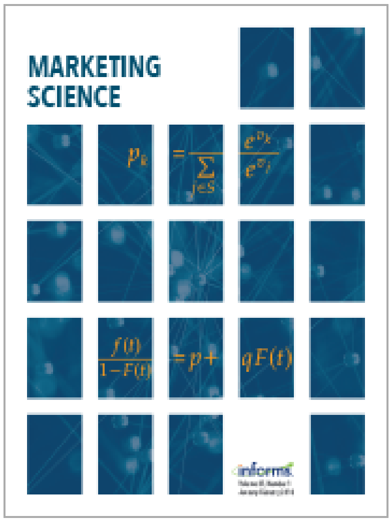

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The Reach and Persuasiveness of Viral Video Ads

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Many video ads are designed to go *viral* so that the total number of views they receive depends on customers sharing the ads with their friends. This paper explores the relationship between the number of views and how persuasive the ad is at convincing consumers to purchase or to adopt a favorable attitude towards the product. The analysis combines data on the total views of 400 video ads, and crowd-sourced measurement of advertising persuasiveness among 24,000 survey responses. Persuasiveness is measured by randomly exposing half of these consumers to a video ad and half to a similar placebo video ad, and then surveying their attitudes towards the focal product. Relative ad persuasiveness is on average 10% lower for every one million views that the video ad achieves. The exceptions to this pattern were ads that generated views *and* large numbers of comments, and video ads that attracted comments that mentioned the product by name. Evidence suggests that such ads remained effective because they attracted views due to humor rather than because they were outrageous.

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1. Introduction

In the past few years, digital marketing strategy has shifted away from an emphasis on "paid" media, where a brand pays to advertise, to "earned" media, where the customers themselves become the channel of delivery (Corcoran 2009). Reflecting this shift, social video advertising is among the fastest-growing segments in advertising today. In 2010, social video advertising views increased 230%, over nine times the growth in online search and display advertising (Olenski 2010). These video ads are crucially different from rich-media banner ads. Rather than the advertiser paying for placement, these ads are designed to be transmitted by consumers through posting on social media feeds or sharing directly with friends. This means that firms commission these video ads and post them on websites such as YouTube.com in the hope and expectation that consumers will encourage others to watch the video. This is evidently attractive for firms as it implies a cost free means of transmitting advertising. However, in common with other forms of earned media, the return on investment (ROI) from views obtained in this manner is unclear (Miller and Tucker 2013).

This paper seeks to understand the relationship between the earning of media and media persuasiveness. The direction of the relationship is unclear. On one hand, the very act of sharing a video ad suggests a degree of investment in the product and a liking of the ad that may speak well to its persuasiveness. On the other hand, advertisers may have to sacrifice elements of ad design to encourage people to share the ad; this may damage the ad's persuasiveness.

The analysis uses historical data on the number of times that 400 different video ad campaigns posted on YouTube during 2010 were viewed. This data comes from a media metrics company that tracks major advertiser video ads and records the number of times these ads are viewed. The persuasiveness of these campaigns is then measured using techniques pioneered by media metrics agencies such as Dynamic Logic and previously used in data analysis by Goldfarb and Tucker (2011a). I obtained 25,000 survey responses through crowdsourcing and measured the effect of exposure to the video ad on purchase intent, using a randomized treatment and control methodology for each campaign. Respondents are either exposed to a focal product video or to a placebo video ad of similar length for another product in the data. They are then asked questions about their purchase intent and brand attitudes towards the focal product.

Randomization induced by the field-test procedure means that econometric analysis is straightforward. First, the analysis documents the direction of the relationship between the number of times an ad was viewed and traditional measures of advertising persuasiveness. Ads that achieved more views were less successful at increasing purchase intent. This is robust to different functional forms and to alternative definitions of the explanatory and dependent variable, such as brand favorability and consideration. It is robust to controls that allow the effect of exposure to vary by video ad length, campaign length, respondent demographics, product awareness, and category. It is also robust to excluding respondents who had seen or heard of the ad before meaning that the results do not reflect satiation.

Estimates of the magnitude of this negative relationship suggest that, on average, ads that have received one million more views are 10% less persuasive. Since the increased number of views may compensate the advertiser for this drop in persuasiveness, the paper also presents some rough projections to determine the point at which decreased persuasiveness outweighs the increased number of views in terms of the total persuasion exerted over the population. Estimates suggest that this point occurs between three and four million views, a viewership achieved by 6% of campaigns in the data.

The *total views* measure, though, is only the static endpoint of a viral process. The analysis also demonstrates that the results hold when looking at other more dynamic measures of virality, such as the pattern of the time trend of views and the views that can be attributed to nonadvertiser-seeded placement of video ads.

The crucial managerial question is whether there are identifiable categories of ads for whom this negative relationship between organic reach and persuasiveness did not exist. Such cases are clearly very attractive to advertising managers as they imply that organic reach does not have to be costly in terms of the persuasiveness of the ad design. Strikingly, the exceptions to this trade-off are ads that either attract a lot of comments or which attract comments that mention the product by name. This has an important managerial implication. In addition to tracking total views for their ads, marketing managers should track the creation of user-generated content surrounding the ads. This should be used as an early indicator of the ads' likely ability to be persuasive as well as achieving high reach.

It is also important to understand which underlying ad characteristics explain the results. The ads that did *not* exhibit this negative relationship between total views and persuasiveness were also less likely to be rated as outrageous by participants. Instead, they were more likely to be rated as funny or, more weakly, as visually appealing. This is in line with an older advertising research literature that emphasized that likeability (such as produced by humor) is an important determinant of ad appeal (Biel and Bridgwater 1990, Weinberger and Gulas 1992, Vakratsas and Ambler 1999, Eisend 2009), and that intentional outrageousness is less likely to be effective (Barnes and Dotson 1990, Vézina and Paul 1997). Therefore, though intentionally outrageous videos command attention (Tellis 2004), an ad design of this type ultimately detracts from the ad's persuasiveness.

This paper contributes to three existing academic literatures.

The first literature is on virality. Aral and Walker (2011) use data from a field experiment for an application on Facebook to show that forcing product users to broadcast a message is more effective than allowing users to post more personalized recommendations at their discretion. There have also been a few studies of campaigns that were explicitly designed to go viral. Toubia et al. (2011) presents evidence that a couponing campaign was more effective when transmitted using a viral strategy on social media than when using more traditional offline methods. Chen et al. (2011) has shown that such social influence is most important at the beginning of a product's life.

Some recent papers have modeled the determinants of whether a video ad campaign goes viral. This is increasingly important given that 71% of online adults now use video-sharing sites (Moore 2011). Porter and Golan (2006) emphasize the importance of outrageous content (specifically, sexuality, humor, violence, and nudity) as a determinant of virality; Brown et al. (2010) echo the importance of comedic violence and argue that the outrageous nature of these ads appears to be a key driver. Eckler and Bolls (2011) emphasize the importance of a positive emotional tone for virality. Outside the video-ad sphere, Chiu et al. (2007) emphasized that hedonic messages are more likely to be shared by e-mail; Berger and Milkman (2012) emphasize that online news content is more likely to be shared if it evokes high or negative arousal as opposed to deactivating emotions such as sadness. Elberse et al. (2011) examined 12 months of data on popular trailers for movies and video games. They found evidence that the trailers' popularity was often driven by their daily advertising budget. Teixeira (2011) examines what drives people to share videos online and distinguishes between social utility and content utility in nonaltruistic sharing behavior. Though these papers provide important empirical evidence about the drivers of virality, they did not measure how persuasive the video ads were and how this related to virality.

