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Why are certain pieces of online content (e.g., advertisements, videos, news articles) more viral than others? This article takes a psychological approach to understanding diffusion. Using a unique data set of all the *New York Times* articles published over a three-month period, the authors examine how emotion shapes virality. The results indicate that positive content is more viral than negative content, but the relationship between emotion and social transmission is more complex than valence alone. Virality is partially driven by physiological arousal. Content that evokes high-arousal positive (awe) or negative (anger or anxiety) emotions is more viral. Content that evokes low-arousal, or deactivating, emotions (e.g., sadness) is less viral. These results hold even when the authors control for how surprising, interesting, or practically useful content is (all of which are positively linked to virality), as well as external drivers of attention (e.g., how prominently content was featured). Experimental results further demonstrate the causal impact of specific emotion on transmission and illustrate that it is driven by the level of activation induced. Taken together, these findings shed light on why people share content and how to design more effective viral marketing campaigns.

Keywords: word of mouth, viral marketing, social transmission, online content

What Makes Online Content Viral?

Sharing online content is an integral part of modern life. People forward newspaper articles to their friends, pass YouTube videos to their relatives, and send restaurant reviews to their neighbors. Indeed, 59% of people report that they frequently share online content with others (Allsop, Bassett, and Hoskins 2007), and someone tweets a link to a *New York Times* story once every four seconds (Harris 2010).

Such social transmission also has an important impact on both consumers and brands. Decades of research suggest that interpersonal communication affects attitudes and decision making (Asch 1956; Katz and Lazarsfeld 1955), and recent work has demonstrated the causal impact of word of mouth on product adoption and sales (Chevalier and Mayzlin 2006; Godes and Mayzlin 2009).

Although it is clear that social transmission is both frequent and important, less is known about *why* certain pieces of online content are more viral than others. Some customer service experiences spread throughout the blogosphere, while others are never shared. Some newspaper articles earn a position on their website's "most e-mailed list," while others languish. Companies often create online ad campaigns or encourage consumer-generated content in the hope that people will share this content with others, but some of these efforts take off while others fail. Is virality just random, as some argue (e.g., Cashmore 2009), or might certain characteristics predict whether content will be highly shared?

This article examines how content characteristics affect virality. In particular, we focus on how emotion shapes social transmission. We do so in two ways. First, we analyze a unique data set of nearly 7000 *New York Times* articles to examine which articles make the newspaper's "most e-mailed list." Controlling for external drivers of attention, such as where an article was featured online and for how long, we examine how content's valence (i.e., whether an

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article is positive or negative) and the specific emotions it evokes (e.g., anger, sadness, awe) affect whether it is highly shared. Second, we experimentally manipulate the specific emotion evoked by content to directly test the causal impact of arousal on social transmission.

This research makes several important contributions. First, research on word of mouth and viral marketing has focused on its impact (i.e., on diffusion and sales; Godes and Mayzlin 2004, 2009; Goldenberg et al. 2009). However, there has been less attention to its causes or what drives people to share content with others and what type of content is more likely to be shared. By combining a large-scale examination of real transmission in the field with tightly controlled experiments, we both demonstrate characteristics of viral online content and shed light on the underlying processes that drive people to share. Second, our findings provide insight into how to design successful viral marketing campaigns. Word of mouth and social media are viewed as cheaper and more effective than traditional media, but their utility hinges on people transmitting content that helps the brand. If no one shares a company's content or if consumers share content that portrays the company negatively, the benefit of social transmission is lost. Consequently, understanding what drives people to share can help organizations and policy makers avoid consumer backlash and craft contagious content.

CONTENT CHARACTERISTICS AND SOCIAL TRANSMISSION

One reason people may share stories, news, and information is because they contain useful information. Coupons or articles about good restaurants help people save money and eat better. Consumers may share such practically useful content for altruistic reasons (e.g., to help others) or for self-enhancement purposes (e.g., to appear knowledgeable, see Wojnicki and Godes 2008). Practically useful content also has social exchange value (Homans 1958), and people may share it to generate reciprocity (Fehr, Kirchsteiger, and Riedl 1998).

Emotional aspects of content may also affect whether it is shared (Heath, Bell, and Sternberg 2001). People report discussing many of their emotional experiences with others, and customers report greater word of mouth at the extremes of satisfaction (i.e., highly satisfied or highly dissatisfied; Anderson 1998). People may share emotionally charged content to make sense of their experiences, reduce dissonance, or deepen social connections (Festinger, Riecken, and Schachter 1956; Peters and Kashima 2007; Rime et al. 1991).

Emotional Valence and Social Transmission

These observations imply that emotionally evocative content may be particularly viral, but which is more likely to be shared—positive or negative content? While there is a lay belief that people are more likely to pass along negative news (Godes et al. 2005), this has never been tested. Furthermore, the study on which this notion is based actually focused on understanding what types of news people encounter, not what they transmit (see Goodman 1999). Consequently, researchers have noted that "more rigorous research into the relative probabilities of transmission of positive and negative information would be valuable to both academics and managers" (Godes et al. 2005, p. 419).

We hypothesize that more positive content will be more viral. Consumers often share content for self-presentation purposes (Wojnicki and Godes 2008) or to communicate identity, and consequently, positive content may be shared more because it reflects positively on the sender. Most people would prefer to be known as someone who shares upbeat stories or makes others feel good rather than someone who shares things that makes others sad or upset. Sharing positive content may also help boost others' mood or provide information about potential rewards (e.g., this restaurant is worth trying).

The Role of Activation in Social Transmission

Importantly, however, the social transmission of emotional content may be driven by more than just valence. In addition to being positive or negative, emotions also differ on the level of physiological arousal or activation they evoke (Smith and Ellsworth 1985). Anger, anxiety, and sadness are all negative emotions, for example, but while anger and anxiety are characterized by states of heightened arousal or activation, sadness is characterized by low arousal or deactivation (Barrett and Russell 1998).

We suggest that these differences in arousal shape social transmission (see also Berger 2011). Arousal is a state of mobilization. While low arousal or deactivation is characterized by relaxation, high arousal or activation is characterized by activity (for a review, see Heilman 1997). Indeed, this excitatory state has been shown to increase action-related behaviors such as getting up to help others (Gaertner and Dovidio 1977) and responding faster to offers in negotiations (Brooks and Schweitzer 2011). Given that sharing information requires action, we suggest that activation should have similar effects on social transmission and boost the likelihood that content is highly shared.

If this is the case, even two emotions of the same valence may have different effects on sharing if they induce different levels of activation. Consider something that makes people sad versus something that makes people angry. Both emotions are negative, so a simple valence-based perspective would suggest that content that induces either emotion should be less viral (e.g., people want to make their friends feel good rather than bad). An arousal- or activation-based analysis, however, provides a more nuanced perspective. Although both emotions are negative, anger might increase transmission (because it is characterized by high activation), while sadness might actually decrease transmission (because it is characterized by deactivation or inaction).

THE CURRENT RESEARCH

We examine how content characteristics drive social transmission and virality. In particular, we not only examine whether positive content is more viral than negative content but go beyond mere valence to examine how specific emotions evoked by content, and the activation they induce, drive social transmission.

We study transmission in two ways. First, we investigate the virality of almost 7000 articles from one of the world's most popular newspapers: the *New York Times* (Study 1). Controlling for a host of factors (e.g., where articles are featured, how much interest they evoke), we examine how the emotionality, valence, and specific emotions evoked by an article affect its likelihood of making the *New York Times*' most e-mailed list. Second, we conduct a series of lab experiments (Studies 2a, 2b, and 3) to test the underlying process we believe to be responsible for the observed effects. By directly manipulating specific emotions and measuring the activation they induce, we test our hypothesis that content that evokes high-arousal emotion is more likely to be shared.

