What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence

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Article

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What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence

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

Abstract

The authors test five theoretically derived hypotheses about what drives video ad sharing across multiple social media platforms. Two independent field studies test these hypotheses using 11 emotions and over 60 ad characteristics. The results are consistent with theory and robust across studies. Information-focused content has a significantly negative effect on sharing, except in risky contexts. Positive emotions of amusement, excitement, inspiration, and warmth positively affect sharing. Various drama elements such as surprise, plot, and characters, including babies, animals, and celebrities arouse emotions. Prominent (early vs. late, long vs. short duration, persistent vs. pulsing) placement of brand names hurts sharing. Emotional ads are shared more on general platforms (Facebook, Google+, Twitter) than on LinkedIn, and the reverse holds for informational ads. Sharing is also greatest when ad length is moderate (1.2 to 1.7 minutes). Contrary to these findings, ads use information more than emotions, celebrities more than babies or animals, prominent brand placement, little surprise, and very short or very long ads. A third study shows that the identified drivers predict sharing accurately in an entirely independent sample.

Keywords

virality, shares, ad cues, emotion, brand prominence

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The goal of this article is to enhance our understanding of ad-related characteristics that drive virality (sharing) of online ads. We investigate this issue in the context of online video ads that advertisers have uploaded to YouTube. We emphasize this context because 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 online ads creates new exposures, as the video reaches new viewers across social media such as Facebook, Twitter, LinkedIn, and Google+. Second, YouTube ads are highly cost-efficient. Aside from the cost of making and optionally promoting the video, YouTube advertising exposure is free. Moreover, advertising through YouTube is unlimited. Advertisers can upload as many videos as they wish at minimum cost. Third, there is almost no length restriction on YouTube ads. Long ads can tell a story or portray a drama that can arouse strong emotions. Fourth, unlike some other advertising methods, viewership is voluntary. The ad is viewed only if a viewer chooses to watch it. 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 influence the sharing of ads that are uploaded to YouTube.

A unique feature of online digital content is that consumers can easily and readily share what they like with others. Such sharing can exponentially impact the total number of views of

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Table 1. How the Current Article Advances Prior Research on Sharing of Online Content.

Focus (DV)	Study	Actual Shares Online	Sharing of Video Ads	Shared by Four Major Media	Number of IVs	Effect of Brand on Sharing	Effect of Ad Length on Sharing	Drivers of Emotions	Out-of-Sample Prediction
Sharing of video ads	Current Article	Yes	Yes	Yes	60+	Yes	Yes	Yes	Yes
	Akpinar and Berger 2017	Yes	Yes	Yes	14	Yes	Yes	No	No
	Nelson et al. 2013	Yes	Yes	No	16	No	No	No	No
	Dafonte-Gómez 2014	Yes	Yes	No	9	No	No	No	No
Intention to share (self-report)	Berger and Milkman 2012	No	No	No	10	No	No	No	No
	Chen and Lee 2014	No	No	No	2	No	No	No	No
	Eckler and Bolls 2011	No	No	No	3	No	No	No	No
	Hagerstrom, Alhabash, and Kononova 2014	No	No	No	2	No	No	No	No
	Hsieh, Hsieh, and Tang 2012	No	No	No	4	No	No	No	No
	Lee, Ham, and Kim 2013	No	No	No	6	No	No	No	No
	Shehu, Bijmolt, and Clement 2016	No	No	No	7	No	No	No	No
	Berger 2011	No	No	No	4	No	No	No	No
	Chiang and Hsiao 2015	No	No	No	10	No	No	No	No
	Yang and Wang 2015	No	No	No	15	No	No	No	No
	Baker, Donthu, and Kumar 2016	No	No	No	3	No	No	No	No
Motivation to share (self-report)	Henning-Thurau et al. 2004	No	No	No	8	No	No	No	No
	Syn and Oh 2015	No	No	No	10	No	No	No	No
	Phelps et al. 2004	No	No	No	23	No	No	No	No
Views	Southgate, Westoby, and Page 2010	No	No	No	7	Yes	No	No	No
WOM of brands	Lovett, Peres, and Shachar 2013	No	No	No	24	Yes	No	No	No
WOM messages	Dubois, Bonezzi, and de Angelis 2016	No	No	No	4	No	No	No	No
Viral messages	Dobele et al. 2007	Yes	No	No	6	No	No	No	No
Retweet of ads	Stieglitz and Dang-Xuan 2013	Yes	No	No	6	No	No	No	No

digital content and the extent to which it goes viral. We define virality 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. The degree of virality is intrinsically dependent on the degree of content sharing (Tucker 2015). Sharing has become vitally important in the current environment because shared content 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. However, what drives the online sharing of marketer-generated content?

The current study advances prior research on sharing online content in several important ways, as suggested by Table 1. First, we examine the real-world behavior of people who have actually shared ads across multiple media. We measure actual sharing as opposed to intentions to share (which prior studies have examined). In contrast to some prior work that has focused only on ads that have already gone viral (e.g., Dobele et al. 2007; Dafonte-Gomez 2014), we examine ads that are highly shared versus those that are not and the extent of sharing. We also emphasize ads (as opposed to other types of communications such as WOM or online reviews) 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 noncommercial content. We also examine sharing behavior across four major social media (Facebook, LinkedIn, Twitter, and Google+[1]) and ask if certain ad-characteristics that influence sharing vary by media. Prior studies (e.g., Stephen, Sciandra, and Inman 2015; Nelson-Field, Riebe, and Newstead 2013) have examined shares on only one social medium (Facebook).

Second, our findings provide advertisers with concrete insight into how to design ads to influence sharing (see the "Implications" section). Taking prior advertising theory and motivations for sharing into account, we predict which ad characteristics should influence sharing and why. We also code over 60 ad characteristics that might influence sharing, which

[1] Google+ has now been shut down, but it was one of the top social media platforms at the time this research started.

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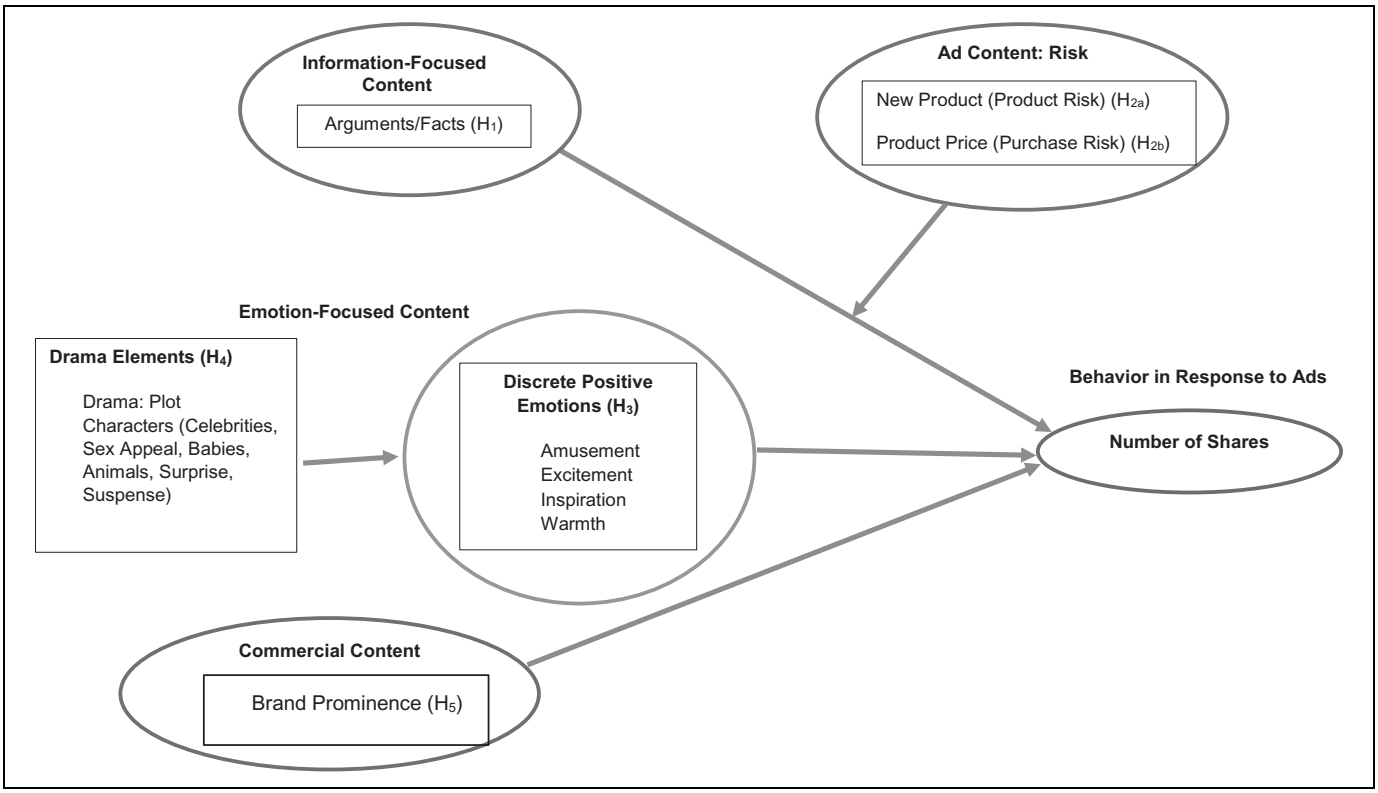


Figure 1. Conceptual framework.

