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Effects of Likeability Dynamics on Consumers' Intention to Share Online Video Advertisements

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Abstract

Understanding how consumer evaluations of online advertisements affect their intention to share advertising content online is essential for successful viral advertising. This article examines consumer decisions whether or not to share video advertisements, in particular the role of their moment-to-moment likeability of the online ad. The study uses a theoretical memory-based framework of temporal sequence effects and unique data for 120 advertisements and more than 43,000 consumer evaluations. The authors find that high likeability at the beginning and the end of a video advertisement is important, though consistent with the memory-based framework, the ending effect is greater. A linear trend in likeability does not influence viral potential, but variance in likeability evaluations (the rollercoaster effect) has positive effects on an advertisement's virality. The moment-to-moment effects are mediated by the overall liking for an online video advertisement. Interestingly, the beginning, end and peak effects influence the viral potential even after controlling for the overall liking. The difference of the peak moment becomes important only when controlling for the overall liking, whereas the direct peak and the rollercoaster effects are suppressed by the overall liking.

Keywords: Viral marketing; Online advertising; Moment-to-moment evaluations; Content sharing

Introduction

Online videos and advertising inserted within them are growing rapidly. According to YouTube statistics (2014), consumers watch more than hundreds of millions of hours of video each day on YouTube; 100 global brands have run TrueView ads over the past year, and 95% of TrueView advertisers have run campaigns across screens. Because companies appreciate the low costs and extensive reach of online video advertising, companies increasingly use online channels for advertising (Nielsen Media Research and the Interactive Advertising Bureau 2012). However, for these efficiency benefits of online advertising to arise, consumers' attitude towards online advertisements must be positive and generate an intention to share it with others (Huang et al. 2013). In other words, consumers must like the online advertisement enough to share it. In this sense, understanding the relationship between consumers' liking of online advertisements and their intention to share them is essential for designing successful viral advertising campaigns.

Word-of-mouth research (e.g., De Angelis et al. 2012; King, Racherla, and Bush 2014) suggests that higher average likeability increases the probability of consumer sharing. Studies of the virality of online content similarly show that viral potential depends on a general measure of positive emotionality (Berger and Milkman 2012). Yet, overall consumer evaluations cannot account for dynamic experiences of content. In online advertisements in particular, which combine sounds and images with a storyline (Huang, Chen, and Wang 2012; Loewenstein, Raghunathan, and Heath 2011), consumer liking of the advertisement varies during its presentation (Baumgartner, Sujan,

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and Padgett 1997). Thus, we must consider specifically how likeability dynamics during online video advertisements relate to consumer intention to share them and, consequently, to their viral potential. Research already has established how likeability dynamics affect overall evaluations of video advertising in offline settings (Baumgartner, Sujan, and Padgett 1997) and how emotional dynamics during online video advertising affect consumers' zapping behaviors (Teixeira, Wedel, and Pieters 2012). However, existing findings pertaining to zapping behavior do not transfer readily to measures of viral potential. Unlike skipping decisions, the decision to share content reveals the liking of a specific online video advertisement to the recipients (e.g., friends in social networks). Sharing a video affects other consumers also and is therefore potentially a more important success factor of online advertising, as compared to other overall judgments, like overall liking or skipping decisions. Thus, to avoid negative image effects, consumers likely watch an advertisement before sharing it (Alexandrov, Lilly, and Babakus 2013), whereas they make the decision to skip an advertisement during their experience of watching it. As consumer behavior research shows, consumers' evaluation processes depend heavily on whether their decision takes place during the experience or after it (Montgomery and Unnava 2009). Accordingly, viral success demands more than non-skipping an online video advertisement, because consumers must be willing to share. Understanding the link between consumers' likeability dynamics and their intention to share the online video advertisement, determining the ad's viral potential, thus, requires specific insights. For example, should advertisers seek to enhance consumers' liking at the start, the end, or throughout the advertisement in order to enhance individuals' intention to share the ad? In addition, do the moment-to-moment effects on the intention to share that go beyond the overall liking effect?

This paper contributes to the literature by assessing the effects of likeability dynamics on consumers' intention to share online advertisements, and whether these effects are mediated by overall ad likeability. While extant research provides insights on the relationship between overall liking and the viral potential of online content (Berger and Milkman 2012), as well as the relationship between the moment-to-moment likeability on the overall liking for advertisements (Baumgartner, Sujan, and Padgett 1997), an extended model that comprises the transmission between all three elements is still lacking. In this research, we examine the relationships between the moment-to-moment likeability, the overall liking and the intention to share, and show direct and indirect effects of the likeability dynamics that are relevant for the viral potential of online video advertisements (see Fig. 1). By this, we expand the viral marketing literature as well as advertising research on moment-to-moment (MtM) evaluations.

To investigate these relationships between MtM likeability, overall liking for an ad, and intention to share it, we rely on a theoretical, memory-based framework from consumer behavior research (Montgomery and Unnava 2009). In this framework, consumers' overall retrospective evaluations of a temporal sequence depend on which experiences they can recall most easily, which helps explain the relationship between likeability dynamics and retrospective decisions to share content. With this memory-based framework and related research as our foundation, we investigate the influence of key features related to beginning, end, and peak likeability; likeability trends; and variability in moment-to-moment likeability during an online video advertisement (Montgomery and Unnava 2009; Teixeira, Wedel, and Pieters 2012).

We develop hypotheses about the effects of these specific features on the viral potential of online advertisements and test them with extensive data, including more than 43,000 observations of 120 video advertisements for varied product categories. The results affirm the relevance of likeability dynamics for advertisements' viral potential; they also identify the key moments that drive individuals' intentions to share the ads and how these dynamic effects are mediated by the overall liking of the ad. Accordingly, our study expands emerging research on viral marketing (e.g., Berger and Milkman 2012) and reveals the mechanism by which consumers develop intentions to share online video advertisements. From a managerial perspective, these results provide novel insights for advertisers that seek to create online advertisements with high viral impact, because we specify which parts of online advertisements are

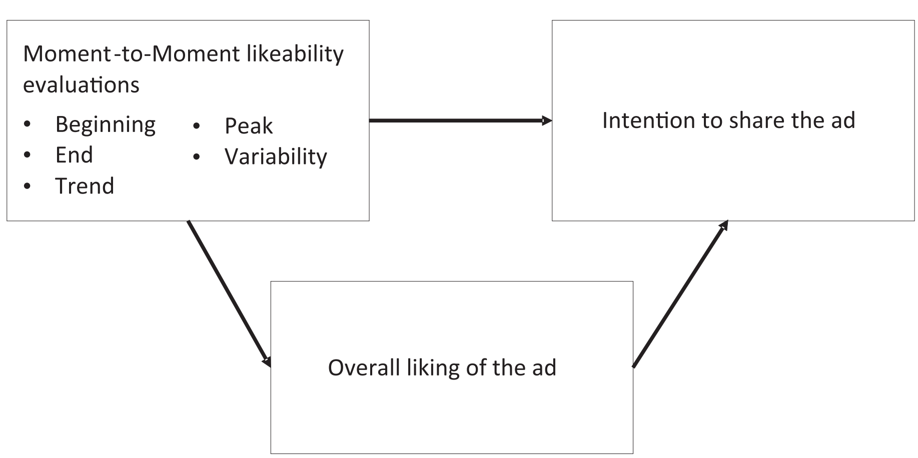

Fig. 1. Research framework.

most important for increasing the probability that they will be shared.

Conceptual Framework and Hypotheses

Viral Advertising Research

Extant viral advertising research mostly focuses on products, recipients, or content. For example, studies of products (Berger and Schwartz 2011; Schulze, Schöler, and Skiera 2014) or brand characteristics (Lovett, Peres, and Shachar 2013) identify key features of product categories or brands that drive word of mouth and motivate people to talk about them. Studies of recipients instead seek to identify persons with a higher propensity to share, according to their personalities (Chiu et al. 2007), motivation (Ho and Dempsey 2010), or positions in a social network (Camarero and San Jose 2011; Hinz et al. 2011; Van der Lans et al. 2010). With regard to content, existing studies show that consumers share messages that offer high entertainment and enjoyment levels (Phelps et al. 2004), high utilitarian or hedonic value (Chiu et al. 2007), or positive arousal (Berger and Milkman 2012). These studies generally investigate overall perceptions invoked by the online content (e.g., Berger and Milkman 2012) and relate them to its viral potential.