STUDY 1: A FIELD STUDY OF EMOTIONS AND VIRALITY

Our first study investigates what types of *New York Times* articles are highly shared. The *New York Times* covers a wide range of topics (e.g., world news, sports, travel), and its articles are shared with a mix of friends (42%), relatives (40%), colleagues (10%), and others (7%),[1] making it an ideal venue for examining the link between content characteristics and virality. The *New York Times* continually reports which articles from its website have been the most e-mailed in the past 24 hours, and we examine how (1) an article's valence and (2) the extent to which it evokes various specific emotions (e.g., anger or sadness) affect whether it makes the *New York Times*' most e-mailed list.

Negative emotions have been much better distinguished from one another than positive emotions (Keltner and Lerner 2010). Consequently, when considering specific emotions, our archival analysis focuses on negative emotions because they are straightforward to differentiate and classify. Anger, anxiety, and sadness are often described as basic, or universal, emotions (Ekman, Friesen, and Ellsworth 1982), and on the basis of our previous theorizing about activation, we predict that negative emotions characterized by activation (i.e., anger and anxiety) will be positively linked to virality, while negative emotions characterized by deactivation (i.e., sadness) will be negatively linked to virality.

We also examine whether awe, a high-arousal positive emotion, is linked to virality. Awe is characterized by a feeling of admiration and elevation in the face of something greater than oneself (e.g., a new scientific discovery, someone overcoming adversity; see Keltner and Haidt 2003). It is generated by stimuli that open the mind to unconsidered possibilities, and the arousal it induces may promote transmission.

Importantly, our empirical analyses control for several potentially confounding variables. First, as we noted previously, practically useful content may be more viral because it provides information. Self-presentation motives also shape transmission (Wojnicki and Godes 2008), and people may share interesting or surprising content because it is entertaining and reflects positively on them (i.e., suggests that they know interesting or entertaining things). Consequently, we control for these factors to examine the link between emotion and virality beyond them (though their relationships with virality may be of interest to some scholars and practitioners).

Second, our analyses also control for things beyond the content itself. Articles that appear on the front page of the newspaper or spend more time in prominent positions on the *New York Times*' home page may receive more attention and thus mechanically have a better chance of making the most e-mailed list. Consequently, we control for these and other potential external drivers of attention.[2] Including these controls also enables us to compare the relative impact of placement versus content characteristics in shaping virality. While being heavily advertised, or in this case prominently featured, should likely increase the chance content makes the most e-mailed list, we examine whether content characteristics (e.g., whether an article is positive or awe-inspiring) are of similar importance.

Data

We collected information about all *New York Times* articles that appeared on the newspaper's home page (www.nytimes.com) between August 30 and November 30, 2008 (6956 articles). We captured data using a web crawler that visited the *New York Times*' home page every 15 minutes during the period in question. It recorded information about every article on the home page and each article on the most e-mailed list (updated every 15 minutes). We captured each article's title, full text, author(s), topic area (e.g., opinion, sports), and two-sentence summary created by the *New York Times*. We also captured each article's section, page, and publication date if it appeared in the print paper, as well as the dates, times, locations, and durations of all appearances it made on the *New York Times*' home page. Of the articles in our data set, 20% earned a position on the most e-mailed list.

Article Coding

We coded the articles on several dimensions. First, we used automated sentiment analysis to quantify the positivity (i.e., valence) and emotionality (i.e., affect ladenness) of each article. These methods are well established (Pang and Lee 2008) and increase coding ease and objectivity. Automated ratings were also significantly positively correlated with manual coders' ratings of a subset of articles. A computer program (LIWC) counted the number of positive and negative words in each article using a list of 7630 words classified as positive or negative by human readers (Pennebaker, Booth, and Francis 2007). We quantified positivity as the difference between the percentage of positive and negative words in an article. We quantified emotionality as the percentage of words that were classified as either positive or negative.

Second, we relied on human coders to classify the extent to which content exhibited other, more specific characteristics (e.g., evoked anger) because automated coding systems were not available for these variables. In addition to coding whether articles contained practically useful information or evoked interest or surprise (control variables), coders quantified the extent to which each article evoked anxiety, anger, awe, or sadness.[3] Coders were blind to our hypotheses. They received the title and summary of each article, a web link to the article's full text, and detailed coding instructions (see the Web Appendix at www.marketingpower.com/jmr_webappendix). Given the overwhelming number of articles in our data set, we selected a random subsample for coding (n = 2566). For each dimension (awe, anger, anxiety, sad-

[1]These figures are based on 343 *New York Times* readers who were asked with whom they had most recently shared an article.

[2]Discussion with newspaper staff indicated that editorial decisions about how to feature articles on the home page are made independently of (and well before) their appearance on the most e-mailed list.

[3]Given that prior work has examined how the emotion of disgust might affect the transmission of urban legends (Heath, Bell, and Sternberg 2001), we also include disgust in our analysis. (The rest of the results remain unchanged regardless of whether it is in the model.) While we do not find any significant relationship between disgust and virality, this may be due in part to the notion that in general, *New York Times* articles elicit little of this emotion.

ness, surprise, practical utility, and interest), a separate group of three independent raters rated each article on a five-point Likert scale according to the extent to which it was characterized by the construct in question (1 = "not at all," and 5 = "extremely"). We gave raters feedback on their coding of a test set of articles until it was clear that they understood the relevant construct. Interrater reliability was high on all dimensions (all α's > .70), indicating that content tends to evoke similar emotions across people. We averaged scores across coders and standardized them (for sample articles that scored highly on the different dimensions, see Table 1; for summary statistics, see Table 2; and for correlations between variables, see the Appendix). We assigned all uncoded articles a score of zero on each dimension after standardization (i.e., we assigned uncoded articles the mean value), and we included a dummy in regression analyses to control for uncoded stories (for a discussion of this standard imputation methodology, see Cohen and Cohen 1983). This enabled us to use the full set of articles collected to analyze the relationship between other content characteristics (that did not require manual coding) and virality. Using only the coded subset of articles provides similar results.

Table 1

ARTICLES THAT SCORED HIGHLY ON DIFFERENT DIMENSIONS

Primary Predictors

Emotionality
- "Redefining Depression as Mere Sadness"
- "When All Else Fails, Blaming the Patient Often Comes Next"

Positivity
- "Wide-Eyed New Arrivals Falling in Love with the City"
- "Tony Award for Philanthropy"

(Low Scoring)
- "Web Rumors Tied to Korean Actress's Suicide"
- "Germany: Baby Polar Bear's Feeder Dies"

Awe
- "Rare Treatment Is Reported to Cure AIDS Patient"
- "The Promise and Power of RNA"

Anger
- "What Red Ink? Wall Street Paid Hefty Bonuses"
- "Loan Titans Paid McCain Adviser Nearly $2 Million"

Anxiety
- "For Stocks, Worst Single-Day Drop in Two Decades"
- "Home Prices Seem Far from Bottom"

Sadness
- "Maimed on 9/11, Trying to Be Whole Again"
- "Obama Pays Tribute to His Grandmother After She Dies"

Control Variables

Practical Utility
- "Voter Resources"
- "It Comes in Beige or Black, but You Make It Green" (a story about being environmentally friendly when disposing of old computers)

Interest
- "Love, Sex and the Changing Landscape of Infidelity"
- "Teams Prepare for the Courtship of LeBron James"

Surprise
- "Passion for Food Adjusts to Fit Passion for Running" (a story about a restaurateur who runs marathons)
- "Pecking, but No Order, on Streets of East Harlem" (a story about chickens in Harlem)

Additional Controls

As we discussed previously, external factors (separate from content characteristics) may affect an article's virality by functioning like advertising. Consequently, we rigorously control for such factors in our analyses (for a list of all independent variables including controls, see Table 3).

