Marketing Science Institute Working Paper Series 2014
Report No. 14-113

Dynamic Likeability Effects on Virality of Online Video Advertisements

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Report Summary

As video advertising grows worldwide, there is substantial managerial interest in designing video advertisements that become viral. Since ads are dynamic, understanding the relationship between ad likeability dynamics and viral potential is essential; however, existing research mostly ignores the dynamic nature of online advertisements.

Edlira Shehu, Tammo Bijmolt, and Michel Clement add new knowledge to the emerging stream of viral marketing studies by investigating the relationship between virality (measured as consumer willingness to share) and the moment-to-moment likeability of ads.

Building on a memory-based theoretical framework, they use data including more than 43,000 observations and 120 spots collected from a YouTube channel, in cooperation with Google and MetrixLab. In a random effects regression, they identify key likeability moments that determine viral potential.

Overall, their results show that likeability dynamics are important and that using average likeability is not sufficient for predicting viral success of video advertisements. Among their findings:

- There are significant positive effects of likeability evaluations for the beginning and end of online advertisements; further, the effect for the end is higher than that for the beginning (consistent with the memory-based framework).

- Peak moments in online ads enhance viral potential, and this influence is amplified when the peak moment differs significantly from its surrounding moments.

- Linear stories may not be helpful to increase viral success.

- Increased variability in moment-to-moment likeability during an online video advertisement does not increase consumers’ willingness to share; further, viral potential decreases when likeability varies too strongly.

- Advertisements longer than the conventional 30 seconds increase willingness to share, and there is a positive product category effect related to technological products.

Managerial implications
This study offers novel managerial insights for developing viral advertising. It is not enough to create online ads that start with a “big bang”; advertising managers should create ads with a distinct, special, peak moment that stands out over the rest and that have a highly likeable ending. In addition, the overall trend of the ad should be non-declining.

The rollercoaster effect due to very high variability in likeability sequences harms the viral potential of online video advertisements. Therefore, very surprising elements or extremely activating storylines will probably backfire.

This study also points to the need for a new pretest mechanism that measures dynamic likeability and willingness to share. In practice, advertising agencies already tend to pretest several advertising plots and launch the most successful online; these findings suggest the need to add a moment-to-moment pretest. By examining dynamic likeability effects, companies can better evaluate the viral potential of their advertisements and select the most promising options.

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Acknowledgments
The authors thank the market research company MetrixLab for generously sharing the project data. They also thank Harald van Heerde, the participants of the 10th Marketing Dynamics Conference, and 36th Marketing Science Conference for valuable comments on prior versions of this article.

Dynamic Likeability Effects on Virality of Online Video Advertisements

Online videos and advertising inserted within them are growing rapidly. According to YouTube statistics (2013), consumers watch more than 6 billion hours of video each month on YouTube; 98 of *AdAge*'s Top100 advertisers appear on YouTube or Google's Display Network. Because they 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 must like the online advertisements enough to share them. In this sense, understanding the relationship between consumers' liking of online advertisements and their viral potential is essential for designing successful viral advertising campaigns.

Word-of-mouth research (e.g., De Angelis et al. 2012) 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), consumers' liking of the advertisement clearly might vary during its presentation (Baumgartner, Sujan, and Padgett 1997). Thus, we must consider specifically how likeability dynamics relate to viral potential. Research already has established how these 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). But how do likeability dynamics relate to the viral potential of advertisements? For example, should advertisers seek to enhance consumers' liking at the start, the end, or through the advertisement?

Insights from past research regarding the influences of likeability dynamics on the virality of online video advertisements are scarce. Existing findings pertaining to zapping behavior for example (Teixeira, Wedel, and Pieters 2012) do not transfer readily to measures of viral potential; unlike skipping decisions, the decision to share content reveals the consumer's liking of a specific online video advertisement to the recipients (e.g., friends in social networks). To avoid negative image effects, consumers likely watch any 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 Unava 2009). Accordingly, viral success demands more than watching the online video advertisement, because consumers must be willing to share. Understanding the link between consumers' likeability dynamics and online video advertisements' viral potential thus requires specific insights.

To investigate this relationship, 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 this viral potential. 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 most important for increasing the probability that they will be shared.

Conceptualization 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, Schoeler, 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, most studies suggest 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 (e.g., Berger and Milkman 2012) and relate them to viral potential.

Psychology research, however, indicates that consumers who make overall evaluations, 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 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 find that dynamic effect 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' willingness to share and the viral success of online video advertisements. Consequently, investigating consumers' likeability dynamics as the online advertisement plays, differentially affecting their willingness to share the advertisement with other consumers is essential for understanding viral success of video advertisements.

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, separate, temporally separated judgments, because some moments exert more influence than others (Montgomery and Unnava 2009; Kahneman et al. 1993; Loewenstein and Prelec 1993). Overall judgments might emerge as the event occurs (e.g., zapping behavior; 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 only 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). For viral advertising, consumers' willingness to forward should not rely equally on their liking of every moment. We build on this memory-based framework to understand the dynamic relationship between likeability and overall willingness to share.

Hypotheses

Our theoretical memory-based framework and related research on dynamic effects in advertising research suggests 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.

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 strongly (Kahneman et al. 1993). In line with primacy effects, initial moment evaluations should be easier for consumers to remember and thus influence their retrospective judgments (Montgomery and Unnava 2009). Substantial experimental support for this effect appears in consumer behavior research (Ariely and Zauberman 2000). Similarly, the recency effect implies that consumers readily recall the liking that they experienced most recently. Consumer behavior research again affirms this effect (Ariely and Zauberman 2003; Kahneman et al. 1993), as does advertising research. Baumgartner, Sujan, and Padgett (1997) find that the end effect provides one of the best predictors of the overall likeability of an advertisement; it also influences overall humor evaluations (Elpers, Mukherjee, and Hoyer 2004) and zapping behavior (Elpers, Wedel, and Pieters 2003; Teixeira, Wedel, and Pieters 2012). These effects should be especially intense for retrospective evaluations.

