution of the tension in the plot with surprise is also important. If the audience guesses the resolution, the plot becomes trivial and uninteresting. However, a surprising resolution provides satisfaction and pleasure. Thus, drama, plot, and surprise are positive triggers of emotional arousal that can, in turn, lead to sharing

Characters are individuals portrayed in the plot. They captivate the audience to the extent they are appealing (attractiveness), typical of the audience's experiences (similarity), and endearing to the audience (likeability) (McCracken 1989). The relationships among characters create tension in the plot, which draws the audience in and immerses them into the unfolding events of the plot (Deighton, Romer and McQueen 1989). Characters can be everyday people, celebrities, animals, babies, or cartoons. We expect more positive emotions, views, and shares as characters become increasingly attractive, likeable, or similar to the customer. Characters depicted as everyday people do so because of their similarity to the audience. Celebrities do so because of their attractiveness and their ability to engage the audience. Babies, animals, and cartoons do so because of their likeability or cuteness (Petty et al 2004. Eisen and Terrahi 2016). Characters can act as affective characteristics that both facilitate the use of drama, and make ads (and brands) more likeable (Petty and Cacioppo 1986; Petty et al 2004).

The above reasoning suggests the following hypothesis:

H₄. Content that uses a drama and drama-supporting cues (e.g., a plot, characters, and surprise) positively impact sharing.

Ad Content that Minimizes Commercial Appearance and Addresses Time/Content Tensions

One important aspect of sharing content is the prominence of the brand name. Advertisers often want their brand name to be prominent since they want consumers to remember the brand. However, a prominent brand name can activate persuasion knowledge (Friestad and Wright 1994), making consumers more resistant to messages that use prominent brand names. Brand name prominence indicates to the viewer who created the content. The more prominent the brand name, the more the content looks like a commercial message. The prominence of the brand name depends on (1) the duration (or frequency of exposure) of the brand name and when it appears (whether early or intermittent) in the content. Prominent brand names can also interfere with those ad characteristics that support the use of drama. Specifically, the more prominent the brand is in the ad the more it interferes with consumers' abilities to engage with story being told in the ad. Prominent brand names also make the video appear commercial decreasing likelihood of consumers wanting to share commercial content.

Recall that individuals share content for purposes of self-enhancement. Individuals do not want to appear as messages of a commercial organization, whether paid or unpaid. The more prominent the brand name, the more it appears to be a commercial message. Hence, we expect that individuals are less likely to share such content both because the brand's prominence interferes with a dramatic portrayal and it highlights the commercial nature of the communication. Similarly, the earlier the brand name appears in the content, the earlier it is tagged as a commercial message, reducing the likelihood sharing. Consistent with this prediction, Teixeira et al. (2010) found that the prominence of brand names in the ad increases ad avoidance. Akpinar and Berger (2017) found that consumers were more likely to share ads when the brand was integral to the narrative. However, the extent to which the brand is integral to the narrative can be independent of the extent to which it is featured prominently. Thus, whereas advertisers are advised to

show the brand name prominently by placing it early in the ad or for a long duration of time, we argue that just the opposite holds for sharing of digital content in online environments. Thus, we expect that:

H₅. The greater the brand prominence (longer duration, earlier placement) in the content, the lower the likelihood of sharing.

As noted earlier, the Internet has created a “content-rich and time-poor environment” (Corhan 2011). The Internet has opened vast avenues where consumers can access content at little or no economic cost. Google’s content is virtually free, as is content on most online newspapers. YouTube videos and some movies and TV programs are also free. Streaming has made TV shows and movies relatively inexpensive. Yet, whereas people today have myriad opportunities to consume content, their ability to do so is constrained by time (Southerton and Tomlinson 2005). Because people have very little time to enjoy the vast opportunities of newly available content, they are trapped in a content-rich but time-poor environment.

Given the tension between time and content, we suggest that an optimal length exists for content to be shared. What constitutes the optimal length for online video ads is an empirical question. However, there are reasons as to why advertising content that is too short or too long will reduce sharing. If the content is too long, people will not consume it and will not want to burden their friends in their communities by passing it around. If the content is too short, it will not be rich enough to engage the viewer and influence him or her to share it. This is particularly true for drama ads, which require sufficient time to engage viewers (Green and Brock; 2002; Green 2004). The above discussion suggests the following hypothesis:

H₆. The response of sharing to length of content is inverted-U shaped with an optimal length. Long content will be less likely to be shared because of the constraints on time mentioned above. Short content will be less likely to be shared because short durations limit the brand’s ability to immerse consumers in the plot. Short content may also be insufficient when risk is high because limited opportunity is provided to credibly communicate product benefits.

Next, we describe the data, sampling, and coding to test the hypotheses. We test these hypotheses in two independent empirical studies covering different time periods, sampled videos, and raters but adopting similar coding and model.

Study 1

This section describes the research context, sampling, data collection, and content coding.

Research Context

The context of the study is online video ads uploaded on YouTube in branded channels. We chose YouTube because it is highly relevant to marketers in ways described in the introduction. From 2009 through 2013, more than six thousand brands released more than 11,500 advertising campaigns and 179,900 video ads on YouTube. These ads generated more than 19 billion video views (Visible Measures 2013). YouTube now has more than 1 billion unique users who watch over 6 billion hours of video each month¹. Thus, advertising on YouTube could reach a large potential audience. Thousands of advertisers have established branded channels on YouTube through which they upload video ads for public viewing. A branded channel is an account on YouTube through which a brand uploads video ads, communicates with users, and manages video information.

Brand Sampling

The number of branded channels and video ads on YouTube is enormous. We had to sample judiciously. We selected the target brands using several criteria. First, we identified the top 100 advertisers in 2012 in the US by expenditure.² Not all of them owned YouTube channels. Second, if there was a channel with descriptions that closely matched the target brand, we recorded that brand's channel name on YouTube and used it in our sample. Third, we included additional brands that were historically active on YouTube. These brands have uploaded at least one video ad per month and had released at least

¹ Source: <http://www.youtube.com/yt/press/statistics.html>

² Source: http://www.adbrands.net/us/top_us_advertisers.htm.

one popular ad (more than 1 million views) in the last 12 months. This helped us to capture as many shared ads as possible, since most ads were barely shared (see below). This process resulted in 109 brand channels considered in our data collection process.

Data Collection

We tracked these brands and recorded all video ads that these brands uploaded between November 25, 2013 and March 4, 2014. During approximately 100 days, the brands uploaded 1,962 video ads. Each channel uploaded one video ad in about 5.6 days during this period. For these video ads, we collected the number of shares of the video ads across various social media and the number of brand channel subscribers.

We relied on the APIs provided by major social media to extract the number of shares of the video on these media. Requests for these APIs returned the number of times the URL of a given video has been shared on these media. The major social media are Facebook, Twitter, Google+, and LinkedIn. For example, to obtain the number of shares of the ad "Amazon prime air", we first looked up its URL on YouTube, which is <https://www.youtube.com/watch?v=98BIu9dpwHU>. We then constructed a query to the social network APIs to retrieve the number of times this URL had been shared. The query request depends on the target social network. For example, the following brought back the shares of the ad on Facebook:

```
https://graph.facebook.com/fql?q= SELECT share_count, like_count
FROM link_stat WHERE
url="https://www.youtube.com/watch?v=98BIu9dpwHU"
```

We sent such requests every hour to retrieve and store the sharing information from the time that the video ad was uploaded to YouTube. This step is critical because the APIs usually limit the query to only look for recent data (of the last weeks or months). Queries sent many months after the ad was uploaded would not get the complete sharing information. Also, we took care not to exceed the daily limit set by the APIs for the maximum number of requests.

While we also tracked other social media, such as StumbleUpon, Pinterest, and so on, shares on these media were considerably smaller than shares on the four major media. So, we defined the total number of shares for each ad as the sum of the shares across the four major social media. Based on this definition, one viewer of a video can share the video on multiple occasions. We observed few substantive changes in shares of the video after it was 30 days old. As such, we used the total number of shares observed during the first 30 days in the following analysis.

We extracted the number of channel subscribers from the YouTube API (<https://developers.google.com/youtube/v3/>) at the time the video ad was uploaded to measure channel popularity. It is important to collect the subscriber information at the time the video ad is uploaded rather than at some time post publication. This is because viewers of the video ad may subscribe to the channel, thus making post-publication channel subscribers endogenous to social shares. Indeed, a viral ad may substantially affect the number of channel subscribers. The advantage of collecting all video ads during a certain period from these channels instead of selectively chosen samples of ads is that the findings based on our data represent typical commercials.

Data Sampling

Given the challenges in coding all video ads, we selected a sample with which to work. Our random sampling procedure was based on stratified sampling because the distribution of the shares across the video ads is highly skewed. Table 2 shows the sample quantiles of the observed shares. About 10% of the ads are not shared at all and more than 50% are shared less than 158 times. Using a simple random sampling procedure would result in a sample that contains a large portion of non-shared ads, making it less informative for identifying the drivers of sharing. In the stratified sampling, we divided all video ads into four groups and sampled from each group randomly. The break points for the four strata are based on the 50, 75, 90% quantiles of the shares.³ We then drew 90 video ads from each group randomly, resulting in 360 video ads. . We excluded 15 duplicates where the advertiser had uploaded the same ad multiple

³These correspond to points close to 100, 1000, and 10000 shares.

times, resulting in a final sample of 345 video ads. Table A1 (in the Online Appendix) reports the number of uploaded video ads for each brand included in the final sample.

Content Coding

We adapted the scales from Chandy et al. (2001) to code the content of the video ads. Below, we discuss the video ad characteristics using these scales.

Information-focused content. We defined information-focused content by the following criteria. First, the ad uses logical reasoning, for example, by comparing the target brand to some competitive brand. Second, the ad makes factual claims of a product. Third, the ad identifies certain benefits to users. Coders considered these aspects together when rating the information-focused content of the ad. Coders used a 6-point scale to rate the extent to which the ad used these characteristics of information (0 = not at all; 5 = very strong). Further, they recorded whether the ad concerns the launch of a new product and service that has not existed in the current market (0 = no; 1 = yes). In addition, two coders rated whether the product's price was low (=1; e.g., consumer packaged goods product) moderate (=2; e.g., consumer electronics or retail store purchases) or high (=3; e.g., automobiles).

Emotion-focused content. For characteristics that trigger emotions, coders rated the extent to which the ad arouses emotions (0 = not at all; 5 = very strong). The coders also rated the degree to which specific emotions were aroused in the ad. The individual emotions included both positive emotions (i.e., love, pride, courage, joy, triumph, warmth and excitement), and negative emotions (i.e., sadness, shame and fear). For the negative emotions, we also included ratings on anger, disgust and hatred; however, these were not present in the sampled video ads and were thus dropped from the analysis. Coders rated humor by how funny the ad appeared to them (0 = not at all funny; 5 = very funny). The intensity of humor was measured on a 6-point scale (0 = not at all; 5 = very strong).