Appearance in the physical newspaper. To characterize where an article appeared in the physical newspaper, we created dummy variables to control for the article's section (e.g., Section A). We also created indicator variables to quantify the page in a given section (e.g., A1) where an article appeared in print to control for the possibility that appearing earlier in some sections has a different effect than appearing earlier in others.

Appearance on the home page. To characterize how much time an article spent in prominent positions on the home page, we created variables that indicated where, when, and for how long every article was featured on the *New York Times* home page. The home page layout remained the same throughout the period of data collection. Articles could appear in several dozen positions on the home page, so we aggregated positions into seven general regions based on locations that likely receive similar amounts of attention (Figure 1). We included variables indicating the amount of time an article spent in each of these seven regions as controls after Winsorization of the top 1% of outliers (to prevent extreme outliers from exerting undue influence on our results; for summary statistics, see Tables WA1 and WA2 in the Web Appendix at www.marketingpower.com/jmr_webappendix).

Release timing and author fame. To control for the possibility that articles released at different times of day receive different amounts of attention, we created controls for the time of day (6 A.M.–6 P.M. or 6 P.M.–6 A.M. eastern standard time) when an article first appeared online. We control for author fame to ensure that our results are not driven by the tastes of particularly popular writers whose stories may be more likely to be shared. To quantify author fame, we capture the number of Google hits returned by a search for each first author's full name (as of February 15, 2009). Because

Table 2

PREDICTOR VARIABLE SUMMARY STATISTICS

	M	*SD*
Primary Predictor Variables		
Emotionality[a]	7.43%	1.92%
Positivity[a]	.98%	1.84%
Awe[a]	1.81	.71
Anger[a]	1.47	.51
Anxiety[a]	1.55	.64
Sadness[a]	1.31	.41
Other Control Variables		
Practical utility[a]	1.66	1.01
Interest[a]	2.71	.85
Surprise[a]	2.25	.87
Word count	1021.35	668.94
Complexity[a]	11.08	1.54
Author fame	9.13	2.54
Author female	.29	.45
Author male	.66	.48

[a]These summary statistics pertain to the variable in question before standardization.

Table 3
PREDICTOR VARIABLES

Variable	Where It Came from
Main Independent Variables	
Emotionality	Coded through textual analysis (LIWC)
Positivity	Coded through textual analysis (LIWC)
Awe	Manually coded
Anger	Manually coded
Anxiety	Manually coded
Sadness	Manually coded
Content Controls	
Practical utility	Manually coded
Interest	Manually coded
Surprise	Manually coded
Other Control Variables	
Word count	Coded through textual analysis (LIWC)
Author fame	Log of number of hits returned by Google search of author's name
Writing complexity	SMOG Complexity Index (McLaughlin 1969)
Author gender	List mapping names to genders (Morton et al. 2003)
Author byline missing	Captured by web crawler
Article section	Captured by web crawler
Hours spent in different places on the home page	Captured by web crawler
Section of the physical paper (e.g., A)	Captured by web crawler
Page in section in the physical paper (e.g., A1)	Captured by web crawler
Time of day the article appeared	Captured by web crawler
Day the article appeared	Captured by web crawler
Category of the article (e.g., sports)	Captured by web crawler

of its skew, we use the logarithm of this variable as a control in our analyses. We also control for variables that might both influence transmission and the likelihood that an article possesses certain characteristics (e.g., evokes anger).

Writing complexity. We control for how difficult a piece of writing is to read using the SMOG Complexity Index (McLaughlin 1969). This widely used index variable essentially measures the grade-level appropriateness of the writing. Alternate complexity measures yield similar results.

Author gender. Because male and female authors have different writing styles (Koppel, Argamon, and Shimoni 2002; Milkman, Carmona, and Gleason 2007), we control for the gender of an article's first author (male, female, or unknown due to a missing byline). We classify gender using a first name mapping list from prior research (Morton, Zettelmeyer, and Silva-Risso 2003). For names that were classified as gender neutral or did not appear on this list, research assistants determined author gender by finding the authors online.

Article length and day dummies. We also control for an article's length in words. Longer articles may be more likely to go into enough detail to inspire awe or evoke anger but may simply be more viral because they contain more information. Finally, we use day dummies to control for both competition among articles to make the most e-mailed list (i.e., other content that came out the same day) as well as any other time-specific effects (e.g., world events that might affect article characteristics and reader interest).

Analysis Strategy

Almost all articles that make the most e-mailed list do so only once (i.e., they do not leave the list and reappear), so we model list making as a single event (for further discussion, see the Web Appendix at www.marketingpower.com/jmr_webappendix). We rely on the following logistic regression specification:

$$(1)\ \text{makes\_it}_{at} = \frac{1}{1+\exp\left[-\begin{pmatrix}\alpha_t+\beta_1\times\text{z-emotionality}_{at}\\ +\beta_2\times\text{z-positivity}_{at}\\ +\beta_3\times\text{z-awe}_{at}+\beta_4\times\text{z-anger}_{at}\\ +\beta_5\times\text{z-anxiety}_{at}\\ +\beta_6\times\text{z-sadness}_{at}+\theta'\times X_{at}\end{pmatrix}\right]},$$

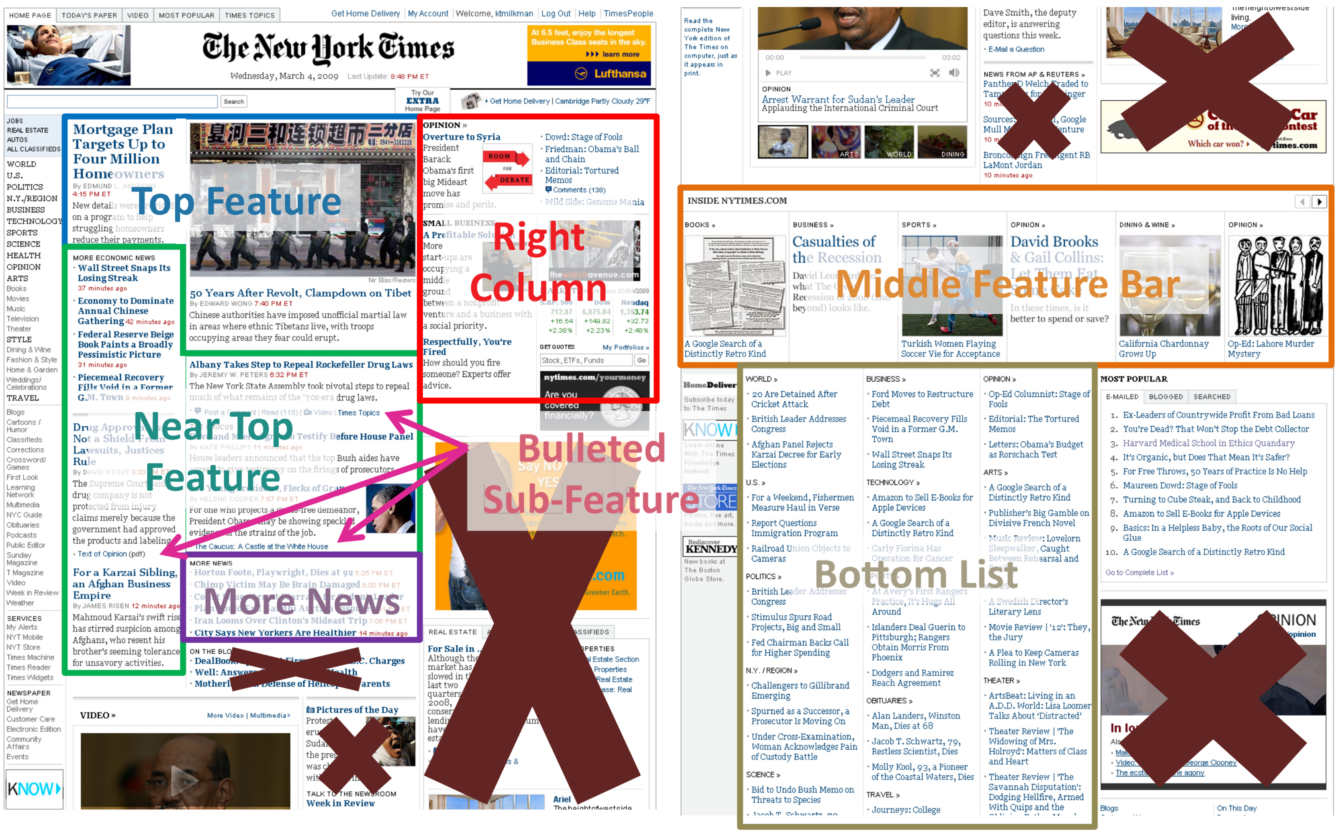
where makes_it_{at} is a variable that takes a value of 1 when an article a released online on day t earns a position on the most e-mailed list and 0 otherwise, and α_t is an unobserved day-specific effect. Our primary predictor variables quantify the extent to which article a published on day t was coded as positive, emotional, awe inspiring, anger inducing, anxiety inducing, or sadness inducing. The term X_{at} is a vector of the other control variables described previously (see Table 3). We estimate the equation with fixed effects for the day of an article's release, clustering standard errors by day of release. (Results are similar if fixed effects are not included.)