The second literature to which this paper contributes is on the persuasiveness of online advertising. Much of this literature has not considered advertising that is designed to be shared, instead focusing on noninteractive banner campaigns (Manchanda et al. 2006, Lambrecht and Tucker 2013). Generally, only the persuasiveness of video-advertising, tangentially, or as part of a larger study, has been considered. For example, Goldfarb and Tucker (2011a) argued that video advertising is less persuasive when placed in a context too closely matched to the product being advertised. In the arena of video advertising, Teixeira et al. (2012) showed that video ads that elicit joy or surprise are more likely to retain visual focus (as measured by eye-tracking) and are less likely to be fast-forwarded through. To my knowledge, however, this is the first study of the relationship between ad virality and ad persuasiveness, that is, how the ability of an ad to endogenously gain *reach* is related to the ad's persuasiveness.

The final literature concerns the trade-off between ad design and attention or reach. It has been suggested that the Internet has reduced the trade-off between richness and reach in information delivery. Before the commercialization of the Internet, firms had to choose between personal selling, an incredibly rich form of marketing communications but which has limited reach because there are no economies of scale, and media such as television advertising, which achieves impressive reach but is not a rich form of marketing communications. Evans and Wurster (2000) argue that the easy replication and personalization facilitated by the Internet reduced this trade-off. This paper suggests, however, that advertisers who try to achieve scale on the Internet through the actions of its users, rather than their own efforts, may still face trade-offs in terms of ad persuasiveness, i.e., creating ads that users can be persuaded to view and share. This finding is more in line with the older literature on advertising content, which suggests that there is a substantial trade-off between achieving ad persuasion and attracting attention using emotive ad characteristics (for a summary, see Tellis 2004, p. 151). For example, Steadman (1969) shows that the sexiness of advertising, though good at commanding attention, negatively affects brand recall. This echoes results on the effects of outrageousness as a characteristic of viral ads. Though outrageousness is effective at increasing total views, outrageous ads are less effective at positively persuading consumers to buy the product.

2. Data

Visible Measures, a large video metrics company, provided the data for this paper. Data for movie campaigns provided by this company has also been used by Elberse et al. (2011) to study the effects of direct advertiser actions on video virality for movie previews. Visible Measures, founded in 2005, is an independent third-party media measurement firm for online video advertisers and publishers. It is the market leader for tracking views and engagement for different types of social video ads. Visible Measures shared data for 2010 campaigns in the consumer goods category. They excluded from the data video ads for product categories such as cars and other expensive items, for which most people were unlikely to be in the market. They also excluded video ads for entertainment products such as movies, video games, and DVDs, whose ads have a short shelf life.

Twenty-nine percent of videos were for consumer packaged goods, 14% for electronics, 13% for apparel, and 8% for fast food. The highest priced items were air travel (around 3% of campaigns). The lowest priced items were sodas and snacks in the consumer packaged goods category. Persuasiveness is allowed to vary by these different product categories as controls in subsequent robustness checks.

Three-hundred ninety-six of these ad videos were still viewable on YouTube and were consequently included in this survey. These 396 videos covered 271 brands and 278 different products. All of these products had been advertised elsewhere, though in 3% of cases (all in the electronics category) the ad was for a new product release. Because Visible Measures is primarily employed as a media measurement company, it does not have data on the design costs or the creative process that is behind the ads it tracks. Although Visible Measures did not share its proprietary system for collecting this data, descriptions on its website suggest that the data is captured daily from major video-sharing websites such as YouTube and Vimeo.com.

Table 1(a) reports the campaign-level summary statistics received from Visible Measures. Total views captures the number of times these videos had been viewed by consumers. This encompasses both the views of the original video as placed by the ad agency, and views that were generated by copies and derivatives of the ad. It is clear from the standard deviation that there is a high variance in the number of total views across the ad campaigns; this is one of the reasons for using log measures in the regressions. The results are also robust to a raw linear measure.

The analysis takes total views, that is, the number of times in total the ad was viewed, as the initial static proxy measure of the outcome of the viral process. Such measures of reach are often loosely referred to as measuring virality of ads.[1] This reflects the idea that views of social video ads on pages such as YouTube are obtained through an organic process wherein users find such ads on blogs or social media sites and then share them with friends. However, since this process could be subject to manipulation[2] by advertisers, the paper presents alternative specifications

[1] See for example https://www.facebook.com/help/285625061456389 where organic reach totals are referred to as "viral reach."

[2] See Wilbur and Zhu (2009) for a general discussion of manipulation of online ads.

Table 1 **Summary Statistics**

	Mean	Std dev	Min	Max
(a) Campaign level				
Total views	777,996.53	2,705,048.25	57	37,761,711
Total comments	1,058.54	4,382.75	0	64,704
Length ad (sec)	56.24	33.31	10	120
Observations	396			
(b) Survey participants' responses				
Exposed	0.50	0.50	0	1
Purchase intent	0.59	0.49	0	1
Intent scale	3.63	1.12	1	5
Would consider	0.60	0.49	0	1
Consideration scale	3.67	1.10	1	5
Favorable opinion scale	3.75	0.99	1	5
Favorable opinion	0.62	0.49	0	1
Aware of product (unexposed)	0.56	0.50	0	1
Age	29.57	9.44	18	65
Male	0.70	0.46	0	1
Income (000,USD)	35.53	24.22	20	100
Weekly Internet hours	26.23	10.93	1	35
Lifetime tasks	6.18	33.68	0	251
Observations	24,367			
(c) Average median campaign ratings from survey participants				
Funny rating	5.64	0.97	2	8
Outrageous rating	5.13	0.74	1	8
Visual appeal rating	6.74	0.66	1	9

that attempt to isolate the views achieved from nonadvertiser-seeded placements as well as measures of virality that more closely reflect the idea of a dynamic process. Total Comments records the number of times that these videos received a written comment from a consumer, typically posted below the ad on websites such as YouTube.

Note that a simple regression that correlated firms' sales with the virality of their ad campaigns is unlikely to be useful as the decision to launch a viral ad campaign is confounded by many other factors. Direct measurement of consumer response rates for online video ads is also difficult. Though it is possible to measure whether a YouTube user subscribes to a channel, not all users maintain accounts of the kind that allow them to subscribe. Typical direct response methods of evaluating digital advertising, such as measuring click-throughs, are not appropriate. Many videos do not have embedded hyperlinks. Many products that are advertised in the videos (e.g., deodorant) are not primarily sold online. As documented by Porter and Golan (2006) and Golan and Zaidner (2008), viral advertising rarely has a clear and measurable call to action, such as visiting a website. Therefore, advertising persuasiveness in this analysis is based on industry standard techniques for measuring the persuasiveness of online brand campaigns. These techniques, developed by Dynamic Logic and Insight Express (among others), combine a randomized control and exposure methodology with surveys on brand attitudes. Major advertisers and agencies use these same techniques to evaluate banner and video campaigns.

Because such ad persuasiveness measures were not used as the campaigns were being rolled out, this data had to be collected retrospectively. Given the number of campaigns in the source data, a large number of participants was required. To this end, 25,000 survey responses were collected using the crowdsourcing platform Mechanical Turk. Ghose et al. (2012) used similar crowdsourcing techniques to design rankings for search results. Each of the participants visited a website that had been designed to resemble popular video sharing websites such as YouTube. There are two important differences between the study website and a traditional video-sharing website. First, on the study website participants had no choice but to watch the entire video. After watching they were asked a series of questions concerning their brand attitudes. Second, unlike regular video-sharing websites, the video was embedded in the survey so that participants were not exposed to the prior number of views or the number or nature of the comments that the video had received.

For each campaign, on average 60 respondents were recruited. Half were exposed to the focal video ad for which there is virality data. The other half (i.e., the control group) watched a placebo video ad for another unrelated (random) product that was also part of the data. The placebo ad was randomized to ensure that it did not drive the results for any one campaign.[3]

Randomization between whether a participant saw the focal video ad or another means that, in expectation, all of the respondents were identical. Therefore, the analysis can causally attribute any differences in subsequent attitudes towards the product to whether participants were exposed to the video ad.