Notes: Circles and ellipses are constructs. Rectangles are measures. Information-Focused Content, Ad Content: Risk, Discrete Positive Emotions, and Commercial Content are independent constructs. Number of Shares is the dependent construct.

is a considerably higher number of characteristics than is considered in other studies (see Table 1).

Third, we study the impact of discrete emotions on sharing. This focus provides advertisers with concrete information about which specific emotional states evoked from ads induce sharing. In addition, we examine which ad content characteristics evoke emotions. Consistent with our theory, highly shared ads are not merely emotional; rather, they unfold as dramas, with highly likable characters and a plot. Although drama ads have been invoked theoretically as a potential predictor of sharing (e.g., Akpinar and Berger 2017), ours is the first study to examine the impact of drama on sharing. Ad sharing is also maximized when ads do not make the brand prominent. Ironically, advertisers rarely use factors that enhance sharing. Thus, our findings have the potential to influence how marketers develop ads so that they have greater potential to be shared and become viral.

Fourth, our field findings are replicated across ads, raters, rating scales, and time, and they show accurate out-of-sample predictability. 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 video ads, we drew stratified random samples of 345 ads in Study 1 and 512 ads in Study 2. The two studies used different ads, coders, and time periods and moderately different brands and rating scales. Only 42 brands and one ad are common to the two studies. Despite these differences, we find consistent results across the studies. A third study further validates our findings with out-of-sample prediction of sharing of videos in Study 2 from the estimated influence of drivers of sharing from Study 1. Those 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 (see Table 1).

Sharing Digital Ads: Conceptual Framework and Hypotheses

We propose a conceptual framework involving the ad characteristics that influence online ad sharing (see Figure 1). This model is grounded both in prior research on the executional elements of advertising and content sharing, as well as in theory. We briefly review this work to highlight our framework and our contributions in relation to prior research (see also Table 1, which further distinguishes our work from prior studies).

Conceptual Framework

Our conceptual framework has several parts: motivation for sharing, informational ad content, emotional ad content, and

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commercial ad content. The motivation for sharing explains the fundamental reasons why people share. Although we do not measure these motivations, we use these motivations to formulate our hypotheses. We do explicitly measure sharing, information content, emotional content, and commercial content.

Motivation for sharing. To understand when and why information-focused, emotion-focused, and commercial-focused content influences sharing of real-world online ads, we briefly review factors that motivate sharing given their instrumentality to our hypotheses. These motives fall into three broad categories: (1) self-serving, (2) social, and (3) altruistic motivations.

First, individuals share content for self-serving motivations; that is, they share content that benefits themselves without directly considering the benefit to others. One often-studied self-serving motivation is the motivation for self-enhancement (e.g., Berger and Milkman 2012; Dubois, Bonezzi, and Angelis 2016; Lovett, Peres, and Shachar 2013). We define self-enhancement as the basic human need to feel good about oneself in the eyes of others. Sharing valuable or impactful content can enhance one's status by making one seem knowledgeable or expert about the marketplace (Lee and Ma 2012). Individuals also share content to foster information sharing by others (i.e., reciprocity) and to learn from others in the future (Lovett, Peres, and Shachar 2013; Syn and Oh 2015). They also share information to express or signal uniqueness (Ho and Dempsey 2010; Lovett, Peres, and Shachar 2013). Finally, individuals share information because they find the act of sharing to be enjoyable (Syn and Oh 2015).

Beyond these self-serving motivations, individuals also share online content for purposes of social engagement. That is, individuals share information to engage with a community (Syn and Oh 2015), learn about community interests (Syn and Oh 2015), socialize with particular community members (Lee and Ma 2012; Lovett, Peres, and Shachar 2013), and/or feel that they belong to or are part of a group (Ho and Dempsey 2010). Finally, altruistic motivations drive sharing. Individuals share content to show concern for others (Hennig-Thurau et al. 2004), show empathy for others (Syn and Oh 2015), and to try to help others (Lovett, Peres, and Shachar 2013). We rely on these sharing motivations to develop our hypotheses about which ad characteristics affect sharing. The left side of Figure 1 identifies three broad ad content domains that are under the control of advertisers and for which theoretical and empirical work on advertising has previously been conducted (informational content, emotional content, and commercial content).

Informational and emotional content of ads. Prior integrative models of advertising (e.g., MacInnis and Jaworski 1989) have proposed two routes by which advertising can influence consumers: an informational route and an emotional route. Researchers have used informational versus emotional ad content to study the effectiveness of ads on dependent variables such as ad and brand attitudes, brand recall (see reviews by Haugtvedt and Kasmer 2012), ad viewing behavior (Southgate, Westoby, and Page 2010), purchase intentions (e.g., Lee and Hong 2016), sales (e.g., Chandy et al. 2001; MacInnis, Rao, and Weiss 2002), sharing intentions (e.g., Berger and Milkman 2012), and, as with our study, actual sharing behavior (e.g., Akpinar and Berger 2017). It has also been used in the study of both online and offline ads. In addition, researchers have used the informational and emotional framework in Figure 1 to study sharing or sharing intentions of non-advertising content (e.g., eWOM, Facebook posts, tweets, and sharing of news articles; see, e.g., Dubois, Bonezzi, and Angelis 2016; Lovett, Peres, and Shachar 2013; Phelps et al. 2004; Stieglitz and Dang-Xuan 2013).

Ad commercial content. We define "commercial content" as content that has a goal of influencing behavior in favor of a branded product or service. Marketing communications such as ads are different from nonmarketer-generated content such as eWOM and news articles because they are commercial in nature. Specifically, marketers develop ads with the goal of influencing or persuading consumers (and inducing actions such as purchase and sharing). Prior theory (Friestad and Wright 1994) indicates that the activation of such "persuasion knowledge" can cause consumers to discount or counterargue persuasive messages. Noncommercial material should not activate such knowledge. For these reasons, prior work on content characteristics that cause consumers to share or intend to share news articles (e.g., Berger and Milkman 2012), tweets (Stieglitz and Dang-Xuan 2013), stories (Berger and Milkman 2012), WOM (Baker, Donthu, and Kumar 2016; Dubois, Bonezzi, and Angelis 2016; Lovett, Peres, and Shachar 2013), or other noncommercial content may not generalize to commercial content such as advertising.

Hypotheses

Overview. Consumers today live in a content-rich and time-poor environment. Consequently, people need to be discerning about what content they consume and share. Millions of pieces of online (ad- and non-ad-related) content are generated each day. Every person who encounters such content must judge whether to consume it or not and whether to share it or not. The repetition of this process ultimately leads to outstanding material going "viral." Our hypotheses deal with how emotional, informational, or commercial content of ads affect sharing.