Results

Is positive or negative content more viral? First, we examine content valence. The results indicate that content is more likely to become viral the more positive it is (Table 4, Model 1). Model 2 shows that more affect-laden content, regardless of valence, is more likely to make the most e-mailed list, but the returns to increased positivity persist even controlling for emotionality more generally. From a different perspective, when we include both the percentage of positive and negative words in an article as separate predictors (instead of emotionality and valence), both are positively associated with making the most e-mailed list. However, the coefficient on positive words is considerably larger than that on negative words. This indicates that while more positive or more negative content is more viral than content that does not evoke emotion, positive content is more viral than negative content.

The nature of our data set is particularly useful here because it enables us to disentangle preferential transmission from mere base rates (see Godes et al. 2005). For example, if it were observed that there was more positive than negative word of mouth overall, it would be unclear whether this outcome was driven by (1) what people encounter (e.g., people may come across more positive events than negative ones) or (2) what people prefer to pass on (i.e., positive or negative content). Thus, without knowing what people could have shared, it is difficult to infer much about what they prefer to share. Access to the full cor-

Figure 1
HOME PAGE LOCATION CLASSIFICATIONS



Notes: Portions with "X" through them always featured Associated Press and Reuters news stories, videos, blogs, or advertisements rather than articles by *New York Times* reporters.

pus of articles published by the *New York Times* over the analysis period as well as all content that made the most e-mailed list enables us to separate these possibilities. Taking into account all published articles, our results show that an article is more likely to make the most e-mailed list the more positive it is.

How do specific emotions affect virality? The relationships between specific emotions and virality suggest that the role of emotion in transmission is more complex than mere valence alone (Table 4, Model 3). While more awe-inspiring (a positive emotion) content is more viral and sadness-inducing (a negative emotion) content is less viral, some negative emotions are positively associated with virality. More anxiety- and anger-inducing stories are both more likely to make the most e-mailed list. This suggests that transmission is about more than simply sharing positive things and avoiding sharing negative ones. Consistent with our theorizing, content that evokes high-arousal emotions (i.e., awe, anger, and anxiety), regardless of their valence, is more viral.

Other factors. These results persist when we control for a host of other factors (Table 4, Model 4). More notably, informative (practically useful), interesting, and surprising articles are more likely to make the *New York Times*' most e-mailed list, but our focal results are significant even after we control for these content characteristics. Similarly, being featured for longer in more prominent positions on the *New York Times* home page (e.g., the lead story vs. at the bottom of the page) is positively associated with making the most e-mailed list, but the relationships between emotional characteristics of content and virality persist even after we control for this type of "advertising." This suggests that the heightened virality of stories that evoke certain emotions is not simply driven by editors featuring those types of stories, which could mechanically increase their virality.[4] Longer articles, articles by more famous authors, and articles written by women are also more likely to make the most e-mailed list, but our results are robust to including these factors as well.

Robustness checks. The results are also robust to controlling for an article's general topic (20 areas classified by the *New York Times*, such as science and health; Table 4, Model 5). This indicates that our findings are not merely driven by certain areas tending to both evoke certain emotions and be particularly likely to make the most e-mailed list. Rather,

[4]Furthermore, regressing the various content characteristics on being featured suggests that topical section (e.g., national news vs. sports), rather than an integral affect, determines where articles are featured. The results show that general topical areas (e.g., opinion) are strongly related to whether and where articles are featured on the home page, while emotional characteristics are not.

Table 4
AN ARTICLE'S LIKELIHOOD OF MAKING THE *NEW YORK TIMES'* MOST E-MAILED LIST AS A FUNCTION OF ITS CONTENT CHARACTERISTICS

	Positivity (1)	*Emotionality (2)*	*Specific Emotions (3)*	*Including Controls (4)*	*Including Section Dummies (5)*	*Only Coded Articles (6)*
Emotion Predictors						
Positivity	.13***	.11***	.17***	.16***	.14***	.23***
	(.03)	(.03)	(.03)	(.04)	(.04)	(.05)
Emotionality	—	.27***	.26***	.22***	.09*	.29***
	—	(.03)	(.03)	(.04)	(.04)	(.06)
Specific Emotions						
Awe	—	—	.46***	.34***	.30***	.36***
	—	—	(.05)	(.05)	(.06)	(.06)
Anger	—	—	.44***	.38***	.29**	.37***
	—	—	(.06)	(.09)	(.10)	(.10)
Anxiety	—	—	.20***	.24***	.21***	.27***
	—	—	(.05)	(.07)	(.07)	(.07)
Sadness	—	—	–.19***	–.17*	–.12†	–.16*
	—	—	(.05)	(.07)	(.07)	(.07)
Content Controls						
Practical utility	—	—	—	.34***	.18**	.27***
	—	—	—	(.06)	(.07)	(.06)
Interest	—	—	—	.29***	.31***	.27***
	—	—	—	(.06)	(.07)	(.07)
Surprise	—	—	—	.16**	.24***	.18**
	—	—	—	(.06)	(.06)	(.06)
Home Page Location Control Variables						
Top feature	—	—	—	.13***	.11***	.11***
	—	—	—	(.02)	(.02)	(.03)
Near top feature	—	—	—	.11***	.10***	.12***
	—	—	—	(.01)	(.01)	(.01)
Right column	—	—	—	.14***	.10***	.15***
	—	—	—	(.01)	(.02)	(.02)
Middle feature bar	—	—	—	.06***	.05***	.06***
	—	—	—	(.00)	(.01)	(.01)
Bulleted subfeature	—	—	—	.04**	.04**	.05*
	—	—	—	(.01)	(.01)	(.02)
More news	—	—	—	.01	.06***	–.01
	—	—	—	(.01)	(.01)	(.02)
Bottom list × 10	—	—	—	.06**	.11***	.08**
	—	—	—	(.02)	(.03)	(.03)
Other Control Variables						
Word count × 10^{-3}	—	—	—	.52***	.71***	.57***
	—	—	—	(.11)	(.12)	(.18)
Complexity	—	—	—	.05	.05	.06
	—	—	—	(.04)	(.04)	(.07)
First author fame	—	—	—	.17***	.15***	.15***
	—	—	—	(.02)	(.02)	(.03)
Female first author	—	—	—	.36***	.33***	.27*
	—	—	—	(.08)	(.09)	(.13)
Uncredited	—	—	—	.39	–.56*	.50
	—	—	—	(.26)	(.27)	(.37)
Newspaper location and web timing controls	No	No	No	Yes	Yes	Yes
Article section dummies (e.g., arts, books)	No	No	No	No	Yes	No
Observations	6956	6956	6956	6956	6956	2566
McFadden's R^2	.00	.04	.07	.28	.36	.32
Log-pseudo-likelihood	–3245.85	–3118.45	–3034.17	–2331.37	–2084.85	–904.76

†Significant at the 10% level.
*Significant at 5% level.
**Significant at 1% level.
***Significant at the .1% level.