Psychology research, however, indicates that consumers who make overall evaluations or decisions, such as whether to share content, base their perceptions on key aspects of the related experience (Montgomery and Unnava 2009). These dynamic aspects of consumers' evaluations are especially relevant in the case of online video advertisements that offer dynamic message content, tell a short story, and communicate a message over the course of the entire advertisement. Indeed, research on consumers' skipping decisions for online video advertisements finds that dynamics of experienced joy and surprise affect consumers' attention and their retention (Teixeira, Wedel, and Pieters 2012). However, we still know little about whether and how dynamic effects influence consumers' intention to share and the viral success of online video advertisements. Sharing content online differs from other overall outcomes examined in former studies, e.g., likeability or skipping decisions, because in contrast to the latter, content sharing directly affects other consumers in the social network and thereby contributes to the overall impact of the advertisement. Previous research has shown that moment-to-moment evaluations of an experience change depending upon the presence of other people during the experience (Ramanathan and McGill 2007). Similarly, we assume that overall decisions that are visible by others, like sharing content online, are likely to be driven by other factors than latent decisions or evaluations that are typically not observed by peers (e.g., overall likeability, surprise, or decisions to skip).

Consequently, investigating consumers' likeability dynamics as the online advertisement plays, differentially affecting their intention to share the advertisement with other consumers is essential for understanding viral potential and overall effectiveness of video advertisements. Besides, it is unclear how the overall liking may mediate the likeability dynamics' effects on the viral potential. While the relationship between overall liking and the viral potential of online content, as well as the relationship between the moment-to-moment likeability on the overall liking for advertisements have been examined in extant research, an extended model that comprises the relationships between all three elements is still lacking.

Memory-based Framework for Temporal Sequences

Research into how consumers build their overall judgments of temporal sequences indicates that their overall evaluations are not merely the average of multiple, temporally separated judgments, because some moments exert more influence than others (Kahneman et al. 1993; Loewenstein and Prelec 1993; Montgomery and Unnava 2009). Overall judgments might emerge as the event occurs (e.g., zapping behavior; Woltman-Elpers, Wedel, and Pieters 2003; Teixeira, Wedel, and Pieters 2012) or be based on memories that result from the temporal sequence that forms an event (e.g., overall liking after seeing advertisements, Baumgartner, Sujan, and Padgett 1997 or an entire television show, Hui, Meyvis, and Assael 2014). Decisions to share content likely reflect the latter type, such that they occur after the person has watched the entire advertisement, because of the risk associated with sharing unappealing content (e.g., negative self-enhancement; Huang, Chen, and Wang 2012). In addition, the video advertisement's story often can be understood and evaluated only after viewing the entire video. Ultimately then, consumers likely watch advertisements completely before sharing and decide whether to share by reviewing their memories of the liking they experienced while watching it. This liking naturally varies over the course of the online video advertisement.

With a grounding in consumer behavior research that focuses on temporal sequences, this memory-based framework implies that consumers evaluate a temporal sequence that forms an event retrospectively, by recalling the most memorable moments, so perceptions of key moments strongly affect overall evaluations (Montgomery and Unnava 2009). Hence, consumer intention to share content should not rely equally on their liking of every moment. We build on this memory-based framework to understand the relationship between likeability dynamics and the intention to share.

Hypotheses

Our theoretical memory-based framework and related research on dynamic effects in advertising research suggest five major effects: beginning, end, peak, and trend effects, as well as variability in evaluation sequences (Montgomery and Unnava 2009; Teixeira, Wedel, and Pieters 2012). We formulate hypotheses pertaining to each effect and the mediation by the overall liking (see Fig. 1).

Beginning and End Effects

The initiation and completion of an experience tend to be weighted more heavily by respondents in their retrospective judgments, due to primacy and recency effects (Greene 1986; Montgomery and Unnava 2009). That is, the first and most recent experiences are more prominent in global judgments of a temporal sequence of experiences, such that they affect overall evaluations, like the decision to share an advertisement, strongly (Kahneman et al. 1993). In line with primacy effects, initial moment evaluations should be easier for consumers to remember and thus influence their intention to share retrospectively (Ariely and Zauberman 2000; Montgomery and Unnava 2009). Similarly, the recency effect implies that consumers readily recall the liking that they experienced most recently (Ariely and Zauberman 2003; Kahneman et al. 1993). Baumgartner, Sujan, and Padgett (1997) find that the end effect provides one of the best predictors of the overall liking of an advertisement; it also influences overall humor evaluations (Woltman-Elpers, Mukherjee, and Hoyer 2004) and zapping behavior (Woltman-Elpers, Wedel, and Pieters 2003; Teixeira, Wedel, and Pieters 2012). These effects should be especially intense for retrospective evaluations.

With the memory-based framework, we acknowledge both primacy and recency effects and anticipate that the likeability evaluations of the beginning and the end of an online video advertisement exert positive impacts on consumers' intention to share it. In addition, primacy effects may be dominated by recency effects in retrospective evaluations of video advertisements (Montgomery and Unnava 2009), because recall diminishes with increasing time since an exposure to a stimulus (Greene 1986), especially in the case of low-attention conditions, like online advertising (Goodrich 2011). For instance, prior research has shown that ending sequences of television series have greater weight in overall evaluations than do the beginning sequences (Hui, Meyvis, and Assael 2014). Therefore, we predict that recency effects dominate primacy effects, because consumers better recall their liking of the last moments of an online advertisement when deciding whether to share it. Formally,

H1. Higher likeability at the beginning of an online video advertisement has a positive influence on consumer intention to share it.

H2. Higher likeability at the end of an online video advertising has a positive influence on consumer intention to share it.

H3. The end likeability effect on consumer intention to share an online video advertising is greater than the beginning likeability effect.

Peak Effect

According to the memory-based framework, a peak evaluation exerts a strong impact on retrospective overall judgments, like the decision to share content, because the most intensive moment is well recalled (Montgomery and Unnava 2009). In the context of online video advertising, if the peak (i.e., greatest liking evaluation) is more intense, that moment becomes distinctive and induces better recall than other moments, such that it has a stronger influence on the intention to share. Support for this peak effect in the context of retrospective overall evaluations in offline settings emerges from multiple empirical studies in consumer behavior (Fredrickson and Kahneman 1993; Kahneman et al. 1993) and advertising (Baumgartner, Sujan, and Padgett 1997; Ramanathan and McGill 2007). Fredrickson and Kahneman (1993) exposed participants to videos of aversive and pleasant scenes and gathered their global evaluations; the most intense clips exerted substantial influences on overall evaluations. Baumgartner, Sujan, and Padgett (1997) also identify high correlations between peak and overall liking in offline contexts.

We further argue that the peak effect should be amplified by the difference between the magnitude of the peak and those of the evaluations around it, due to the von Restorff effect (Montgomery and Unnava 2009). The von Restorff effect refers to the superior recall of distinctive items in a sequence, such that memory is more enhanced when the difference between the peak and the surrounding moments is greater, independent of the position of that peak in a sequence (Montgomery and Unnava 2009). As Montgomery and Unnava (2009) show, the distinctiveness of the peak affects retrospective overall evaluations significantly, even if it offers (relatively) low absolute intensity. Accordingly, we posit:

H4a. Peak likeability during an online video advertisement has a positive influence on consumer intention to share it.

H4b. The peak effect is amplified by high differences between the peak evaluation and evaluations of the surrounding moments.

Trend Effect

A trend of an experience refers to increasing or decreasing evaluations over a temporal sequence. Consumers prefer improving sequences (increasing in positive valence) to declining ones, which is referred to as their negative time preferences (Loewenstein and Prelec 1993). From a psychological perspective, people are more satisfied by improvements (Hsee and Abelson 1991). Similarly, the memory-based framework implies that with improving sequences, consumers recall the improving trend, leading to better retrospective evaluations overall. In contrast, declining sequences cause subsequent evaluations to be relatively lower and retrospective overall judgments to be worse (Montgomery and Unnava 2009). Empirical support for such a trend effect has been found in multiple domains, including pain (Ariely 1998), discomfort (Kahneman et al. 1993), and advertising. Woltman-Elpers, Wedel, and Pieters (2003) show that increasing emotional and informational levels decrease zapping probability, as do heightening levels of joy and surprise (Teixeira, Wedel, and Pieters 2012). Generally, improving emotional sequences have been shown to improve consumer attitudes towards advertisements (Labroo and Ramanathan 2007). Basing on these findings, we expect individuals to be more willing to share content with a positive dynamics and avoid sharing content with a negative dynamics because they might want to avoid the risk of negative self-enhancement (Koritzky and Yechiam 2010). We predict:

H5. Likeability sequences with greater overall trends increase the intention to share online video advertisements.