Ad Characteristics that Drive Emotions. We hypothesize that ads with the characteristics of drama and those that facilitate the use of drama will enhance sharing. The use of character and plot in the ad served as indicators of the dramatization scale (Deighton et al. 1989). Coders rated the presence of both character and plot on a 6-point scale (0 = not at all; 5 = very strong). We defined the dramatization

scale as the average of character and plot. Coders also identified the specific type of characters in the ad. We focused on celebrities, babies, animals, and cartoons. We created a binary indicator for each type of character, with one indicating its use and zero otherwise. Multiple characters can appear in the same ad. We originally used separate indicators for babies and animals but combined them given their potential to create similar feelings of endearment and given their limited occurrence in our sample. We coded the use of a narrator; a third-party voice or text that describes what is going on in the ad (definition follows Deighton et al. 1989). We assessed surprise by the extent to which the ad is inconsistent with a common viewer's prior belief. The intensity of surprise was measured on a 6-point scale (0 = not at all; 5 = very strong). Coders rated the extent of suspense in the ad (0 = not at all; 5 = very strong). Ad length refers to the duration of the ad in seconds, which was collected directly from YouTube. The raters also counted in seconds the total time the brand name/logo was present or the brand was mentioned in the ad. We operationalized brand prominence as a function of brand name exposure frequency and ad length. That is, we normalized the duration of brand name appearance by the length of the ad to account for differences in ad length. The location where the brand name appeared was recorded as ``none'', ``early'', ``end'' or ``intermittent''. It was coded as ``intermittent'' if the brand name appeared in multiple places in the middle of the ad.

Control Variables. We included additional content characteristics to control for factors that were not part of our theoretical model but which could affect sharing. Ads can also contain content pertinent to a contemporary event, such as the Olympics, the World Cup, the Super Bowl, and the like. Hence, coders indicated whether the ad was (= 1) or was not (= 0) relevant to a contemporary event. Sexual appeals are commonly used in certain product categories, such as fashion and cosmetics. Coders used a 0/1 scale to indicate whether the ad contained (= 1) or did not contain (= 0) sexual appeals.

Except for price (which was coded by two raters), three paid raters, who were blind to the purpose of this research, coded the data independently. We explained the rating scales, trained the coders using test video ads unrelated to the selected sample, discussed their results of the test cases, and clarified the definitions so that raters understood the meaning of each scale. Raters were given copies of each ad,

which were downloaded from YouTube. Only the title of each video ad and the brand channel that published it were available to raters. Raters were instructed to base their ratings on only the information provided. They were instructed to not search for or gather additional information. Following these instructions, the three raters rated the sampled video ads independently.

After coders finished the ratings, we computed the inter-rater reliability measures. The inter-rater agreement percentage was 0.76, and the Kappa and Tau correlations were 0.67 and 0.63. Since brand duration is a continuous variable, it has the lowest agreement percentage. If we exclude this variable, the inter-rater agreement percentage was 0.81, and the Kappa and Tau correlations were 0.70 and 0.60. According to Multon (2010), an adequate level of agreement is generally considered to be 70%, and an adequate level of Kappa is considered to be 0.50. The level of agreement we observed is quite good considering that number of characteristics of content were rated on continuous (vs. binary) scales.

To determine the final scale for each variable in the analysis, we set the scale of the variable to reflect the agreed-upon value when at least two raters gave the same rating on a characteristic. Otherwise, we use the mean of the three ratings. The percentage of scales on which all three raters disagreed is about 4% (excluding brand duration).

Results

This section covers descriptive statistics, principal component analysis, analysis of drivers of shares, analysis of drivers of emotion, and analysis by platform.

Descriptive Statistics

Table A2 (in the Online Appendix) shows the frequency of each scale for all characteristics of content (except for the numeric ones). The median ad length is about 60 seconds, with first and third quantile being about 30 and 120 seconds. The last column shows the result of a simple regression of the logarithmic shares over the rated scale of each ad characteristic.

Principal Component Analysis of Emotions

Recall that we measured the extent to which the ad aroused 11 specific emotions. Since certain types of emotions may be highly correlated with other emotions, we factor analyzed the rated emotions and derived latent factors for use in the empirical analysis. The analysis used principal components along with Varimax rotation to estimate the factor loadings. Table 3 (panel 1) shows the loadings for the first six factors, which are sufficient to explain the variances in the original dimensions. Based on the factor analysis, we extracted the scores corresponding to the six latent factors (linear combination of the original scales using the factor loadings as weights). We labeled these newly derived scores as representing positive emotions (“inspiration”, “warmth”, “amusement”, “excitement”) and negative emotions (“fear” and “shame”). We used these factor scores in the analyses that follow.

Analysis of Drivers of Shares

Our empirical analysis follows the structure laid out in Figure 2. We first describe the model, then the results.

Model of Drivers of Shares. We investigate the effect of ad characteristics on social shares by estimating a mixed-effects model as follows:

$$\begin{aligned} E[\log(\text{shares})] = & \alpha_{\text{brand}} + \beta_1 \times \text{information} + \beta_2 \times \text{new product} + \beta_3 \times \text{information} \times \text{new} \\ & \text{product/service} + \beta_4 \times \text{information} \times \text{price level} + \beta_5 \times \text{positive emotion: inspiration} + \beta_6 \times \\ & \text{positive emotion: warmth} + \beta_7 \times \text{positive emotion: amusement} + \beta_8 \times \text{negative emotion: fear} + \\ & \beta_9 \times \text{negative emotion: shame} + \beta_{10} \times \text{positive emotion: excitement} + \beta_{11} \times \log(\text{subscribers}) + \\ & \beta_{12} \times \text{timeliness} + \beta_{13} \times \text{brand frequency} + \beta_{14} \times \text{brand early} + \beta_{15} \times \text{brand none} + \beta_{16} \times \text{brand} \\ & \text{intermittent} + \beta_{17} \times \text{ad length} + \beta_{18} \times \text{ad length}^2 + \beta_{19} \times \text{price level} + \varepsilon \end{aligned} \quad (1)$$

Where α and β_i are coefficients to be estimated and ε are error terms initially assumed to be independently and identically distributed. The subscripts for individual ads are suppressed for ease of reading. We include the level of information and the four emotion dimensions and the six characteristics used in emotion-focused content (see Figure 2). We also include the interaction terms of information x new product/services and information x price levels (low, medium and high) so as to test Hypotheses H_{2a}

and H_{2b} . We also test hypotheses about the other characteristics of ad content such as brand prominence and ad length.

There may be substantial differences due to brand and product category that influence the sharing of video ads. When estimating the impact of ad characteristics we control the brand effect in two ways. First, we include the observed channel followers to account for the observed heterogeneity in brand popularity - some brands may have more followers on their channels, leading to higher views and shares. Second, we include a brand-level random intercept (α_{brand}) to account for any additional unobserved heterogeneity in brand or product characteristics that may influence sharing. We use the logarithmic shares as the response variable to account for skewness in the sharing data. We standardize the response and the numeric scales so that the magnitude of the coefficients can be compared. No scaling is applied to binary or categorical covariates.

Results of Drivers of Shares

Information-Focused Content. Table 4 reports the estimated effects of the ad characteristics on shares. We discuss the results in terms of information-focused content, emotion-focused content, and attribute-focused content, following Figure 2. We note several results. First, the use of information (argument and factual descriptions) is significant and negatively related to social shares. This result implies that information-focused content is less likely to be shared, supporting Hypothesis H_1 . This result is likely due to the dryness of arguments and facts that constitute information. However, the main effect of new product is positive and significant as hypothesized. Ads introducing new products are generally shared more often, because they contain novel and interesting facts, the sharing of which may make senders look like they are “in the know”.

Information-Focused Content and Risk. Hypothesis H_2 proposes that consumers might share information-focused ads when the product, purchase, or social context involves risk (see Figure 2). As Table 4 shows, the interaction between the information and new product is positive and significant. From the interaction, we can compute the estimated effect of information in ads with new product introduction. This effect is 0.086 with a p-value of 0.10, which is positive and marginally significant. The result

indicates that for new products, greater use of information in ads could indeed facilitate social sharing. This result may be because the information about new products is likely to be novel and valuable to recipients, making the sharer look good. These results are consistent with Hypothesis H_{2a}.

The interaction effect of information x price level is also positive and significant. We use three price levels, low, medium and high. In the model, we exclude the low level and use dummy variables for medium and high. As such, the coefficients of these two variables must be interpreted against the reference low level. Both coefficients are significant and positive. The high price brands have a greater impact on sharing, than the moderately priced brands. All these results support Hypothesis H_{2b}.

Hypothesis H_{2c} proposed that consumers would be more likely to share information-focused ads on LinkedIn than on the other networks because such ads would seem more appropriate when shared on a platform geared toward professionals. For this analysis, we ran a sequence of mixed-effect models, which link the number of ad shares on each of the four major social media, Facebook, Twitter, Google+ and LinkedIn, to the rated characteristics of content. The important effects of characteristics across social media are in Table 5. The detailed estimates of the effects of characteristics for each platform are in Table A3 (in the Online Appendix).

Several conclusions emerge. Across the four social media for which we tracked sharing, LinkedIn is the most distinct in the ad characteristics that drive sharing. This result is likely because LinkedIn is a business-oriented social networking environment where the users are mostly professionals. The others are social networking sites that can connect a variety of people. In particular, information-focused ads do not have a significant negative effect on shares for LinkedIn, as opposed to the other social media, supporting Hypothesis H_{2c}. We surmise that individuals on the other social media are more motivated to watch video ads for entertainment, while entertainment is less likely to be the primary motivation on LinkedIn. Moreover, the use of amusement, celebrity, and baby/animals, which may be a source of entertainment (see below), do not significantly affect shares on LinkedIn.

Evoked Emotions. Table 4 shows that ads that evoke positive emotions generate more shares, supporting Hypothesis H₃. Among the different types of emotions, ads that evoke inspiration, warmth,

amusement and excitement are most likely to be shared. None of the coefficients for the negative emotions is significant in the analysis, also supporting Hypothesis H₃. However, in our data, few ads evoke negative emotions (Online Appendix Table A2). This pattern may be because advertisers have already anticipated the negative effects from ads with negative emotions.

Ad Characteristics that Drive Emotions. We hypothesized (H₄) that the ad characteristics that arouse emotions include the degree of dramatization, surprise, suspense, and the type of characters in the ad (celebrity, babies, animals). We regressed each of the four significant latent factors of emotions over these characteristics. Table 6 reports the estimated effects of these characteristics on emotions.