With our 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' willingness to share it. In addition, primacy effects may be dominated by recency effects in retrospective evaluations (Montgomery and Unnava 2009), because recall diminishes with increasing time since an exposure to a stimulus (Greene 1986). 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, because consumers better recall their liking of the last moments of an online advertisement when deciding whether to share it. Formally,

H_1: Higher likeability at the beginning of an online video advertisement has a positive influence on consumers' willingness to share it.

H_2: Higher likeability at the end of an online video advertising has a positive influence on consumers' willingness to share it.

H_3: The end likeability effect on consumers' willingness to share an online video advertising is greater than the beginning effect.

Peak effect. According to the memory-based framework, a peak evaluation exerts a strong impact on retrospective overall judgments, 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 overall evaluations. Support for this peak effect 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 likeability in offline contexts.

We further argue that the peak effect on retrospective overall evaluations should be amplified by the difference between the magnitude of the peak and those of the sequences 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 Unava (2009) show, the distinctiveness of the peak affects retrospective overall evaluations significantly, even if it offers (relatively) low absolute intensity. Accordingly, we posit:

H$_{4a}$: Peak likeability during an online video advertisement has a positive influence on consumers' willingness to share it.

H$_{4b}$: The peak effect is amplified by high differences between the peak evaluation and evaluations of the surrounding moments.

Trend effect. With respect to an experience, a trend 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, our 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). We find empirical support for this trend effect in multiple domains, including pain (Ariely 1998), discomfort (Kahneman et al. 1993), and advertising. 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). We predict:

H_{5a}: Likeability sequences with greater positive overall trends increase willingness to share online video advertisements, compared with neutral sequences.

H_{5b}: Likeability sequences with greater negative overall trends decrease willingness to share online video advertisements, compared with neutral sequences.

Variability. Research into consumers' zapping behavior toward 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). 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 consumers' willingness to share the online video advertisement should be greater with higher variability in the likeability sequence evaluations.

However, evidence also shows that people prefer intermediate levels of stimulation and seek to maintain this preferred optimum stimulation level (McReynolds 1971; Steenkamp and Baumgartner 1992). An optimal simulation level in turn determines online consumer behavior, such as inclinations to browse (Raju 1980) or exploratory behavior in the web (Richarda and Chandrab 2005). When stimulation is lower than optimal, consumers seek more novelty to satisfy their need for arousal (Zuckerman 1994). However, very high levels of stimulation, beyond the optimal point, can negatively affect evaluations of an advertisement (Steenkamp, Baumgartner and Van der Wulp 1996) and its self-enhancement value (Richarda and Chandrab 2005). We therefore expect an inverted U-shaped effect of likeability variability: Higher levels of variability increase viral potential up to a certain point (optimal stimulation level), whereas strong upward or downward movements of consumers' likeability around this optimal stimulation point negatively influence overall evaluations, or at least increase consumers' uncertainty, leading them to avoid sharing the advertisement (Anderson 2003; Jin and Villegas 2007). Therefore, we hypothesize:

H_6: The variability of likeability evaluations has an inverted U-shaped effect on the viral potential of video advertisements.

Empirical Study

Data

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 seconds 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 1 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 YouTube users who had joined a representative panel. Every respondent evaluated five video advertisements. On average, each advertisement was watched and evaluated by 361 respondents, with a minimum of 232 and a maximum of 536 respondents.

Measures

The dependent variable, reflecting the viral potential of an online video advertisement (Table 1), assessed participants' stated probability of sharing 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"). (Tables follow References.)

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 MtM 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 likeabilty for advertisements (Baumgartner, Sujan, and Padgett 1997) or slider scale to indicate likeabilty for music videos (Nelson et al. 2009).

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 consumers' 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 Figure 1, Panels a and b). In addition, the volatility in likeability evaluations varied substantially: Whereas some respondents' trajectories were smooth (e.g., Figure 1, Panel b), other trajectories indicated strong upward and downward movements (Figure 1, 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 online advertisements, we measured average likeability for the second and third second of each video advertisement. The final likeability values were the average likeability for the last two seconds of each online 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 two seconds before and after the peak. 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:

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

We estimated Equation 1 separately for every moment-to-moment likeability sequence of each respondent. The parameter β_1 depicted the linear trend, and then we derived two variables, representing the magnitude of positive/negative trends, 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. Thus, the two variables captured the distinct effects of increasing linear positive and negative trends (Table 2).

For the operationalization of the variability of likeability sequences, we used the standard deviation of the error terms, after separating the linear trend and the intercept according to Equation 1. This approach followed established methods of calculating volatility in time-series analyses (e.g., Chandrasekaran et al. 2013; Luo 2009).

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 (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 seconds, between 27 and 30 seconds, or longer. The typical advertisement length was 30 seconds, so we used the second indicator as the reference category and measured for any effects of shorter or longer advertisements.

The correlation coefficients across all the variables revealed no multicollinearity issues (see Appendix 2). Our collinearity analyses also offered no indication of multicollinearity (maximal variance inflation factor [VIF] = 5.68 for the end evaluation; mean VIF = 2.17).

Analysis

To test our hypotheses, we identified the effects of likeability evaluations on the viral potential of each online video advertisement, using a random effects regression model. Willingness to share the online advertisement served as the dependent variable. We controlled for unobserved heterogeneity across advertisements and respondents with two non-nested random intercepts at the advertisement and respondent levels, respectively:

$$\begin{aligned} \text{Virality}_{ij} = {} & \beta_o + \beta_1 \text{Begin}_{ij} + \beta_2 \text{End}_{ij} + \beta_3 \text{Peak}_{ij} + \beta_4 \text{Pos\_Trend}_{ij} + \\ & \beta_5 \text{Neg\_Trend}_{ij} + \beta_6 \text{Variability}_{ij} + \beta_7 \text{Variability}^2{}_{ij} + \\ & \beta_8 \text{Peak}_{ij} (\text{Peak}_{ij} - \text{Difference\_Context}) + \sum_{k=1}^{K} \theta_k X_{ik} + \sum_{m=1}^{M} \theta_m X_{jm} + \nu_i + \eta_j + \varepsilon_{ij}, \end{aligned} \tag{2}$$

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 effects (Model 1, Table 3). To test the robustness of the model specification, we estimated Model 2, where the interaction of the peak evaluation with the (mean-centered) difference of the peak moment from its surrounding context is excluded from the model specification.