Variability

Research into consumer zapping behavior towards online advertisements highlights the relevance of variability in emotional moment-to-moment evaluations for overall (zapping) decisions, which constitutes the so-called rollercoaster effect (Teixeira, Wedel, and Pieters 2012). Variance in likeability evaluations during an online video advertisement may indicate stimulation or arousal, and arousal is a prominent driver of virality for online content (Berger and Milkman 2012). Psychological research shows that advertisements with mixed emotional content may lead to positive outcomes, because they may lead to amusement (Scott 1994). Moreover, alternating positive and negative feelings may facilitate coping processes and enhance attitudes towards an advertisement (Friestad and Wright 1994). On the basis of these findings, we assume that higher variability in moment-to-moment likeability increases the viral potential of online advertisements, such that consumer intention to share the online video advertisement should be greater with higher variability in the likeability sequence evaluations.

On the other hand, variability of moment-to-moment likeability evaluations may also increase uncertainty regarding whether an ad is likeable or not. High levels of stimulation, can negatively affect evaluations of an advertisement (Steenkamp, Baumgartner and van der Wulp 1996) and its self-enhancement value (Richarda and Chandrab 2005). These arguments suggest that higher levels of variability decrease consumer intention to share, or at least increase consumer uncertainty, leading them to avoid sharing the advertisement (Anderson 2003; Jin and Villegas 2007).

These arguments suggest that the effect of variability on the intention to share may be positive or negative. Therefore, we hypothesize two competing effects (Armstrong, Brodie, and Parsons 2001):

H6a. Higher variability of likeability evaluations increases the intention to share a video advertisement.

H6b. Higher variability of likeability evaluations decreases the intention to share a video advertisement.

Mediation Effect of Overall Liking

Extant research has examined the relationship between moment-to-moment likeability and overall liking for video advertisements indicating that the overall liking is primarily driven by the end and peak moment-to-moment effects (Baumgartner, Sujan, and Padgett 1997). The overall liking itself is expected to influence the intention to share, because consumers are less likely to share content for they fear of negative self-enhancement (Alexandrov, Lilly, and Babakus 2013). Therefore, we expect a mediation relationship between the moment-to-moment likeability, the overall liking and the intention to share: Moment-to-moment likeability affects the overall liking judgment for an online ad, based on which a consumer decides whether to share an ad or not. However, consumers may like a specific part of an online video advertisement very much, and this may affect their intention to share an advertisement next to the overall liking. Based on this argumentation we expect that the moment-to-moment likeability effects might be mediated partially by the overall liking because the intention to share an online advertisement goes beyond the overall liking of an ad. Consequently, we posit:

H7. The overall liking for an online ad mediates the moment-to-moment likeability effects of (a) the beginning, (b) the ending, (c) the peak, (d) the trend, and (e) the variability on the intention to share a video advertisement.

Empirical Study

Sample

We test our hypotheses using empirical data collected through an online survey, conducted in Germany between October 2010 and July 2011, among a representative online panel of consumers. The survey was conducted on a popular Google-owned YouTube channel, by the marketing research company MetrixLab.

The sample of advertisements considered included 120 regular commercials, each between 9 and 73 s in length. The advertisements featured both well-known brands (e.g., eBay, MTV, BMW, Apple) and less familiar ones (e.g., 13th Street, Zott), across a wide range of product categories (e.g., consumer goods, services, electronics, apparel; see Appendix A for an overview). All the advertisements were new, such that their launch had been no more than three weeks before the survey.

The participants were 10,717 YouTube users who were sampled from a representative online panel. Participants were invited to join the study and after initial instructions they were forwarded to the online survey. Every respondent evaluated five video advertisements. Each video advertisement was exposed twice: in the first exposure participants had the option to skip the video advertisement similar to real YouTube conditions. During the second exposure, participants stated their moment-to-moment likeability by moving a cursor along an evaluation slider. The moment-to-moment likeability evaluations for every ad second were tracked. After each video advertisement, participants' intention to share the video was measured. On average, each advertisement was watched and evaluated by 361 respondents, with a minimum of 232 and a maximum of 536 respondents. In total, 43,295 observations are available.

Measures

The dependent variable, reflecting the viral potential of an online video advertisement (Table 1), assessed participants' stated intention to share an online advertisement. To measure it, we used a single item: "How likely is it for you to share this ad with your family or friends?" on an 11-point scale (1 = "very unlikely," 11 = "very likely").

Table 1
Data measurement levels and operationalization.

	Construct	Measurement level	Source	Scale/operationalization
Consumer-specific information	Intention to share (dependent variable)	Respondent/advertisement	Survey	1 (“very unlikely”) to 11 (“very likely”)
	Moment-to-moment likeability	Respondent/advertisement second	Survey	−5 (“do not like at all”) to 5 (“like very much”)
	Overall liking	Respondent/advertisement	Survey	1 (“do not like at all”) to 5 (“like very much”)
	Gender	Respondent	Survey	Dummy coded, 1 for female
	Education	Respondent	Survey	Dummy coded, 1 for academic degree
	Age	Respondent	Survey	Age segments (18–25 years, 26–40 years, 41–55 years, 56+ years [reference category])
Ad-specific information	Ad length	Advertisement	Survey	Length segments (9–29 s, 30 s [reference category], 31–73 s)
	Product category	Advertisement	4 raters	Dummy coding for consumer goods, services (reference category), retail, automobile, media, technology, pharmacy

To measure the moment-to-moment likeability of advertisements, we used an evaluation slider, such that participants moved a cursor along an 11-point scale (−5 = “do not like it at all,” 5 = “like it very much”). Thus, we registered likeability for every second of the evaluated commercial (Table 1). This procedure is analogous to moment-to-moment measures used in former marketing studies, such as stated consumer likeability for television shows (Hui, Meyvis, and Assael 2014), electronic dialing to indicate consumer reactions to sequences of pictures (Pham et al. 2001), mouse movements to indicate consumer likeability for advertisements (Baumgartner, Sujan, and Padgett 1997) or slider scale to indicate likeability for music videos (Nelson, Meyvis, and Galak 2009).

Before starting the moment-to-moment evaluation respondents were shown an instruction video on how to express their moment-to-moment likeability by moving the cursor along the 11-point scale. At the starting point, the slider appeared at the zero point of the scale. We excluded the evaluations during the first second, because of the high share of zero values. We also disregarded all observations for which a respondent never moved the cursor for the duration of the advertisement (6,164 cases), leaving 43,295 observations for our further analyses. When we considered likeability sequences, we determined that consumer likeability during each advertisement varied substantially and the patterns of the likeability dynamics also differed. Thus we found peak-and-stable trajectories and patterns that indicated (inverted) U-shaped or S-shaped curves (see Fig. 2, Panels a and b). In addition, the volatility in likeability evaluations varied substantially: Whereas some trajectories were smooth (e.g., Fig. 2, Panel b), other trajectories indicated strong upward and downward movements (Fig. 2, Panels c and d).

To examine these patterns more closely, we operationalized their beginning, end, and peak effects, linear trends, and variability (volatility). For the likeability values of the start of the video advertisements, we measured average likeability for the second and third seconds of each video advertisement. The final likeability values were the average likeability for the last 2 s of each video advertisement. The peak values reflected the maximum likeability value for each respondent. We captured the difference between this peak intensity and its surrounding context by the (mean-centered) difference with likeability evaluations in the 2 s before and after the peak[3]. Table 2 contains descriptive statistics for these moment-to-moment values.

We next calculated the linear trend for each (mean-centered) likeability sequence for all t moments of each advertisement:

$$MtM_t = \beta_o + \beta_1 t + \varepsilon_t. \tag{1}$$

We estimated Eq. (1) separately for every moment-to-moment likeability sequence of each respondent. The parameter β_1 depicted the linear trend (Table 2)[4].