Several results are noteworthy. First, greater use of dramatization has a significant positive effect on emotions, as hypothesized by H₄. In particular, the use of drama increases the emotions of inspiration, warmth and amusement. Second, surprise plays an important role in arousing emotions as hypothesized. In particular, the use of surprise leads to significantly higher amusement. Third, the use of a celebrity is important in arousing positive emotions as hypothesized. In particular, celebrities significantly increase the emotions of excitement and inspiration. Fourth, the use of babies/animals is also effective as hypothesized. They are especially effective at stimulating the emotions of inspiration, warmth, and amusement. Notably, the effect of suspense is not significant in arousing emotions. The probable reason may be that its effect is already captured by dramatization.

We controlled for use of sexual appeals and cartoons. Sexual appeals had no significant effect. Cartoons only affected amusement. Notably though, these characteristics are infrequently used in our sample.

We predicted that the length of the ad is crucial. TV ads are historically short (15 or 30 seconds). In marked contrast, almost no restrictions are placed on the length of video ads on YouTube. Longer ads allow for more development and unfolding of the plot and play of characters, which is necessary for drama ads. That said, viewers (and ad receivers) live in a time-constrained environment and generally lack the patience to stay with a very long ad. Thus, although longer ads facilitate an unfolding drama, there are limits on the ad lengths consumers will tolerate. For this reason, we expected an inverted U

shape between social shares and ad length, as hypothesized in H₆. We operationalized length on a logarithmic scale and included a quadratic term to test the potential non-linearity. Both the linear and quadratic terms were significantly different from zero. The coefficient of the quadratic term was negative, which determines an inverted U shape between social shares and ad length. These results support Hypothesis H₆.

One disadvantage of the quadratic polynomial is that it implies a symmetric relationship that may be too strict. For this reason, we replaced the quadratic polynomial of ad length by a penalized spline term (Eilers and Marx 1996), keeping other aspects of the model unchanged. Using a nonparametric spline function on ad length allows flexible patterns between shares and ad length to be estimated from the data. Penalty on the spline coefficients was imposed to avoid over-fitting. Figure A1a (in the Online Appendix) shows the estimated relationship between social shares and ad length from the penalized spline model. It still displays an inverted U shape, with a peak at 1.2 minutes. The asymmetry of the curve indicates that compared to very short ads, consumers are more likely to share longer ads. For example, based on the estimates, a two-minute ad is three times more likely to be shared than a 15-second ad. The 15-second ads are the least shared among the ads with different length.

We investigated the relationship between social shares and ad length separately for information-focused and emotion-focused ads. Figure A1b (in the Online Appendix) shows these relationships. Consistent with our analysis, and using all ads, we observe an inverted U shape relationship between social shares and ad length. The optimal length is around 1.5 minutes. However, the effect of ad length decays much faster after the peak in informational ads than emotional ads. Thus, consumers appear to more easily tire of and are less likely to share long ads that resort to information compared to long ads that arouse emotions.

The location of brand appearance has an influence on sharing as predicted by Hypothesis H₅ ("Brand end" is set to be the reference level). The estimates in Table 4 for "Brand none", "Brand early" and "Brand intermittent" represent the differential effect from that of "Brand end". Based on these estimates, showing the brand at the end of the ad is significantly better than placing it at the beginning and

intermittently for the purpose of promoting social shares, supporting Hypothesis H₅. Ads that show later brand placement may allow the viewer to become absorbed in the ad as a form of drama-based entertainment, rather than as a commercial message. When ad exposure is voluntary, as with YouTube ads, the prominence of brand names in the ad can increase the likelihood of ad avoidance, as hypothesized. When brand names become prominent, they look less like entertaining stories and more like traditional ads. Consumers are unlikely to feel that others will look at them favorably by sharing a traditional, marketer driven message. Teixeira et al. (2010) suggest that pulsing is the best strategy of placing brand names for TV ads, but our results suggest that end placement of brand names is best for YouTube ads.

Study 2

Study 2 is a replication of Study 1 using an entirely different time period, different raters, and a different set of YouTube video ads. Only the rating instrument and the analytical model are common to the two studies. The purpose of Study 2 is to test the robustness or generalizability of the results of Study 1. If the results replicate, despite the multiple differences noted above, we may consider the results robust and potentially generalizable. If not, further research is required before reaching any firm conclusions.

Video Sampling

We randomly sampled about 7700 video ads uploaded on YouTube between January 2014 and February 2017. We retained only English language videos and products that targeted customers in the United States. We did this first using automated language detection of the title, followed by manual verification of the sampled videos. We filtered the videos to eliminate copies of old video ads or adaptations of prior video ads (e.g., funny commercial compilations, bloopers etc.). As in Study 1, we adopted a stratified sampling on shares due to the skewed nature of the social media shares. We divided the videos into groups based on the share counts and randomly sampled the video ads from each of these groups. This process yielded 512 videos across 228 brands in the sample for the analysis.

Data Collection

As in Study 1, we used the YouTube Application Programming Interface (API) to capture the characteristics of the video ads. We captured the video characteristics of unique video ID assigned by YouTube (used later to track the shares on social media platforms), public availability of the video, title, upload time, length (duration), total views, number of likes, and number of dislikes. We also collected information on the corresponding channel characteristics (name, and the subscriber count).

We counted total shares across four major the social media platforms - Facebook, Twitter, Google Plus, and LinkedIn. We use the same procedure as Study 1, using the API's platform to collect shares. For example, we counted Facebook shares using the Facebook Graph API. We used the updated URL⁴ to retrieve the number of shares through the API calls. A similar procedure was adopted for the rest of the platforms (LinkedIn, Twitter, Google Plus) using their respective APIs.

Coding

As with Study 1, we trained and paid raters to code the content of the videos, using the same 10 training videos and the same instrument as in Study 1. We used two coders (versus the three used in Study 1) given resource constraints.

Results

We used the same mixed-effects regression model (Equation 1) as in Study 1 to analyze the drivers of sharing. We summarize the results of the replication study below. We highlight the main difference between the two studies before proceeding to the results.

All of the results of Study 1 were replicated in Study 2, with one exception. Unlike the first analysis where we find that information content of the ad influences the sharing for both moderately and high-priced products, in Study 2 we find that the that information content of the ad influences sharing only for the high-priced products and not for moderately priced products. Note, however, that this result still accords with Hypothesis H2_b.

⁴[http://graph.facebook.com/?fields=og_object{likes.summary\(true\).limit\(0\)},share&id=https://www.youtube.com/watch?v={VideoId}](http://graph.facebook.com/?fields=og_object{likes.summary(true).limit(0)},share&id=https://www.youtube.com/watch?v={VideoId}), where the VideoId refers to the Youtube specific ID given to the video.

As in Study 1, we reduced the 11 measured emotions to their latent components using Principal Components Analysis (PCA) with Varimax rotation. The results of the PCA analysis are in Panel 2 of Table 3. Figure A2 (in the Online Appendix) shows the scree plot of the principal components extracted. The PCA yielded six latent factors that capture 85% of the variance in emotions: four positive (inspiration, warmth, amusement, and excitement) and two negative emotions (fear and shame). The estimated value of these six factors was used in the mixed-effect model.

Table 7 summarizes the estimated effects of video ad content on social shares. The results show that information (argument and factual descriptions) is significant and negatively related to social shares, supporting Hypothesis H1. The main effect of new product is significant and positive, indicating the propensity of viewers to share videos of new products. The interaction between information and new product status is again positive and significant, supporting Hypothesis H2_a. Thus, informational ads facilitate social sharing for new (vs. old) products. As with Study 1, the interaction between high price and information is also positive and significant. As with Study 1, we exclude the low level and use dummy variables for moderately-priced and high-priced products. Hence the coefficients must be interpreted against the reference, low-priced products. We replicate H2_b, finding that the coefficient for high priced products is significant and positive. As mentioned before, unlike Study 1, moderately priced products do not significantly influence sharing of the videos. However, this does not affect H2_b. Information-focused content is more likely to be shared for high-priced products.

We again find that ads that evoke positive emotions generate more shares. Ads evoking inspiration, warmth, amusement and excitement have significantly higher shares. Negative emotions are not significant in the analysis. These results support H3. Replicating Study 1, we find that placing brands at the end of the video has a significant positive influence on sharing, compared to placing ads early or using intermittent placement (H5).

We also find that the linear and quadratic terms of the video ad's length are significant. While the ad length is positively related to sharing, the quadratic term of the ad length is negative, as predicted by H6. The quadratic term of length of video ad is negative and significant, suggesting an inverted –U-

shaped relationship between shares and length. To further examine this effect, we followed Study 1's procedure. We used a penalized spline term for the ad length in the model to avoid overfitting. Figure A1c (in the Online Appendix) depicts the estimated relationship. The results replicate Study 1. The relationship between the social shares and ad length is indeed an inverted U shape, with a peak at 1.7 minutes. These results support H6. As in Study 1, the response curve is asymmetric, which indicates that relatively longer ads have higher shares than shorter ones do.

Study 3

In order to assess the predictive strength of the factors that were significant in the mixed-effects regression, we develop a predictive model. Specifically, we use a logit regression to test if the factors that were significant in results of the Studies 1 and 2 would indeed predict the likelihood of the videos to be shared among the consumers across various platforms. We divided the videos into high and low shares based on the median of the distribution of shares. We use the information-focused content (argument, price, new product), the emotion-focused content (emotions of inspiration, warmth, amusement and excitement) and attribute-focused content (timing of appearance of the brand and the length of the ads) that were significant in the prior studies as the predictor of shares. To simplify the analysis, we also group the continuous predictor variables as high or low based on their averages.

We perform the predictive test with data across the two studies as well as within each study. For the first case of out of sample prediction, we use the sample from Study 1 as the calibration data to construct the predictive model. We use the sample from Study 2 as the holdout sample to check the predictive power of the resulting model. For the second case (in-sample prediction), we use 80% of the data in Study 1 as the calibration data and use the rest of the sample as the holdout sample for prediction. We use a five-fold cross validation in order to ensure that the results are not obtained by chance due to one shot sampling. We repeat this procedure for the sample of videos in Study 2.

We use three commonly used metrics to evaluate goodness of prediction: Precision, Recall, and the F1 Score). These metrics are commonly used to assess predictive performance of binary classification (e.g., Chung, Wedel and Rust 2016; Blattberg, Kim and Neslin 2008). *Precision* measures the proportion of high-shared videos that were correctly classified in the predicted sample. *Recall* measures the sensitivity of the classification by measuring the fraction of the videos classified correctly in the actual sample. The F1 Score is the harmonic mean of the Precision and Recall, thus measuring accuracy. The simplified calculation is shown below. Here “true” means the prediction values match the actual values while “false” means the prediction values do not match the actual values.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

$$F1\ Score = \frac{2 * True\ Positives}{2 * True\ Positives + False\ Positives + False\ Negatives}$$

The results are in Table 8. Note that all the prediction rates are around 70%. These results indicate that the significant drivers of virality have high predictive power. The important and notable result is the cross-sample prediction: the prediction of shared videos in Study 2, based on the estimate of the model in Study 1. Note that samples of Study 1 and Study 2 were collected in different time periods, by different raters, covering different videos. The high performance of prediction suggests that the identified drivers of sharing or virality are potentially generalizable.