The data recorded whether the respondent watches the video all the way through; the analysis excludes those who did not. Also excluded were participants who, despite the controls in place, took the survey multiple times.[4] Despite the author's best efforts,

[3] This could have occurred if the advertising was directly combative (Chen et al. 2009).

[4] A natural concern on Mechanical Turk is that not all participants are unique. In our data processing, we addressed this concern in three ways:

1. We set up Mechanical Turk so that each Mechanical Turker was asked to complete a single survey.

2. We ensured that no answers had identical Mechanical Turker IDs. We dropped subsequent responses from Mechanical Turkers who had responded multiple times to the survey.

3. Since Mechanical Turkers could have multiple accounts, we tracked IP addresses to try to eliminate duplicates, which were dropped where identified.

survey-takers may still have been able to take the survey multiple times if they masked their IP address effectively. However, it seems reasonable to think that the steps that were put in place means the majority of multiple survey-takers were detected. In the end, there were 24,367 responses, which is fewer than the original 25,000 survey responses received.[5] Table 1(b) summarizes responses to the subsequent survey questions. These include questions about purchase intent towards the focal product and likelihood of product consideration. There were also decoy questions about another brand. All of these questions are asked on a five-point scale in line with traditional advertising persuasiveness questioning (Morwitz et al. 2007). To facilitate comparison with the estimates of Goldfarb and Tucker (2011a), who use a similar methodology but in a nonforced exposure setting, for the main analysis this variable is converted from a five-point scale to a binary purchase intent measure that captures whether someone is very likely or likely to purchase the product. However, this is shown to be robust to the full scale in subsequent regressions. As seen in Table 1(b), average purchase intent was relatively high, reflecting the mainstream nature of the products in the ads.

Using purchase intent as the key dependent measure means that the analysis is focused on the effect of advertising at the later stages of the purchase funnel or traditional purchase decision process (Vakratsas and Ambler 1999). Our methodological approach, which necessitates forced exposure, makes it hard to analyze awareness or other stages of customer attitudes earlier in the purchase process.[6] The analysis does, however, control for heterogeneity in product awareness in subsequent regressions.

Survey responses are weaker measures of advertising persuasiveness than purchasing or profitability (as used by Lewis and Reiley 2014); users may say they will purchase, but not actually do so. Still, as long as there is a positive correlation between whether someone intends to purchase a product and whether they actually do so, the directionality of the results should hold. Although positive correlation between stated purchase intent and purchase outcomes has been broadly established (Bemmaor 1995, Morwitz et al. 2007), there is a more conservative interpretation: The results reflect how total views are related to an established and widely-used measure of advertising persuasiveness that is used as input for advertising allocation decisions.

In addition to asking about purchase intent, the survey asked participants whether they recalled seeing the focal video ad before or had heard it discussed by friends and/or in the media. This information is used in a robustness check to ensure that the fact that respondents are more likely to have seen viral videos before is not driving the results.

The survey also asked respondents to report their gender, income, age, and the number of hours they spent on the Internet. These descriptives are reported in Table 1(b). They are used as controls in the regression. Since respondents were allocated to the exposed and control group at random, the controls primarily improve efficiency and indicate how representative the participants were. Most of the respondents were lower-income, young males who spend considerable time online. It is still possible, however, that they reflect the general population of viewers of video-sharing websites.

Specifically, 70% of participants were male. This is similar to statistics reported by Moore (2011), i.e., that men are 28% more likely than women to have recently used a video-sharing site. The participants were on average 30 years old. ComScore, a website audience tracking service, reports in its Searchplanner tool that in September 2010, YouTube users were on average 31.6 years old; this is reasonably similar to the Mechanical Turk population. In the comScore YouTube user data, 41% of users had an income under $40,000 a year, which is lower than this survey where 62.2% had a comparably low income. This suggests that the income level is different for the YouTube population and the Mechanical Turk population. However, work by Goldfarb and Prince (2008) suggests that this simple comparison of unique visitor income may overstate the difference as it fails to adjust for time spent on the website. They argue instead that poorer YouTube users are likely to account disproportionately for the time spent on that website. In general, however, as participants were recruited via a crowdsourcing website, it is also possible that the populations differ in unobserved ways.

Another caveat as to the representativeness of the responses is that data collection takes place in a forced exposure setting, which does not mimic the social process.[7] Therefore, persuasiveness should be

[5] Also excluded were 161 participants who incorrectly gave the length of the video as a veracity check for paying attention to it.

[6] The data does not contain time-stamps for when consumers completed different parts of the survey. In general, completing the survey took only a few minutes longer than watching the video. This lack of interruption in completing the survey prevented the collection of measures on ad memorability.

[7] Supplementary analysis also collected information on persuasiveness of videos for a randomly selected subset of 30 of the original 400 videos with slightly different instructions. In this slightly altered scenario, rather than being instructed to watch a video ad, participants were told to imagine they had just been sent the link to the YouTube video by a friend with the instruction to "Check it out." We compared the relative persuasiveness of this setting to our original setting and found no statistically significant difference for purchase intent–($t = 0.47$, p-value $= 0.63$), favorable brand opinion ($t = 0.78$, p-value $= 0.43$), or consideration ($t = 0.34$, p-value $= 0.72$). Though

thought of as the direct persuasiveness that can only be attributed to exposure to the video between the treated and exposed conditions. This does not reflect any incremental lift beyond that found in the video content that might come from a friend's recommendation.

The issue of how representative respondents' answers are is faced by all research using survey-based evaluation techniques, as discussed in Goldfarb and Tucker (2011b). What is crucial is that there is no a priori reason to think that the kinds of ads that would favorably impress these participants would differ from those that impress the more general video-sharing population, even if the magnitudes of their responses may differ. There is also evidence that the magnitudes of the measured effects match existing estimates of video-advertising efficacy that have been collected in less artificial settings (Goldfarb and Tucker 2011a).

In addition, participants rated the videos on a ten-point sliding scale based on the extent to which they found it humorous, visually appealing or outrageous.[8] Table 1(c) reports these ratings at the campaign level based on the median response of the participants.

3. Empirical Analysis

The randomized procedure for collecting data makes the empirical analysis relatively straightforward.

For person i who was assigned to the testing cell for the video ad for product j, their purchase intent $Intent_{ij}$ is a binary variable that is a function of

$$Intent_{ij} = I(\alpha\, Exposed_i + \beta\, Exposed_i \times LogViews^j + \theta X_i + \delta_j + \epsilon_{ij} > 0). \quad (1)$$

Therefore, α captures the main effect of being exposed to a video ad on purchase intent. Purchase intent is a binary variable for whether the respondent said they were likely or very likely to purchase the product. The core coefficient of interest for the paper, β, which captures whether ad exposure is more or less effective if the ad has received a high number of views; X_i is a vector of controls for gender, age, income, and time online; the vector θ is associated coefficients; δ^j is a series of 396 campaign-level product fixed effects that control for heterogeneity in baseline purchase intent for the product in that campaign, and includes the main effect of Ad Views ($LogViews_j$), which is why this lower-order interaction is not included in the specification.[9] Using a log measure of ad views avoids having the results driven by extreme values given the large variance in distribution of ad views. The initial specification assumes that the error term ϵ_j is normally distributed, implying a probit specification. Standard errors are clustered at the product level in accordance with the simulation results presented by Bertrand et al. (2004). This represents a conservative empirical approach as, in this setting, there is randomization at the respondent level as well.

Table 2 builds incrementally to the full specification in Equation (1). Column (1) reports an initial specification measuring the main effect of *Exposed* on purchase intent. As expected, being exposed to the video ad has a positive and significant effect on the participant's purchase intent for that product.

The estimate in Column (1) suggests that exposure to a video ad increases purchase probability by 6.6 percentage points, which is similar to the average effect of exposure to "in-stream" video ads reported by Goldfarb and Tucker (2011a). This is reassuring because that research used industry-collected data where participants had naturally come across the ad in the process of web browsing. This suggests that the recruitment method and forced exposure did not overly influence the measure.