The variability of likeability sequences is measured by the autocorrelation of the error terms, after separating the linear trend and the intercept according to Eq. (1). Specifically, the variability of moment-to-moment likeability evaluations is measured by the negative autocorrelation. The higher the negative autocorrelation of a moment-to-moment sequence, the higher its variability. In contrast, positive autocorrelation indicates that the moment-to-moment likeability evaluations move in the same direction, i.e., low variability. As a measure for the autocorrelation we use the Durbin–Watson statistic which ranges in value from 0 to 4. A value close to 0 indicates positive autocorrelation, a value close to 2 non-autocorrelation, and close to 4 negative autocorrelation. Hence, higher values of the Durbin Watson statistic indicate higher variability of the moment-to-moment likeability evaluations. In our data, the average Durbin Watson statistic is .634, indicating that most of the patterns show strong positive autocorrelation, or no strong variability.

[3] We also tested different specifications of the peak effect in which the surrounding context consisted of 1, 3 or 4 s before and after the peak. All model specifications led to consistent results.

[4] We also tested a different operationalization of the linear trends and derived two variables, representing the magnitude of positive and negative trends separately, on the basis of the individual linear trend coefficients. Each variable corresponded to the values of the calculated linear trend β_1 if it was positive or negative but was set to 0 otherwise. Both, the positive and negative trend effects were non-significant.

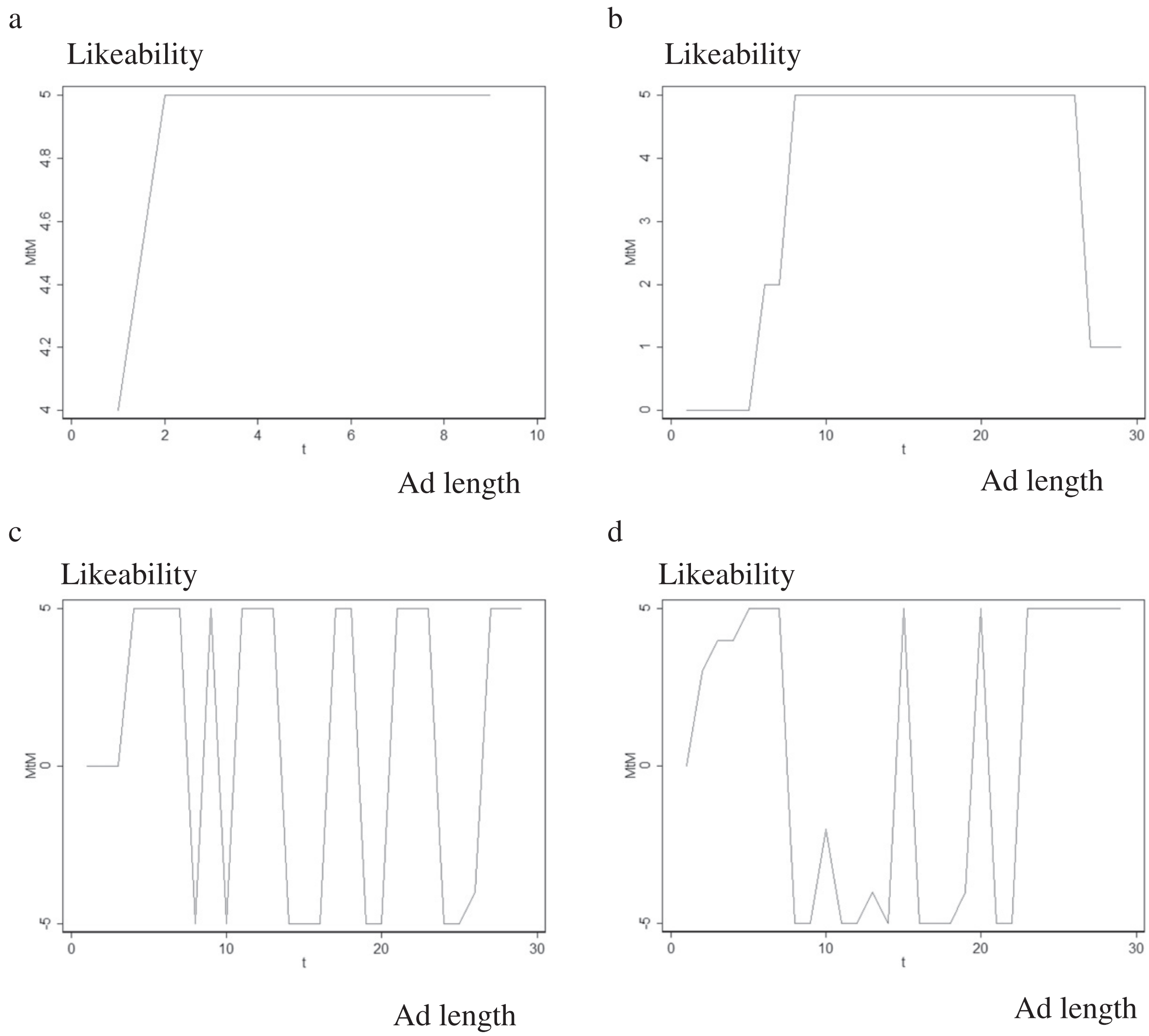

Fig. 2. Moment-to-moment evaluation patterns: low and high variability.

In addition, the respondents stated their overall liking for an online video advertisements on a single-item 5-point scale ("Do you like the video advertisement?", 1 = "do not like it at all", 5 = "like it very much"). To separate out the effects of liking evaluations and generate efficient estimates, we controlled for consumer characteristics that might affect the likelihood that a person shares online advertisements (Woltman-Elpers, Wedel, and Pieters 2003; Teixeira, Wedel, and Pieters 2010, 2012). In particular, we controlled for gender (1 = "female"), educational level (1 = "academic degree"), and age category (four dummy variables, with participants older than 56 years as a reference category). Furthermore, we controlled for product category effects (Berger and Schwartz 2011). Four raters (two men and two women) were unanimous in their assignments of the advertisements to one of seven categories: fast moving consumer goods (39.28%), services (17.78%), retail (13.33%), automobile (11.33%), media (7.38%), high-tech (6.41%), or pharmacy (4.48%; Table 2). Using services as a reference category, we included six dummy variables to account for category effects. Finally, we controlled for length effects by defining three indicator variables for advertisements shorter than 27 s, between 27 and 30 s, or longer. The typical advertisement length is 30 s, so we used the second indicator as the reference category and measured for any effects of shorter or longer advertisements. By this, we can show whether shorter or longer ads than the typical 30 s have better/worse chances to get shared online[5].

The correlation coefficients between all the variables (see Appendix B) and the variance inflation factors (maximal variance inflation factor [VIF] = 5.10 for the end evaluation; mean VIF = 2.06) revealed no multicollinearity problems.

Analysis

To test our hypotheses H_1–H_{6a} and H_{6b}, we identified the effects of likeability evaluations on the intention to share each online video advertisement, using a random effect regression

[5] We also estimated a model using the ad length as a continuous variable. All effects remain consistent in terms of sign and significance.

Table 2
Descriptive statistics.

	Variables	Mean	Standard deviation	Min	Max
	Intention to share	3.689	3.205	1	11
Likeability	Begin	.205	1.467	−5	5
	End	.856	3.144	−5	5
	Peak	2.645	2.136	−5	5
	Peak x Diff. to context	4.255	4.882	−5.500	50.000
	Trend	.027	.160	−1.283	1.283
	Variability	.634	.403	0	3.561
	Overall liking	3.304	1.441	1	5
Consumer-specific controls	Gender (Female = 1)	.493			
	Academic degree (Yes = 1)	.283			
	<25 years	.099			
	26–40 years	.370			
	41–55 years	.423			
	56+ years	.108			
Ad-specific controls	Ad length short (9–26 s)	.560			
	Ad length regular (27–30 s)	.314			
	Ad length long (31–73 s)	.125			
	Fast moving consumer goods	.386			
	Services	.180			
	Retail	.134			
	Automobile	.115			
	TV/media	.073			
	Technology	.064			
	Pharmacy	.044			

model. The intention to share the online advertisement served as the dependent variable, which reflects the viral potential of an advertisement. We controlled for unobserved heterogeneity across advertisements and respondents with two non-nested random intercepts at the advertisement and respondent levels, respectively:

$$Virality_{ij} = \beta_o + \beta_1 Begin_{ij} + \beta_2 End_{ij} + \beta_3 Peak_{ij} + \beta_4 Trend_{ij} + \beta_5 Variability_{ij} + \beta_6 Peak_{ij} \text{ x } Difference\_Context + \sum_{k=1}^{K} \theta_k X_{ik} + \sum_{m=1}^{M} \theta_m X_{jm} + \nu_i + \eta_j + \varepsilon_{ij} \tag{2}$$

where i = 1–10,717 denotes the respondents, j = 1–120 refers to the advertisements, X_{ik} represents the K consumer-specific control variables, X_{jm} reflects the M advertisement-specific control variables, and ν_i and η_j are the respondent-specific and advertisement-specific random intercepts, respectively.