Study 4

Study 4 examines the impact of virality (measured as shares) on a firm’s stock performance. Studies in marketing suggest that online word of mouth affects sales (Babić et al 2015) and firm performance (e.g. Tirunillai and Tellis 2012). We test if the same holds in the context of virality of YouTube videos. In our

context, the viral phenomenon is observed across numerous brands at a daily level. Assessing the impact of the viral videos on sales of individual brands is not possible because daily sales data are not available. However, given the rich high frequency data we have on shares at the daily level, we test the impact of virality on firm's stock market returns.

Such an analysis has three advantages. It assesses whether virality has any impact on measures firm performance or whether it is merely noise. At least one study suggests that highly shared videos are less persuasive (Tucker 2015). Second, stock market returns are also available at high frequency (daily level), so such an analysis benefits from statistical power. Third, stock market returns are forward looking and reflect the ultimate goal of many firms. Under the efficient market hypothesis, at any point of time, stock prices reflect all current knowledge about a firm. Any new event reflects new information that may cause stock prices to increase or decrease, depending on what impact investors think that event will have on the firm's financial performance. In our case, investors may expect that the virality of a video would increase recipients' and sharers' attention to the brand, leading to increased sales, profits, and earnings in the period after the event. The null hypothesis is that we would find no such effect, either because of the great noise in the data or because investors do not pay attention to viral videos. Finding any significant effect would confirm that virality matters.

For this purpose, we use the event study method, which has been increasingly used in marketing. Srinivasan and Hanssens (2009) provide a detailed review of the method and its applications in marketing. The event of interest is the time at which the distribution of video sharing reaches its peak. Results indicate that this peak is sharp for viral videos and the window is narrow. We follow the literature in marketing and finance to assess the stock market reaction to the videos going viral by calculating the abnormal returns. We summarize the procedure and results below.

We use the sample of videos for which the cumulative share is greater than one million. For each viral video, we take the date at which the videos had the maximum number of shares as the event of interest, thus ending with a sample of 137 events of interest. For each event, we find the stock market's reaction to the viral videos using abnormal returns. Abnormal returns refer to the difference in returns of

the individual stock from the expected returns based on the stock's past movement with the market. It reflects the market's valuation of information about the impact of the viral videos on firm performance. To calculate the daily abnormal returns, we compare the actual returns of the firm to that of the predicted returns of the firm's stock performance based on the market returns in the calibration period. We use a window from 255 days to 46 days prior to the event as the calibration period for assessing the relationship between a firm's stock and the general market. In this window, we do not use the immediate dates prior to the event for calculating the expected returns in order to avoid confounds with the window of virality. This window is also the standard in using event studies in the Eventus database.

To measure the total impact of virality over the short term, we calculate the cumulative abnormal returns (CAR), which is the sum of the abnormal returns over the period of 30 trading days following the videos reaching the peak sharing. This window is the standard post-event duration commonly used to calculate the CAR for such studies (Eventus Manual V8.0, p 6). Using a longer window also assures the robustness of the effect because the longer time window usually results in larger standard errors that are more likely to cause a rejection of the alternative hypothesis. We calculate the average cumulative abnormal returns of the firms in our sample that undergo the viral event.

We can conclude that the viral videos had an impact on the stock performance if the average cumulative abnormal returns of the portfolio of stocks is statistically significant. We use the Standardized cross-sectional Z test (StdCsect Z), which adjusts for the cross-sectional variance in the Patell's t test. This test is common for assessing the significance of cumulative abnormal returns (e.g. Gielens et al 2008). To ensure the robustness of our results, we also test if the fraction of observations of positive returns in the post-event period is same as that observed in the estimation period. We use the Generalized Sign Test for this purpose (e.g. Homburg et al 2014).

The results indicate that the stock market reacts positively to the viral videos. For the 137 events in our sample, the mean cumulative abnormal return is 1.41% with a StdCsect Z value of 2.93 ($p = 0.002$) and the Generalized sign Z statistics of 1.81 ($p = 0.04$). Thus, the stock market reaction to virality in our sample is positive and statistically significant. These results suggest that the stock markets indeed use the

information in the videos going viral as a positive leading indicator of firm performance, possibly through increased sales, profits, and earnings.

Discussion

Content that goes viral gets a great deal of exposure at minimal cost. Thus, getting content to go viral is important for marketers. We ascertain what drivers affect sharing of content, which is critical to virality. Advertising on YouTube using video ads has gained increasing interest over the years given this medium's potential to create effective ad campaigns at relatively low cost. The primary distinction from traditional TV advertising is that the exposure to video ads is generally voluntary and driven largely by social sharing. Sharing increases subsequent exposures to content at no added cost to marketers. Understanding the drivers of sharing might help marketers develop ads that get high shares and go viral.

We developed a theoretical model of online sharing of video content based on well-established theories of communication and persuasion. Our model identifies six hypotheses regarding the characteristics of content that could drive sharing. We collected social sharing of ads in four media using two independent samples covering different time periods, video ads. We rated the videos on over 60 measures, including over 30 characteristics or cues of video ads. Some of those measures are infrequently used to predict sharing. This section describes the conclusions, implications, contributions, and limitations of the study.

Conclusions

Two studies using different ads, different time periods, and different raters find consistent support for the hypotheses. First, the use of information appeals generally has a significant negative effect on social sharing. Second, three variables moderate the extent to which information focused ads are shared. Specifically, information-focused ads positively affect sharing when the advertised item involves product, purchase or social risk, as is true when the product or service is new, when its price is high, and when content is shared on LinkedIn as opposed to Facebook, Twitter, and Google+. Third, ads that evoke

positive emotions of inspiration, warmth, amusement, and excitement stimulate significantly positive social sharing. Fourth, ads that use drama, surprise, celebrities, and babies/animals significantly affect positive uplifting emotions and induce sharing. Fifth, our results suggest that brand prominence impairs sharing. Early or intermittent display of the brand name drives significantly less sharing than late placement of the brand name. Sixth, the relationship between social shares and ad length is characterized by an asymmetric inverted U curve, with ads between 1.2 to 1.7 minutes being most likely to be shared. These effects are significant and robust. Effects for other variables are either not significant or not robust.

Implications

These results have important implications for advertising via video ads. First, about 55% of our sample's ads used information-focused (vs. emotion-focused) content. This number would likely have been even higher had we not used a stratified sample to eliminate ads that were not shared. However, our results imply that content that incorporates information is in general negatively correlated with social shares and is only effective under conditions where consumers perceive some degree of risk. Content that evokes positive emotions is generally more effective than information-focused content in driving social sharing. To engage consumers in more social sharing, marketers may be better off reducing logical reasoning and factual claims shown in the ad, except when introducing new or high-priced products or services. In the current sample, 45% of the ads were rated as emotion-focused; and only 7% of the ads were rated as evoking strong positive emotions (rated emotional scale ≥ 4). These results suggest that marketers are underutilizing or failing to maximize the positive impact of uplifting emotions to encourage sharing.

Second, we find that strong drama, surprise, and the use of celebrities, babies, and animals are effective in arousing emotions and creating social shares. However, only 11% of ads used strong drama (≥ 4), only 10% elicited surprise, and only less than 3% used babies or animals as characters in the ad. Because of the low cost and minimum length restriction, YouTube gives marketers great opportunities to design ads that tell a good story or portray strong drama. Consumers are more likely to react positively to such ads and share them. In the data, more than 26% of the ads use celebrities. While the use of

celebrities can arouse emotions and generate shares, it can be costly. In comparison, babies and animals are much less expensive. Appropriate use of these sources can help achieve a higher return for the campaign, and their use may be viable for companies with high budget constraints.

Third, whereas our results suggest it is better to place the brand name or logo at the end of the ad, only 30% of the ads in the sample used late placement. Additionally, ad length is easy to control. Our results suggest that the optimum length of ads for sharing is generally between 1.2 and 1.7 minutes. In contrast, only about 25% of ads were between 1 and 1.5 minutes. 50% of the ads were shorter than 1 minute and about 25% were longer than 2 minutes in the sample. While the length of the ad can improve storytelling, it can also detract from the viewing experience if length exceeds interest value. Viewers are often impatient with lengthy content and disengage from it. On the other hand, content that is too short may be insufficient to arouse strong emotions. Advertisers should manage the length of the ad to both attract and sustain viewers' interest while not exceeding their levels of patience.

Fourth, advertiser may want to use different ads for different social media. While the use of amusement, celebrities, babies/animals may be effective on Facebook, Twitter and Google+, they may not be as effective when the goal is to communicate one's professional profile on LinkedIn.

Limitations

This study has several limitations that suggest avenues for future research. Due to the effort involved in training and supervising human raters in coding data, the study was restricted to only two samples of video ads. Future research can consider focusing on a larger sample with coding only the significant drivers of sharing. Second, future research may consider machine coding of video content as opposed to human coding, to establish consistency in coding and increase sample size. Third, this study focused on only video ads. Future research should ascertain the generalizability of the results to print ads. Fourth, shares were the primary dependent variable of this study. Future research could also consider the effects of sharing on channel subscriptions, clicks, and purchases.