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 = .062, $p < .001$) and end (b = .207, $p < .001$) 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 = 44.94; $p < .001$). We also tested the difference of the estimated coefficients for the end and the beginning effects, which offered further support for H_3 (Wald $\chi^2 = 85.76$, $p < .001$). In line with the memory-based framework, the end likeability effect on the viral potential of online advertisements was greater than the beginning effect.

We found a significant, positive impact of the peak moment-to-moment evaluation (b = .313, $p < .001$), in line with H_{4a}. This positive effect was amplified when the peak differed significantly from its surrounding moments (Model 1; b = .019, $p < .001$), in support of $H_{4b.}$

For the trend effects hypotheses, we investigated whether viral potential increased with higher positive trends and decreased for higher negative trends. In Model 1 the positive effect of increasing positive trends on consumers' willingness to share, as we predicted in H_{5a}, was not supported. The effect even was negative, though not significant (b = -.151, p =.432). The significant, positive coefficient of the negative trend variable (b = .259, p = .158) also does not provide support for the harming effect of increasing negative trend of likeability according to H_{5a}. Obviously, the linear trend effects do not determine the viral potential of online video advertisements. In Model 2, which excludes the interaction between peak and the surrounding moments, however, we find an emerging significant effect of the negative trend matching our expectations of the effects of negative trends according to H_{5b} (b = .305, $p < .095$). This leads to the assumption that the significance level of the negative trend parameter moves above the significance of .10 as a result of higher multicollinearity, which resulted from due to the additional interaction effect in this model specification. Still, because this effect does not seem to be stable, we only find minor support for hypothesis H_{5b}.

Regarding the variability of likeability evaluations, we found a non-significant linear effect (b = –.071, p = .251), whereas the squared effect influenced consumers' willingness to share negatively (b = –.116, $p < .001$). That is, we found partial support for H_6: Increasing variability in moment-to-moment likeability during an online video advertisement did not increase consumers' willingness to share, in contrast with our expectations, but the viral potential decreased when likeability varied too strongly. Figure 2 displays this inverse U-shaped relationship, in which the increase of the viral potential, due to greater moment-to-moment variability, is not steep enough, and viral potential decreases substantially in the case of very high variability levels.

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 seconds increased willingness to share. Finally, we found a positive product category effect related to technological products.

Alternative specification and sensitivity checks

We computed a series of consistency 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 3; Table 3.1). The effect is 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 shows a significantly better fit of our model with the dynamic likeability effects ($z=169.29$; $p < .001$). This indicates that basing virality judgments only on average evaluations may not be sufficient.

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 fit 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 3; Table 3.2). 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) are significant, whereas the remaining dimensions have no significant effects. All hypothesized likeability effects remain consistent 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 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, as described previously. To test the robustness of our results to potential biases related to this forced exposure setting, we median split the sample according to the time the participants spent viewing each advertisement 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 some of the advertisement and those who would have watched (almost) the entire video (see Appendix 3, Table 3.3). 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 amount (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 both the positive (.068 versus .082, $p < .01$) and negative (-.054 versus -.042, $p < .01$) trends appeared significantly lower in the groups that exhibited lower viewing times. 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 willingness to share remained consistent.

We also tested whether the amplification of the peak effect due to the difference from its surrounding moments varied with our definition of how long the peak or its surrounding context lasted. Specifically, we tested different specifications of the peak effect in which it lasted 1, 3, or 5 seconds and the surrounding context consisted of 1, 2, 3 or 4 seconds before and after the peak. All model specifications led to results that were consistent with those we obtained from Model 1, with regard to the size and significance findings that emerged from the models (see Appendix 4).

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 seconds, all the effects remained consistent (see Appendix 5).

Discussion

The 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 consumers' liking of an advertisement probably changes during the advertisement's timeline. We therefore have examined how viral success (measured by willingness to share) relates to consumers' likeability dynamics over the course 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. In a random effects regression, we identify key likeability moments that determine viral potential.

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 consumers' 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 (e.g., 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 any significant effects of linear trends. These findings complement existing results on viral advertising, which show that overall negative emotions do not always harm virality content, and even may increase transmissions (Berger and Milkman 2012). Whereas these prior findings did not consider the sequence (trend) of the negative emotions, which requires capturing the likeability trend of online video advertisements according to the sequence of the advertisements, we show that magnitude of the linear trends does not help the viral potential showing that linear stories may not be helpful to increase the viral success. We find indications, however, that stronger negative trends can harm viral potential.

Very high variability in likability also can harm viral success. Shedding light on the transmission process, our results expand findings related to online zapping behavior that indicate that variability effects may be ambiguous, in the sense that they increase consumers' attention but attenuate their retention (Teixeira, Wedel, and Pieters 2012). We go a step further and confirm an ambiguous effect of variability for viral advertising purposes. Our prediction that increasing levels of variability, up to a certain point, would indicate higher activation during online video advertisements and increase viral potential was not supported empirically. Greater variability did not enhance viral potential; after a certain point, it even led to negative effects. This effect might stem from a lack of optimal stimulation, such that overly high stimulation exerts negative effects on consumers' overall evaluation and the self-enhancement value of the advertisement.

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 make sure that the overall trend is non-declining.

The rollercoaster effect due to very high variability in likeability sequences also harms the viral potential of online video advertisements. Therefore, very surprising elements or extremely activating storylines probably will backfire, because consumers avoid sharing them as a result of their strong uncertainty. 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 willingness to share. 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 people’s underlying motivations to share 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 consumers’ stated willingness to share. Further studies could complement and validate our findings by investigating the actual sharing behavior displayed by consumers.