Notes: The logistic regressions models that appear in this table predict whether an article makes the *New York Times*' most emailed list. Successive models include added control variables, with the exception of Model 6. Model 6 presents our primary regression specification (see Model 4), including only observations of articles whose content was hand-coded by research assistants. All models include day fixed effects. Models 4–6 include disgust (hand-coded) as a control because disgust has been linked to transmission in previous research (Heath et al. 2001), and including this control allows for a more conservative test of our hypotheses. Its effect is never significant, and dropping this control variable does not change any of our results.

this more conservative test of our hypothesis suggests that the observed relationships between emotion and virality hold not only across topics but also within them. Even among opinion or health articles, for example, awe-inspiring articles are more viral.

Finally, our results remain meaningfully unchanged in terms of magnitude and significance if we perform a host of other robustness checks, including analyzing only the 2566 hand-coded articles (Table 4, Model 6), removing day fixed effects, and using alternate ways of quantifying emotion (for more robustness checks and analyses using article rank or time on the most e-mailed list as alternate dependent measures, see the Web Appendix at www.marketingpower.com/jmr_webappendix). These results indicate that the observed results are not an artifact of the particular regression specifications we rely on in our primary analyses.

Discussion

Analysis of more than three months of *New York Times* articles sheds light on what types of online content become viral and why. Contributing to the debate on whether positive or negative content is more likely to be shared, our results demonstrate that more positive content is more viral. Importantly, however, our findings also reveal that virality is driven by more than just valence. Sadness, anger, and anxiety are all negative emotions, but while sadder content is less viral, content that evokes more anxiety or anger is actually more viral. These findings are consistent with our hypothesis about how arousal shapes social transmission. Positive and negative emotions characterized by activation or arousal (i.e., awe, anxiety, and anger) are positively linked to virality, while emotions characterized by deactivation (i.e., sadness) are negatively linked to virality.

More broadly, our results suggest that while external drivers of attention (e.g., being prominently featured) shape what becomes viral, content characteristics are of similar importance (see Figure 2). For example, a one-standard-deviation increase in the amount of anger an article evokes increases the odds that it will make the most e-mailed list by 34% (Table 4, Model 4). This increase is equivalent to spending an additional 2.9 hours as the lead story on the *New York Times* website, which is nearly four times the average number of hours articles spend in that position. Similarly, a one-standard-deviation increase in awe increases the odds of making the most e-mailed list by 30%.

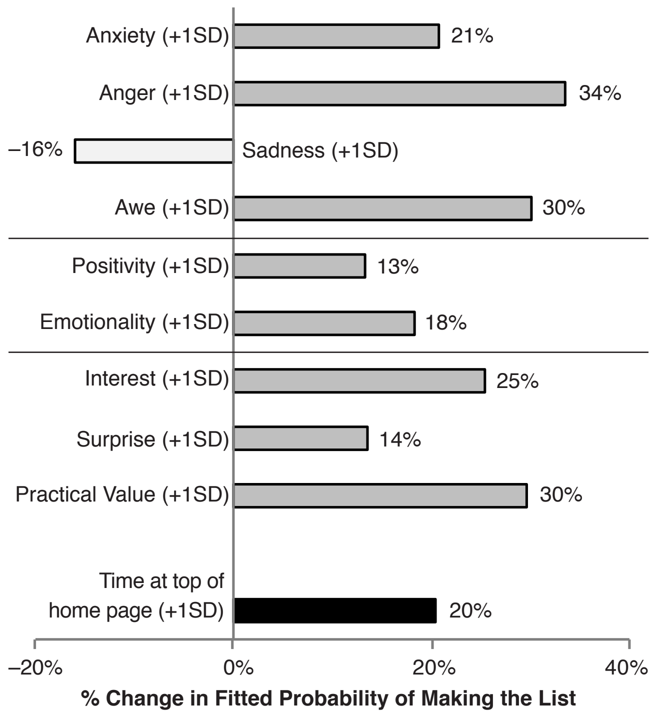
These field results are consistent with the notion that activation drives social transmission. To more directly test the process behind our specific emotions findings, we turn to the laboratory.

STUDY 2: HOW HIGH-AROUSAL EMOTIONS AFFECT TRANSMISSION

Our experiments had three main goals. First, we wanted to directly test the causal impact of specific emotions on sharing. The field study illustrates that content that evokes activating emotions is more likely to be viral, but by manipulating specific emotions in a more controlled setting, we can more cleanly examine how they affect transmission. Second, we wanted to test the hypothesized mechanism behind these effects—namely, whether the arousal induced by content drives transmission. Third, while the *New York Times* provided a broad domain to study transmission, we wanted to test whether our findings would generalize to other marketing content.

Figure 2

PERCENTAGE CHANGE IN FITTED PROBABILITY OF MAKING THE LIST FOR A ONE-STANDARD-DEVIATION INCREASE ABOVE THE MEAN IN AN ARTICLE CHARACTERISTIC



We asked participants how likely they would be to share a story about a recent advertising campaign (Study 2a) or customer service experience (Study 2b) and manipulated whether the story in question evoked more or less of a specific emotion (amusement in Study 2a and anger in Study 2b). To test the generalizability of the effects, we examined how both positive (amusement, Study 2a) and negative (anger, Study 2b) high-arousal emotions characterized influence transmission. If arousal increases sharing, content that evokes more of an activating emotion (amusement or anger) should be more likely to be shared. Finally, we measured experienced activation to test whether it drives the effect of emotion on sharing.

Study2a: Amusement

Participants (N = 49) were randomly assigned to read either a high- or low-amusement version of a story about a recent advertising campaign for Jimmy Dean sausages. The two versions were adapted from prior work (McGraw and Warren 2010) showing that they differed on how much humor they evoked (a pretest showed that they did not differ in how much interest they evoked). In the low-amusement condition, Jimmy Dean decides to hire a farmer as the new spokesperson for the company's line of pork products. In the high-amusement condition, Jimmy Dean decides to hire a rabbi (which is funny given that the company makes pork products and that pork is not considered kosher). After reading about the campaign, participants were asked how likely they would be to share it with others (1 = "not at all likely," and 7 = "extremely likely").

Participants also rated their level of arousal using three seven-point scales ("How do you feel right now?" Scales were anchored at "very passive/very active," "very mellow/very fired up," and "very low energy/very high energy": α = 82; we adapted this measure from Berger [2011] and averaged the responses to form an activation index).