Figure 1: Theoretical Model

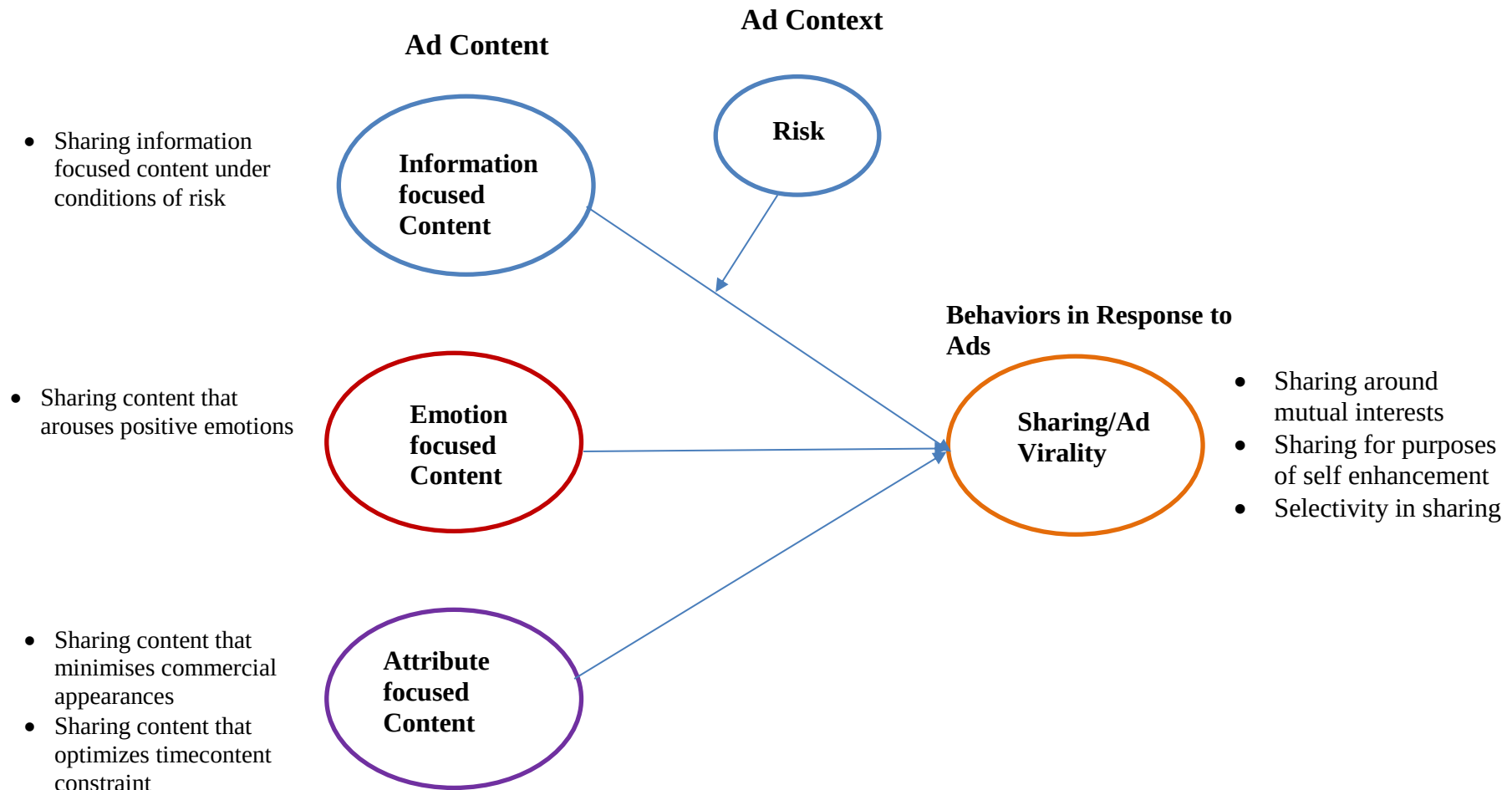


Figure 2: Empirical Model

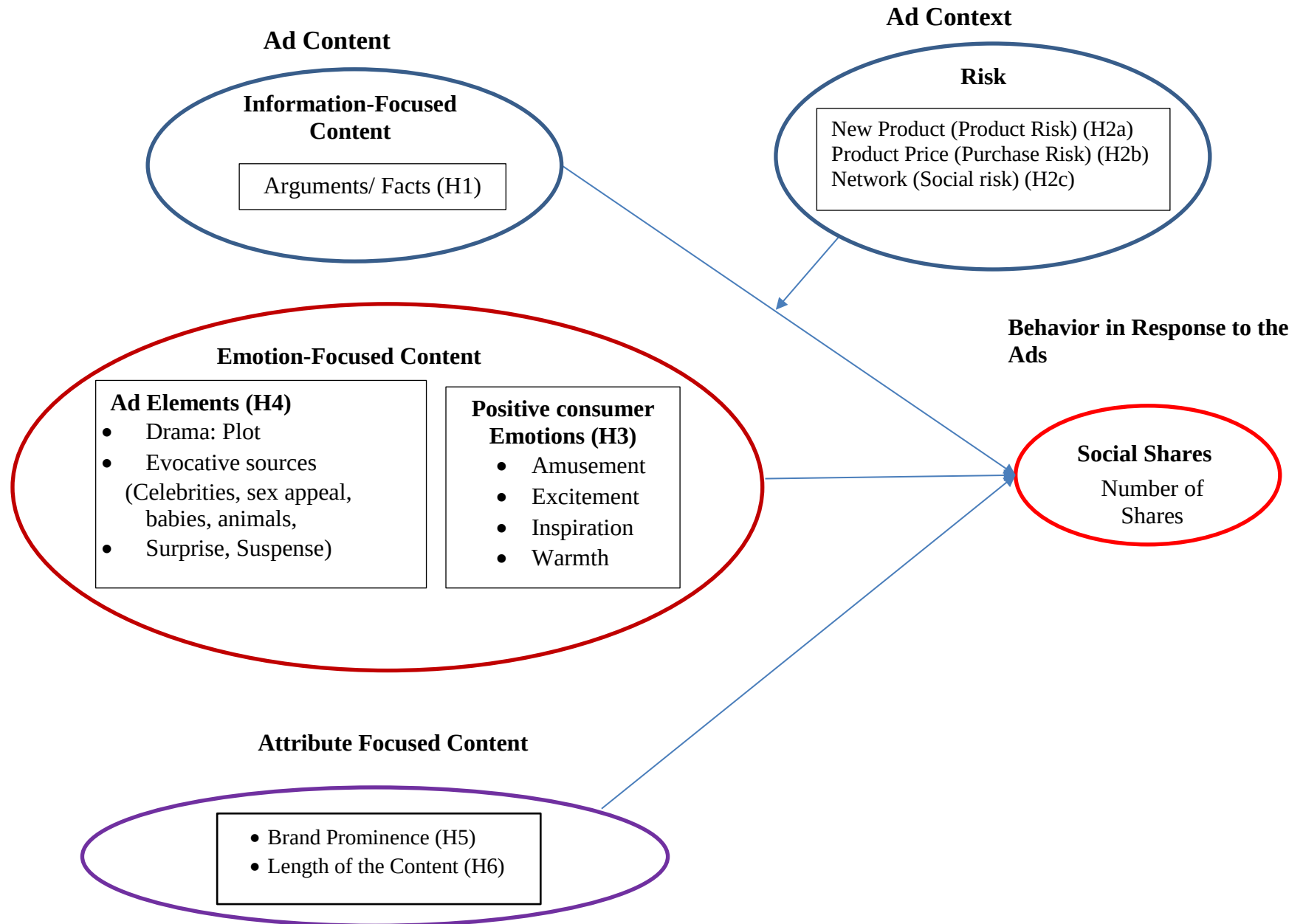


Table 1: Positioning This Study in the Literature on Message Characteristics on Sharing

Focus (DV)	Study	Public Sharing In Field	Sharing of Video Ads	Shared on Four Major Media	IVs	Effect of Brand On Sharing	Effect of Ad Length On Sharing	Drivers of Emotions	Out of Sample Prediction	Effect of Sharing on Stock Price
Sharing of Video Ads	This Study	Yes	Yes	Yes	60 +	Yes	Yes	Yes	Yes	Yes
	Akpinar et al 2017	Yes	Yes	Yes	14	Yes	Yes	No	No	No
	Nelson et al 2013	Yes	Yes	No	16	No	No	No	No	No
	Dafonte-Gómez 2014	Yes	Yes	No	9	No	No	No	No	No
Intention to Share (self-report)	Berger et al 2012	No	No	No	10	No	No	No	No	No
	Chen and Lee 2014	No	No	No	2	No	No	No	No	No
	Eckler et al 2011	No	No	No	3	No	No	No	No	No
	Hagerstrom et al	No	No	No	2	No	No	No	No	No
	Hsieh et al 2012	No	No	No	4	No	No	No	No	No
	Lee et al 2013	No	No	No	6	No	No	No	No	No
	Shehu et al 2016	No	No	No	7	No	No	No	No	No
	Berger 2011	No	No	No	4	No	No	No	No	No
	Chiang et al 2015	No	No	No	10	No	No	No	No	No
	Yang et al 2015	No	No	No	15	No	No	No	No	No
Motivation to Share (self-report)	Baker et al 2016	No	No	No	3	No	No	No	No	No
	Henning-Thurau et al 2004	No	No	No	8	No	No	No	No	No
	Syn et al 2015	No	No	No	10	No	No	No	No	No
Views	Phelps et al 2004	No	No	No	23	No	No	No	No	No
WOM of brands	Southgate et al 2010	No	No	No	7	Yes	No	No	No	No
	Lovett et al 2013	No	No	No	24	Yes	No	No	No	No
WOM messages	Dubois et al 2016	No	No	No	4	No	No	No	No	No
Viral Messages	Dobele et al 2007	Yes	No	No	6	No	No	No	No	No
Retweet of ads	Stieglitz et al 2013	Yes	No	No	6	No	No	No	No	No

Table 2: Sample quantiles of the number of social shares

Probability	Min	10%	25%	50%	75%	90%	Max
Quantiles	0	1	11	158	1,058	6,574	1,621,272

Table 3: Loadings from the Principal Components Analysis of Individual Emotions

Estimated Emotional Components – Study 1						
Rated Variable	Inspiration	Warmth	Amusement	Fear	Shame	Excitement
Triumph	0.84	0.15	-0.05	-0.02	-0.05	0.04
Courage	0.83	0.1	-0.1	0.03	-0.04	-0.05
Pride	0.49	0.24	-0.01	-0.05	0.48	0.05
Warmth	0.21	0.79	-0.14	0.1	-0.09	-0.06
Love	0.19	0.77	0.09	-0.06	0.20	0.01
Joy	-0.12	0.52	0.65	-0.06	-0.09	-0.01
Humor	-0.08	-0.13	0.85	0.05	-0.02	-0.06
Fear	0.12	-0.18	0.24	0.79	0.07	0.08
Sadness	-0.14	0.25	-0.24	0.75	-0.08	-0.08
Shame	-0.09	0	-0.05	0.01	0.89	-0.04
Excitement	0	-0.02	-0.04	0	-0.02	0.99

Estimated Emotional Components – Study 2						
Rated Variable	Inspiration	Warmth	Amusement	Fear	Shame	Excitement
Courage	0.84	0.22	-0.06	0.14	0.09	0.03
Excitement	0.22	0.25	0.02	-0.01	0.04	0.9
Fear	0.11	-0.06	0.01	0.89	0.07	0.16
Warmth	0.33	0.83	0	0.04	0.01	0.1
Triumph	0.85	0.26	0.01	0.08	0.02	0.17
Shame	0.03	-0.01	0.01	0.22	0.97	0.03
Pride	0.83	0.29	-0.03	0.06	-0.07	0.15
Sadness	0.1	0.21	-0.05	0.79	0.2	-0.18
Joy	0.21	0.73	0.17	0.06	-0.07	0.38
Love	0.28	0.87	-0.02	0.07	0.03	0.04
Humor	-0.05	0.06	0.99	-0.03	0.01	0.03

Panel 1 (top) and Panel 2 (bottom) shows the results of the principal component analysis of Study 1 and Study 2 respectively. The first column shows the names of the original rated variables. First row of the table shows the names corresponding to the latent factors.