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Figure 1. Moment-to-Moment Evaluation Patterns: Low and High Variability

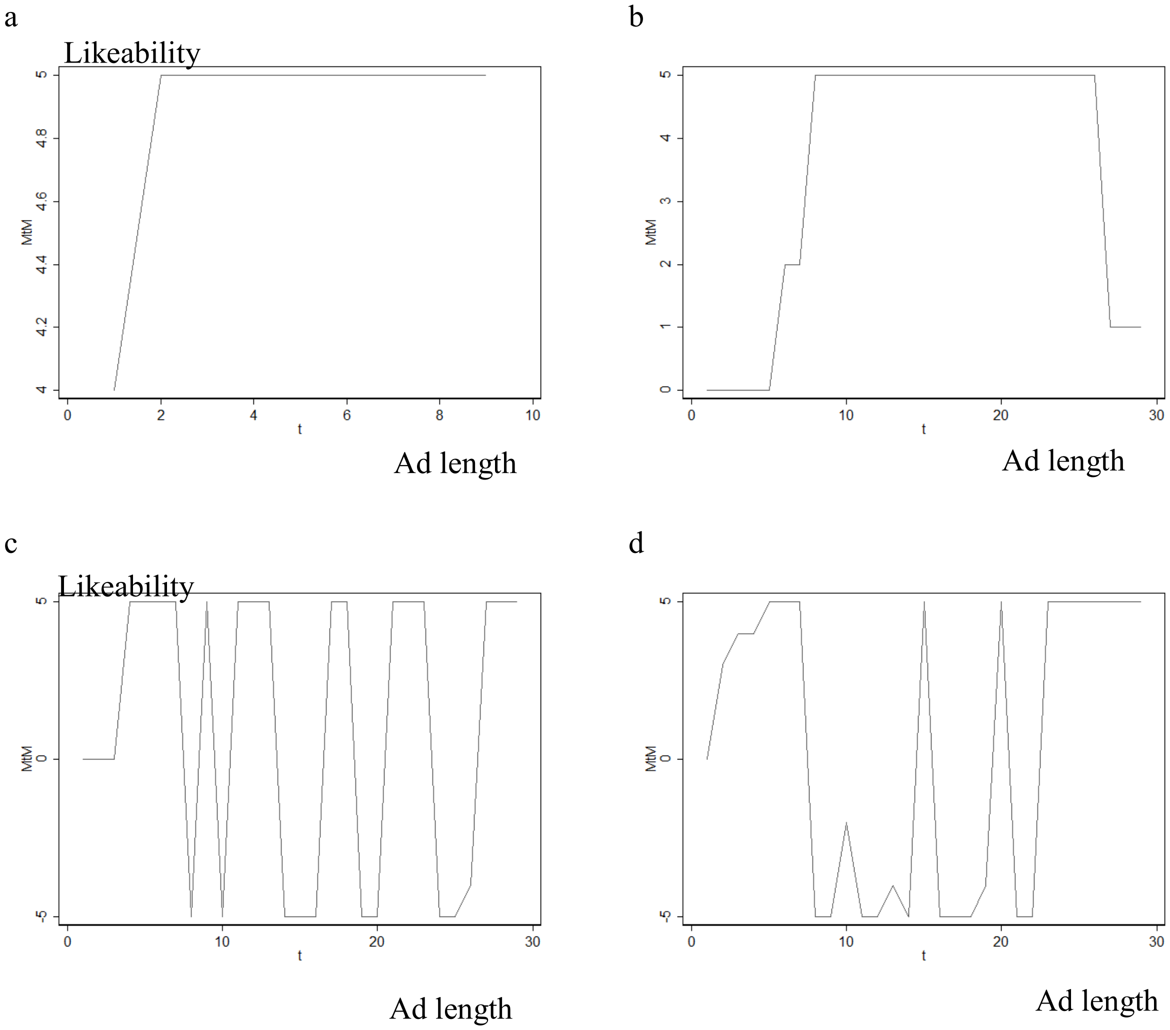
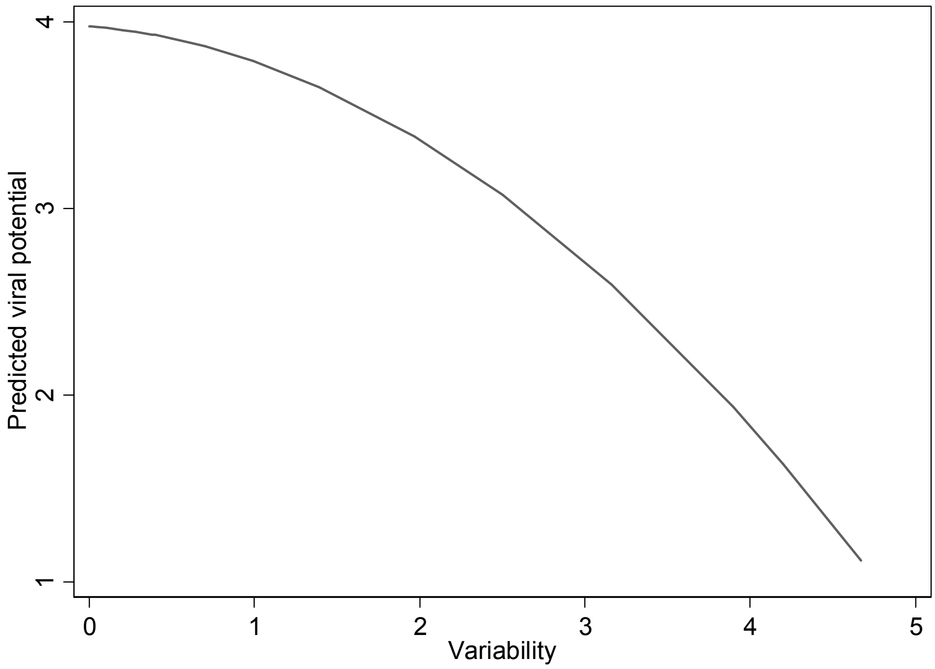


Figure 2. Effect of Variability in Likeability Evaluations



Note: This figure displays the predicted willingness to share spots according to Model 1 for sample range of variability (0-4.67, see Table 2) and sample mean of all remaining variables.