Results. As we predicted, participants reported they would be more likely to share the advertising campaign when it induced more amusement, and this was driven by the arousal it evoked. First, participants reported that they would be more likely to share the advertisement if they were in the high-amusement (M = 3.97) as opposed to low-amusement condition (M = 2.92; $F(1, 47) = 10.89$, $p < .005$). Second, the results were similar for arousal; the high-amusement condition (M = 3.73) evoked more arousal than the low-amusement condition (M = 2.92; $F(1, 47) = 5.24$, $p < .05$). Third, as we predicted, this boost in arousal mediated the effect of the amusement condition on sharing. Condition was linked to arousal ($\beta_{high\_amusement} = .39$, SE = .17; $t(47) = 2.29$, $p < .05$); arousal was linked to sharing ($\beta_{activation} = .58$, SE = .11; $t(47) = 5.06$, $p < .001$); and when we included both the amusement condition and arousal in a regression predicting sharing, arousal mediated the effect of amusement on transmission (Sobel z = 2.02, $p < .05$).

Study2b: Anger

Participants (N = 45) were randomly assigned to read either a high- or low-anger version of a story about a (real) negative customer service experience with United Airlines (Negroni 2009). We pretested the two versions to ensure that they evoked different amounts of anger but not other specific emotions, interest, or positivity in general. In both conditions, the story described a music group traveling on United Airlines to begin a week-long-tour of shows in Nebraska. As they were about to leave, however, they noticed that the United baggage handlers were mishandling their guitars. They asked for help from flight attendants, but by the time they landed, the guitars had been damaged. In the high-anger condition, the story was titled "United Smashes Guitars," and it described how the baggage handlers seemed not to care about the guitars and how United was unwilling to pay for the damages. In the low-anger condition, the story was titled "United Dents Guitars," and it described the baggage handlers as having dropped the guitars but United was willing to help pay for the damages. After reading the story, participants rated how likely they would be to share the customer service experience as well as their arousal using the scales from Study 2a.

Results. As we predicted, participants reported that they would be more likely to share the customer service experience when it induced more anger, and this was driven by the arousal it evoked. First, participants reported being more likely to share the customer service experience if they were in the high-anger condition (M = 5.71) as opposed to low-anger condition (M = 3.37; $F(1, 43) = 18.06$, $p < .001$). Second, the results were similar for arousal; the high-anger condition (M = 4.48) evoked more arousal than the low-anger condition (M = 3.00; $F(1, 43) = 10.44$, $p < .005$). Third, as in Study 2a, this boost in arousal mediated the effect of condition on sharing. Regression analyses show that condition was linked to arousal ($\beta_{high\_anger} = .74$, SE = .23; $t(44) = 3.23$, $p < .005$); arousal was linked to sharing ($\beta_{activation} = .65$, SE = .17; $t(44) = 3.85$, $p < .001$); and when we included both anger condition and arousal in a regression, arousal mediated the effect of anger on transmission (Sobel z = 1.95, $p = .05$).

Discussion

The experimental results reinforce the findings from our archival field study, support our hypothesized process, and generalize our findings to a broader range of content. First, consistent with our analysis of the *New York Times*' most e-mailed list, the amount of emotion content evoked influenced transmission. People reported that they would be more likely to share an advertisement when it evoked more amusement (Study 2a) and a customer service experience when it evoked more anger (Study 2b). Second, the results underscore our hypothesized mechanism: Arousal mediated the impact of emotion on social transmission. Content that evokes more anger or amusement is more likely to be shared, and this is driven by the level of activation it induces.

STUDY 3: HOW DEACTIVATING EMOTIONS AFFECT TRANSMISSION

Our final experiment further tests the role of arousal by examining how *de*activating emotions affect transmission. Studies 2a and 2b show that increasing the amount of high-arousal emotions boosts social transmission due to the activation it induces, but if our theory is correct, these effects should reverse for low-arousal emotions. Content that evokes more sadness, for example, should be less likely to be shared because it deactivates rather than activates.

Note that this is a particularly strong test of our theory because the prediction goes against several alternative explanations for our findings in Study 2. It could be argued that evoking more of any specific emotion makes content better or more compelling, but such an explanation would suggest that evoking more sadness should increase (rather than decrease) transmission.

Method

Participants (N = 47) were randomly assigned to read either a high- or low-sadness version of a news article. We pretested the two versions to ensure that they evoked different amounts of sadness but not other specific emotions, interest, or positivity in general. In both conditions, the article described someone who had to have titanium pins implanted in her hands and relearn her grip after sustaining injuries. The difference between conditions was the source of the injury. In the high-sadness condition, the story was taken directly from our *New York Times* data set. It was titled "Maimed on 9/11: Trying to Be Whole Again," and it detailed how someone who worked in the World Trade Center sustained an injury during the September 11 attacks. In the low-sadness condition, the story was titled "Trying to Be Better Again," and it detailed how the person sustained the injury falling down the stairs at her office. After reading one of these two versions of the story, participants answered the same sharing and arousal questions as in Study 2.

As we predicted, when the context evoked a deactivating (i.e., de-arousing) emotion, the effects on transmission were reversed. First, participants were *less* likely to share the story if they were in the high-sadness condition (M = 2.39) as opposed to the low-sadness condition (M = 3.80; $F(1, 46) = 10.78$, $p < .005$). Second, the results were similar for arousal; the high-sadness condition (M = 2.75) evoked less arousal than the low-sadness condition (M = 3.89; $F(1, 46) = 10.29$, $p < .005$). Third, as we hypothesized, this decrease in arousal mediated the effect of condition on sharing. Condition was linked to arousal ($\beta_{high\_sadness} = -.57$, SE = .18; $t(46) = -3.21$, $p < .005$); arousal was linked to sharing ($\beta_{activation} = .67$, SE = .15, $t(46) = 4.52$, $p < .001$); and when we included both sadness condition and arousal in a regression predicting sharing, arousal mediated the effect of sadness on transmission (Sobel $z = -2.32$, $p < .05$).

Discussion

The results of Study 3 further underscore the role of arousal in social transmission. Consistent with the findings of our field study, when content evoked more of a low-arousal emotion, it was less likely to be shared. Furthermore, these effects were again driven by arousal. When a story evoked more sadness, it decreased arousal, which in turn decreased transmission. The finding that the effect of specific emotion intensity on transmission reversed when the emotion was deactivating provides even stronger evidence for our theoretical perspective. While it could be argued that content evoking more emotion is more interesting or engaging (and, indeed, pretest results suggest that this is the case in this experiment), these results show that such increased emotion may actually decrease transmission if the specific emotion evoked is characterized by deactivation.

GENERAL DISCUSSION

The emergence of social media (e.g., Facebook, Twitter) has boosted interest in word of mouth and viral marketing. It is clear that consumers often share online content and that social transmission influences product adoption and sales, but less is known about why consumers share content or why certain content becomes viral. Furthermore, although diffusion research has examined how certain people (e.g., social hubs, influentials) and social network structures might influence social transmission, but less attention has been given to how characteristics of content that spread across social ties might shape collective outcomes.

The current research takes a multimethod approach to studying virality. By combining a broad analysis of virality in the field with a series of controlled laboratory experiments, we document characteristics of viral content while also shedding light on what drives social transmission.

Our findings make several contributions to the existing literature. First, they inform the ongoing debate about whether people tend to share positive or negative content. While common wisdom suggests that people tend to pass along negative news more than positive news, our results indicate that positive news is actually more viral. Furthermore, by examining the full corpus of *New York Times* content (i.e., all articles available), we determine that positive content is more likely to be highly shared, even after we control for how frequently it occurs.