**Table 4: Estimated Effects of Ad Characteristics on Social Shares from Mixed Effects Model
(Study 1 - Dependent Variable is Log of Shares)**

		Beta Coeff.	Effect Size (%)	Std. Error	p-value
Information	Extent of Argument	-0.39	-32.56	0.13	0.002**
	New Product	0.46	57.78	0.13	0.002**
	Argument*New Product	0.25	27.76	0.12	0.042*
	Price2 (Moderate)	-0.12	-11.22	0.15	0.43
	Price3 (High)	0.01	1.11	0.18	0.94
	Argument*Moderate	0.28	31.92	0.13	0.030*
	Argument*High	0.33	39.38	0.15	0.028*
Emotion	Extent of Inspiration	0.11	11.52	0.05	0.018**
	Extent of Warmth	0.13	14.00	0.05	0.002**
	Extent of Amusement	0.20	21.53	0.04	0.001**
	Extent of Fear	-0.05	-5.26	0.04	0.19
	Extent of Shame	0.07	7.36	0.04	0.06
	Extent of Excitement	0.12	13.09	0.04	0.008**
Attribute-Focused Content	Brand Duration	0.01	0.50	0.14	0.46
	Brand None	-0.67	-48.73	0.43	0.10
	Brand Early	-0.36	-29.88	0.12	0.002**
	Brand Intermittent	-0.31	-26.51	0.11	0.008**
	Ad Length	0.12	12.98	0.05	0.024*
	Ad Length Sq	-0.10	-9.06	0.03	0.004**
	log(subscribers)	0.39	48.14	0.06	0.001**
	Timeliness	-0.11	-10.06	0.14	0.46

The parameter in the first row is the effect of argument when used for old products (when new product =0). Effect sizes are in percentage terms as they are estimates of a log linear model. They represent the percent change in shares due to unit change in the dependent variable. For small values, they are close to the coefficient value expressed as percent. Significance levels: *** 0.001, ** 0.01, *0.05

Table 5: Estimated Effect Of Key Emotions on Sharing By Platform (Study 1)

	Facebook		Twitter		Google Plus		LinkedIn	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
Extent of Argument	-0.232 (0.112)	0.039**	-0.22 (0.081)	0.007**	-0.12 (0.086)	0.162	-0.044 (0.077)	0.569
Extent of Amusement	0.431 (0.156)	0.006**	0.238 (0.115)	0.039**	0.265 (0.121)	0.029**	-0.04 (0.107)	0.711
Use of celebrity	0.854 (0.329)	0.010**	0.817 (0.247)	0.001**	0.591 (0.257)	0.023**	0.298 (0.225)	0.186
Use of baby/animal	2.382 (0.789)	0.003**	1.561 (0.599)	0.010**	1.522 (0.62)	0.015**	0.851 (0.537)	0.114

Table 6: Estimated Effects of Ad Characteristics on Emotions (Study 1)

Characteristics	Extent of inspiration		Extent of warmth		Extent of amusement		Extent of excitement	
	Mean	p-value	Mean	p-value	Mean	p-value	Mean	p-value
Extent of drama	0.166	0.004**	0.128	0.024**	0.54	0.000**	0.022	0.699
Extent of surprise	-0.13	0.015**	0.042	0.433	0.183	0.000**	0.098	0.073*
Use of celebrity	0.358	0.003**	-0.141	0.242	-0.104	0.283	0.261	0.035**
Use of baby/animal	0.588	0.035**	1.237	0.000**	0.453	0.043**	0.044	0.876
Use of cartoon	-0.232	0.233	-0.243	0.211	0.544	0.001**	0.035	0.862
Use of sex appeal	-0.254	0.355	-0.233	0.396	0.075	0.732	-0.263	0.349
Extent of suspense	0.037	0.505	-0.089	0.108	-0.037	0.409	0.101	0.074*

**Table 7: Estimated Effects of Ad Characteristics on Social Shares from Mixed-Effects Model
(Study 2)**

Dependent Variable is Log of Shares

		Beta Coeff.	Effect Size	Std. Error	p-value
Information	Extent of Argument	-0.203	-18.13	0.073	0.005**
	New Product	0.234	25.86	0.114	0.040*
	Argument*New Product	0.254	28.40	0.129	0.050*
	Price2 (Moderate)	0.073	7.25	0.143	0.612
	Price3 (High)	-0.110	-10.42	0.152	0.470
	Argument*Moderate	0.073	7.25	0.105	0.487
	Argument*High	0.264	29.69	0.119	0.027*
Emotion	Extent of Inspiration	0.207	23.37	0.047	0.000***
	Extent of Warmth	0.278	32.31	0.048	0.000***
	Extent of Amusement	0.104	10.52	0.050	0.038*
	Extent of Fear	-0.006	-1.00	0.047	0.902
	Extent of Shame	-0.043	-3.92	0.047	0.357
	Extent of Excitement	0.113	11.63	0.046	0.015*
Attribute-Focused Content	Brand Duration	-0.067	-6.76	0.054	0.222
	Brand None	-0.420	-34.30	0.448	0.349
	Brand Early	-0.440	-35.60	0.141	0.002**
	Brand Intermittent	-0.384	-31.61	0.150	0.010*
	Ad Length	0.429	53.73	0.126	0.001***
	Ad Length Sq	-0.334	-28.11	0.118	0.005**
	log(subscribers)	0.289	33.64	0.055	0.000***
	Timeliness	0.040	4.08	0.051	0.431

Effect sizes are in percentage terms as they are estimates of a log linear model. They represent the percent change in shares due to unit change in the dependent variable. For small values, they are close to the coefficient value expressed as percent. Significance levels: *** 0.001, ** 0.01, *0.05

Table 8: Performance of the Predictive Analysis Using 3 Methods

Method	Calibration Sample	Holdout Sample	Precision	Recall	F1 Score
Cross Sample	Study 1	Study 2	72.7	70.5	71.6
Within Sample 1	80% Study 1	20% Study 1	70.6	69.3	68.6
Within Sample 2	80% Study 2	20% Study 2	70.4	67.4	67.6

References

- Aaker, D. A., Stayman, D. M. and Hagerty, M. R. (1986), "Warmth in advertising: Measurement, impact, and sequence effects," *Journal of Consumer Research* (12:4), pp. 365--381.
- Aaker, David A., Douglas M. Stayman, and Richard Vezina (1988), "Identifying Feelings Elicited by Advertising," *Psychology & Marketing* 5 (1), 1-16.
- Aaker, Jennifer L. and Patti Williams (1998), "Empathy versus Pride: The Influence of Emotional Appeals Across Cultures," *Journal of Consumer Research*, 25 (3), 241-261.
- Akpınar, Ezgi and Jonah Berger (2017), "Valuable Virality," *Journal of Marketing Research*, LIV (April), 318-330.
- Babić, Rosario, A., Francesca Sotgiu, Kristine De Valck and Tammo H. A. Bijmolt (2016), "The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors," *Journal of Marketing Research*, 53 (3), 297-318.
- Baker, Andrew M., Naveen Donthu, and V. Kumar (2016), "Investigating How Word-of-Mouth Conversations about Brands Influence Purchase and Retransmission Intentions." *Journal of Marketing Research* 53 (2), 225-239.
- Barasch, Alixandra, Jonah Berger (2014), "Broadcasting and Narrowcasting: How Audience Size Affects What People Share," *Journal of Marketing Research*, 51 (3), 286–299.
- Berger, Jonah (2011), "Arousal Increases Social Transmission of Information." *Psychological Science* ,22 (7), 891-893.
- Berger, Jonah and Katherine L. Milkman (2012), "What Makes Online Content Viral?," *Journal of Marketing Research*, 49 (2), 192–205.
- Blattberg, Robert. C., Kim, B. D and Scott A. Neslin, (2008), Collaborative Filtering. *Database Marketing* Springer, New York, NY. (pp. 353-376).
- Cavanaugh, Lisa A., James R. Bettman, and Mary Frances Luce (2015), "Feeling Love and Doing More for Distant Others: Specific Positive Emotions Differentially Affect Prosocial Consumption." *Journal of Marketing Research* 52 (5), 657-673.
- Chandy, Rajesh, Gerard J. Tellis, Deborah J. MacInnis, and Pattana Thaivanich (2001), "What to Say When: Advertising Appeals in Evolving Markets," *Journal of Marketing Research* 38 (4) 399–414.
- Chen, Tsai, and Hsiang-Ming Lee (2014), "Why Do We Share?:The Impact of Viral Videos Dramatized to Sell," *Journal of Advertising Research* 54 (3), 292-303.
- Chiang, Hsiu-Sen and Kuo-Lun Hsiao (2015), YouTube Stickiness: The Needs, Personal, and Environmental Perspective," *Internet Research* 5 (1) 85–106.
- Chung, Tuck Siong, Michel and Roland T. Rust (2016), Adaptive Personalization Using Social Networks," *Journal of the Academy of Marketing Science*, 44 (1), 66-87.

- Corhan, Jeff (2011), "What is Content Marketing," <http://www.jeffkorhan.com/2011/03/what-is-content-marketing.html> as accessed on March 28, 2016.
- Dafonte-Gómez, Alberto (2014), "The Key Elements of Viral Advertising. From Motivation to Emotion in the Most Shared Videos" *Comunicar* 22 (43), 199-207.
- De Angelis, Matteo, Andrea Bonezzi, Alessandro M. Peluso, Derek D. Rucker, and Michele Costabile (2012), "On Braggarts and Gossips: A Self-Enhancement Account of Word-of-Mouth Generation and Transmission," *Journal of Marketing Research*, 49 (4), 551–563.
- Deighton, John, Daniel Romer, and Josh McQueen (1989), "Using Drama to Persuade", *Journal of Consumer Research* 16 (3) 335–343.
- Dens, Nathalie and Patrick De Pelsmacker (2010), "Consumer Response to Different Advertising Appeals for New Products: The Moderating Influence of Branding Strategy and Product Category Involvement," *Journal of Brand Management*, 18 (1) 50-65.
- Dobele, Angela, Adam Lindgreen, Michael Beverland, Joelle Vanhamme, and Robert van Wijk (2007), "Why Pass on Viral Messages? Because They Connect Emotionally," *Business Horizon*, 50 (4) 291– 304.
- Dowling, Grahame R. and Richard Staelin (1994), "A Model of Perceived Risk and Intended Risk-Handling Activity", *Journal of Consumer Research*, 21 (June), 119-134.
- Dubois, David, Andrea Bonezzi, and Matteo De Angelis (2016), "Sharing with Friends versus Strangers: How Interpersonal Closeness Influences Word-of-Mouth Valence." *Journal of Marketing Research* 53 (5), 712-727.
- Eckler, Petya and Paul Bolls (2011), "Spreading the Virus: Emotional Tone of Viral Advertising and its Effect on Forwarding Intentions and Attitudes," *Journal of Interactive Advertising*, 11 (2) 1–15.
- Edell, Julie A. and Marian Chapman Burke (1987), "The Power of Feelings in Understanding Advertising Effects," *Journal of Consumer Research*, 14 (3) 421–433.
- Eilers, Paul H.C. and Brian D. Marx (1996), "Flexible Smoothing with B-Splines and Penalties," (with comments and rejoinder), *Statistical Science* 11 (2) 89–121.
- Eisend, Martin (2009), "A Meta-Analysis of Humor in Advertising." *Journal of the Academy of Marketing Science* 37 (2), 191-203.
- Escalas, Jennifer Edson, and Barbara B. Stern (2003), "Sympathy and Empathy: Emotional Responses to Advertising Dramas," *Journal of Consumer Research*, 29 (4), 566-578.
- Fishbein, Martin, and Icek Ajzen (2011), *Predicting and Changing Behavior: The Reasoned Action Approach*. Taylor & Francis.
- Friestad, Marian, and Peter Wright (1994), "The Persuasion Knowledge Model: How People Cope with Persuasion Attempts," *Journal of Consumer Research*, 21 (1), 1-31.
- Gielens, Katrijn, Linda M. Van de Gucht, Jan Benedict M. Steenkamp, and Marnik G. Dekimpe, (2008), "Dancing with a Giant: The Effect of Wal-Mart's Entry into the United Kingdom on the