This model represents our baseline for testing our hypothesized moment-to-moment effects on the intention to share (Model 1, Table 3). To test for the mediating effect of the overall liking, we estimated two additional random effect regression equations (Hayes 2013): We estimated the same model specification as above with the overall liking as a dependent variable (Model 2, Table 3) to examine the moment-to-moment likeability effects on the overall liking. In addition, we estimated Eq. (1) with the overall liking as an additional independent variable (Model 3, Table 3) to examine the overall liking effect on the intention to share and the moment-to-moment effects when accounting for overall liking.

Results

Main Results

The empirical results offered support for both H_1 and H_2 (Table 3), revealing significant, positive effects of likeability evaluations for the beginning (b = .094, p < .001) and end (b = .256 p < .001) of the online advertisements. These results also confirmed H_3, because the estimated effect for the end was higher than that for the beginning. To test the significance of this difference, we estimated a restricted model, in which we fixed the coefficients for the beginning and end values to be equal and compared its goodness-of-fit against that of the unrestricted model. A Vuong (1989) likelihood ratio test revealed the significantly better fit of the unrestricted model compared with the restricted model (z = 58.19; p < .001). We also tested the difference of the estimated coefficients for the end and the beginning effects, which offered further support for H_3 (Wald χ^2 = 105.85, p < .001). In line with the memory-based framework, the end likeability effect on the intention to share a video advertisement was greater than the beginning effect.

We found a significant, positive impact of the peak moment-to-moment evaluation (b = .210, p < .001), in line with H_{4a}. This positive effect, however, was not amplified when the peak differed significantly from its surrounding moments (b = .002, p = .449), which did not support H_{4b}.

For the trend effect hypothesis, we investigated whether the intention to share increased with higher positive trend. In Model 1 we see a positive, though non-significant trend effect (b = .099, p = .450), which does not provide support for H_5. Hence, the linear trend effects do not affect the viral potential of online video advertisements.

Table 3
Effects of likeability dynamics on viral potential.

Dependent variable:		Model 1: Intention to share		Model 2: Overall liking		Model 3: Intention to share	
		b	se	b	se	b	se
Likeability	Begin	0.094 ***	0.011	0.034 ***	0.004	0.071 ***	0.011
	End	0.256 ***	0.008	0.180 ***	0.003	0.120 ***	0.008
	Peak	0.210 ***	0.010	0.262 ***	0.004	−0.012	0.010
	Peak x Diff. to context	0.002	0.003	−0.014 ***	0.001	0.012 ***	0.003
	Trend	0.099	0.131	0.333 ***	0.052	−0.126	0.124
	Variability	0.141 ***	0.035	0.149 ***	0.013	0.026	0.033
	Overall liking					0.768 ***	0.012
Consumer-specific controls	Gender	0.344 ***	0.045	0.048 ***	0.010	0.304 ***	0.043
	Academic degree	−0.213 ***	0.049	0.008	0.011	−0.217 ***	0.048
	Age 18–25	0.766 ***	0.098	0.018	0.022	0.767 ***	0.095
	Age 26–40	0.602 ***	0.076	−0.013	0.017	0.619 ***	0.074
	Age 41–55	0.342 ***	0.074	0.007	0.017	0.343 ***	0.072
Ad-specific controls	Ad length short	0.011	0.092	−0.073 *	0.041	0.058	0.085
	Ad length long	0.313 **	0.129	0.212 ***	0.058	0.158	0.119
	FMCG	0.074	0.113	0.041	0.050	0.041	0.104
	Pharmacy	0.145	0.204	0.038	0.091	0.119	0.188
	Retail	0.084	0.133	0.053	0.059	0.045	0.122
	Automobile	0.059	0.144	0.047	0.064	0.025	0.132
	Media	0.142	0.161	−0.069	0.072	0.190	0.148
	Technology	0.332 *	0.174	0.033	0.077	0.307 *	0.161
	Constant	2.133 ***	0.127	2.366 ***	0.048	0.362 ***	0.122
	N	43,295		43,295		43,295	
	χ^2	9,476.840		50,967.560		14,746.060	

Notes: se = standard error. FMCG = fast moving consumer goods.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Regarding the variability of likeability evaluations, we found a positive, significant effect (b = .141, $p < .01$). That is, we found support for the competing hypothesis H_{6a}: Increasing variability in moment-to-moment likeability during an online video advertisement increased consumer intention to share.

The mediation effects of likeability were tested by Model 2 (capturing the moment-to-moment effects on overall liking) and Model 3 (capturing the effect of overall liking on intention to share and the direct effects of moment-to-moment likeability variables). Indeed, the results showed that, as expected, mediation occurs. Most moment-to-moment effects on the overall liking were significant: the beginning, end, trend variability and peak effects were positive and highly significant, which is consistent with existing literature. The positive peak effect was diminished by high differences of the peak likeability to its context, although the negative effect was much smaller in magnitude compared to the positive peak effect (b = −.014, $p < .01$ for the difference of peak to context versus b = .262, $p < .01$ for the peak effect).

The overall liking affected the intention to share positively, which is in line with the predicted mediation (b = .768, $p < .01$). The moment-to-moment likeability effects on intention to share changed when we controlled for overall liking (compare results of Models 1 and 3). The beginning and end effects were only partially mediated, respectively 24 and 53%, and had a significant direct effect of intention to share next to the indirect effect through overall liking. Specifically, the beginning effect decreased from b = .094 (Model 1) to b = .071 (Model 3) and the ending effects were only half as strong as in the model without the overall liking (b = .256 in Model 1 compared to b = .120 in Model 3). In addition, we found a twist of the peak effect: In Model 1 higher peak moment-to-moment likeability increased the intention to share and the difference of the peak likeability to its context did not show a significant influence. When the overall liking was accounted for in Model 3, the peak effect on the intention to share was fully mediated, while the difference of the peak to the context became significant and positive (b = .012, $p < .01$). Also, the variability effect was fully mediated by the overall liking and becomes non-significant in the model with the overall liking as the independent variable.

Regarding the control variables (Table 3), consumers without an academic degree, men, and younger consumers generally were more prone to share online video advertisements. Advertisement length mattered too: Advertisements longer than the conventional 30 s have increased intention to share. Finally, we found a positive product category effect related to technological products.

Robustness and Sensitivity Analyses

We computed a series of robustness checks to validate the model specification and the robustness of our results. First, we estimated a model specification with the average likeability evaluation instead of the dynamic likeability effects (Appendix C; Table C.1). The effect was as expected positive, i.e., advertisements with higher average likeability have higher viral potential. To test the appropriateness of our model with dynamic effects we compared its goodness-of-fit with that of the model including only the average likeability. A Vuong test for non-nested models showed a significantly better fit of our model with the dynamic likeability effects ($z = 492.53$; $p < .001$). This indicates that basing virality judgments only on average evaluations is less appropriate.

Furthermore, we control for the robustness of our results towards ad content effects. Previous studies have shown that advertising content influences perceived likeability and attention (e.g., Aaker and Stayman 1990), as well as viral potential (Berger and Milkman 2012). We included a measure of ad content along six dimensions established by prior advertising research (Aaker and Stayman 1990; Smit, van Meurs, and Neijens 2006). Four independent raters used a seven-point scale (1 = "not at all," 7 = "very much") to indicate how each advertisement fits the following descriptions: entertainment, stimulation, relevance, warmth, irritation, and familiarity. The interjudge agreement was sufficient (Cronbach's alphas range from .65 to .98). We used average evaluations across raters as additional controls (see Appendix C; Table C.2). In line with findings from past research the effects of relevance (Berger and Schwartz 2011) and entertainment (Berger and Milkman 2012; Eckler and Bolls 2011) were significant. A certain level of irritation also significantly increased the intention to share. This may be due to the fact that irritation may reflect unexpected stories that usually have a higher tendency to get viral. The remaining dimensions had no significant effects. All hypothesized likeability effects remained consistent with the main results regarding size and significance underlining the robustness and stability of our results.