Second, our results illustrate that the relationship between emotion and virality is more complex than valence alone and that arousal drives social transmission. Consistent with our theorizing, online content that evoked high-arousal emotions was more viral, regardless of whether those emotions were of a positive (i.e., awe) or negative (i.e., anger or anxiety) nature. Online content that evoked more of a deactivating emotion (i.e., sadness), however, was actually less likely to be viral. Experimentally manipulating specific emotions in a controlled environment confirms the hypothesized causal relationship between activation and social transmission. When marketing content evoked more of specific emotions characterized by arousal (i.e., amusement in Study 2a or anger in Study 2b), it was more likely to be shared, but when it evoked specific emotion characterized by deactivation (i.e., sadness in Study 3), it was less likely to be shared. In addition, these effects were mediated by arousal, further underscoring its impact on social transmission.

Demonstrating these relationships in both the laboratory and the field, as well as across a large and diverse body of content, underscores their generality. Furthermore, although not a focus of our analysis, our field study also adds to the literature by demonstrating that more practically useful, interesting, and surprising content is more viral. Finally, the naturalistic setting allows us to measure the relative importance of content characteristics and external drivers of attention in shaping virality. While being featured prominently, for example, increases the likelihood that content will be highly shared, our results suggest that content characteristics are of similar importance.

Theoretical Implications

This research links psychological and sociological approaches to studying diffusion. Prior research has modeled product adoption (Bass 1969) and examined how social networks shape diffusion and sales (Van den Bulte and Wuyts 2007). However, macrolevel collective outcomes (such as what becomes viral) also depend on microlevel individual decisions about what to share. Consequently, when trying to understand collective outcomes, it is important to consider the underlying individual-level psychological processes that drive social transmission (Berger 2011; Berger and Schwartz 2011). Along these lines, this work suggests that the emotion (and activation) that content evokes helps determine which cultural items succeed in the marketplace of ideas.

Our findings also suggest that social transmission is about more than just value exchange or self-presentation (see also Berger and Schwartz 2011). Consistent with the notion that people share to entertain others, surprising and interesting content is highly viral. Similarly, consistent with the notion that people share to inform others or boost their mood, practically useful and positive content is more viral. These effects are all consistent with the idea that people may share content to help others, generate reciprocity, or boost their reputation (e.g., show they know entertaining or useful things). Even after we control for these effects, however, we find that highly arousing content (e.g., anxiety evoking, anger evoking) is more likely to make the most e-mailed list. Such content does not clearly produce immediate economic value in the traditional sense or even necessarily reflect favorably on the self. This suggests that social transmission may be less about motivation and more about the transmitter's internal states.

It is also worthwhile to consider these findings in relation to literature on characteristics of effective advertising. Just as certain characteristics of advertisements may make them more effective, certain characteristics of content may make it more likely to be shared. While there is likely some overlap in these factors (e.g., creative advertisements are more effective [Goldenberg, Mazursky, and Solomon 1999] and are likely shared more), there may also be some important differences. For example, while negative emotions may hurt brand and product attitudes (Edell and Burke 1987), we have shown that some negative emotions can actually increase social transmission.

Directions for Further Research

Future work might examine how audience size moderates what people share. People often e-mail online content to a particular friend or two, but in other cases they may broadcast content to a much larger audience (e.g., tweeting, blogging, posting it on their Facebook wall). Although the former (i.e., narrowcasting) can involve niche information (e.g., sending an article about rowing to a friend who likes crew), broadcasting likely requires posting content that has broader appeal. It also seems likely that whereas narrowcasting is recipient focused (i.e., what a recipient would enjoy), broadcasting is self focused (i.e., what someone wants to say about him- or herself or show others). Consequently, self-presentation motives, identity signaling (e.g., Berger and Heath 2007), or affiliation goals may play a stronger role in shaping what people share with larger audiences.

Although our data do not allow us to speak to this issue in great detail, we were able to investigate the link between article characteristics and blogging. Halfway into our data collection, we built a supplementary web crawler to capture the *New York Times*' list of the 25 articles that had appeared in the most blogs over the previous 24 hours. Analysis suggests that similar factors drive both virality and blogging: More emotional, positive, interesting, and anger-inducing and fewer sadness-inducing stories are likely to make the most blogged list. Notably, the effect of practical utility reverses: Although a practically useful story is more likely to make the most e-mailed list, practically useful content is marginally *less* likely to be blogged about. This may be due in part to the nature of blogs as commentary. While movie reviews, technology perspectives, and recipes all contain useful information, they are already commentary, and thus there may not be much added value from a blogger contributing his or her spin on the issue.

Further research might also examine how the effects observed here are moderated by situational factors. Given that the weather can affect people's moods (Keller et al. 2005), for example, it may affect the type of content that is shared. People might be more likely to share positive stories on overcast days, for example, to make others feel happier. Other cues in the environment might also shape social transmission by making certain topics more accessible (Berger and Fitzsimons 2008; Berger and Schwartz 2011; Nedungadi 1990). When the World Series is going on, for example, people may be more likely to share a sports story because that topic has been primed.

These findings also raise broader questions, such as how much of social transmission is driven by the sender versus the receiver and how much of it is motivated versus unmotivated. While intuition might suggest that much of transmission is motivated (i.e., wanting to look good to others) and based on the receiver and what he or she would find of value, the current results highlight the important role of the sender's internal states in whether something is shared. That said, a deeper understanding of these issues requires further research.

Marketing Implications

These findings also have important marketing implications. Considering the specific emotions content evokes should help companies maximize revenue when placing advertisements and should help online content providers when pricing access to content (e.g., potentially charging more for content that is more likely to be shared). It might also be useful to feature or design content that evokes activating emotions because such content is likely to be shared (thus increasing page views).

Our findings also shed light on how to design successful viral marketing campaigns and craft contagious content. While marketers often produce content that paints their product in a positive light, our results suggest that content will be more likely to be shared if it evokes high-arousal emotions. Advertisements that make consumers content or relaxed, for example, will not be as viral as those that amuse them. Furthermore, while some marketers might shy away from advertisements that evoke negative emotions, our results suggest that negative emotion can actually increase transmission if it is characterized by activation. BMW, for example, created a series of short online films called "The Hire" that they hoped would go viral and which included car chases and story lines that often evoked anxiety (with such titles as "Ambush" and "Hostage"). While one might be concerned that negative emotion would hurt the brand, our results suggest that it should increase transmission because anxiety induces arousal. (Incidentally, "The Hire" was highly successful, generating millions of views). Following this line of reasoning, public health information should be more likely to be passed on if it is framed to evoke anger or anxiety rather than sadness.

Similar points apply to managing online consumer sentiment. While some consumer-generated content (e.g., reviews, blog posts) is positive, much is negative and can build into consumer backlashes if it is not carefully managed. Mothers offended by a Motrin ad campaign, for example, banded together and began posting negative YouTube videos and tweets (Petrecca 2008). Although it is impossible to address all negative sentiment, our results indicate that certain types of negativity may be more important to address because they are more likely to be shared. Customer experiences that evoke anxiety or anger, for example, should be more likely to be shared than those that evoke sadness (and textual analysis can be used to distinguish different types of posts). Consequently, it may be more important to rectify experiences that make consumers anxious rather than disappointed.

In conclusion, this research illuminates how content characteristics shape whether it becomes viral. When attempting to generate word of mouth, marketers often try targeting "influentials," or opinion leaders (i.e., some small set of special people who, whether through having more social ties or being more persuasive, theoretically have more influence than others). Although this approach is pervasive, recent research has cast doubt on its value (Bakshy et al. 2011; Watts 2007) and suggests that it is far from cost effective. Rather than targeting "special" people, the current research suggests that it may be more beneficial to focus on crafting contagious content. By considering how psychological processes shape social transmission, it is possible to gain deeper insight into collective outcomes, such as what becomes viral.