- Performance of European Retailers," *Journal of Marketing Research* (45:5), 2008, pp. 519–534.
- Godes, David and Dina Mayzlin, (2004), "Using Online Conversations to Study Word-of-mouth Communication", *Marketing Science* 23(4) 545-560.
- Green, Melanie C. (2004), "Transportation into Narrative Worlds: The Role of Prior Knowledge and Perceived Realism," *Discourse Processes* 38 (2), 247-266.
- 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), 701-721.
- Hagerstrom, Amy, Saleem Alhabash, and Anastasia Kononova (2014), Emotional Dimensionality and Online Ad Virality: Investigating the Effects of Affective Valence and Content Arousingness on Processing and Effectiveness of Viral Ads, In *American Academy of Advertising. Conference. Proceedings* (Online) (p. 109). American Academy of Advertising.
- Hennig-Thurau, Thorsten, Kevin P. Gwinner, Gianfranco Walsh, and Dwayne D. Gremler (2004), "Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet?," *Journal of Interactive Marketing*, 18 (1), 38–52.
- Holbrook, Morris B. and Rajeev Batra (1987), "Assessing the Role of Emotions as Mediators of Consumer Responses to Advertising," *Journal of Consumer Research*, 14 (3), 404–420.
- Homburg, Christian, Josef Vollmayr and Alexander Hahn (2014), "Firm Value Creation Through Major Channel Expansions: Evidence from an Event Study in the United States, Germany, and China," *Journal of Marketing*, 78 (3), 38-61.
- Hsieh, Jung-Kuei, Yi-Ching Hsieh, and Yu-Chien Tang (2012), "Exploring the Disseminating Behaviors of eWOM Marketing: Persuasion in Online Video," *Electronic Commerce Research* 12 (2), 201-224.
- Kim, Hyun Suk (2015), "Attracting Views and Going Viral: How Message Features and News-sharing Channels Affect Health News Diffusion", *Journal of Communication*, 65(3), 512-534.
- Lee, Joonghwa, Chang-Dae Ham, and Mikyoung Kim (2013), "Why People Pass Along Online Video Advertising: From the Perspectives of the Interpersonal Communication Motives Scale and the Theory of Reasoned Action," *Journal of Interactive Advertising* 13 (1), 1-13.
- MacInnis, Deborah J., Ambar Rao, and Allen M. Weiss (2002), "Assessing When Increased Media Weight of Real-World Advertisements Helps Sales", *Journal of Marketing Research*, 39 (November), 391-407.
- McCracken, Grant (1989), "Who is a Celebrity Endorser," *Journal of Consumer Research*, 16 (December), 310-321.
- McWilliam, Gil (2000), "Building Stronger Brands Through Online Communities," *Sloan Management Review*, 41 (3), 43.
- Muniz Jr., Albert M., and Hope Jensen Schau (2005), "Religiosity in the Abandoned Apple Newton Brand Community," *Journal of Consumer Research*, 31 (4), 737-747.

- Murray, Keith B. (1991), "A Test of Services Marketing Theory: Consumer Information Acquisition Activities." *Journal of Marketing*, 55 (1), 10-25.
- Multon, Karen D. (2010), "Interrater Reliability," *Encyclopedia of Research Design*. CA: Sage, Thousand Oaks, 627–629.
- Nelson-Field, Karen, Erica Riebe, and Kellie Newstead (2013), "The Emotions that Drive Viral Video," *Australasian Marketing Journal*, 21 (4), 205–211.
- Olney, Thomas J., Morris B. Holbrook, and Rajeev Batra (1991), "Consumer Responses to Advertising: The Effects of Ad Content, Emotions, and Attitude Toward the Ad on Viewing Time." *Journal of Consumer Research* 17 (4), 440-453.
- Petty, Richard E. and John T. Cacioppo (1986), *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*, NY: Springer-Verlag.
- Petty, Richard E., Derek D. Rucker, George Y. Gizer, and John T. Cacioppo (2004), "The Elaboration Likelihood Model of Persuasion." In *Perspectives on Persuasion, Social Influence and Compliance Gaining*, Allyn & Bacon.
- Phelps, Joseph E., Regina Lewis, Lynne Mobilio, David Perry, and Niranjana Raman (2004), "Viral Marketing or Electronic Word-of-Mouth Advertising: Examining Consumer Responses and Motivations to Pass along Email," *Journal of Advertising Research*, 44 (4), 333-348.
- Shehu, Edlira, Tammo HA Bijmolt, and Michel Clement (2016), "Effects of Likeability Dynamics on Consumers' Intention to Share Online Video Advertisements." *Journal of Interactive Marketing* 35, 27-43.
- Southgate, Duncan, Nikki Westoby, and Graham Page (2010), "Creative Determinants of Viral Video Viewing," *International Journal of Advertising*, 29 (3), 2–14.
- Southerton, Dale and Mark Tomlinson (2005), "'Pressed for Time': The Differential Impacts of a 'Time Squeeze,'" *The Sociological Review*, 53 (2), 215-239.
- Srinivasan, S. and Dominique M. Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46 (3), 293-312.
- Stephen, Andrew T., Michael Sciandra and Jeffrey Inman (2015), "Is it What You Say or How You Say it? How Content Characteristics Affect Consumer Engagement with Brands on Facebook", working paper. Saïd Business School RP 2015-19.
- Stayman, D. M. and Rajeev R. Batra (1991), "Encoding and Retrieval of Ad Affect in Memory," *Journal of Marketing Research*, XXVIII (May), 232-239.
- Stieglitz, Stefan, and Linh Dang-Xuan (2013), "Emotions and Information Diffusion in Social Media: Sentiment of Microblogs and Sharing Behavior," *Journal of Management Information Systems*, 29 (4), 217-248.
- Syn, Sue Yeon, and Sanghee Oh (2015), "Why do Social Network Site Users Share Information on Facebook and Twitter?," *Journal of Information Science*, 41 (5), 553-569.

- Taylor, David G., David Strutton, and Kenneth Thompson (2012), "Self-Enhancement as a Motivation for Sharing Online Advertising," *Journal of Interactive Advertising*, 12 (2) 13–28.
- Teixeira, Thales, Michel Wedel, and Rik Pieters (2010), "Moment-to-Moment Optimal Branding in TV Commercials: Preventing Avoidance by Pulsing," *Marketing Science*, 29(5), 783-804.
- Teixeira, Thales, Michel Wedel, Rik Pieters (2012), "Emotion-Induced Engagement in Internet Video Advertisements," *Journal of Marketing Research*, 49 (2), 144–159.
- Tellis, Gerard J. (2003), *Effective Advertising: Understanding When, How, and Why Advertising Works*, Sage Publications.
- 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, Seshadri, Gerard J. Tellis. (2012). "Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance". *Marketing Science*, 31(2) 198-215.
- Tucker, Catherine E. (2015), "The Reach and Persuasiveness of Viral Video Ads," *Marketing Science*, 34 (2) 281–296.
- Visible Measures (2013), 2013 *Branded Video Annual Report*. [http:// www. visiblemeasures.com/ 2014/ 03/ 24/ 2013-branded-video-report/](http://www.visiblemeasures.com/2014/03/24/2013-branded-video-report/).
- Yang, Hongwei Chris, and Yingqi Wang (2015), "Social Sharing of Online Videos: Examining American Consumers' Video Sharing Attitudes, Intent, and Behavior," *Psychology & Marketing* 32 (9), 907-919.