Column (2) reruns this simple regression for the websites that had a below-median number of views. Column (3) reports results for the same regression for websites that have an above-median number of views. It is clear that on average the effect of exposure to the ad on purchase intent is greatest for video ads that have a below-median number of views. This is initial evidence of a negative relationship between the total views of the ad and its ability to persuade a viewer to purchase the product.

To test this more robustly, Column (4) provides an explicit test of the apparent difference in size in the coefficients for *Exposed* in Columns (2) and (3) by reporting the results of a basic version of (1). The key variable of interest, $Exposed_i \times LogViews_j$, is negative and significant. This suggests that exposure to an ad that received more views is less likely to persuade an ad viewer to purchase the product.

This finding remains unchanged when adding log-linear controls for consumer characteristics in Column (5), which is as expected due to randomization.

this is somewhat encouraging, the findings should be treated as suggestive rather than conclusive; this is a lab study that relies on subjects being capable of simulating behavior in a social context in an artificial setting.

[8] There was supplementary data on provocativeness ratings, but this was highly correlated with outrageousness as a measure. To avoid issues with collinearity and convergence, the analysis uses only the outrageousness measure.

[9] Because this does not give a baseline, the author also explored an alternative specification using category fixed effects rather than product level fixed effects to allow separate identification of the baseline effect of $LogViews_j$. The coefficient was highly insignificant, suggesting a baseline of zero. Similarly, a coefficient that captured the average views for the placebo ad was also insignificant.

Table 2 More Viewed Ads Are Less Persuasive

	Probit (1)	Probit (2) $\geq$ Med total view	Probit (3) $<$ Med total view	Probit (4)	Probit (5)	Probit (6)	OLS (7)	OLS (8)
Exposed × *LogViews*				−0.0153** (0.00738)	−0.0153** (0.00747)	−0.0164** (0.00752)	−0.00658** (0.00268)	
Exposed × *TotalViews* (m)								−0.0153** (0.00722)
Exposed	0.181*** (0.0177)	0.150*** (0.0259)	0.212*** (0.0239)	0.246*** (0.0363)	0.250*** (0.0368)	0.259*** (0.0370)	0.0951*** (0.0134)	0.0738*** (0.00691)
Age					−0.00316*** (0.000965)			
Income (USD,000)					0.00116*** (0.000342)			
WeeklyInternetHours					−0.0000646 (0.000797)			
Male					0.310*** (0.0199)	0.247*** (0.0208)	0.0893*** (0.00747)	0.0893*** (0.00689)
Product controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demo controls	No	No	No	No	No	Yes	Yes	Yes
Observations	24,367	12,221	12,146	24,367	24,367	24,367	24,367	24,367
Log-likelihood	−15,353.9	−7,531.9	−7,820.3	−15,351.7	−15,193.8	−14,896.6	−15,687.3	−15,688.4
R-squared							0.121	0.121

Notes. Dependent variable is a binary indicator for whether participant states that they are likely or very likely to purchase the product. Probit estimates Columns (1)–(6) and Ordinary Least Squares (OLS) estimates Columns (7) and (8). Robust standard errors clustered at the product level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

These log-linear controls suggest that richer, younger males who do more tasks are more likely in general to say they will purchase. Column (6) uses an alternative nonparametric set of controls for consumer characteristics that are indicators for six levels of income, age, and Internet usage. As can be seen in the log-likelihood, this nonparametric approach to controls is more efficient, which is why it forms our focal specification. In each case the use of such controls is indicated by "Yes" in the Demo Controls row at the bottom of the table.

An econometric concern is the interpretation of the main interaction terms. Research by Ai and Norton (2003) suggests that the interaction in a nonlinear model may not capture the true cross-derivative. To ensure that the results are not a function of the nonlinearity of the estimation function, Column (7) demonstrates that a linear probability model gives qualitatively similar results. This provides reassurance that the nonlinear functional form does not drive the results. Column (8) shows that the result is also robust when using a linear version of the key explanatory variable *TotalViews* rather than *LogViews*. The r-squared in each of these columns is relatively low, but this is very much in line with previous studies in this area, such as Aral and Walker (2011).

On the basis of the probit model estimates for the linear measure of views and the appropriate Ai and Norton (2003) correction, Table 2 suggests that for approximately every 1 million views an ad receives, the ad is on average 10% less persuasive. However, if a video ad is less persuasive for any individual viewer but has the potential to persuade more people because it has higher reach, that is not necessarily harmful to advertiser objectives. Figure 1 plots these rough estimates of a simulation that takes into account the total expected persuasion from a video ad. This is defined as "*Reach* × *Persuasiveness*" and reflects how persuasive the ad was multiplied by the number of consumers who viewed it. This exercise suggests that, at three to four million total views, there are eventually decreasing returns to achieving a large number of total views overall. At this point the reduction in ad persuasiveness due to high total reach is large enough that an incremental increase in the number of consumers viewing the ad achieves little. Only 6% of videos in the data achieved this level of organic reach. Therefore, the plot suggests that negative returns to high levels of total reach are limited. Although Figure 1 is a very rough calculation, inverse-U-shaped returns from achieving high total reach in viral forms of advertising is a new finding deserving of managerial attention.

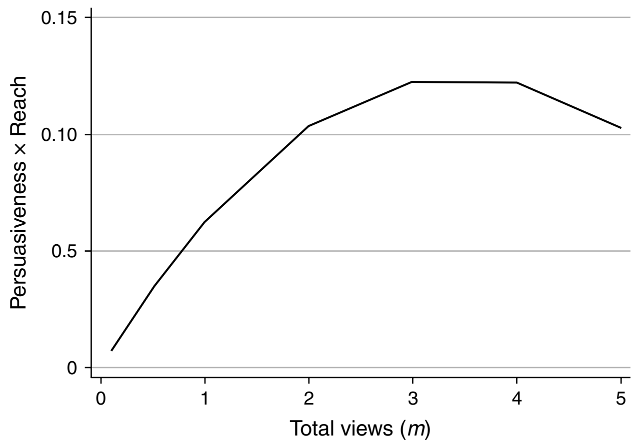
3.1. Robustness

This section conducts a battery of robustness checks for the results in Table 2.

3.2. Alternative Definitions of Dependent Variables

Table 3 checks the robustness of the results to alternative dependent variables. Column (1) shows robustness to using the entire purchase intent scale. In this OLS specification, the direction of the main effect

Figure 1 **Predictions of Trade-Off from Probit Model**



of interest remains the same. This is to be expected given that the binary indicator for purchase intent was based on this scale. Column (2) repeats this robustness check, but uses an ordered probit specification to reflect the potential for nonlinearities in scale interpretation.

Column (3) shows robustness to examining an alternative measure of brand persuasiveness, which is whether the consumer would consider the brand. This is an important check as most video advertising is explicitly brand advertising without a clear call to action. Therefore, it makes sense to determine whether the result applies to an earlier stage in the purchase process (Hauser 1990). However, the results remain robust (both in significance and approximate magnitude) to a measure that attempts to capture inclusion in a consideration set. This suggests that the documented negative relationship holds across attempts to influence customer attitudes across different stages of the purchase cycle. Similarly, Column (4) shows that the results are robust to using as a dependent variable whether the respondent had a "favorable" or "very favorable" opinion of the brand.

3.3. Potential Confounds

This section investigates the robustness of the results in Table 2 for potential confounds that may provide alternative explanations.

One natural concern is that more viral video ads are less effective because the respondents have already been influenced by them, and repeated exposure is less effective (Tellis 1988). To address this, Column (1) of Table 4 excludes the participants who stated they had seen or heard of the advertising campaign before. The results are robust to excluding such observations. This suggests that the explanation of the measured negative relationship is not ad wearout.