Sharing information-focused content. Information-focused content is verbally rich. It typically involves a narrator or a voice-over delivering arguments or factual descriptions about products, attributes, people, behaviors, and events. Because of its argumentative or factual focus, however, information-focused content can be dry and uninteresting, particularly when the brand is familiar and well-known. Rather than being shared, information-focused content may irritate consumers and be avoided. So, sharing such ads should be limited. People risk reputational harm and lower prospects for self-enhancement

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when they share content that others do not find relevant, interesting, or compelling. Sharing information about known and familiar brands is also inconsistent with other self-serving motivations such as the motivation to demonstrate one's uniqueness. In addition, altruistic motives for sharing may be limited when ads focus on factual features of the product or brand as opposed to the higher order (emotional) goals that consumers can achieve from product use. Finally, individuals are unlikely to encourage reciprocity from other consumers if they share dry and factual information. Considering these factors, we predict that:

H_1: Information-focused content negatively influences sharing, except under high-risk conditions.

Although we predict that information-focused content is generally negatively related to sharing, we also anticipate that risk moderates this effect (see Figure 1) such that consumers share ads with information-focused content only when risk is high. We consider two types of risk: (1) product risk, which may be high when products are new and unknown, and (2) purchase risk, which is high when products are expensive.

Product risk: new offer (product or service). Product risk is high when buying a new product or service, as the consequences of product usage are unknown. Consumers often search for information that reduces usage uncertainties when risk is high (Locander and Hermann 1979). In these cases, information-focused content can provide compelling facts and arguments that describe new benefits and/or reduce risk perceptions associated with the new product. 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; Chandy et al. 2001; MacInnis, Rao, and Weiss 2002). However, that work did not examine sharing as a dependent variable. In an online sharing context, Akpinar and Berger (2017) found that information-focused ads were less likely to be shared (which is consistent with H_1). However, they did not examine the moderating role of product newness to the market (or risk in general). As such, our examination of the moderating role of risk on sharing behavior is novel.

New products may trigger several motivations for sharing. Consumers appear to be more knowledgeable about the marketplace when sharing information about new products, perhaps enhancing their reputation as being an opinion leader or a market maven. Burnishing one's reputation in this manner is consistent with a motivation for self-enhancement. Sharing information about new products also enhances the potential for future reciprocity and personal gain, as others might subsequently help the sharer by sharing information about new products they have discovered. Sharing information about new products may endear the sharer to members of a community of like-minded others, as is consistent with a motivation to socialize. Individuals may also share information about new products to express their uniqueness by showing what new products they find to be of personal interest. Finally, sharing information about new products is consistent with altruistic motivations for sharing, as consumers may aim to help others for whom the new product is also relevant. We expect that the extent of positive sharing is directly related to the newness of the information. This reasoning suggests the following hypothesis:

H_{2a}: The effect of information-focused ad content on sharing is positive when products or services are new (vs. not new) to the market.

Purchase risk. Consumers might also share information-focused content when purchase risk is high, as would be the case with high-priced products. There are several reasons for this prediction. 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 enhances consumers' involvement in the choice process. In such contexts, consumers are generally attentive and receptive to information about the product or service, and they process this information deeply to minimize purchase risk (Petty et al. 2004). Therefore, consumers may more carefully process information-focused content for high-priced (vs. low-priced) products and services.

Consumers may share information with others to minimize the recipient's purchase risk, as is consistent with an altruistic motivation for sharing. Sharing such information also places the sharer in the position of one who is concerned about the welfare of the recipient, thus enhancing the self. Individuals may also share information about high-priced products in the hopes that recipients will reciprocate by sharing their own information about high priced products, which is an effect consistent with self-serving motivations. To the best of our knowledge, no prior research has examined the moderating role of purchase risk on the relationship between information-focused ad content and ad sharing. We expect that:

H_{2b}: The effect of information-focused ad content on sharing is positive when products or services are high (vs. low) in price.

Emotion-focused content. Emotion-focused content can arouse either positive or negative emotions. Most research in advertising and on content sharing emphasizes emotions evoked by (vs. those depicted in) ads. The reason is that evoked emotions influence important advertising outcomes such as attitudes toward the ad and brand (e.g., Edell and Burke 1987), purchase intentions (e.g., Lee and Hong 2016), recall (e.g., Stayman and Batra 1991), viewing time (e.g., Teixeira, Wedel, and Pieters 2012), sales (e.g., Chandy et al. 2001; MacInnis, Rao, and Weiss 2002), ad sharing (Akpinar and Berger 2017), and retweeting (Stieglitz and Dang-Xuan 2013). Within the literature on advertising and on content sharing, work has examined the effect of (1) emotional versus informational content, (2) the general emotionality of content (high vs. low), (3) the role of

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specific discrete emotions, and (4) the dimensions to describe emotions. In particular, these dimensions include whether emotions are positive versus negative in valence and high versus low in arousal.

Pertinent to the first point, work on advertising outside the sharing context finds that compared with information-focused ads, emotion-focused ads generally have more impact (Lee and Hong 2016), except under conditions of risk, as when markets or products are new (Chandy et al. 2001; MacInnis, Rao, and Weiss 2002). Only Akpinar and Berger (2017) studied the effect of information- versus emotion-focused ads on sharing, finding that the latter induce more sharing/sharing intentions. This finding is generally consistent with H_1; however, H_1 emphasizes the degree of information in ads as opposed to the effect of informational versus emotionally focused ads. Given the limited number of studies on the relative impact of these two types of ad content, replicating the effects of emotional ads on sharing is warranted. Relevant to the second point, Phelps et al. (2004) found that the extent of emotionality of content positively influenced sharing; however, they examined sharing of emails, not ads. Again, assessing whether the extent of emotion in ads affects sharing is warranted.

Consistent with the third point, some prior work on sharing/sharing intentions has examined content that evokes discrete emotions such as amusement, awe, inspiration, surprise, joy, affection, anger, disgust, sadness, and fear (see Berger and Milkman 2012; Dafonte-Gomez 2014; Dobele et al. 2007; Hsieh, Hsieh, and Tang 2012; Nikolinakou and King 2018; Phelps et al. 2004). However, none of these studies examined whether the extent to which ads evoked these discrete emotions created variation in sharing of real-world ads. Instead, prior research has used experimentally created ads (Berger and Milkman 2012) or non-ads (Phelps et al. 2004) or has examined sharing of ads that had already gone viral (Dafonte-Gomez 2014; Dobele et al. 2007). Therefore, it is important to examine whether the degree to which ads create specific discrete emotions influences sharing.

Finally, some work on content sharing examines the valence and/or arousal dimensions of evoked emotions on sharing/sharing intentions, as previously suggested by the fourth point. Prior work suggests that content that evokes high (vs. low) arousal emotions evokes greater sharing or sharing intentions (Berger 2011; Berger and Milkman 2012; Hagerstrom, Alhabash, and Kononova 2014; Nelson-Field, Riebe, and Newstead 2013). However, only Nelson-Field, Riebe, and Newstead's (2013) study on sharing of real-world ads found that arousal is related to video ad sharing. In terms of valence, Eckler and Bolls (2011) found that consumers had stronger intentions to forward ads that were positive (vs. negative or mixed in affective tone), though they did not study actual shares. Several other studies suggest that both high arousal and positive valence are related to sharing (Hagerstrom, Alhabash, and Kononova 2014; Nelson-Field, Riebe, and Newstead 2013). However, only Nelson-Field, Riebe, and Newstead (2013) studied actual shares.

Whereas prior research examines many different aspects of emotional ad content (as previously noted in points 1–4), our research emphasizes the role of discrete emotions on sharing (point 3) for several reasons. First, understanding which discrete emotions prompt sharing provides specific guidance to marketers on exactly what type of emotional content is most shared. This knowledge can help advertisers design ads that maximize sharing. Second, studying discrete emotions allows us to determine whether sharing is influenced by the emotionality of ads in general (as previously suggested by point 2). Third, the study of discrete emotions allows for the subsequent categorization of these emotions into their arousal and valence components, as previously suggested by point 4. This allows us to determine if we replicate prior work on arousal and valence when examining the sharing of real-world ads.

We predict that people are more likely to share ad content that arouses discrete positive (vs. negative) emotions. Sharing negative ad content might be consistent with an altruistic motive; that is, individuals might share content that warns others of fear, shame, or sadness-inducing outcomes that may befall them due to lack of product use. However, such content is likely to be disconcerting to the receiver, negatively impacting the sharer's potential for self-enhancement, limiting the potential for reciprocity, and mitigating opportunities for socializing.