Table 1. Data Measurement Levels and Operationalization

	Construct	Measurement Level	Source	Scale/ Operationalization
Consumer-specific information	Viral potential (dependent variable)	Respondent/ advertisement	Survey	1 ("very unlikely") to 11 ("very likely")
	Likeability	Respondent/ advertisement second	Survey	–5 ("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 seconds, 30 seconds [reference category], 31–73 seconds)
	Product category	Advertisement	4 raters	Dummy coding for consumer goods, services (reference category), retail, automobile, media, technology, pharmacy

Table 2. Descriptive Statistics

	Variables	Mean	Standard Deviation	Min	Max
Viral potential	Willingness 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
	Difference, peak to context	1.071	1.103		
	Positive trend	.076	.120	0	1.283
	Negative trend	-.058	.129	-1.283	0
	Variability	1.096	.649	0	4.670
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 (27-30s)	.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			

Table 3. Effects of Likeability Dynamics on Viral Potential

		Model 1				Model 2			
		Coef.		SE	*p*	Coef.		SE	*p*
Likeability	Begin	0.062	***	0.012	0.001	0.056	***	0.012	0.001
	End	0.207	***	0.009	0.001	0.212	***	0.009	0.001
	Peak	0.313	***	0.012	0.001	0.309	***	0.012	0.001
	Peak ′ Diff. to context	0.019	***	0.003	0.001				
	Positive trend	-0.151		0.192	0.432	-0.238		0.191	0.211
	Negative trend	0.259		0.183	0.158	0.305	*	0.183	0.095
	Variability	-0.071		0.062	0.251	-0.025		0.062	0.681
	Variability^2	-0.116	***	0.018	0.001	-0.115	***	0.018	0.001
Consumer-specific controls	Gender	0.346	***	0.044	0.001	0.345	***	0.044	0.001
	Academic degree	-0.198	***	0.049	0.001	-0.204	***	0.049	0.001
	Age 18–25	0.804	***	0.097	0.001	0.807	***	0.097	0.001
	Age 26–40	0.630	***	0.076	0.001	0.635	***	0.076	0.001
	Age 41–55	0.357	***	0.074	0.001	0.359	***	0.074	0.001
Ad-specific controls	Ad length short	0.046		0.094	0.626	0.057		0.094	0.543
	Ad length long	0.269	**	0.131	0.041	0.263	**	0.132	0.047
	FMCG	0.075		0.115	0.515	0.078		0.116	0.501
	Pharmacy	0.167		0.208	0.422	0.169		0.209	0.419
	Retail	0.075		0.135	0.581	0.075		0.136	0.583
	Automobile	0.075		0.146	0.607	0.073		0.147	0.621
	Media	0.123		0.164	0.453	0.123		0.165	0.456
	Technology	0.323	*	0.177	0.068	0.322	*	0.178	0.07
	Constant	2.227	***	0.13	0.001	0.727	***	0.004	0.001
	N	43295				43295			
	χ^2	9758.94				9741.55			

Notes: Coef. = coefficient. SE = standard error. FMCG = fast moving consumer goods.

*$p < .10$.

**$p < .05$.

***$p < .01$.

Appendix 1: Overview of Spots

#	Category	Brand	Length (s)	N	Frequency (%)	Cumulative Frequency
1	Auto.	Suzuki	19	370	0.855	0.855
2	Auto.	Mercedes	29	353	0.815	1.670
3	Auto.	BMW	39	345	0.797	2.467
4	Auto.	Renault	73	331	0.765	3.231
5	Auto.	Porsche	29	324	0.748	3.980
6	Auto.	Toyota	19	243	0.561	4.541
7	Auto.	Dacia	29	283	0.654	5.195
8	Auto.	Mercedes	29	368	0.850	6.045
9	Auto.	Renault	39	412	0.952	6.996
10	Auto.	VW	29	395	0.912	7.909
11	Auto.	Audi	44	330	0.762	8.671
12	Auto.	Toyota	15	339	0.783	9.454
13	Auto.	Mini	29	462	1.067	10.521
14	Auto.	VW	41	437	1.009	11.530
15	FMCG	Whiskas	20	402	0.929	12.459
16	FMCG	Rittersport	20	399	0.922	13.380
17	FMCG	Ahoi Brause	15	386	0.892	14.272
18	FMCG	Sensodyne	19	386	0.892	15.163
19	FMCG	Schwarze Dose	9	284	0.656	15.819
20	FMCG	Hanuta	15	338	0.781	16.600
21	FMCG	Landliebe	21	304	0.702	17.302
22	FMCG	Fa	20	272	0.628	17.930
23	FMCG	Syoss	20	265	0.612	18.543
24	FMCG	Philadelphia	11	290	0.670	19.212
25	FMCG	Capri Sonne	29	332	0.767	19.979
26	FMCG	Krombacher	34	337	0.778	20.758
27	FMCG	Right	20	320	0.739	21.497
28	FMCG	Purina	23	305	0.704	22.201
29	FMCG	Coca Cola	41	300	0.693	22.894
30	FMCG	Hohes C	27	296	0.684	23.578
31	FMCG	Hochland	18	271	0.626	24.204
32	FMCG	Cesar	20	347	0.801	25.005
33	FMCG	Müller	16	315	0.728	25.733
34	FMCG	Max Factor	19	249	0.575	26.308
35	FMCG	Rügenwalder Mühle	23	243	0.561	26.869
36	FMCG	AXE	19	253	0.584	27.454
37	FMCG	Zoltarella	21	270	0.624	28.077
38	FMCG	Cleopatra	19	358	0.827	28.904
39	FMCG	Danone	20	365	0.843	29.747