Another concern is that the results are driven by differences between the product advertising categories. For example, more aspirational or hedonic products may receive more views (Chiu et al. 2007, Berger and Milkman 2012). Yet such ads may also be less persuasive in terms of consumer purchase intent. Column (2) of Table 4 addresses this concern, showing that the results are robust to allowing the persuasiveness of the ad to vary according to the product category (for example, whether it is food or a personal care item). The results remain robust to adding these interactions between category-specific indicators and the exposure indicator, which would capture any differences in ad potential to persuade respondents for that product category.

Column (3) addresses the concern that the results are driven by differences in ad length. For example, it could be that longer video ads are more persuasive but less likely to be viewed. To control for this, the specification in Column (3) includes an interaction between exposure and ad length. The results are

Table 3 **Checking Robustness to Different Dependent Variables**

	OLS (1) Intent scale	Oprobit (2) Intent scale	Probit (3) Would consider	Probit (4) Favorable opinion
Exposed × *LogViews*	−0.00829**	−0.0119*	−0.0145**	−0.0167**
	(0.00411)	(0.00692)	(0.00737)	(0.00744)
Exposed	0.115***	0.193***	0.274***	0.311***
	(0.0204)	(0.0333)	(0.0359)	(0.0361)
Product controls	Yes	Yes	Yes	Yes
Demo controls	Yes	Yes	Yes	Yes
Observations	24,367	24,367	24,367	24,367
Log-likelihood	−25,792.5	−21,530.4	−14,712.0	−14,463.4
R-squared	0.107			

Notes. OLS estimates in Column (1). Ordered Probit estimates in Column (2). Probit estimates in Columns (3) and (4). Dependent variable is the full five-point purchase intent scale in Columns (1) and (2). Dependent variable is whether the customer is likely or very likely to "consider" purchasing the product in Column (3). Dependent variable is whether the customer is likely or very likely to have a "favorable" opinion towards the product in Column (4). Robust standard errors clustered at the product level.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4 Exploring Different Explanations

	Seen before (1)	Cat int (2)	Ad length (3)	Campaign length (4)	Tasks (5)	Age (6)	Awareness (7)
Exposed × LogViews	-0.0181^{**}	-0.0152^{**}	-0.0158^{**}	-0.0194^{**}	-0.0159^{**}	-0.0211^{***}	-0.0158^{**}
	(0.00775)	(0.00755)	(0.00775)	(0.00768)	(0.00743)	(0.00784)	(0.00806)
Exposed × AdLength			−0.000140				
			(0.000504)				
Exposed × CampaignLength				0.000139^{*}			
				(0.0000747)			
Exposed	0.227^{***}	0.211^{***}	0.264^{***}	0.228^{***}	0.258^{***}	0.280^{***}	0.274^{***}
	(0.0379)	(0.0576)	(0.0420)	(0.0408)	(0.0364)	(0.0394)	(0.0379)
Exposed × Age × LogViews						0.0195	
						(0.0148)	
Exposed × Age						−0.0886	
						(0.0725)	
Age × LogViews						−0.0160	
						(0.0121)	
Exposed × HighAware × LogViews							0.0269
							(0.0240)
LifetimeTasks					0.00322^{***}		
					(0.000891)		
Exposed × LifetimeTasks					0.0000373		
					(0.00118)		
LogViews × LifetimeTasks					−0.000108		
					(0.000177)		
Exposed × LogViews × LifetimeTasks					−0.0000381		
					(0.000249)		
Exposed × HighAware							-0.274^{**}
							(0.138)
Category interactions	No	Yes	No	No	No	No	No
Product controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demo controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,528	24,617	24,617	24,617	24,617	24,617	24,617
Log-likelihood	−13,807.3	−15,056.9	−15,060.0	−15,058.4	−15,033.3	−15,059.1	−15,055.9

Notes. Probit estimates. Dependent variable is a binary indicator for whether participant states that they are likely or very likely to purchase the product. Robust standard errors clustered at the product level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

robust to the inclusion of this control. They also suggest that ad length appears to have little relationship to the perceived persuasiveness of the ad.

Column (4) addresses the concern that the results are driven by differences in elapsed time for the campaign. For example, it could be that older campaigns gained more views, but that products with older but still live campaigns (perhaps those that were more traditional and less fast-paced) were less persuasive in terms of purchase potential. To control for this, Column (4) includes an interaction between exposure and the number of days the campaign had run according to Visible Measures data. The results are robust to the inclusion of this control. They also suggest that, on average, longer campaigns are more persuasive, which makes sense as ineffective campaigns are likely to be withdrawn.

Column (5) addresses the concern that the results may be driven by the fact that survey-respondents have different levels of experience on Mechanical Turk. Perhaps Mechanical Turk's more sophisticated workers were more likely to exhibit "demand effects" by answering the questions in the way they thought the questioner preferred. Therefore, if randomization failed, this could drive the result. To control for this possibility, Column (5) allows the results to vary by the workers' number of previous tasks for other firms on Mechanical Turk. The results are again similar.

Column (6) addresses the concern that the result could be related to variation in viewers' ages. Suppose, for example, video ads are targeted toward young people who are (perhaps) more likely to share ads to which older people would react poorly. This could explain the result. However, the addition of an interaction between the main effect with a variable for age does not change the focal estimates, suggesting that age is not a moderating factor.

Another concern is that the ads could be primarily designed to promote awareness for new products. Suppose, for example, that the majority of the viral ads were for the newest products. In such case, persuading participants to purchase would be more

Table 5 Exploring Different Measures of Virality

	Nonseeded placements (1)	Correlation (2)	Nonlinear time trend (3)	No. of comments (4)	Product mentioned (5)	Product not mentioned (6)
Exposed × *CopyViews*	−0.0189* (0.0102)					
Exposed × *DailyViewsCorrelation*		−0.125** (0.0612)				
Exposed × *NonlinearTimeTrend*			−1.731* (1.012)			
Exposed × *LogViews*				−0.0379*** (0.0143)	−0.00689 (0.0119)	−0.0220** (0.00938)
Exposed × *LogComments*				0.0281** (0.0141)		
Exposed	0.340*** (0.0845)	0.250*** (0.0349)	0.220*** (0.0248)	0.420*** (0.0931)	0.206*** (0.0554)	0.291*** (0.0477)
Product controls	Yes	Yes	Yes	Yes	Yes	Yes
Demo controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,138	24,617	24,617	24,617	10,189	14,428
Log-likelihood	−10,589.9	−15,159.9	−15,061.0	−15,057.8	−6,264.2	−8,789.8

Notes. Probit estimates. Dependent variable is a binary indicator for whether participant states that they are likely or very likely to purchase the product. Robust standard errors clustered at the product level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

difficult. This could explain the results. To test this, Column (7) adds an extra interaction with an indicator for whether the product had an above-average level of awareness as recorded among consumers who were not exposed to the ad. The interaction $Exposed_i \times HighAwareness \times LogViews_j$ is insignificant, suggesting that awareness is not an important mediator of the effect.

3.4. Other Measures of the Viral Process

One natural concern about the analysis is whether the use of reach in terms of total views captures the essence of what is commonly thought of or talked about as virality, since it does not directly measure the organic sharing of videos, but only the outcome. This section explores measures that use alternative approaches to approximate virality.

Cruz and Fill (2008) and Elberse et al. (2011) discuss many actions that marketers can take to increase reach of a video ad. These actions do not actually represent true sharing of a viral video. For example, external advertising expenditures can drive viewers towards the website where the advertising agency originally placed the video. Significantly, Elberse et al. (2011) found that the majority of views of a truly viral video stem from user-generated versions of the advertisement. They suggest that one way to assess the successfulness of a viral campaign is by observing how many views are associated with copies of the video, i.e., copies that were not placed by the agency but by fans of the video. The latter is a more organic process.