Our research setting entailed a forced exposure, though during the first part of the survey, respondents viewing the online video advertisements had the option of skipping parts of them. In a second part, which provided the input for our analysis in this study, the online video advertisements appeared again in a forced exposure condition, and respondents stated their moment-to-moment likeability and the intention to share, as described previously. Hence, the moment-to-moment data are collected in a forced exposure setting. Although this setting is used in recent studies (e.g., Tucker 2014), we conduct a consistency check to test the robustness of our results to potential biases related to this forced exposure setting. We median split the sample according to the portion of time the participants spent viewing each advertisement relative to its length in the first part (the median corresponded to approximately 90% of the overall advertisement length), then replicated our model estimates for the subsamples of respondents who would have skipped large parts of the advertisement and those who would have watched (almost) the entire video (see Appendix C, Table C.3). All the effects remained stable for both subsamples. This consistency check provided results consistent with our main model, thus emphasizing their robustness. Especially striking is the consistency in the effects of the beginning, end, peak, and variability, whether respondents viewed the entire advertisement or less than the median viewing time. As expected, lower moment-to-moment evaluations characterized this group compared with those consumers who watched more than the median portion of the ad (beginning .088 versus .301, $p < .01$; end .443 versus 1.201; $p < .01$; peak 2.373 versus 2.871; $p < .01$). The trend of the sequences also differed significantly, in that it appeared significantly lower in the groups that exhibited lower viewing times (.013 versus .039; $p < .01$). These findings affirmed the face validity of the data: People skip video advertisements that they like less, whereas consumers with longer viewing times express greater liking of the key moments of an online video advertisement, along with more positive and less negative trend dynamics. Despite these differences, it is striking that the effects of the moments' likeability on the intention to share remained consistent.

Finally, we tested whether the beginning/end effects depended on the definition of their lengths. When we examined different specifications of the beginning/end effect that lasted 3 or 4 s, the main results remained largely consistent (see Appendix C, Table C.4).

Discussion

The viral impact of online advertisements depends heavily on the extent to which they get shared among consumers; it is the foundation of a successful viral campaign. Advertisers have a strong interest in understanding the mechanisms that define consumers' sharing intentions. Furthermore, the dynamic nature of online video advertisements means that consumer liking of an advertisement probably changes during the advertisement's timeline. We therefore have examined how viral success (measured by consumer intention to share) relates to likeability dynamics over the course of an online video advertisement, and how this relationship is mediated by the overall liking of an online video advertisement. Building on a memory-based theoretical framework, we use unique data that consist of more than 43,000 observations and 120 spots collected from a YouTube channel, in cooperation with Google and MetrixLab. We identify key likeability moments that determine consumer intention to share the content and hence viral potential of the ad.

Conclusions

Our study provides new insights into the drivers of advertisements' viral potential. Likeability at the beginning and end of an advertisement enhances its viral potential, though the end effect is stronger than the beginning effect. These findings are in line with a memory-based framework that suggests such effects due to primacy and recency influences (Montgomery and Unnava 2009). The stronger effect of ending likeability also fits with consumer behavior research that indicates the greater relative importance of recency effects in temporal sequences (Ariely 1998; Ariely and Zauberman 2003); with research on how moment evaluations inform overall judgments, such that the influence of ending evaluations generally are much higher than those at the beginning (Hui, Meyvis, and Assael 2014); and with advertising research that indicates that in offline contexts, peak and end effects determine overall consumer evaluations (Baumgartner, Sujan, and Padgett 1997). We expand on these findings by addressing the missing link between likeability dynamics and the viral potential of online video advertisements. We did not identify significant effects of the linear trend, but we find a positive influence of the rollercoaster effect: a positive effect of the variability of the moment-to-moment likeability judgments. This finding complements extant research which showed that the effect of variability effects in the zapping context is ambiguous, in the sense that they increase consumer attention but attenuate their retention (Teixeira, Wedel, and Pieters 2012). We go a step further and confirm the positive effect of variability for viral advertising purposes: higher levels of variability increase the intention to share the online ad.

Furthermore, we establish the relationships between the moment-to-moment likeability, the overall liking and the intention to share. By this, we expand existing research which has only examined the first part of this relationship (Baumgartner, Sujan, and Padgett 1997). We find that the overall liking is a mediator of the likeability dynamics on the intention to share. Specifically, the peak and the variability effect are fully mediated by the overall liking, and the beginning effect and end effect are partially mediated. These results show that, indeed, the likeability dynamics influences the intention to share beyond the overall liking effect. This implies that future research on viral potential should include likeability dynamic effects besides overall attitudinal measures.

Managerial Implications

Our model reveals important findings about some specific key moments that trigger consumers to share online video advertisements. Viral advertising managers tend to accept the rule that the first seconds of an advertising video are the most important ones and that a video should “kick off with a bang” (Chappaz 2013). In expert interviews with online advertising managers of Google and MetrixLab, we confirmed this managerial belief, which also seems reasonable, in that the first few seconds attract consumers’ attention and motivate them to continue watching. Many online platforms also offer consumers an option to skip online advertisements after the first seconds. Although our results confirm the relevance of the beginning moments, we also find a significantly greater impact of the end of the advertisement on viral potential. Advertising managers therefore should realize that it is not enough to create ads that start with a “big bang”; they also must ensure that they create a distinct, special, peak moment that stands out over the rest, have a highly likeable ending and create a rollercoaster effect with high variability in likeability sequences. Our research thus offers some novel managerial insights for developing viral advertising, including the need for a new pretest mechanism that measures dynamic likeability and intention to share, since measuring only the overall liking is obviously not sufficient to predict the viral potential. The R-square of the model with overall liking is .24 versus .27 in the model with the dynamic measures. This indicates that the insights generated by the dynamic likeability effects help managers to better pretest video advertisements regarding their viral potential, because likeability dynamic measures allow more accurate insights regarding which parts of video advertisements are liked or not by consumers and how this affects consumers’ intention to share the ad. By examining dynamic likeability effects, companies can better evaluate the viral potential of their advertisements and select the most promising options. In practice, advertising agencies already tend to pretest several advertising plots and launch the most successful online; our findings suggest the need to add a moment-to-moment pretest, which should improve the advertising development process.

Limitations and Further Research

Despite its basis in rich empirical data, our article suffers some limitations. First, our data set consists of advertisements broadcast on television in the three weeks prior to the survey, so they were not completely new. Additional research might examine a broader range of advertisements, from completely new to well-known communications. Second, our data cannot reveal underlying motivations of consumers to share an advertisement. We hope further studies distinguish the specific motives for sharing content, including dynamic moment-to-moment likeability measures, to investigate their joint effects on viral potential. Third, our analyses relied on stated intention to share. We think that the intention to share content is an adequate measure of the viral potential basing on the rich evidence on positive intention–behavior relationships (e.g., Brown et al. 2005). However, we encourage further studies to complement and validate our findings by investigating the actual sharing behavior displayed by consumers as well as the type and strength of their relationships within social networks. From a managerial perspective, it would also be interesting to analyze segment level effects which potentially help to better target key segments with specific formats of online advertising.

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Appendix A. Overview of Advertisements