Instead, ads that create discrete positive emotions, such as amusement and excitement, love, joy, warmth, inspiration, and pride, make viewers feel good, which induces a positive mood. Sharing content that evokes these emotional states should make the receiver feel positively toward the sharer, enhancing the sharer's opportunities for self-enhancement in the present and reciprocity by the recipient in the future. We base this prediction on the well-known finding that a positive mood (evoked by the positive emotions just mentioned) creates feelings that generalize toward other entities (i.e., in this case, the sharer; e.g., Isen 2008). Finally, discrete positive emotions are conducive to socializing motivations for sharing. Receivers are likely to feel more positively inclined toward socializing with those individuals who make them feel good. This reasoning suggests that:

> **H_3:** Content that arouses discrete positive emotions such as warmth, love, pride, and joy has a positive effect on sharing compared to ads that evoke negative emotions such as fear, sadness, and shame.

Ad characteristics that drive emotions. Emotion-focused content can be created by using drama rather than a third-party narrator or "voice-over" (Deighton, Romer, and McQueen 1989). Drama ads include three critical characteristics: plot, characters, and surprise. Dramatization increases to the extent that any piece of content uses these elements.

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; Tellis 2019). The plot is effective when the sequence of events flows smoothly, is captivating, and has an unexpected solution (surprise). This solution should flow from the internal nature of characters rather than an external event. The more the plot evokes surprise, the

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higher the interest, engagement, and emotional arousal of the viewer. If the ad's resolution lacks surprise, the plot becomes trivial and uninteresting. Thus, drama, plot, and surprise are positive triggers of the emotions that can, in turn, lead to sharing.

Characters are individuals portrayed in the plot. They captivate the audience when they are (1) appealing (attractive), (2) similar to the audience, and (3) endearing or likable (Petty et al. 2004). 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, likable, or similar to the customer. Characters depicted as everyday people evoke positive emotions because of their similarity to the audience. Celebrities do the same because of their attractiveness and ability to grab the attention of the audience. Babies, animals, and cartoons do so because of their likeability or cuteness (Petty et al. 2004). Characters enrich drama, make ads (and brands) more likable (Petty et al. 2004), and enhance positive emotions.

In contrast to these three elements of drama (plot, character, and surprise), ads could also include a narrator or voice-over. This element involves a third party between the ad and the receiver. It distracts from the characters and plot and hinders engagement and emotional arousal (Deighton, Romer, and McQueen 1989). So, the more an ad includes drama and plot and the less it uses a narrator, the higher the dramatization, arousal of emotion, and engagement.

Drama ads are likely to arouse more intense emotions than information-focused content, for three reasons (Tellis 2003; Tellis 2019). First, ads with drama are easier to process than are ads with information. Transportation theory (Green and Brock 2000) suggests that individuals naturally gravitate to stories as relayed through drama. Moreover, processing drama-based messages involving characters and a plot requires limited effort.

Second, ads containing drama are engaging. Transportation theory (Green and Brock 2000; Green 2004) suggests that characters can transport the reader into the plot by evoking empathy and mental imagery with the characters. The characters draw the viewer into the plot, transporting them into their lives and experiences (Green and Brock 2000). The viewer can become immersed in the plot and the experiences of the characters (Deighton, Romer, and McQueen 1989).

Third, drama ads are also 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 thus the more likely the content will arouse emotions and engagement. By virtue of their plot, such ads have been found to evoke strong positive emotions like pride, warmth, joy, amusement, and love (Aaker, Stayman, and Hagerty 1986; Cavanaugh, Bettman, and Luce 2015; Eisend 2009). Viewers likely assume that others will find such ads emotionally evocative as well and will therefore share the content. Chen and Lee (2014) suggest that ads rated as high in transportation (i.e., those that use plot to engage the viewer) enhance sharing intentions. However, their study did not examine actual shares. This reasoning suggests the following hypothesis:

H_4: Content that uses drama and drama-supporting elements (e.g., a plot, characters, surprise) positively impacts engagement and the arousal of emotions.

Commercial content. As noted earlier, an important factor differentiating ads from non-marketer-generated content (e.g., WOM) is that they are commercial in nature and designed to persuade. Viewers' awareness that content is commercial can create resistance to persuasion (Friestad and Wright 1994). One important ad characteristic that might enhance an ad's commercial appearance is the extent to which the brand is prominent in the ad. Although advertisers often want their brand name to be prominent to encourage recall at the time of purchase, a prominent brand name can also activate persuasion knowledge by triggering thoughts about the advertiser and their commercial motives. Such a process can make consumers resistant to the message (Teixeira, Wedel, and Pieters 2010).

Beyond inducing ad avoidance, we predict that brand prominence reduces sharing. Prominent brand names can interfere with those ad characteristics that support the use of drama, thereby limiting (1) consumers' abilities to engage with the plot, (2) the ad's ability to arouse emotions, and (3) the ad's ability to induce sharing (H_3, H_4). Moreover, if consumers resist ads with strong commercial content because they activate persuasion knowledge, they are unlikely to share such ads with others. Doing so would be inconsistent with the self-serving motivation of self-enhancement. Sharing ads with a strong commercial message is also inconsistent with socializing and altruistic motives.

Akpinar and Berger (2017; Studies 1 and 2) 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. Moreover, that study involved a fictitious ad/brand as opposed to real-world ads and brands. Their field study, which looked at sharing of actual real-world ads, found that emotional (vs. informational) ads affected actual sharing even when controlling for the presence of the brand in the ad. However, they did not report the independent effect of brand prominence on sharing.

Considering the logic we have presented, we expect that:

H_5: High levels of brand prominence (longer duration, earlier placement) in ads negatively impact sharing.

Next, we describe the data, sampling, and coding to test the hypotheses. We test these hypotheses in two independent empirical studies that cover substantially different time periods, videos, and raters, and moderately different scales and brands.

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Study 1

Research Context

The context of the study is online video ads freely uploaded on YouTube in branded channels, which viewers voluntarily view and share. It does not include paid ads. We chose YouTube because it is highly relevant to marketers in ways described in the introduction. Moreover, advertising on YouTube offers the potential to reach a large audience. From 2009 through 2013, more than 6,000 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 one billion unique users who watch over one billion hours of video daily.[2] Thousands of advertisers have established branded channels on YouTube. A branded channel is an account on YouTube through which a brand (a) uploads video ads, (b) communicates with users, and (c) manages video information.

Brand Sampling

The number of branded channels and video ads on YouTube is enormous. We had to sample judiciously by using several criteria to select target brands. First, we identified the top 100 U.S. advertisers in 2012 by expenditure.[3] Not all of them owned YouTube channels. Second, if there was a channel 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 had uploaded at least one video ad per month and had released at least one popular ad (more than 1 million views) in the last 12 months. This step helped us capture as many shared ads as possible because most ads were barely shared (see section on Data Sampling). Our sampling process resulted in a sample of 109 brands. Out of these, we used 79 brands (see the Data Sampling section for details) for the final analysis, 50 of which were in the top 100 brands and the rest were the additional brands. The list of brands is in Web Appendix Table A1.

Data Collection

We tracked these brands and recorded all video ads that these brands uploaded between November 25, 2013 and March 4, 2014. The brands uploaded 1,962 video ads over approximately 100 days. Each channel uploaded one video ad per 5.6 days during this period. 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 application programming interfaces (APIs) provided by major social media to extract the number of shares of the video ads on these media. Requests for these APIs returned the number of times the URL of a given video had 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 networks' APIs to retrieve the number of times users shared this URL. The query request depends on the target social network.[4] We sent such requests every hour to retrieve and store the sharing information, beginning with the time the video ad was uploaded to YouTube. This step was 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. We also took care not to exceed the daily limit set by the APIs for the maximum number of requests.

Although we also tracked other social media (StumbleUpon, Pinterest, etc.), shares on these media were considerably smaller than shares on the four major media. We thus defined the total number of shares for each ad as the sum of the shares across the four major social media. According to this definition, one viewer of a video can share the video on multiple occasions. We observed no 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[5] 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.

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 was highly skewed. Web Appendix Table A2 shows the sample quantiles of the observed shares. Approximately 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 nonshared ads, making it less informative for identifying the drivers of sharing. In the stratified sampling, we

[2] http://www.youtube.com/yt/press/statistics.html
[3] http://www.adbrands.net/us/top_us_advertisers.htm
[4] For example, the following returned the shares of the ad on Facebook: https://graph.facebook.com/fql?q=SELECTshare_count,like_countFROMlink_statWHEREurl=https://www.youtube.com/watch?v=98BIu9dpwHU.
[5] https://developers.google.com/youtube/v3/

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Table 2. Important Ad Characteristics that Drive Social Shares.