40	FMCG	Syoss	20	397	0.917	30.664
41	FMCG	Air Wick	19	375	0.866	31.530
42	FMCG	Milka	24	438	1.012	32.542
43	FMCG	Zott	29	298	0.688	33.230
44	FMCG	Wrigley	20	364	0.841	34.071
45	FMCG	Haribo	29	377	0.871	34.942
46	FMCG	Coca-Cola	59	389	0.898	35.840
47	FMCG	Alete	24	409	0.945	36.785
48	FMCG	Swiffer	20	439	1.014	37.799
49	FMCG	Adidas	20	424	0.979	38.778
50	FMCG	Nivea	20	479	1.106	39.885
51	FMCG	Milka	30	536	1.238	41.123
52	FMCG	real	27	467	1.079	42.201
53	FMCG	Pepsi	23	454	1.049	43.250
54	FMCG	Head and Shoulders	20	492	1.136	44.386
55	FMCG	ültje	20	488	1.127	45.513
56	FMCG	Reis fit	21	417	0.963	46.476
57	FMCG	Kitkat	23	416	0.961	47.437
58	FMCG	Fisherman’s Friend	9	357	0.825	48.262
59	FMCG	Pick up	19	418	0.965	49.227
60	FMCG	Ferrero	19	429	0.991	50.218
61	Media	13th Street	29	346	0.799	51.017
62	Media	Base	18	340	0.785	51.803
63	Media	O2	29	289	0.668	52.470
64	Media	Telekom	23	272	0.628	53.099
65	Media	O2	29	362	0.836	53.935
66	Media	MTV	29	318	0.734	54.669
67	Media	Vodafone	41	308	0.711	55.381
68	Media	O2	20	482	1.113	56.494
69	Media	Congstar	29	471	1.088	57.582
70	Pharmacy	Ratiopharm	18	316	0.730	58.312
71	Pharmacy	Kytta Salbe	23	255	0.589	58.901
72	Pharmacy	Voltaren	28	487	1.125	60.025
73	Pharmacy	herzbewusst.de	20	432	0.998	61.023
74	Pharmacy	Dolormin	16	430	0.993	62.016
75	Retail	Reebok	29	411	0.949	62.966
76	Retail	Adler	19	365	0.843	63.809
77	Retail	Deichmann	29	341	0.788	64.596
78	Retail	Hagebau	29	373	0.862	65.458
79	Retail	Praktiker	28	296	0.684	66.142
80	Retail	Ecco	29	271	0.626	66.768
81	Retail	McDonalds	23	294	0.679	67.447
82	Retail	IKEA	19	277	0.640	68.086

83	Retail	Saturn	23	323	0.746	68.832
84	Retail	Diesel	19	304	0.702	69.535
85	Retail	Media Markt	23	335	0.774	70.308
86	Retail	Ebay	29	330	0.762	71.071
87	Retail	Hugo	19	280	0.647	71.717
88	Retail	Obi	39	380	0.878	72.595
89	Retail	IKEA	23	286	0.661	73.256
90	Retail	Zalando	20	491	1.134	74.390
91	Retail	Takko	20	461	1.065	75.454
92	Services.	Mastercard	29	400	0.924	76.378
93	Services	Gothaer	24	446	1.030	77.408
94	Services	Preis24.de	29	399	0.922	78.330
95	Services	Aachener Münchener	15	363	0.838	79.168
96	Services	Autohaus24.de	29	306	0.707	79.875
97	Services	Prokon	19	295	0.681	80.557
98	Services	Flexstrom.de	9	232	0.536	81.093
99	Services	LBS	33	325	0.751	81.843
100	Services	Volks-und Raiffeisenbanken	13	253	0.584	82.428
101	Services	Deutsche Bahn	27	311	0.718	83.146
102	Services	ADAC	24	352	0.813	83.959
103	Services	Allianz	30	354	0.818	84.777
104	Services	Postbank	19	296	0.684	85.460
105	Services	Google	47	386	0.892	86.352
106	Services	Deutsche Post	23	359	0.829	87.181
107	Services	Deutsche Telekom	29	381	0.880	88.061
108	Services	Sparkasse	29	492	1.136	89.197
109	Services	McFit	29	488	1.127	90.325
110	Services	Dell	29	453	1.046	91.371
111	Services	Thomas Cook	23	465	1.074	92.445
112	Services	Evonik	29	464	1.072	93.517
113	Techn.	AEG	39	365	0.843	94.360
114	Techn.	Nintendo	20	250	0.577	94.937
115	Techn.	Bosch	47	276	0.637	95.575
116	Techn.	Wii	18	275	0.635	96.210
117	Techn.	iPad	29	278	0.642	96.852
118	Techn.	Euronics	15	362	0.836	97.688
119	Techn.	Panasonic	39	508	1.173	98.861
120	Techn.	hp	29	493	1.139	100.000
	Total			43,295	100	

Note: Auto.=Automobile; Techn.=Technology

Appendix 2: Correlations of Independent Variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Viral potential	1.00															
2	Begin	0.25	1.00														
3	End	0.43	.39	1.00													
4	Peak	0.36	.55	.68	1.00												
5	Positive trend	0.02	-.02	.63	.44	1.00											
6	Negative trend	0.25	.03	.67	.28	.40	1.00										
7	Variability	0.26	.01	-.14	.39	-.01	-.22	1.00									
8	Gender	-0.06	-.03	-.07	-.15	.18	-.16	-.08	1.00								
9	Academic degree	0.01	.03	.09	.13	-.12	.10	.04	-.43	1.00							
10	Age 18–25	-0.06	-.03	-.08	-.07	-.06	-.04	-.01	.00	.00	1.00						
11	Age 26–40	0.03	-.03	-.09	-.03	-.06	-.07	.07	.00	.00	.10	1.00					
12	Age 41–55	0.03	.02	-.01	.03	-.02	-.01	.05	-.01	.00	-.07	-.07	1.00				
13	Ad length short	-0.02	.00	-.02	.01	-.02	-.01	.05	.00	.00	-.07	.05	-.25	1.00			
14	Ad length long	-0.04	-.01	.02	-.02	.02	.01	-.04	.00	.00	.03	-.04	-.28	-.66	1.00		
15	FMCG	0.07	.02	.01	-.03	.09	-.04	-.03	.39	-.15	.00	.00	.00	.00	-.01	1.00	
16	Pharmacy	0.00	.04	-.01	-.01	-.01	-.04	.01	.08	-.08	.00	.00	.00	.00	.00	-.17	1.00
17	Retail	0.00	-.02	.00	.02	.01	.02	.02	.02	-.07	.00	.00	.00	.00	.00	-.31	-.08
18	Automobile	0.00	.02	.04	.06	-.05	.04	.04	-.27	.27	.01	.00	.00	.00	.00	-.29	-.08
19	Media	0.02	-.04	-.03	-.03	-.05	.01	-.01	-.12	-.02	.00	.00	.00	.00	.01	-.22	-.06
20	Technology	-0.02	.02	.00	.03	-.05	.00	.01	-.13	.23	.00	.01	.01	.00	.00	-.21	-.06

		17	18	19	20
17	Retail	1.00			
18	Automobile	-.14	1.00		
19	Media	-.11	-.10	1.00	
20	Technology	-.10	-.10	-.07	1.00

Appendix 3: Alternative Specifications and Robustness Checks

Table 3.1. Results of Model Specification with Mean Overall Likeability

		Coeficient		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	43295.000		
	χ^2	10260.300		

Notes: SE = standard error. FMCG = fast moving consumer goods.