#	Category	Brand	Length (s)	N	Frequency (%)
1	Auto.	Suzuki	19	370	0.855
2	Auto.	Mercedes	29	353	0.815
3	Auto.	BMW	39	345	0.797
4	Auto.	Renault	73	331	0.765
5	Auto.	Porsche	29	324	0.748
6	Auto.	Toyota	19	243	0.561
7	Auto.	Dacia	29	283	0.654
8	Auto.	Mercedes	29	368	0.850
9	Auto.	Renault	39	412	0.952
10	Auto.	VW	29	395	0.912
11	Auto.	Audi	44	330	0.762
12	Auto.	Toyota	15	339	0.783
13	Auto.	Mini	29	462	1.067
14	Auto.	VW	41	437	1.009
15	FMCG	Whiskas	20	402	0.929
16	FMCG	Rittersport	20	399	0.922
17	FMCG	Ahoi Brause	15	386	0.892
18	FMCG	Sensodyne	19	386	0.892
19	FMCG	Schwarze Dose	9	284	0.656
20	FMCG	Hanuta	15	338	0.781
21	FMCG	Landliebe	21	304	0.702
22	FMCG	Fa	20	272	0.628
23	FMCG	Syoss	20	265	0.612
24	FMCG	Philadelphia	11	290	0.670
25	FMCG	Capri Sonne	29	332	0.767
26	FMCG	Krombacher	34	337	0.778
27	FMCG	Right	20	320	0.739
28	FMCG	Purina	23	305	0.704
29	FMCG	Coca Cola	41	300	0.693
30	FMCG	Hohes C	27	296	0.684
31	FMCG	Hochland	18	271	0.626
32	FMCG	Cesar	20	347	0.801
33	FMCG	Müller	16	315	0.728
34	FMCG	Max Factor	19	249	0.575
35	FMCG	Rügenwalder Mühle	23	243	0.561
36	FMCG	AXE	19	253	0.584
37	FMCG	Zoltarella	21	270	0.624
38	FMCG	Cleopatra	19	358	0.827
39	FMCG	Danone	20	365	0.843
40	FMCG	Syoss	20	397	0.917
41	FMCG	Air Wick	19	375	0.866
42	FMCG	Milka	24	438	1.012
43	FMCG	Zott	29	298	0.688
44	FMCG	Wrigley	20	364	0.841
45	FMCG	Haribo	29	377	0.871
46	FMCG	Coca-Cola	59	389	0.898
47	FMCG	Alete	24	409	0.945
48	FMCG	Swiffer	20	439	1.014
49	FMCG	Adidas	20	424	0.979
50	FMCG	Nivea	20	479	1.106
51	FMCG	Milka	30	536	1.238
52	FMCG	Real	27	467	1.079
53	FMCG	Pepsi	23	454	1.049
54	FMCG	Head and Shoulders	20	492	1.136
55	FMCG	Ültje	20	488	1.127
56	FMCG	Reis fit	21	417	0.963
57	FMCG	Kitkat	23	416	0.961
58	FMCG	Fisherman's Friend	9	357	0.825
59	FMCG	Pick up	19	418	0.965
60	FMCG	Ferrero	19	429	0.991
61	Media	13th Street	29	346	0.799
62	Media	Base	18	340	0.785
63	Media	O2	29	289	0.668
64	Media	Telekom	23	272	0.628
65	Media	O2	29	362	0.836
66	Media	MTV	29	318	0.734
67	Media	Vodafone	41	308	0.711
68	Media	O2	20	482	1.113
69	Media	Congstar	29	471	1.088
70	Pharmacy	Ratiopharm	18	316	0.730
71	Pharmacy	Kytta Salbe	23	255	0.589
72	Pharmacy	Voltaren	28	487	1.125
73	Pharmacy	herzbewusst.de	20	432	0.998
74	Pharmacy	Dolormin	16	430	0.993
75	Retail	Reebok	29	411	0.949
76	Retail	Adler	19	365	0.843
77	Retail	Deichmann	29	341	0.788
78	Retail	Hagebau	29	373	0.862
79	Retail	Praktiker	28	296	0.684
80	Retail	Ecco	29	271	0.626
81	Retail	McDonalds	23	294	0.679
82	Retail	IKEA	19	277	0.640
83	Retail	Saturn	23	323	0.746
84	Retail	Diesel	19	304	0.702
85	Retail	Media Markt	23	335	0.774
86	Retail	Ebay	29	330	0.762
87	Retail	Hugo	19	280	0.647
88	Retail	Obi	39	380	0.878
89	Retail	IKEA	23	286	0.661
90	Retail	Zalando	20	491	1.134
91	Retail	Takko	20	461	1.065
92	Services.	Mastercard	29	400	0.924
93	Services	Gothaer	24	446	1.030
94	Services	Preis24.de	29	399	0.922
95	Services	Aachener Münchener	15	363	0.838
96	Services	Autohaus24.de	29	306	0.707
97	Services	Prokon	19	295	0.681
98	Services	Flexstrom.de	9	232	0.536
99	Services	LBS	33	325	0.751
100	Services	Volks-und Raiffeisenbanken	13	253	0.584
101	Services	Deutsche Bahn	27	311	0.718
102	Services	ADAC	24	352	0.813
103	Services	Allianz	30	354	0.818
104	Services	Postbank	19	296	0.684
105	Services	Google	47	386	0.892
106	Services	Deutsche Post	23	359	0.829
107	Services	Deutsche Telekom	29	381	0.880
108	Services	Sparkasse	29	492	1.136
109	Services	McFit	29	488	1.127
110	Services	Dell	29	453	1.046
111	Services	Thomas Cook	23	465	1.074
112	Services	Evonik	29	464	1.072
113	Techn.	AEG	39	365	0.843
114	Techn.	Nintendo	20	250	0.577
115	Techn.	Bosch	47	276	0.637
116	Techn.	Wii	18	275	0.635
117	Techn.	Apple	29	278	0.642
118	Techn.	Euronics	15	362	0.836
119	Techn.	Panasonic	39	508	1.173
120	Techn.	Hp	29	493	1.139
Total				43,295	100

Note: Auto. = automobile; Techn. = technology.

Appendix B. Correlations Between Dependent and Independent Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1 Intention to share	1.00																				
2 Overall liking	0.49	1.00																			
3 Begin	0.25	0.41	1.00																		
4 End	0.43	0.70	0.39	1.00																	
5 Peak	0.36	0.68	0.55	0.68	1.00																
6 Peak x Diff. to context	0.17	0.28	0.17	0.28	0.48	1.00															
7 Variability	0.31	0.51	0.00	0.77	0.44	0.19	1.00														
8 Trend	0.01	−0.08	0.02	−0.04	−0.19	0.17	0.00	1.00													
9 Gender	0.01	−0.04	−0.03	−0.08	−0.07	−0.04	−0.06	0.01	1.00												
10 Academic degree	−0.06	−0.05	−0.03	−0.09	−0.03	−0.03	−0.08	−0.02	0.10	1.00											
11 Age 18–25	0.03	0.01	0.02	−0.01	0.03	0.03	−0.02	0.02	−0.07	−0.07	1.00										
12 Age 26–40	0.03	−0.02	0.00	−0.02	0.01	0.03	−0.02	0.02	−0.07	0.05	−0.25	1.00									
13 Age 41–55	−0.02	0.01	−0.01	0.02	−0.02	−0.03	0.02	−0.02	0.03	−0.04	−0.28	−0.66	1.00								
14 Ad length short	−0.04	−0.12	−0.03	−0.07	−0.15	−0.03	0.01	0.30	0.00	0.00	−0.01	0.00	0.00	1.00							
15 Ad length long	0.07	0.14	0.03	0.09	0.13	0.03	−0.01	−0.21	0.00	0.00	0.00	0.00	0.00	−0.43	1.00						
16 FMCG	0.00	−0.01	0.02	0.01	−0.03	0.01	0.03	0.13	0.00	0.00	0.00	0.00	−0.01	0.39	−0.15	1.00					
17 Pharmacy	0.00	−0.01	0.04	−0.01	−0.01	0.00	−0.03	0.04	0.00	0.00	0.00	0.00	0.00	0.08	−0.08	−0.17	1.00				
18 Retail	0.00	0.00	−0.02	0.00	0.02	0.02	0.02	−0.01	0.00	0.00	0.00	0.00	0.00	0.02	−0.07	−0.31	−0.08	1.00			
19 Automobile	0.02	0.06	0.02	0.04	0.06	0.01	−0.01	−0.10	0.01	0.00	0.00	0.00	0.00	−0.27	0.27	−0.29	−0.08	−0.14	1.00		
20 Media	−0.02	−0.05	−0.04	−0.03	−0.03	−0.02	−0.02	−0.05	0.00	0.00	0.00	0.00	0.01	−0.12	−0.02	−0.22	−0.06	−0.11	−0.10	1.00	
21 Technology	0.03	0.03	0.02	0.00	0.03	0.00	−0.03	−0.06	0.00	0.01	0.01	0.00	0.00	−0.13	0.23	−0.21	−0.06	−0.10	−0.10	−0.07	1.00

Appendix C. Alternative Specifications and Robustness Checks

Table C.1
Results of model specification with mean overall liking.

		b	se
Likeability	Overall mean	0.530 ***	0.005
Consumer-specific controls	Gender	0.318 ***	0.045
	Academic degree	−0.202 ***	0.049
	Age 18–25	0.776 ***	0.097
	Age 26–40	0.618 ***	0.076
	Age 41–55	0.344 ***	0.074
Ad-specific controls	Ad length short	0.032 *	0.090
	Ad length long	0.268 **	0.127
	FMCG	0.082	0.112
	Pharmacy	0.132	0.202
	Retail	0.100	0.131
	Automobile	0.060	0.142
	Media	0.141	0.159
	Technology	0.247	0.172
	Constant	2.586 ***	0.122
	N	43,295	
	χ^2	10,260.300	

Notes: se = standard error. FMCG = fast moving consumer goods.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Table C.2
Results of model specification with ad content.