Column (1) of Table 5 explores this by looking only at views that can be attributed to the nonadvertiser-seeded placements. Not all videos had copies, which explains the smaller number of observations than in the main specification. A similar negative relationship remains, wherein the persuasiveness of the ad appears to decrease in these nonadvertiser-driven views.[10]

As described by Yoganarasimhan (2012) in her study on the effect of bloggers' social relationships on the propagation of YouTube videos, one way to conceptualize the virality of videos is by examining the extent to which they are shared across social networks. Unlike Yoganarasimhan (2012), this paper does not have data on the underlying social relationships between the video viewers. Videos used in our study were professionally produced by advertising agencies, rather than consisting of organic, homemade content posted by bloggers on their public social networks. The analysis uses panel data on the growth of views to develop measures to approximate a viral growth pattern and more accurately reflect the dynamic rather than static nature of virality.

Generally, virality is used to define a process whereby an ad is successively shared by viewers. To capture this, Column (2) of Table 5 uses as a proxy measure of virality, i.e., the interday correlation in views for that particular campaign. Ads whose views were the result of a successive sharing process are more likely to have daily views that are positively

[10] Earlier versions of the paper also checked that the result was not related to the fact that total views includes views of derivatives of the original ad. It is possible that if an ad were poorly executed, it could have invited scorn in the form of multiple parodies that could have artificially inflated the number of views of the original video. However, the robustness check shows that the results remain robust to excluding views that can be attributed to parodies.

correlated with views from the previous day. This correlation is unlikely to be causal and highly likely to be biased upwards as there is no exogenous shifter that allows identification of causal network effects (Tucker 2008). With this caveat, the results are similar when using this alternative proxy measure.

The Oxford English Dictionary definition of virality is "the tendency of an image, video, or piece of information to be circulated rapidly and widely from one Internet user to another; the quality or fact of being viral." To capture this idea of diffusion speed, the paper uses another proxy measure for virality, i.e., whether the time trend for the growth of views is linear or convex. A convex time trend is closer to the common idea of virality, reflecting an increasing spread of content across a growing social network. Column (3) of Table 5 reports the result of this new interaction between persuasiveness and the convexity of the time trend as measured by the extent to which the daily views time trend follows a convex rather than linear relationship with days elapsed. Though less precisely estimated, the estimate suggests that a convex pattern of growth of views is again associated with lower ad persuasiveness.

Column (4) of Table 5 investigates the relationship between ad persuasiveness and the number of comments that the video posting received. Total comments are user-generated content.[11] Figure A.1 in the appendix displays how comments usually appear below the ad on a video-sharing website.

Of course, total comments are positively linked to the total number of views an ad receives; without viewers there can be no comments. Still, comments are conceptually distinct and require a different investment from the viewer. Reflecting these investments, when Visible Measures promote their data on total comments to advertisers, they label this viewer behavior as capturing viewer engagement.[12]

Column (4) of Table 5 explores what happens when $Exposed_i \times LogComments_i^j$ is added to the regression. The pattern for $Exposed_i \times LogViews_i^j$ is similar, if more precise, than before. However, crucially, $Exposed_i \times LogComments_i^j$ is both positive and significant. This suggests that video ads that are successful at provoking users to comment on them and directly engage with them are also more persuasive in terms of product purchase. Because this is a striking result, Table A.1 provides reassuring evidence of the robustness of this specification in the appendix.

Since the number of comments may be subject to spam and other forms of manipulation, I also collected data on the actual text of the top five comments as rated by YouTube users. This data allows identification of whether one of these comments mentioned the product by name.

Only 41% of campaigns had a top five comment that mentioned the product by name. Columns (5) and (6) report the results for a stratified analysis of the main sample using this distinction. This strengthens the linkage of the results to this measure of how well the ad engaged consumer attention to the product. As shown in Column (5), ads that successfully generated comments in which the product was mentioned by name do not experience the key trade-off identified in the paper. By contrast, Column (6) reports results for campaigns where none of the top five comments mentioned the ad by name. For these campaigns, there is the familiar negative and significant relationship between ad reach and persuasiveness. These results appear to bolster the suggested theoretical mechanism for the results, i.e., many viral video ads fail to engage consumers around the product versus the nonproduct-related contents of the video ad.[13]

The next section seeks to enrich these findings by determining how total views, total comments, and ad persuasiveness are jointly determined by underlying ad characteristics.

4. When Is There No Negative Relationship?

4.1. Ad Characteristics

So far, this paper has documented a negative relationship between the total views that ads achieve and their persuasiveness. It has also shown that the trade-off is weaker if there are multiple user comments, or if the comments mention the product by name. Of crucial interest for managers, however, is what actions they can take to design ads that mitigate this negative result.

Table 6 provides evidence concerning how different advertising characteristics moderate this negative relationship. It repeats the estimation from Table 2, but stratifies by whether participants rated the ad as below or above median in terms of humor, visual appeal, and outrageousness. It shows that the trade-off is weak for ads that are above the median in terms of humor and visual appeal; but the trade-off is larger and more significant for ads that were rated as highly outrageous, humorless or having no visual appeal.

[11] Such content is distinct from more general forms of online reputation systems (Dellarocas 2003), and has been shown by Ghose and Han (2011); Ghose and Ipeirotis (2011) to correlate with product success. Moe and Schweidel (2012) have also shown that comment ratings themselves may be subject to cascades and herding.

[12] This is distinct from physical engagement as measured by Teixeira et al. (2012) using eye-tracker technology.

[13] In the spirit of Ghose et al. (2012), the analysis also examined average comment length, spelling mistakes, and mentions of television as potential moderators of the effect. No statistically significant relationship was found.

Table 6 Effects of Underlying Ad Characteristics

	Not funny (1) Purchase intent	Funny (2) Purchase intent	Not visual (3) Purchase intent	Visual (4) Purchase intent	Not outrageous (5) Purchase intent	Outrageous (6) Purchase intent
Exposed × *LogViews*	−0.0211**	−0.0133	−0.0254**	−0.0109	−0.0152	−0.0225**
	(0.00970)	(0.0119)	(0.0116)	(0.00986)	(0.0108)	(0.0111)
Exposed	0.255***	0.270***	0.334***	0.203***	0.294***	0.245***
	(0.0460)	(0.0612)	(0.0580)	(0.0474)	(0.0579)	(0.0487)
Product controls	Yes	Yes	Yes	Yes	Yes	Yes
Demo controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,341	12,026	12,381	11,986	12,270	12,097
Log-likelihood	−7555.7	−7326.3	−7321.4	−7567.6	−7443.0	−7436.2

Notes. Probit estimates. Dependent variable is a binary indicator for whether participant states that they are likely or very likely to purchase the product. Robust standard errors clustered at the product level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{**}p < 0.01$.

4.2. Combined System of Equations

The results in Table 6 concern the potential mechanism that underscores the results. As formalized in Tellis (2004, p. 151), ads can achieve high levels of attention, but simultaneously experience decreased persuasiveness if they use emotional responses from the viewer to evoke attention. Clearly, some video ads are purposely designed to be outrageous; this commands attention and encourages consumers to share the videos with friends (Porter and Golan 2006, Brown et al. 2010, Moore 2011). On average, however, outrageous ads are not succeeding in persuading consumers to buy products. This is in line with existing research (Vézina and Paul 1997) on how outrageousness affects ad response. By contrast, ad characteristics such as humor appear to be successful at promoting user ad response and encouraging high levels of organic reach. This is underscored by behavioral research into humor in ads, which suggests that, unlike strong emotional stimuli, humor does not, on average, harm the advertising message and can sometimes enhance it by increasing engagement (Weinberger and Gulas 1992).