Video Characteristics	Type of Measure or Cue
Information and Risk Characteristics	
Argument	Six-point scale (0 = "very weak," and 5 = "very strong") "To what extent does the ad use logical reasoning, factual claims, or offers?"
New product	Binary scale (0 indicates absence; 1 indicates presence) "Is the ad about the introduction of a new product/service?"
Price	Categorical: 1 = "low" (e.g., consumer packaged goods), 2 = "intermediate" (e.g., consumer electronic goods), and 3 = "high" (e.g., automobiles) "Is the product price low (more like a consumer packaged good), moderate (more like a consumer electronic good) or high (more like an automobile)?"
Emotional Characteristics	
Love, pride, courage, joy, triumph, warmth, excitement, sadness, shame, fear, humor, anger, disgust, hatred, deprivation, failure	Six-point scale (0 = "very weak," and 5 = "very strong") "To what extent does the ad arouse the specified emotion?"
Drivers of Emotions	
Surprise, suspense, drama, narrative, character, plot, sex	Six-point scale (1 = "very weak," and 5 = "very strong") "To what extent does the ad have the specified driver of emotion?"
Surprise location	Categorical: no element, at beginning, at middle, at end, throughout "Where in the ad does the surprising outcome occur?"
Baby, animal, cartoon, celebrity	Binary scale (0 indicates absence; 1 indicates presence) "Does the ad use the specified ad element?"
Commercial Features	
Brand timing: early, end, intermittent, none	Binary scale (0 indicates absence; 1 indicates presence of the brand in the ad)
Brand duration	Duration of a brand's appearance in the ad (in seconds)
Control Characteristics	
Ad length	Total duration of the video ad (in seconds)
Number of subscribers	Total number of subscribers to the channel
Timeliness	Binary scale (0 indicates absence; 1 indicates presence) "Is the ad related to a contemporary event?"

divided all video ads into four groups and sampled from each group randomly. The breakpoints for the four strata are based on the 50%, 75%, and 90% quantiles of the shares.[6] We then drew 90 video ads from each group randomly, resulting in 360 video ads. We excluded 15 duplicates in which the advertiser had uploaded the same ad multiple times, resulting in a final sample of 345 English-language video ads belonging to 79 brands. The top panel of Web Appendix Figure A3 depicts the frequency distribution of the brands in these videos.

Content Coding

We adapted the scales from Chandy et al. (2001) to code the content of the video ads. Next, we describe the video ad characteristics for which coders provided ratings, how coders were trained, and intercoder reliabilities. Summaries of these characteristics are in Table 2.

Information-focused content. We defined information-focused content (H_1) by the following criteria. First, the ad uses logical reasoning. For example, the ad could compare the target brand with a competitive brand. Second, the ad makes factual claims of a product. Third, the ad identifies certain functional benefits to users. Coders considered these aspects together when rating the information-focused content of the ad. Coders used a six-point scale to rate the extent to which the ad used these characteristics of information (0 = "not at all," and 5 = "very strong"). Furthermore, coders recorded whether the ad concerns the launch of a new product or service (0 = "no," and 1 = "yes"; H_{2a}). In addition, another two coders rated whether the product's price was low (= 1; e.g., a consumer packaged good), moderate (= 2; e.g., consumer electronics or retail store purchases), or high (= 3; e.g., automobiles; H_{2b}).

[6] These correspond to points close to 100, 1,000, and 10,000 shares.

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Emotion-focused content. For characteristics that trigger discrete emotions (H_3), coders rated the extent to which the ad arouses emotions (0 = "not at all," and 5 = "very strong"). The coders also rated the degree to which specific discrete emotions were aroused by the ad. The individual emotions included both discrete positive emotions (e.g., love, pride, joy, warmth, excitement), and negative emotions (e.g., sadness, shame, anger, fear). For the negative emotions, we also included ratings for 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 was to them (0 = "not at all funny," and 5 = "very funny"). The intensity of humor was measured on a six-point scale (0 = "not at all," and 5 = "very strong").

Drama-based characteristics. We hypothesize that ads with the elements of drama and characteristics that facilitate the use of drama will enhance positive emotions and sharing (H_4). The use of character and plot in the ad served as indicators of the dramatization scale (Deighton, Romer, and McQueen 1989). Coders rated the presence of both character and plot on a six-point scale (0 = "not at all," and 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 1 indicating its use and 0 indicating 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, defined as a third-party voice or text that describes what is going on in the ad (this definition follows Deighton, Romer, and McQueen 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 six-point scale (0 = "not at all," and 5 = "very strong"). Coders also rated the extent of suspense in the ad (0 = "not at all," and 5 = "very strong").

Commercial content. The coders counted in seconds the total time (1) the brand name/logo was present or (2) the brand was mentioned in the ad. We operationalized brand prominence (H_5) as a function of brand name exposure frequency and ad length. In other words, 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 also coded factors that were not part of our theoretical model but could affect sharing. Ad length refers to the duration of the ad in seconds, which was collected directly from YouTube. Ads can also contain content pertinent to a contemporary event, such as the Olympics, the World Cup, and the Super Bowl. Coders indicated whether the ad was (= 1) or was not (= 0) relevant to a contemporary event. Coders also used a 0/1 scale to indicate whether the ad contained (= 1) or did not contain (= 0) sexual appeals.

Coder training. Except for price (which was coded by two coders), three paid coders who were blind to the purpose of this research coded the data independently. We explained the rating scales and engaged in extensive coder training using test video ads unrelated to the selected sample. Coders discussed the results of the test cases. We reviewed discrepancies and clarified the definitions to minimize future discrepancies in the coding of the actual ads used in the study. We then gave coders copies of each of the video ads that comprised our sample. We asked them to base their ratings on only the information provided (not on further search or additional information). Beyond the video ad itself, coders saw only the title of each ad and the brand channel that published it. Following these instructions, the three coders rated the sampled video ads independently.

Intercoder reliabilities. The overall interrater agreement percentage was .76, and the kappa and tau correlations were .67 and .63, respectively. Since brand duration is a continuous variable, it had the lowest agreement percentage. If we exclude this variable, the interrater agreement percentage was .81, and the kappa and tau correlations were .70 and .60, respectively. According to Multon (2010), a 70% level of agreement and a kappa of .50 are generally regarded as adequate. The level of agreement we observed is high considering that many 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 coders gave the same rating on a characteristic. Otherwise, we used the mean of the three ratings. The percentage of scales on which all three coders disagreed is approximately 4% (excluding brand duration).

Results

Descriptive Statistics and Principal Component Analysis (PCA) of Emotions

Web Appendix Table A3 shows that we coded over 60 ad characteristics. However, not all characteristics were sufficiently frequent in our sample to include in the analysis. Web Appendix Table A4 shows those characteristics for which there was sufficient frequency and variability to warrant inclusion. Web Appendix Table A4 shows the frequency of each scale for all characteristics of content (except for those that are numeric). The median ad length is approximately 60 seconds, with first and third quantiles being approximately 30 and 120 seconds. The last column of Table A4 shows the result of a simple regression of the logarithmic shares over the rated scale of each ad characteristic.

Recall that we measured the extent to which the ad aroused 11 emotions. Recall as well that our focus is on discrete emotions as opposed to the dimensions of arousal and valence

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studied in prior work on sharing. At the same time, we aimed to develop as parsimonious a model as possible by reducing collinearity among the set of discrete emotions. We use PCA with Varimax rotation to extract the underlying emotional components from the 11 measured emotions. Web Appendix Figure A2 shows the scree plot of eigenvalues for the extracted components. Table A5, Panel 1 shows the loadings for the first six components, which are sufficient to explain the variances in the originally measured emotions. We label the positive components as "inspiration," "warmth," "amusement," and "excitement," and the negative components as "fear" and "shame" on the basis of the components on which the emotions load. We then use these derived components in the empirical analysis.