*p < .10.

**p < .05.

***p < .01.

Table 3.2. Results of Model Specification with Ad Content

		Coefficient		SE
Likeability	Begin	0.061	***	0.012
	End	0.208	***	0.009
	Peak	0.295	***	0.013
	Peak ´ Diff. to context	0.019	***	0.003
	Positive trend	-0.172		0.192
	Negative trend	0.259		0.184
	Variability	-0.068		0.063
	Variability^2	-0.118	***	0.018
Consumer-specific controls	Gender	0.344	***	0.044
	Academic degree	-0.198	***	0.049
	Age 18–25	0.794	***	0.097
	Age 26–40	0.626	***	0.076
	Age 41–55	0.353	***	0.074
Ad-specific controls	Ad length short	0.247	**	0.121
	Ad length long	0.493	***	0.147
	FMCG	0.179		0.126
	Pharmacy	0.423	**	0.203
	Retail	0.174		0.146
	Automobile	0.129		0.147
	Media	0.103		0.167
	Technology	0.363	**	0.177
	Irritating	0.118		0.074
	Relevant	0.114	*	0.068
	Stimulating	-0.016		0.047
	Entertaining	0.187	***	0.054
	Familiar	-0.05		0.049
	Warm	0.039		0.038
	Constant	0.903	**	0.454
	N	42933		
	χ^2	9780.75		

Notes: SE = standard error. FMCG = fast moving consumer goods.

*p < .10.

**p < .05.

***p < .01.

Table 3.3. Robustness Check Towards Forced Exposure Effects

		C3.1: Viewing time ≤ ad medium viewing time			C3.2: viewing time > ad medium viewing time		
		Coefficient		SE	Coefficient		SE
Likeability	Begin	.043	**	.017	.093	***	.017
	End	.207	***	.013	.214	***	.013
	Peak	.273	***	.017	.349	***	.018
	Peak × Diff. context	.020	***	.004	.019	***	.004
	Positive trend	.101		.289	-.418		.268
	Negative trend	.315		.264	.339		.266
	Variability	-.131		.089	-.144		.09
	Variability^2	-.094	***	.026	-.11	***	.026
Consumer-specific controls	Gender	.362	***	.054	.349	***	.056
	Academic degree	-.195	***	.06	-.218	***	.061
	Age 18–25	.951	***	.119	.711	***	.124
	Age 26–40	.688	***	.096	.603	***	.094
	Age 41–55	.406	***	.094	.389	***	.092
Ad-specific controls	Ad length short	.076		.099	-.014		.101
	Ad length long	.292	**	.139	.183		.141
	FMCG	.04		.12	.108		.123
	Pharmacy	.169		.23	.157		.221
	Retail	.051		.141	.109		.145
	Automobile	.06		.151	.092		.157
	Media	.156		.167	.09		.176
	Technology	.311	*	.182	.328	*	.19
	Constant	2.109	***	.148	2.329	***	.15
	N	19727			23568		
	χ^2	4447.85			5230.42		

Notes: SE = standard error. FMCG = fast moving consumer goods.

**p* < .10.

***p* < .05.

****p* < .01.

Appendix 4: Alternative Specifications of the Peak SurroundingEffect

	Specification	1_1*			1_3			1_4		
		Coefficient		SE	Coefficient		SE	Coefficient		se
Likeability	Begin	0.06	***	0.01	0.06	***	0.01	0.06	***	0.01
	End	0.21	***	0.01	0.21	***	0.01	0.21	***	0.01
	Üeal	0.31	***	0.01	0.31	***	0.01	0.24	***	0.02
	Peak*Diff to context	0.01	***	0.00	0.02	***	0.00	0.02	***	0.00
	Positive trend	-0.19		0.19	-0.12		0.19	-0.12		0.19
	Negative trend	0.28		0.18	0.23		0.18	0.23		0.18
	Variability	-0.05		0.06	-0.08		0.06	-0.08		0.06
	Variability^2	-0.12	***	0.02	-0.12	***	0.02	-0.12	***	0.02
Consumer-specific controls	Gender	0.35	***	0.04	0.35	***	0.04	0.35	***	0.04
	Academic degree	-0.20	***	0.05	-0.20	***	0.05	-0.20	***	0.05
	Age 18-25	0.81	***	0.10	0.80	***	0.10	0.80	***	0.10
	Age 26-40	0.63	***	0.08	0.63	***	0.08	0.63	***	0.08
	Age 41-55	0.36	***	0.07	0.36	***	0.07	0.36	***	0.07
Ad-specific controls	Ad length short	0.05		0.09	0.04		0.09	0.04		0.09
	Ad length long	0.27	**	0.13	0.27	**	0.13	0.27	**	0.13
	FMCG	0.08		0.12	0.08		0.12	0.08		0.12
	Pharmacy	0.17		0.21	0.16		0.21	0.16		0.21
	Retail	0.08		0.14	0.08		0.14	0.08		0.14
	Automobile	0.07		0.15	0.07		0.15	0.07		0.15
	Media	0.12		0.16	0.12		0.16	0.12		0.16
	Technology	0.32	*	0.18	0.32	*	0.18	0.32	*	0.18
	Constant	2.22	***	0.13	2.23	***	0.13	2.23	***	0.13
	N	43295.00			43295.00			43295.00		
	χ^2	9758.04			9809.97			9809.97		