ONLINE APPENDIX

Figure A1: Estimated Relationship between Social Shares and Ad Length

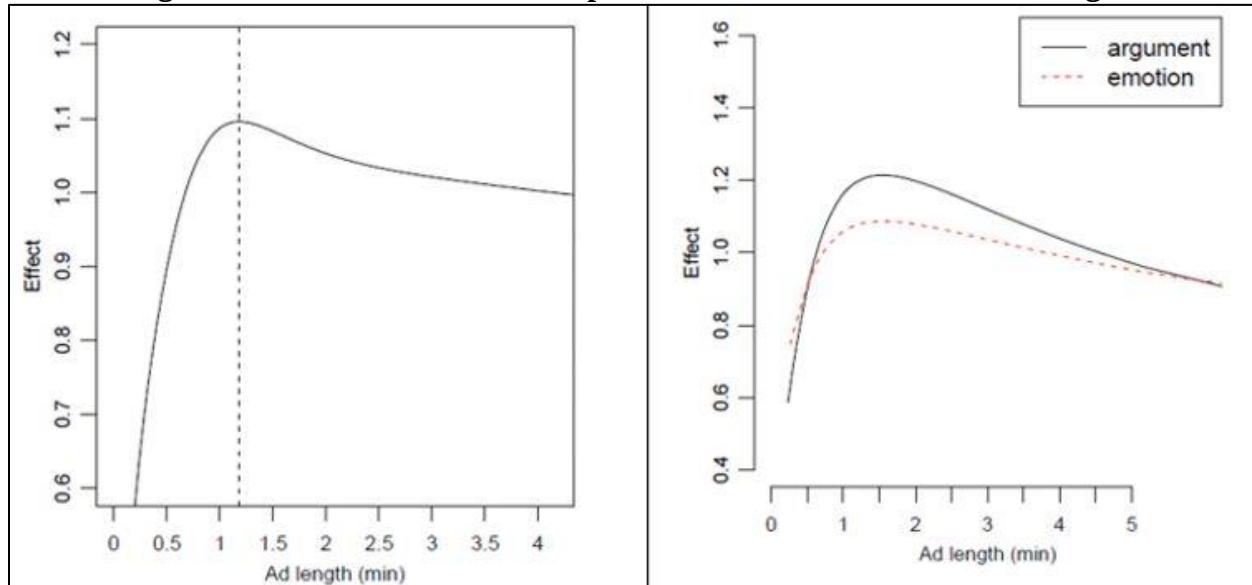


Figure A1a

Figure A1b

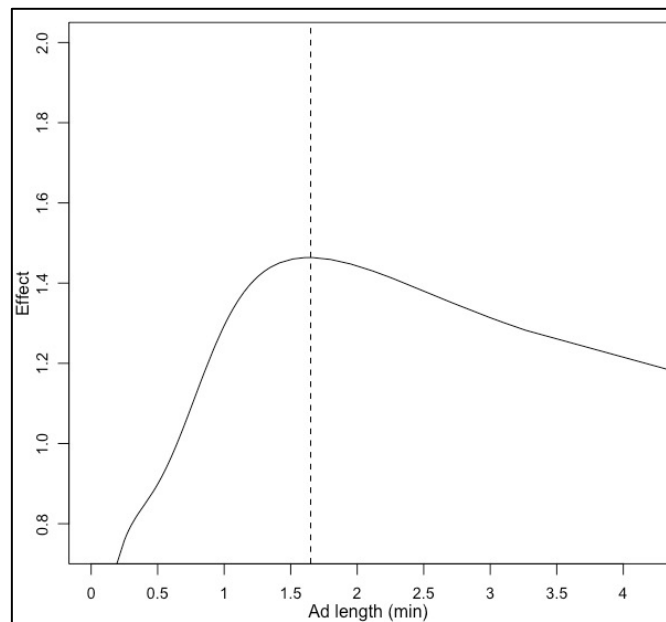


Figure A1c

Note: The dashed line in A1a indicates the optimal ad length based on the estimates. Figure A1b depicts the relationship between social shares and ad length for informational (argument) ads and emotional ads, respectively. Figure A1c depicts the optimal ad length in Study 2.

Figure A2: Scree Plot of the Eigen Values of the Components of Emotions

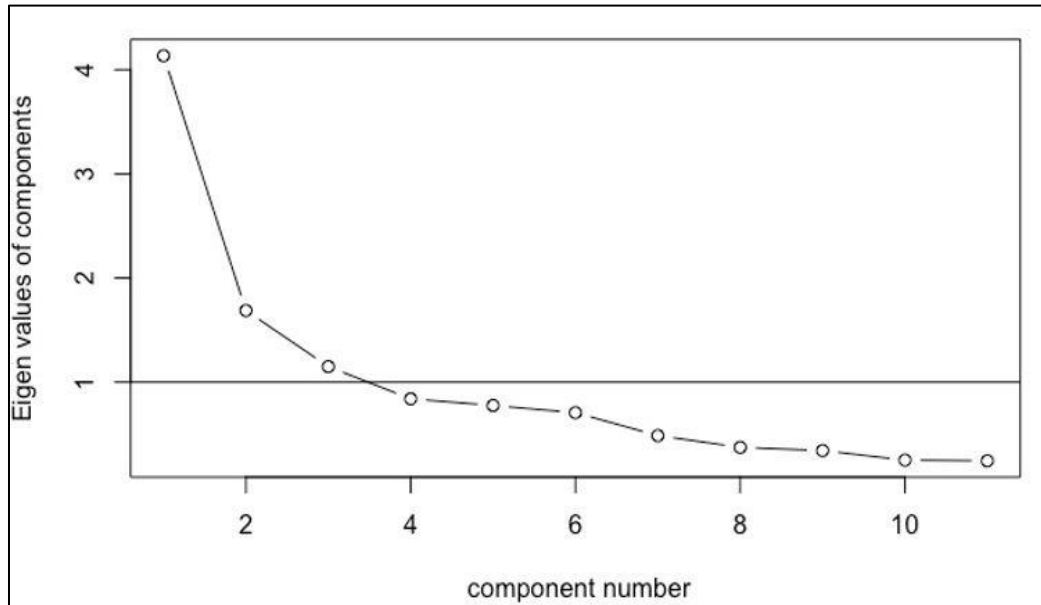


Table A1: Number Of Video Ads For Each Brand Included In The Sample Of Ads

Brand	# ads	Brand	# ads	Brand	# ads	Brand	# ads
Samsung	27	MasterCard	5	State Farm	3	Capital One	2
Toyota	20	Procter & Gamble	5	Dr. Pepper	3	Estee Lauder	2
Coca-Cola Company	14	MINI	5	M&M	3	H&M	2
AT&T	11	Progressive Insurance	5	Taco Bell	3	Red Bull	2
Bud Light	10	CHANEL	4	5hourENERGY	3	TurboTax	1
Nike	10	Citigroup	4	Amazon	3	Unilever	1
Pepsi	9	Gillette	4	Walmart Stores	3	eBay	1
Kia Motors	9	Hyundai Motors	4	General Mills	3	Expedia	1
Kohl's Corp	8	Lowe's	4	Kmart	3	Kellogg Co	1
BMW	8	Snickers	4	Apple	3	Mars Inc	1
Dish Network	7	T-Mobile	4	Go Pro	3	Nestle	1
IBM	7	Calvin Klein	4	Macy's	2	Wells Fargo	1
Louis Vuitton	7	University of Phoenix	4	Allstate	2	Chrysler	1
Sony Corporation	7	Budweiser	4	Doritos	2	JC Penney	1
Dell	7	Dove	4	Walgreen	2	Adidas	1
Mercedes-Benz	7	Microsoft	4	American Express	2	Butterfinger	1
GEICO	6	Visa	4	Denny's	2	Ford Motor Company	1
Target Corp	6	Absolut	3	McDonalds	2	Johnson & Johnson	1
Daimler	5	DirecTV	3	Volkswagen	2	Wonderful Pistachios	1
Google	5	Old Spice	3	Bank of America	2		

Table A2: The Frequency Distribution of Measures

	Distribution					Estimates	
Binary	0	1					
new product	304	41					1.46**
price	319	26					-1.89**
celebrity	254	91					1.30**
baby/animal	332	13					3.13**
cartoon	317	28					0.3
timeliness	298	47					1.35**
sex	332	13					-0.3
Likert Type Scales	1	2	3	4	5	6	
argument	157	36	44	58	45	5	-0.06**
emotion	190	35	52	43	21	4	0.63**
pride	332	4	4	2	3		1.18**
joy	275	19	25	24	1	1	0.70**
love	323	4	6	6	5	1	0.56**
warmth	299	13	12	9	12		0.46**
courage	304	11	10	12	7	1	0.41**
triumph	320	6	8	5	5	1	0.53**
excitement	308	19	16	2			0.96**
love/warmth	294	19	20	7	5		0.60**
courage/triumph	297	20	16	6	4	2	0.48**
shame	343	1	1				-0.1
sadness/fear	337	5	3				-1.38**
fear	340	3	1	1			-0.6
sadness	341	2	1	1			-1.14**
humor	351	23	27	37	6	1	0.51**
surprise	312	3	9	13	7	1	1.01**
suspense	330	3	5	5	2		0.66**
narrative	173	38	35	24	47	28	-0.3**
dramatization	107	87	48	66	29	8	0.48**
Categorical	None	Early	End	Intermittent			
brand location	3	104	123	115			
surprise location	315	11	19				
Others							
ad length							0.01**
brand duration							-1.22**

The last column shows the estimated coefficient from the univariate regression of the logarithmic shares on each ad elements.

Table A3: Estimated Effects of Ad Characteristics on Shares by Platform.

Variable	Facebook			Twitter			Google+			LinkedIn		
	Mean	SD	p-value	Mean	SD	p-value	Mean	SD	p-value	Mean	SD	p-value
Intercept	-10.447	3.538	0.003	-9.849	2.629	0.000	-10.948	2.750	0.000	-9.009	2.419	0.000
log(Subscribers)	0.562	0.119	0.000	0.590	0.074	0.000	0.634	0.086	0.000	0.307	0.084	0.000
Extent of argument	-0.232	0.112	0.039	-0.220	0.081	0.007	-0.120	0.086	0.162	-0.044	0.077	0.569
New product	0.521	0.620	0.402	0.407	0.470	0.387	0.473	0.487	0.332	0.449	0.422	0.288
Argument * New product	0.505	0.242	0.037	0.373	0.183	0.042	0.425	0.189	0.026	0.276	0.165	0.094
Extent of inspiration	0.270	0.149	0.070	0.280	0.107	0.009	0.123	0.114	0.283	0.345	0.102	0.001
Extent of warmth	0.442	0.157	0.005	0.382	0.113	0.001	0.401	0.121	0.001	0.285	0.108	0.009
Extent of amusement	0.431	0.156	0.006	0.238	0.115	0.039	0.265	0.121	0.029	-0.040	0.107	0.711
Extent of excitement	0.419	0.142	0.004	0.174	0.108	0.108	0.282	0.112	0.012	0.202	0.097	0.037
Extent of surprise	0.776	0.501	0.122	0.357	0.380	0.349	0.924	0.393	0.019	0.702	0.341	0.040
Use of celebrity	0.854	0.329	0.010	0.817	0.247	0.001	0.591	0.257	0.023	0.298	0.225	0.186
Use of baby/animal	2.382	0.789	0.003	1.561	0.599	0.010	1.522	0.620	0.015	0.851	0.537	0.114
Use of cartoon	0.624	0.541	0.250	-0.029	0.403	0.942	0.256	0.422	0.544	0.776	0.370	0.037
Brand early	1.364	1.363	0.318	0.653	1.034	0.528	0.872	1.070	0.416	-0.037	0.928	0.969
Brand end	2.456	1.360	0.072	1.530	1.029	0.138	1.704	1.066	0.111	0.276	0.927	0.766
Brand intermittent	1.624	1.366	0.236	0.736	1.033	0.477	1.256	1.071	0.242	0.054	0.931	0.954
Surprise early	-1.948	1.591	0.222	-0.270	1.209	0.823	-2.219	1.250	0.077	-1.505	1.083	0.166
Surprise end	0.307	1.366	0.822	1.555	1.046	0.138	-0.110	1.076	0.918	0.607	0.928	0.514
Ad length	4.152	1.521	0.007	3.155	1.149	0.006	2.998	1.192	0.012	3.135	1.036	0.003
Ad length^2	-0.471	0.180	0.009	-0.359	0.136	0.009	-0.322	0.141	-0.023	-0.332	0.122	0.007

This table reports the effect of each cues on shares by social platform. We ran a mixed-effect model of shares on each platform over the important cues. The cues included are the identified drivers of social sharing from the mediation analysis using the aggregate shares.