	Dependent variable:	Intention to share		Overall liking		Intention to share	
		b	se	b	se	b	se
Likeability	Begin	0.093 ***	0.011	0.034 ***	0.004	0.070 ***	0.011
	End	0.257 ***	0.008	0.179 ***	0.003	0.122 ***	0.008
	Peak	0.209 ***	0.01	0.262 ***	0.004	−0.013	0.011
	Peak x Diff. to context	0.002	0.003	−0.014 ***	0.001	0.012 ***	0.003
	Trend	0.091	0.131	0.350 ***	0.053	−0.146	0.125
	Variability	0.146 ***	0.035	0.147 ***	0.013	0.032	0.033
	Overall liking					0.769 ***	0.012
Consumer-specific controls	Gender	0.342 ***	0.045	0.049 ***	0.01	0.302 ***	0.043
	Academic degree	−0.214 ***	0.049	0.006	0.011	−0.217 ***	0.048
	Age 18–25	0.755 ***	0.098	0.014	0.022	0.759 ***	0.095
	Age 26–40	0.598 ***	0.076	−0.016	0.017	0.618 ***	0.074
	Age 41–55	0.339 ***	0.074	0.007	0.017	0.339 ***	0.072
Ad-specific controls	Ad length short	0.227 **	0.115	0.044	0.049	0.195 *	0.109
	Ad length long	0.550 ***	0.141	0.315 ***	0.061	0.325 **	0.132
	FMCG	0.176	0.121	0.046	0.052	0.137	0.114
	Pharmacy	0.403 **	0.194	0.098	0.085	0.333 *	0.183
	Retail	0.179	0.14	0.077	0.061	0.120	0.132
	Automobile	0.117	0.141	0.109 *	0.061	0.035	0.132
	Media	0.123	0.159	−0.049	0.07	0.156	0.15
	Technology	0.371 **	0.17	0.08	0.073	0.312 *	0.16
	Irritating	0.118 *	0.071	0.003	0.031	0.119 *	0.067
	Relevant	0.116 *	0.065	0.049 *	0.028	0.080	0.061
	Stimulating	−0.010	0.045	0.006	0.02	−0.013	0.042
	Entertaining	0.187 ***	0.052	0.060 ***	0.022	0.143 ***	0.049
	Familiar	−0.049	0.047	−0.006	0.02	−0.039	0.044
	Warm	0.048	0.037	0.056 ***	0.016	0.005	0.034
	Constant	0.746 *	0.435	1.764 ***	0.187	−0.611	0.411
	N	42,933		42,933		42,933	
	χ^2	9,474.85		50,779.94		14,714.85	

Notes: se = standard error. FMCG = fast moving consumer goods.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Table C.3
Robustness check towards forced exposure effects.

Dependent variable		C3.1: Viewing time ≤ ad medium viewing time					
		Intention to share		Overall liking		Intention to share	
		b	se	b	se	b	se
Likeability	Begin	0.077***	0.016	0.028***	0.007	0.060***	0.016
	End	0.253***	0.012	0.188***	0.005	0.114***	0.012
	Peak	0.171***	0.015	0.234***	0.006	−0.017	0.015
	Peak * Diff. to context	0.002	0.004	−0.010***	0.002	0.008**	0.004
	Trend	0.246	0.194	0.273***	0.079	0.079	0.185
	Variability	0.166***	0.050	0.150***	0.020	0.060	0.047
	Overall liking					0.747***	0.017
Consumer-specific controls	Gender	0.357***	0.054	0.056***	0.015	0.312***	0.053
	Academic degree	−0.209***	0.060	−0.006	0.016	−0.201***	0.058
	Age 18–25	0.899***	0.119	0.009	0.032	0.907***	0.115
	Age 26–40	0.648***	0.096	−0.013	0.026	0.660***	0.093
	Age 41–55	0.383***	0.095	0.008	0.026	0.371***	0.091
Ad-specific controls	Ad length short	0.043	0.097	−0.074	0.045	0.094	0.088
	Ad length long	0.332**	0.136	0.189***	0.065	0.203*	0.123
	FMCG	0.035	0.118	0.042	0.055	−0.001	0.107
	Pharmacy	0.135	0.225	0.088	0.107	0.076	0.204
	Retail	0.059	0.138	0.057	0.065	0.016	0.125
	Automobile	0.046	0.148	0.039	0.070	0.017	0.134
	Media	0.165	0.164	−0.059	0.078	0.207	0.148
	Technology	0.318*	0.179	0.025	0.084	0.282*	0.162
	Constant	1.987***	0.143	2.355***	0.056	0.265*	0.140
	N	19,727		19,727		19,727	
	χ^2	4,310.650		23,510.370		6,668.820	

Dependent variable		C3.2: viewing time > ad medium viewing time					
		Intention to share		Overall liking		Intention to share	
		b	se	b	se	b	se
Likeability	Begin	0.130***	0.016	0.045***	0.006	0.098***	0.015
	End	0.273***	0.012	0.169***	0.004	0.141***	0.011
	Peak	0.230***	0.015	0.284***	0.005	−0.015	0.016
	Peak x Diff. to context	0.000	0.004	−0.018***	0.002	0.014***	0.004
	Trend	0.011	0.188	0.396***	0.070	−0.259	0.179
	Variability	0.164***	0.050	0.138***	0.018	0.047	0.047
	Overall liking					0.793***	0.017
Consumer-specific controls	Gender	0.353***	0.056	0.047***	0.013	0.317***	0.054
	Academic degree	−0.238***	0.061	0.013	0.015	−0.250***	0.060
	Age 18–25	0.680***	0.124	0.044	0.029	0.653***	0.121
	Age 26–40	0.585***	0.094	0.000	0.022	0.585***	0.092
	Age 41–55	0.381***	0.092	0.016	0.022	0.366***	0.090
Ad-specific controls	Ad length short	−0.064	0.098	−0.079*	0.041	−0.008	0.093
	Ad length long	0.240*	0.137	0.224***	0.059	0.071	0.130
	FMCG	0.111	0.121	0.046	0.051	0.071	0.114
	Pharmacy	0.138	0.216	0.024	0.092	0.112	0.204
	Retail	0.125	0.142	0.047	0.060	0.085	0.134
	Automobile	0.077	0.153	0.052	0.065	0.040	0.145
	Media	0.123	0.172	−0.082	0.073	0.181	0.162
	Technology	0.338*	0.186	0.044	0.078	0.308*	0.176
	Constant	2.172***	0.146	2.380***	0.052	0.336**	0.145
	N	23,568		23,568		23,568	
	χ^2	5,053.850		26,366.340		7,692.670	

Notes: se = standard error. FMCG = fast moving consumer goods.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Table C.4
Alternative specifications of beginning and ending sequences.

Dependent variable		Model C4.1		Model C4.2	
		Begin and end 3 s long		Begin and end 4 s long	
		Intention to share		Intention to share	
		b	se	b	se
Likeability	Begin	0.111 ***	0.011	0.130 ***	0.011
	End	0.282 ***	0.009	0.288 ***	0.010
	Peak	0.162 ***	0.011	0.130 ***	0.011
	Peak * Diff. to context	0.007 **	0.003	0.010 ***	0.003
	Trend	−0.064	0.144	0.007	0.148
	Variability	0.103 ***	0.034	0.084 **	0.034
Consumer-specific controls	Gender	0.342 ***	0.044	0.342 ***	0.044
	Academic degree	−0.207 ***	0.049	−0.202 ***	0.049
	Age 18–25	0.769 ***	0.097	0.774 ***	0.097
	Age 26–40	0.604 ***	0.076	0.606 ***	0.076
	Age 41–55	0.342 ***	0.074	0.343 ***	0.074
Ad-specific controls	Ad length short	0.011	0.091	0.007	0.090
	Ad length long	0.314 **	0.128	0.319 **	0.127
	FMCG	0.074	0.112	0.074	0.111
	Pharmacy	0.113	0.202	0.103	0.201
	Retail	0.087	0.132	0.089	0.131
	Automobile	0.062	0.143	0.064	0.141
	Media	0.153	0.160	0.157	0.158
	Technology	0.324 *	0.173	0.315 *	0.171
	Constant	2.220 ***	0.126	2.277 ***	0.125
	N	43,295		43,295	
	χ^2	9,696.870		9,883.150	

Notes: se = standard error. FMCG = fast moving consumer goods.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

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