Speculatively, the difference in effect of humor and outrageousness may be because, as discussed by Percy and Rossiter (1992), the trade-off between attention and persuasion is at higher levels of emotion. This can be avoided if the stimulus is closely linked to the ad's message. Potentially emotional characteristics such as humor and visual appeal are easier to link to the ads' message. Echoing this, perhaps the majority of the literature (e.g., Duncan and Nelson 1985) has found positive effects on both attention and persuasiveness from incorporating humor into ad messages.

To reflect this, it is possible to expand the analysis to reflect a joint system of equations[14] for both survey-taker i's stated purchase intent and campaign j's total views and commments.

$$
\begin{aligned}
Intent_{ij} &= I(\alpha_{j1} + \alpha_{j2} Exposed_i + \theta DemoVariables_{ij} + \epsilon_{ij}),\\
\alpha_{j1} &= \mu_0 + \mu_1 Views_j + \mu_1 Comments_j + \mu_{31} Funny_j\\
&\quad + \mu_{32} Visual_j + \mu_{32} Outrageous_j + \lambda_{j1},\\
\alpha_{j2} &= \mu_4 + \mu_5 Views_j + \mu_6 Comments_j + \mu_{71} Funny_j\\
&\quad + \mu_{72} Visual_j + \mu_{73} Outrageous_j + \lambda_{j2},\\
Views_j &= \gamma_1 + \gamma_{21} Funny_j + \gamma_{22} Visual_j\\
&\quad + \gamma_{23} Outrageous_j + \zeta_{j1},\\
Comments_j &= \gamma_3 + \gamma_{41} Funny_j + \gamma_{42} Visual_j\\
&\quad + \gamma_{43} Outrageous_j + \zeta_{j2}.
\end{aligned} \tag{2}
$$

The random effects λ_{j1}, λ_{j2}, ζ_{j1}, and ζ_{j2} are jointly estimated using a multivariate normal as a generalized structural equation model. The key vectors of coefficients for understanding the effect of ad characteristics on views and comments are $\gamma_{2\ldots}$ and $\gamma_{4\ldots}$. The key vectors of coefficients for understanding the effect of ad characteristics on ad persuasiveness are captured by the vector $\mu_{7\ldots}$.

Column (1) of Table 7 reports the initial results of this approach. The results for $\gamma_{2\ldots}$ suggest that total views increase significantly in the ratings for outrageousness and humor, but do not significantly increase in the rating for visual appeal. By contrast, the estimates for $\gamma_{4\ldots}$ suggest that total comments increase predominantly in humor, but not in outrageousness or visual appeal. The positive estimates for μ_2 and the negative estimates for μ_5 suggest that, in general, product categories with more views have a higher underlying purchase intent for those who see the placebo ad. After watching the ad, however, this result is less pronounced. Instead purchase intent is driven by ad characteristics.

[14] The author is most grateful to an anonymous reviewer for helping to lay out this system of equations.

Table 7 The Joint Effects of Ad Characteristics on Persuasiveness, Views, and Comments

	Simple (1)	Polynomials (2)
	Total views	
γ_1	4.146***	4.434***
	(0.0485)	(0.0922)
γ_{21}	0.0133*	0.0372
	(0.00766)	(0.0296)
γ_{22}	0.00265	−0.130***
	(0.00784)	(0.0336)
γ_{23}	0.0159**	0.0103
	(0.00692)	(0.0275)
γ_{24}		−0.00227
		(0.00268)
γ_{25}		0.0112***
		(0.00279)
γ_{26}		0.000612
		(0.00268)
	Total comments	
γ_3	−2.503***	−2.395***
	(0.0459)	(0.0872)
γ_{41}	0.0128*	0.0466*
	(0.00724)	(0.0280)
γ_{42}	−0.00760	−0.0725**
	(0.00741)	(0.0318)
γ_{43}	0.00952	0.000104
	(0.00654)	(0.0260)
γ_{44}		−0.00318
		(0.00254)
γ_{45}		0.00551**
		(0.00264)
γ_{46}		0.000940
		(0.00253)
	Main	
μ_0	−1.142***	−0.608***
	(0.0912)	(0.111)
μ_1	0.0754***	0.0746***
	(0.00901)	(0.00903)
μ_2	−0.0335***	−0.0329***
	(0.00942)	(0.00944)
μ_{31}	0.0772***	0.0335
	(0.00596)	(0.0233)
μ_{32}	0.0633***	−0.0324
	(0.00610)	(0.0264)
μ_{33}	0.0412***	−0.0397*
	(0.00544)	(0.0218)
μ_{34}		0.00394*
		(0.00213)
μ_{35}		0.00757***
		(0.00220)
μ_{36}		0.00847***
		(0.00215)
μ_4	0.0434	0.428***
	(0.0988)	(0.134)
μ_5	−0.0407***	−0.0442***
	(0.0125)	(0.0125)
μ_6	0.0206	0.0228*
	(0.0132)	(0.0133)
μ_{71}	0.0147*	0.0438
	(0.00861)	(0.0338)
μ_{72}	0.0746***	−0.0303
	(0.00874)	(0.0379)
μ_{73}	−0.0355***	−0.133***
	(0.00791)	(0.0317)
μ_{74}		0.00886***
		(0.00320)
μ_{75}		0.0105***
		(0.00316)
μ_{76}		−0.00278
		(0.00311)
Demo controls	Yes	Yes
Observations	23,673	23,673
Log-likelihood	−120,521.5	−120,369.2

Notes. Joint estimates for purchase intent, total views, and total comments using multivariate normal distribution. Column (1) reports results for estimation based on Equation (3). Column (2) reports results for estimation based on Equation (3). Robust standard errors clustered at the product level.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The estimates for $\mu_{7\ldots}$ suggest that ad persuasiveness is a positive function of humor and visual appeal but is negatively affected by ad outrageousness. These estimates for $\mu_{7\ldots}$ are in line with the estimates observed in Table 6, which suggested that the persuasiveness and reach trade-off was less severe for ads that are popular due to their humor or visual appeal. In particular, ads that are rated as humorous can achieve both high persuasiveness and reach. These estimates also shed light on the result that ad outrageousness appears to augment the trade-off. Outrageousness increases ad views, but decreases persuasiveness.

There may also be nonlinearities in the effects of ad characteristics on both total views and the effects of exposure. Tellis (2004, p. 151) note that the relationship between attention and the strength of the emotional stimulus may be increasing and linear. Ad persuasiveness may be concave in that persuasiveness originally increases in emotion but subsequently decreases. To explore this possibility, Equation (3) adds polynomials for ratings for the ad characteristics, i.e., humor, outrageousness, and visual appeal.

$$Intent_{ij} = I(\alpha_{j1} + \alpha_{j2}\, Exposed_i + \theta\, DemoVariables_{ij} + \epsilon_{ij}),$$

$$\begin{aligned}\alpha_{j1} = \mu_0 &+ \mu_1\, Views_j + \mu_1\, Comments_j + \mu_{31}\, Funny_j \\ &+ \mu_{32}\, Visual_j + \mu_{33}\, Outrageous_j + \mu_{34}\, Funny_j^2 \\ &+ \mu_{35}\, Visual_j^2 + \mu_{36}\, Outrageous_j^2 + \lambda_{j1},\end{aligned}$$

$$\begin{aligned}\alpha_{j2} = \mu_4 &+ \mu_5\, Views_j + \mu_6\, Comments_j + \mu_{71}\, Funny_j \\ &+ \mu_{72}\, Visual_j + \mu_{73}\, Outrageous_j + \mu_{74}\, Funny_j^2 \\ &+ \mu_{75}\, Visual_j^2 + \mu_{76}\, Outrageous_j^2 + \lambda_{j2},\end{aligned}$$

$$\begin{aligned} Views_j = {} & \gamma_1 + \gamma_{21} Funny_j + \gamma_{22} Visual_j \\ & + \gamma_{23} Outrageous_j + \gamma_{24} Funny_j \\ & + \gamma_{25} Visual_j + \gamma_{26} Outrageous_j + \zeta_{j1}, \\ Comments_j = {} & \gamma_3 + \gamma_{41} Funny_j + \gamma_{42} Visual_j \\ & + \gamma_{43} Outrageous_j + \gamma_{44} Funny_j \\ & + \gamma_{45} Visual_j \\ & + \gamma_{46} Outrageous_j + \zeta_{j2}. \end{aligned} \tag{3}$$