Analysis of Drivers of Shares

Our empirical analysis follows the structure laid out in Figure 1. 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:

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

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, the four emotion dimensions, and the six characteristics used in emotion-focused content (see Figure 1). We also include the interaction terms of information x new product/services and information x price levels (low, medium, and high) to test H_{2a} and H_{2b}. We also test hypotheses regarding brand prominence. We treat ad length as a control variable and examine both the linear and curvilinear effect of length. A positive coefficient on the former and negative on the latter would suggest that longer ads increase sharing up to a point, after which longer ads reduce sharing.

There may be substantial differences regarding the brand and product category that influence the sharing of video ads. When estimating the impact of ad characteristics, we control for brand effects 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 parameter estimates can be compared. No scaling is applied to binary or categorical covariates. There are no multicollinearity concerns. The ad length and the square of the ad length have variance inflation values that are higher than others (7.17 and 6.64, respectively) due to their definition. However, they are well below the conventional limits expected in the models.

Results of Drivers of Shares

Information-focused content. Table 3 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 1. We note several results. First, the use of information (argument and factual descriptions) is significant (–.39, $p = .002$) and negatively related to social shares. This result implies that information-focused content is less likely to be shared, which supports H_1. This result is likely due to the dryness of arguments and facts that constitute information. However, the main effect of new products is positive and significant (.46, $p = .002$) as hypothesized. Ads introducing new products are generally shared more often because they contain novel and interesting facts, the sharing of which may make sharers look like they are knowledgeable about the marketplace. Our model is log-linear, and the measures are standardized. Thus, we can interpret the effect sizes as the change in the (log of) shares due to one standard deviation change in the independent variable.

Information-focused content and risk. H_2 proposes that consumers might share information-focused ads when the product or purchase context involves risk (see Figure 1). As Table 3 shows, the interaction between the information and new product is positive and significant (.25, $p = .042$). This result indicates that greater use of information in ads could indeed facilitate social sharing for new products, possibly 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 H_{2a}.

The interaction effect of information and 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 low reference level. Both coefficients are

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Table 3. Estimated Effects of Ad Characteristics on Social Shares from Mixed-Effects Model (Study 1. Dependent Variable is Log of Shares).

	Beta Coefficient	Effect Size (%)	Standard Error	*p*-Value
Information-Focused Content				
Extent of argument	–.39	–32.56	.13	.002**
New product	.46	57.78	.13	.002**
Argument × new product	.25	27.76	.12	.042*
Price (moderate)	–.12	–11.22	.15	.43
Price (high)	.01	1.11	.18	.94
Argument × moderate	.28	31.92	.13	.030*
Argument × high	.33	39.38	.15	.028*
Emotion-Focused Content				
Extent of inspiration	.11	11.52	.05	.018**
Extent of warmth	.13	14.00	.05	.002**
Extent of amusement	.20	21.53	.04	.001**
Extent of fear	–.05	–5.26	.04	.19
Extent of shame	.07	7.36	.04	.06
Extent of excitement	.12	13.09	.04	.008**
Commercial Content				
Brand duration	.01	.50	.14	.46
Brand none	–.67	–48.73	.43	.10
Brand early	–.36	–29.88	.12	.002**
Brand intermittent	–.31	–26.51	.11	.008**
Ad length	.12	12.98	.05	.024*
Ad length sq	–.10	–9.06	.03	.004**
log(subscribers)	.39	48.14	.06	.001**
Timeliness	–.11	–10.06	.14	.46

The parameter in the first row is the effect of argument when used for old and low-priced products (when new product = 0 and price = low). 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 a percentage. Significance levels: *** .001, ** .01, and *.05.

significant and positive (.28, $p = .03$ for argument interacted with moderate pricing and .33, $p = .028$ for argument interacted with high pricing). The high price brands have a greater impact on sharing than moderately priced brands. All these results support H_{2b}.

Evoked emotions. Table 3 shows that ads evoking discrete positive emotions generate more shares, which supports H_3. Among the different types of emotions, ads that evoke inspiration (.11, $p = .018$), warmth (.13, $p = .002$), amusement (.20, $p = .001$), and excitement (.12, $p = .008$) are most likely to be shared. None of the coefficients for the negative emotions are significant in the analysis, which also supports H_3. However, in our data, few ads evoke negative emotions (see Web Appendix Table A4). This pattern may exist because advertisers have already anticipated the negative effects of ads that evoke negative emotions. Our findings confirm the results of studies that have examined the effect of ads with positive emotional valence on sharing intentions (e.g., Hagerstrom, Alhabash, and Kononova 2014). Nelson-Field, Riebe, and Newstead (2013) show similar effects, with discrete positive emotions influencing sharing. Note that we find no evidence that high arousal emotions (e.g., inspiration, excitement, fear) affect sharing more than low arousal emotions (e.g., warmth, amusement, shame). This finding contrasts with prior work on the sharing implications of highly arousing non-ad content and users' ad-sharing intentions (e.g., Berger and Milkman 2012). In contrast with such work, our findings more clearly support a valence account, with discrete positive emotions resulting in sharing. As noted earlier, Phelps et al. (2004) found that the emotionality of content positively influences the sharing of emails. Our results suggest that when it comes to advertising, the extent to which the ad evokes greater emotionality is restricted to discrete positive emotions.

Ad characteristics that drive emotions. We hypothesized (H_4) that the ad characteristics that arouse emotions include dramatization, surprise, suspense, and the type of characters in the ad (celebrity, babies, or animals). We regressed each of the four significant (latent) components of emotions over these characteristics. Table 4 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 in H_4. In particular, the use of drama increases the emotions of inspiration (.17, $p = .004$), warmth (.13, $p = .024$), and amusement (.54, $p = .00$). Second, surprise plays an important role in arousing emotions, as hypothesized. Specifically, the use of surprise leads to significantly higher amusement (.18, $p < .0001$). Third, the use of a celebrity is important in arousing positive emotions, as hypothesized. In particular, celebrities significantly increase the emotions of excitement (.26, $p = .035$) and inspiration (.36, $p = .003$). Fourth, the use of endearing sources like babies and 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.

The location of brand appearance has an influence on sharing, as predicted in H_5 ("brand end" is set to be the reference level). The estimates in Table 3 for "brand none," "brand early," and "brand intermittent" represent the differential effect from that of "brand end." According to these estimates, showing the brand at the end of the ad is significantly better than placing it at the beginning (–.36, $p = .002$) and intermittently (–.31, $p = .008$) for the purpose of promoting social shares, which supports H_5. 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 it is with our choice of freely uploaded 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

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Table 4. Estimated Effects of Drama-Based Elements on Emotions (Study 1).

	Extent of Inspiration		Extent of Warmth		Extent of Amusement		Extent of Excitement	
Characteristics	Mean	*p*-Value	Mean	*p*-Value	Mean	*p*-Value	Mean	*p*-Value
Dramatization	.17	.004**	.13	.024**	.54	.000**	.02	.699
Extent of surprise	–.13	.015**	.04	.433	.18	.000**	.1	.073*
Use of celebrity	.36	.003**	–.14	.242	–.10	.283	.26	.035**
Use of baby/animal	.59	.035**	1.24	.000**	.45	.043**	.04	.876
Use of cartoon	–.23	.233	–.24	.211	.54	.001**	.04	.862
Use of sex appeal	–.25	.355	–.23	.396	.08	.732	–.26	.349
Extent of suspense	.04	.505	–.09	.108	–.04	.409	.10	.074*

Significance levels: *** .001, ** .01, and *.05.

message. Teixeira, Wedel, and Pieters (2010) suggest that pulsing is the best strategy for placing brand names in TV ads, but our results suggest that end placement of brand names is best for YouTube ads.

Control variables. 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 also controlled for length. Whereas 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 of characters and unfolding of the plot, 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 H_6. We operationalized length on a logarithmic scale and included a quadratic term to test the potential nonlinearity. Both the linear (.12, $p = .024$) and quadratic (–.10, $p = .004$) 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.

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. Web Appendix Figure A1a shows the estimated relationship between social shares and ad length from the penalized spline model. It still displays an inverted U-shape, and it peaks at 1.2 minutes. The asymmetry of the curve indicates that compared with very short ads, consumers are more likely to share longer ads. For example, according to 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 various ad lengths.

We investigated the relationship between social shares and ad length separately for information-focused and emotion-focused ads. Web Appendix Figure A1b 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, after the peak, the effect of ad length decays much faster for informational ads than for emotional ads. Thus, consumers appear to more easily tire of and are less likely to share long ads that resort to providing information than long ads that arouse emotions.