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

		3_1			3_2			3_3			3_4		
		Coeff.		SE	Coeff.		SE	Coeff.		SE	Coeff.		se
Likeability	Begin	0.06	***	0.01	0.06	***	0.01	0.06	***	0.01	0.06	***	0.01
	End	0.21	***	0.01	0.21	***	0.01	0.21	***	0.01	0.21	***	0.01
	Peak	0.31	***	0.01	0.31	***	0.01	0.31	***	0.01	0.31	***	0.01
	Peak*Diff to context	0.01	***	0.00	0.01	***	0.00	0.01	***	0.00	0.01	***	0.00
	Positive trend	-0.16		0.19	-0.19		0.19	-0.16		0.19	-0.15		0.19
	Negative trend	0.26		0.18	0.28		0.18	0.26		0.18	0.26		0.18
	Variability	-0.06		0.06	-0.05		0.06	-0.06		0.06	-0.06		0.06
	Variability^2	-0.12	***	0.02	-0.12	***	0.02	-0.12	***	0.02	-0.12	***	0.02
Consumer-specific controls	Gender	0.35	***	0.04	0.35	***	0.04	0.35	***	0.04	0.35	***	0.04
	Academic degree	-0.20	***	0.05	-0.21	***	0.05	-0.20	***	0.05	-0.20	***	0.05
	Age 18-25	0.81	***	0.10	0.80	***	0.10	0.80	***	0.10	0.80	***	0.10
	Age 26-40	0.63	***	0.08	0.63	***	0.08	0.63	***	0.08	0.63	***	0.08
	Age 41-55	0.36	***	0.07	0.36	***	0.07	0.36	***	0.07	0.36	***	0.07
Ad-specific controls	Ad length short	0.05		0.09	0.05		0.09	0.05		0.09	0.05		0.09
	Ad length long	0.27	**	0.13	0.27	**	0.13	0.27	**	0.13	0.27	**	0.13
	FMCG	0.08		0.12	0.08		0.12	0.08		0.12	0.08		0.12
	Pharmacy	0.17		0.21	0.17		0.21	0.17		0.21	0.17		0.21
	Retail	0.08		0.14	0.08		0.14	0.08		0.14	0.08		0.14
	Automobile	0.07		0.15	0.07		0.15	0.07		0.15	0.07		0.15
	Media	0.12		0.16	0.12		0.17	0.12		0.16	0.12		0.17
	Technology	0.32	*	0.18	0.32	*	0.18	0.32	*	0.18	0.32	*	0.18
	Constant	2.23	***	0.13	2.23	***	0.13	2.23	***	0.13	2.24	***	0.13
	N	43295.00			43295.00			43295.00			43295.00		
	χ^2	9775.26			9758.94			9768.46			9770.45		

Notes: Coeff. = coefficient. SE = standard error. FMCG = fast moving consumer goods. **p* < .10. ***p* < .05. ****p* < .01.

		5_1			5_2		
		Coefficient		SE	Coefficient		SE
Likeability	Begin	0.06	***	0.01	0.06	***	0.01
	End	0.21	***	0.01	0.21	***	0.01
	Peak	0.31	***	0.01	0.31	***	0.01
	Peak*Diff to context	0.02	***	0.00	0.01	**	0.00
	Positive trend	-0.16		0.19	-0.22		0.19
	Negative trend	0.26		0.18	0.29		0.18
	Variability	-0.07		0.06	-0.04		0.06
	Variability^2	-0.12	***	0.02	-0.12	***	0.02
Consumer-specific controls	Gender	0.35	***	0.04	0.35	***	0.04
	Academic degree	-0.20	***	0.05	-0.20	***	0.05
	Age 18-25	0.80	***	0.10	0.81	***	0.10
	Age 26-40	0.63	***	0.08	0.63	***	0.08
	Age 41-55	0.36	***	0.07	0.36	***	0.07
Ad-specific controls	Ad length short	0.05		0.09	0.05		0.09
	Ad length long	0.27	**	0.13	0.27	**	0.13
	FMCG	0.08		0.12	0.08		0.12
	Pharmacy	0.17		0.21	0.17		0.21
	Retail	0.08		0.14	0.08		0.14
	Automobile	0.07		0.15	0.07		0.15
	Media	0.12		0.16	0.12		0.17
	Technology	0.32	*	0.18	0.32	*	0.18
	Constant	2.23	***	0.13	2.22	***	0.13
	N	43295.00			43295.00		
	χ^2	9786.23			9749.11		

Notes: Coeff. = coefficient. SE = standard error. FMCG = fast moving consumer goods. **p* < .10. ***p* < .05. ****p* < .01.

The first number represents the peak length and the second the number of seconds before and after the peak. I.e., 1_1 represents an operationalization with peak amounting 1 second and the surrounding moments being defined as 1 second before and after the peak.

Appendix 5: Alternative Specifications of Beginning and Ending Sequences

		Beginning/End length 3 seconds			Beginning/End length 4 seconds		
		Coefficient		SE	Coefficient		SE
Likeability	Begin (3s)	0.089	***	0.01			
	End (3s)	0.237	***	0.01			
	Begin (4s)				0.115	***	0.01
	End(4s)				0.249	***	0.01
	Peak	0.255	***	0.01	0.211	***	0.01
	Peak ′ Diff. to context	0.021	***	0.01	0.022	***	0.01
	Positive trend	0.008		0.20	0.289		0.21
	Negative trend	-0.102		0.19	-0.207		0.20
	Variability	-0.006		0.06	0.041		0.06
	Variability^2	-0.117	***	0.02	-0.117	***	0.02
Consumer-specific controls	Gender	0.345	***	0.04	0.345	***	0.04
	Academic degree	-0.194	***	0.05	-0.191	***	0.05
	Age 18–25	0.805	***	0.10	0.808	***	0.10
	Age 26–40	0.630	***	0.08	0.632	***	0.08
	Age 41–55	0.357	***	0.07	0.357	***	0.07
Ad-specific controls	Ad length short	0.022		0.09	0.001		0.09
	Ad length long	0.287	**	0.13	0.303	**	0.13
	FMCG	0.078		0.11	0.079		0.11
	Pharmacy	0.140		0.21	0.132		0.21
	Retail	0.085		0.13	0.091		0.13
	Automobile	0.079		0.15	0.080		0.14
	Media	0.140		0.16	0.150		0.16
	Technology	0.320	*	0.18	0.315	*	0.18
	Constant	2.240	***	0.13	2.253	***	0.13
	N	43295			43295		
	χ^2	9947			10092.1		

Notes: Coeff. = coefficient. SE = standard error. FMCG = fast moving consumer goods.

*p < .10.

**p < .05.

***p < .01.