Column (2) of Table 7 reports the results for this extended model. From the γ estimates, it seems clear that the major nonlinearity in the effect of ad characteristics on total views and total comments is in visual appeal. Both comments and views seem to exhibit a convex relationship with visual appeal. This suggests that visual appeal only matters at very high ratings in terms of provoking either views or comments. As to the effect of ad characteristics on persuasiveness, as captured by $\mu_{7\ldots}$, the major nonlinearities appear to be for visual appeal and humor, which exhibit convexity. This suggests that very funny or very visually appealing ads are disproportionately appealing relative to those that are quite funny or quite visually appealing. The point estimate for outrageousness, while suggesting some degree of concavity, is not significant at conventional levels. This finding of nonincreasing returns echoes Vézina and Paul (1997), who identified a lack of resonant emotional appeal in outrageous ads. This contrasts with emotions such as sadness or anger, which as shown by Kamp and MacInnis (1995), tend to be more strongly associated with concavity.

5. Implications

Online firms are increasingly switching their emphasis from paid media, such as online display advertising, to earned media where consumers transmit the message. This is reflected in the growth of social video advertising, where video ads are now designed to go viral and achieve cost free reach. This is a very different distribution system for advertising compared to a typical placement process wherein an advertising manager decides how many exposures they want and on what medium. In viral advertising, the advertising manager oversees the design of ads that will generate their own exposures.

Here we hope to quantify the empirical relationship in social advertising between ads that earn multiple views and ads that are persuasive. Combining historical data and a randomized treatment and control methodology among a large crowdsourced population of participants, the analysis measures this relationship empirically. There is a significant negative relationship between total ad views and ad persuasiveness. Ads that receive the most views are relatively less able to persuade consumers to purchase the product. Accounting for viral ad's larger reach, the negative relationship between views and persuasiveness leads to negative consequences after an ad reaches 3–4 million views. This result is robust to a variety of robustness checks.

Videos receive more comments alongside their views; comments that mention the product were less likely to experience this trade-off. In other words, successful ads not only encourage consumers to share the ad with others but also to take time to respond to the ad itself. This suggests that when evaluating ad campaign success managers should not simply track views but also the nature of user-generated content.

Underlying ad characteristics appear to explain this phenomenon. A joint specification suggests that outrageous ads that achieve high views are also less persuasive. Though outrageousness is sufficient to induce participants to share an ad, the effect on ad persuasiveness is negative. By contrast, humorous ads can achieve high views and be simultaneously persuasive.

There are of course limitations to this study. First, despite the extensive data collection, these results hold for 400 ad campaigns from the consumer goods category from 2010. It is unclear whether the results would hold for other products or across time. Second, the recruited participants may not be representative of the population, though may closely reflect the YouTube population. However, unless this groups' responses to different ads are very different from the rest of the population, the general conclusions should hold. Third, all ad design and consequently organic reach or virality is exogenous to the study and was not explicitly manipulated. Fourth, video sharing website advertisers may have other objectives such as gathering subscriptions to their online video channel or another form of direct response, i.e., a separate objective from simply shifting purchase intent. The analysis does not have data on these other forms of consumer response. Last, since the data is video ads for well known consumer goods, it does not allow the study of viral video ads on product awareness. Notwithstanding these limitations, this study documents the potential for an empirical negative relationship between earned reach and ad persuasiveness for ad managers who are trying to exploit the new medium of video advertising.

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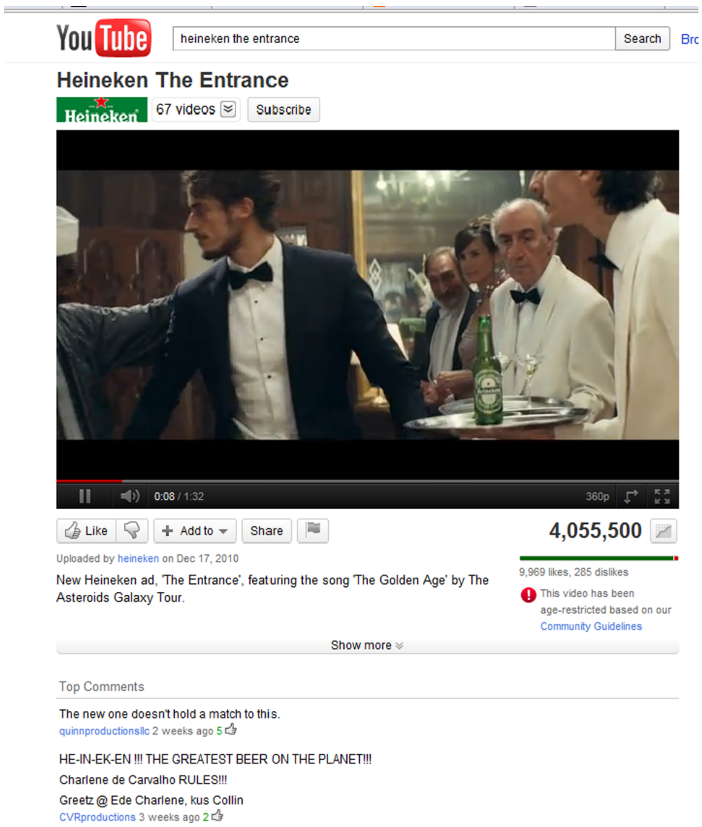
Appendix

Figure A.1 (Color online) Screenshot from Typical Video Ad Campaign Showing Comments and Total Views



Source. Heineken YouTube Channel Screenshot (2012).

Table A.1 Checks for Robustness of Total Comments Interaction in Column (4) of Table 5

	Probit (1) Purchase intent	Probit: Not seen (2) Purchase intent	OLS (3) Purchase intent	OLS (4) Intent scale	Probit (5) Would consider	Probit (6) Favorable opinion
Exposed × *LoggedViews*	−0.0379***	−0.0397***	−0.0145***	−0.0202***	−0.0327***	−0.0416***
	(0.0143)	(0.0132)	(0.00510)	(0.00774)	(0.0126)	(0.0127)
Exposed × *LoggedComments*	0.0281**	0.0282**	0.0103**	0.0156**	0.0238*	0.0326**
	(0.0142)	(0.0139)	(0.00504)	(0.00765)	(0.0133)	(0.0133)
Product controls	Yes	Yes	Yes	Yes	Yes	Yes
Demo controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,367	22,298	24,367	24,367	24,367	24,367
Log-likelihood	−14,894.3	−13,653.6	−15,684.8	−25,790.0	−14,710.4	−14,460.4
R-squared			0.121	0.107		

Notes. In Column (2) all respondents who had seen or heard of the ad before are excluded. In Columns (1)–(3), the dependent variable is whether someone is likely or very likely to purchase the product. Dependent variable is the 5-point purchase intent scale in Column (4). Dependent variable is whether someone is likely or very likely to consider the product in Column (5). Dependent variable is whether someone is likely or very likely to have a favorable opinion of the product in Column (6). Robust standard errors clustered at the product level.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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CORRECTION

In this article, "The Reach and Persuasiveness of Viral Video Ads" by Catherine E. Tucker (first published in *Articles in Advance*, September 29, 2014, *Marketing Science*, DOI:10.1287/mksc.2014.0874), equation 1 was corrected as follows:

$$Intent_{ij} = I(\alpha\, Exposed_i + \beta\, Exposed_i \times LogViews^j + \theta X_i + \delta_j + \epsilon_{ij} > 0). \quad (1)$$