Although Study 1 supports our hypotheses and observes interesting effects by medium and for ad length, it is limited in several ways. First, the sample size is restricted to 345 ads, warranting replication with an entirely new sample of ads. Second, the brands in Study 1 were relatively limited. Replication over a wider sample of brands would help generalizability. Third, one might wonder if the effects are restricted to the time period in which the data was collected. Because various environmental forces (e.g., economic uncertainty, political forces) might influence sharing, replication across time is useful. Fourth, one might also wonder whether the results are specific to the coders who coded the ads, warranting replication across coders. Fifth, Study 1 uses a six-point rating scale to evaluate emotions and their predicted drivers. Replicating the effects using a five-point scale in which 3 represents the scale midpoint would provide greater confidence that the results are not specific to the rating scale used.

Information-focused content and sharing medium. For exploratory purposes, we also examined whether sharing of information-focused ads varies by medium. The four major media for sharing are Facebook, Twitter, Google+, and LinkedIn. For this analysis, we ran a sequence of mixed-effect models, which link the number of ad shares on each of these four major social media 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 Web Appendix Table A6.

Across the four social media for which we tracked sharing, LinkedIn is the most distinct regarding the ad characteristics that drive sharing. This result is likely because LinkedIn is a

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Table 5. Estimated Effect of Key Ad Characteristics (Information and Emotions) on Sharing by Platform (Study 1).

	Facebook		Twitter		Google+		LinkedIn	
	Estimate	*p*-Value	Estimate	*p*-Value	Estimate	*p*-Value	Estimate	*p*-Value
Extent of argument	–.23 (.11)	.039**	–.22 (.08)	.007**	–.12 (.086)	.162	–.044 (.08)	.569
Extent of amusement	.43 (.15)	.006**	.238 (.12)	.039**	.265 (.12)	.029**	–.04 (.11)	.711
Use of celebrity	.85 (.329)	.010**	.817 (.25)	.001**	.591 (.26)	.023**	.298 (.23)	.186
Use of baby/animal	2.38 (.79)	.003**	1.561 (.60)	.010**	1.522 (.62)	.015**	.851 (.54)	.114

Significance levels: *** .001, ** .01, and *.05.

business-oriented social networking environment where the users are mostly professionals. The other three media 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 compared to the other social media. We surmise that individuals on the other social media are more motivated to watch video ads for entertainment, whereas entertainment is less likely to be the primary motivation on LinkedIn. Moreover, the use of amusement, celebrity, and babies or animals, which may be a source of entertainment, do not significantly affect shares on LinkedIn but generally do affect sharing on the other three media.

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, as well as a moderately different rating scale. Only the rating instrument items 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 in the studies, we may consider the results robust and potentially generalizable. If not, further research is required before reaching firm conclusions.

Video Sampling

We randomly sampled approximately 7,700 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 by first using automated language detection on the titles, 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). 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.

Web Appendix Figure A3 depicts the frequency distribution of the ads by brands in Study 2. Note that Study 2 has a wider sampling of brands than Study 1. Whereas Study 1 has 79 brands in the sample of 345 videos, Study 2 has 228 brands spanning the sample of 512 videos. Only 42 brands overlap, and only one ad overlaps.

Data Collection and Ad Coding

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

We counted total shares across the four major social media platforms: Facebook, Twitter, Google+, and LinkedIn. We used the same procedure as described in Study 1, using each platform's API to collect shares. For example, we counted Facebook shares using the Facebook Graph API. We used the updated URL[7] to retrieve the number of shares through the API calls. A similar procedure was adopted for the rest of the platforms (LinkedIn, Twitter, and Google+) using their respective APIs.

We trained coders in a similar manner to Study 1. We asked them to rate the content of the videos after undergoing the same training and using the same instruments as in Study 1, with minor variation between the two studies. First, we used an odd-numbered, five-point scale for the items in Study 2 instead of the even numbered, six-point scale in the previous study. Web Appendix Table A3 presents the scales used in Study 2. Second, we used two coders (vs. the three used in Study 1) given resource constraints. Any disagreements between the coders were decided using the evaluation of a third coder. To ensure consistency between the studies, we benchmarked the coders with a subset of Study 1 videos. The interrater agreement of Study 2 raters on this benchmark is high (kappa = .62). This suggests consistency among raters between the two studies.

[7] "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.

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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 subsequently. We highlight the main difference between the two studies before proceeding to the results.

All the results of Study 1 were replicated in Study 2, with one exception. Unlike the first analysis in which 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 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 H_{2b}.

As in Study 1, we reduced the 11 measured emotions to their components using PCA with Varimax rotation. The results of the PCA analysis are in Web Appendix Table A5, Panel 2. Web Appendix Figure A2 shows the scree plot of the principal components extracted. The PCA yielded six components that capture 85% of the variance in emotions: four positive emotions (inspiration, warmth, amusement, and excitement) and two negative emotions (fear and shame). The results are similar to those of Study 1 (see Web Appendix Table A5, Panel 1). The estimated value of these six components was used in the mixed-effect model.

We tested multiple models and compared fits using various statistics. We benchmarked the models using the mixed-effects model-specific R^2 following the Nakagawa and Schielzeth (2013) approach, as has been done in some of the prior studies in marketing (e.g., Boksem and Smidts 2015). Mixed-effects models account for both within-individual variance and between-individual variance. Thus, conventional R^2s for linear models are not appropriate for capturing the model fit. Nakagawa and Schielzeth 2013 suggest using modified R-square values for mixed-effects model comparison. We use this approach to compare the models and demonstrate the relative importance of the three major content domains of the video ads: information-focused content, emotion-focused content, and commercial content, as discussed in Figure 1. The conditional R^2 captures the variance explained by the fixed effects (e.g., informational, emotional, and commercial content) and the random effects (brands) in the model. We also report the marginal R^2 measures to reflect the variance due to the fixed effects for comparison. In addition, we present the Akaike information criterion statistic of these models. The model fit statistics are at the bottom of Web Appendix Table A7.

Model 4 is the full model that includes all three major content domains: informational, emotional, and commercial content. Each of the first three models excludes one major domain to show the decrease in R^2 due to that domain. Model 1 excludes information content and includes the other two. Model 2 excludes commercial content (i.e., brand prominence) but includes the other two ad content domains. Model 3 excludes emotional content but includes the other two. As can be seen, the full model has a better fit as reflected by the conditional R-square. Excluding the emotional domain reduces the explained variation by 7%. Informational and commercial focused content each account for 3% of the variance. We observe a similar fit when we compare the model fit with the Akaike information criteria.

Web Appendix Table A7 summarizes the estimated effects of video ad content on social shares. The results show that the effect of informational content (argument and factual descriptions) is significant (–.20, $p = .01$) and negatively related to social shares, which supports H_1. The main effect of new product status is significant and positive, indicating the propensity of viewers to share videos of new products. The interaction between informational content and new product status is again positive and significant (.25, $p = .05$), which supports H_{2a}. Thus, informational ads facilitate social sharing for new (vs. old) products. As with the results of Study 1, the interaction between high price and informational content is also positive and significant (.26, $p = .03$). Similar to Study 1, we exclude the low level and use dummy variables for moderately priced and high-priced products. Therefore, the coefficients must be interpreted against low-priced products. We replicate H_{2b}, finding that the coefficient for high-priced products is significant and positive. As mentioned previously (and unlike Study 1), moderately priced products do not significantly influence video sharing. However, this does not affect H_{2b}. Information-focused content is more likely to be shared for high-priced products.

We again find that ads that evoke discrete positive emotions generate more shares. Ads evoking inspiration, warmth, amusement, and excitement have significantly higher shares. Negative emotions are not significant in the analysis, perhaps due to inadequate variation in the sample. There is no evidence that sharing is restricted to high arousal content. These results support H3. We do not find significant impact of different emotions under the conditions of risk (i.e., of price or new product information), with the exception of the emotion of inspiration. The interaction between the extent of inspiration and moderately or high- priced products is negatively related to sharing. 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 (–.44, $p < .001$) or using intermittent placement (–.38, $p = .01$), which supports H_5.

Although we treat ad length as a control variable in Study 2, we also find that the linear (.43, $p < .001$) and quadratic (–.33, $p < .001$) terms of the video ad's length are significant. While ad length is positively related to sharing, the quadratic term of the ad length is negative. These results suggest an inverted U-shape 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. Web Appendix Figure A1c depicts the estimated relationship. The results replicate Study 1. The relationship between social shares and ad length is indeed an inverted U-shape, with a peak at 1.7 minutes. As in Study 1, the response

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Table 6. Performance of the Predictive Analysis Including All Variables.

Method	Calibration Sample	Holdout Sample	Precision[a]	Recall[b]	F1 Score[c]
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

[a]"Precision" measures the proportion of highly shared videos that were correctly classified in the predicted sample.
[b]"Recall" measures the sensitivity of the classification by measuring the fraction of the videos classified correctly in the actual sample.
[c]The F1 score is the harmonic mean of the precision and recall, thus measuring the overall predictive accuracy.

curve is asymmetric, which indicates that relatively longer ads have higher shares than shorter ones.

Study 3: Out-of-Sample Predictive Model

To assess the strength of the factors that were significant in the mixed-effects regression, we developed an out-of-sample predictive model. Specifically, we used a logit regression to test if the factors that were significant in the results of Studies 1 and 2 would indeed predict the likelihood of video sharing among consumers across various platforms. We divided the videos into high and low shares on the basis of the median of the distribution of shares. We used the information-focused content (argument, price, and new product), the emotion-focused content (emotions of inspiration, warmth, amusement, and excitement), and the commercial-focused content (timing of brand appearance) that were significant in the prior studies as the predictor of shares. To simplify the analysis, we grouped the continuous predictor variables as high or low on the basis of their averages, and we controlled for the duration.

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

We used three commonly used metrics to evaluate goodness of prediction in the computational sciences literature: precision, recall, and the F1 score. (e.g., Blattberg, Kim, and Neslin 2008; Chung, Wedel, and Rust 2016). "Precision" measures the proportion of highly shared videos that are correctly classified in the predicted sample. "Recall" measures the proportion of the videos correctly classified in the actual sample. The F1 score is the harmonic mean of the precision and recall, capturing the overall predictive accuracy. The calculation is as follows:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (2)$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (3)$$

$$\text{F1 Score} = \frac{2 \times \text{True Positives}}{2 \times \text{True Positives} + \text{False Positives} + \text{False Negatives}} \quad (4)$$

The results are in Table 6. Note that all the prediction rates are around 70%. These results indicate that the significant and hypothesized drivers of sharing have high predictive power. The important and notable result is the high accuracy of the cross-sample prediction: the prediction of shared videos in Study 2 based on the estimates of the coefficients of the model in Study 1. Note that the Study 1 and Study 2 samples were collected in substantially different time periods, rated by different coders, and included substantially different videos and moderately different brands and rating scales. The high accuracy in out-of-sample prediction suggests that the drivers of sharing are potentially generalizable and not idiosyncratic.

In addition, we tested the robustness of the model prediction with and without the emotion variables to ascertain the predictive value of emotions in the ads (Table 7). Without emotions, cross-sample precision decreases by approximately 7%, recall decreases by approximately 50%, and the F1 score decreases 35%. These results imply that emotions play a vital role in the sharing of online video ads.

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 ad characteristics affect sharing of real-world ads on YouTube. Understanding the drivers of sharing might help marketers develop ads that get high shares and go viral. The primary distinction from traditional TV advertising is that the exposure to video ads is generally voluntary and driven largely by social sharing. Understanding ad sharing on YouTube has gained increasing interest over the years, given this medium's potential to create effective ad campaigns at relatively low cost. Subsequent sharing of such ads increases exposure to content at no further cost to marketers.

We developed five hypotheses regarding the characteristics of video ad content that drive sharing on the basis of a conceptual framework of online sharing of video content. We

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Table 7. Performance of the Predictive Analysis Without Emotions.

Method	Calibration Sample	Holdout Sample	Precision[a]	Recall[b]	F1 Score [c]
Cross sample	Study 1	Study 2	88	22	35
Within sample 1	80% Study 1	20% Study 1	62	78	66
Within sample 2	80% Study 2	20% Study 2	67	59	62

[a]"Precision" measures the proportion of highly shared videos that were correctly classified in the predicted sample.
[b]"Recall" measures the sensitivity of the classification by measuring the fraction of the videos classified correctly in the actual sample.
[c]The F1 score is the harmonic mean of the precision and recall, thus measuring the overall predictive accuracy.

collected social sharing of ads on four platforms using two independent samples covering substantially different time periods, video ads, and coders, and moderately different scales and brands. We had coders rate the video ads on over 60 measures, including over 30 executional characteristics.

Conclusions

Two studies using different ads, time periods, and coders show consistent support for the hypotheses. First, the use of information appeals generally has a significant negative effect on social sharing. Second, two variables moderate the extent to which users share information-focused ads. Specifically, information-focused ads positively affect sharing only when product or purchase risk is high: the product or service is new or its price is high. Third, ads that evoke positive emotions of inspiration, warmth, amusement, and excitement stimulate significantly positive social sharing. Fourth, ads that use elements of a drama, such as surprise, likable characters, and a plot, significantly affect positive uplifting emotions and induce sharing. Fifth, a prominent brand name impedes sharing. Early or intermittent display of the brand name drives significantly less sharing than late placement of the brand name. Finally, an asymmetric inverted U-curve characterizes the relationship between social shares and ad length, 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 with video ads. First, approximately 55% of our sample's ads (see Web Appendix Table A4) 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 the effectiveness of such content is limited to conditions in which consumers perceive risk. Content that evokes positive emotions is generally more effective than information-focused content in driving social sharing. However, in the current sample, only 45% of the ads were rated as emotion-focused, and only 7% of them 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.

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 less than 3% used babies or animals as characters in the ad. Because of the low cost and lack of 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. Although 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.

Our results suggest it is better to place the brand name at the end of the ad. However, only 30% of the ads in the sample used late placement. In addition, 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 approximately 25% of ads were between 1 and 1.5 minutes; 50% of the ads were shorter than one minute and approximately 25% were longer than two minutes in the sample. Although 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. In contrast, 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.

Finally, advertisers may want to use different ads for different social media. Although the use of amusement, celebrities, and 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.

Readers may wonder whether drivers of ad sharing in Figure 1 differ from those of ad likability, also known as attitude toward the ad. Likable ads may be shared. Moreover, emotional content, informational content, and brand prominence may affect ad likability (e.g., Edell and Burke 1987; Petty et al. 2004; Stewart and Furse 1986). However, although some of the same factors that drive ad likability might also enhance sharing, sharing depends greatly on social motivations, whereas likability does not. Individuals might share even disliked ads if they believe that these ads might help others

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(altruistic motivation), burnish their reputation (self-serving motivation), or help to connect them with others (social motivation). Moreover, likability is a soft measure obtained from self-reporting, whereas number of shares is a hard measure from field data.

In addition, liked ads need not induce sharing if they do not foster or activate sharing motives. For example, consumers may not share humorous ads (which are often liked) if they believe that others regard the humor as offensive. Furthermore, many factors known to affect ad likability in a traditional advertising context are not present in video ad contexts in which sharing is possible. For example, likeability of traditional ads varies as a function of competitive clutter, the program or editorial context in which the ad is embedded, and ad repetition (see MacKenzie and Lutz 1989). YouTube ads are not placed in a competitive or editorial/program context, and the viewer controls repetition, not the advertiser. That said, future research might explore the conditions under which the same factors that induce ad likability also induce sharing.

Limitations

This study has several limitations that suggest avenues for future research. First, due to the effort involved in training and supervising human raters in coding, the study was restricted to only two samples of video ads. Second, machine coding of video content, as opposed to the human coding done in this study, may help consistency and increase sample size. Third, this study focused only on video ads in YouTube and not on ads in other media. Fourth, shares were the primary dependent variable of this study. Other relevant dependent variables are likes, comments, subscriptions, clicks, or purchases. Fifth, advertisers tend to use more positive emotions than negative emotions. Thus, the lack of variation in ads with negative emotions limits our ability to draw strong conclusions about the sharing of such ads. Sixth, this study focused on sharing as a dependent variable. It did not measure brand liking, recall, and purchase intention. All these aspects may be worthwhile avenues for future research.

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