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Appendix

CORRELATIONS BETWEEN PREDICTOR VARIABLES

	Emotion-ality	*Positivity*	*Awe*	*Anger*	*Anxiety*	*Sadness*	*Practical Utility*	*Interest*	*Surprise*	*Word Count* $\times 10^{-3}$	*Complex-ity*	*Author Fame*	*Author Female*	*Missing*	*Top Feature*	*Near Top Feature*	*Right Column*	*Bulleted Sub-feature*	*More News*	*Middle Feature Bar*
Emotionality	1.00																			
Positivity	.04*	1.00																		
Awe	–.02	.02	1.00																	
Anger	.04*	–.16*	–.21*	1.00																
Anxiety	.03*	–.18*	–.11*	.50*	1.00															
Sadness	.00	–.18*	.08*	.42*	.45*	1.00														
Practical utility	.06*	.04*	–.11*	–.12*	.07*	–.05*	1.00													
Interest	.054*	.07*	.26*	–.13*	–.24*	–.19*	–.06*	1.00												
Surprise	–.10*	–.04*	.24*	–.01	.00	.05*	–.05*	.18*	1.00											
Word count $\times 10^{-3}$	.06*	.05*	.04*	.02	.00	.00	–.01	.06*	.02*	1.00										
Complexity	.05*	–.05*	–.04*	.10*	.13*	.05*	.01	–.11*	.04*	–.06*	1.00									
Author fame	–.09*	–.03*	.06*	.01	.03*	.01	–.02	.00	.02	.01	.01	1.00								
Author female	–.07*	.06*	.01	–.03*	.00	.00	.05*	–.01	.07*	.00	–.02*	.00	1.00							
Missing	.21*	.03*	–.06*	.03*	–.02	.00	.01	.02	–.09*	–.01	.02*	–.71*	–.15*	1.00						
Top feature	.01	–.02	–.03*	.06*	.06*	.05*	.02	–.03*	–.02*	.28*	.01	.00	–.02	.01	1.00					
Near top feature	–.01	–.06*	–.02	.15*	.07*	.07*	–.03*	–.05*	.01	.27*	.06*	.06*	–.01	–.05*	.27*	1.00				
Right column	.16*	.05*	.04*	.00	–.02	–.02	.05*	.06*	–.02*	.05*	–.01	–.03*	–.02	.16*	.02	–.04*	1.00			
Bulleted subfeature	.00	–.02	–.05*	.09*	.08*	.06*	.04*	–.05*	–.04*	.07*	.03*	.03*	.01	–.04*	.12*	.12*	–.03*	1.00		
More news	–.08*	–.11*	–.01	.07*	.06*	.06*	–.08*	–.04*	.07*	–.02	.09*	.05*	–.01	–.07*	.01	.10*	–.06*	–.05*	1.00	
Middle feature bar	.11*	.10*	.06*	–.06*	–.06*	–.05*	.00	.10*	.04*	.16*	–.06*	–.13*	.00	.13*	.02	–.05*	.07*	–.04*	–.08*	1.00
Bottom list	.03*	.15*	.07*	–.11*	–.09*	–.06*	.06*	.09*	.04*	.29*	–.04*	–.06*	.05*	.00	.04*	–.05*	.10*	.00	–.09*	.13*

*Significant at the 5% level.

What Makes Online Content Viral?

JONAH BERGER and KATHERINE L. MILKMAN

WEB APPENDIX

Data Used

The *New York Times* does not store the content of Associated Press, Reuters, and Bloomberg articles, as well as blogs, and so it was not available for our analyses. We also did not include videos and images with no text.

Modeling Approach

We used a logistic regression model because of the nature of our question and the available data. While more complex panel-type models are appropriate when there is time variation in at least one independent variable and the outcome, we do not have period-by-period variation in the dependent variable. Rather than having the number of e-mails sent in each period, we only have a dummy variable that switches from 0 (not on the most e-mailed list) to 1 (on the most e-mailed list) at some point due to events that happened not primarily in the same period but several periods earlier (e.g., advertising in previous periods). Furthermore, our interest is not in when an article makes the list but whether it ever does so. Finally, although it could be imagined that when an article is featured might affect when it makes the list, such an analysis is far from straightforward. The effects are likely to be delayed (where an article is displayed in a given time period is extremely unlikely to have any effect on whether the article makes the most e-mailed list during that period), but it is difficult to predict a priori what the lag between being featured prominently and making the list would be. Thus, the only way to run an appropriate panel model would be to include the full lag structure on all our time-varying variables (times spent in various positions on the home page). Because we have no priors on the appropriate lag structure, the full lag structure would be the only appropriate solution. So imagine, for example, that there are two slots on the home page (we actually have seven): Position A and Position B. Our model would then need to be something like the following:

Being on the list in period t =

$$\begin{aligned}
&\beta_1 \times \text{(being in Position A in period t)}\\
&+ \beta_2 \times \text{(being in Position A in period t – 1)}\\
&+ \beta_3 \times \text{(being in Position A in period t – 2)} + \ldots\\
&+ \beta_N \times \text{(being in Position A in period t – N)}\\
&+ \beta_{N+1} \times \text{(being in Position B in period t)}\\
&+ \beta_{N+2} \times \text{(being in Position B in period t – 1)}\\
&+ \beta_{N+3} \times \text{(being in Position B in period t – 2)} + \ldots\\
&+ \beta_{2N} \times \text{(being in Position B in period t – N)}\\
&+ \beta\text{(a vector of our other time-invariant predictors)}.
\end{aligned}$$

If we estimated this model, we would end up with an equivalent model to our current logistic regression specification in which we have summed all of the different periods for each position. The two are equivalent models unless we include interactions on the lag terms, and it is unclear what interactions it would make sense to include. In addition, there are considerable losses in efficiency from this panel specification compared with our current model. Thus, we rely on a simple logistic regression model to analyze our data set.

Coding Instructions

Anger. Articles vary in how angry they make most readers feel. Certain articles might make people really angry, while others do not make them angry at all. Here is a definition of anger: http://en.wikipedia.org/wiki/Anger. Please code the articles based on how much anger they evoke.

Anxiety. Articles vary in how much anxiety they would evoke in most readers. Certain articles might make people really anxious while others do not make them anxious at all. Here is a definition of anxiety: http://en.wikipedia.org/wiki/Anxiety. Please code the articles based on how much anxiety they evoke.

Awe. Articles vary in how much they inspire awe. Awe is the emotion of self-transcendence, a feeling of admiration and elevation in the face of something greater than the self. It involves the opening or broadening of the mind and an experience of wow that makes you stop and think. Seeing the Grand Canyon, standing in front of a beautiful piece of art, hearing a grand theory, or listening to a beautiful symphony may all inspire awe. So may the revelation of something profound and important in something you may have once seen as ordinary or routine or seeing a causal connection between important things and seemingly remote causes.

Sadness. Articles vary in how much sadness they evoke. Certain articles might make people really sad while others do not make them sad at all. Here is a definition of sadness: http://en.wikipedia.org/wiki/Sadness. Please code the articles based on how much sadness they evoke.

Surprise. Articles vary in how much surprise they evoke. Certain articles might make people really surprised while others do not make them surprised at all. Here is a definition of surprise: http://en.wikipedia.org/wiki/Surprise_(emotion). Please code the articles based on how much surprise they evoke.

Practical utility. Articles vary in how much practical utility they have. Some contain useful information that leads the reader to modify their behavior. For example, reading an article suggesting certain vegetables are good for you might cause a reader to eat more of those vegetables. Similarly, an article talking about a new Personal Digital Assistant may influence what the reader buys. Please code the articles based on how much practical utility they provide.

Interest. Articles vary in how much interest they evoke. Certain articles are really interesting while others are not interesting at all. Please code the articles based on how much interest they evoke.

Additional Robustness Checks

The results are robust to (1) adding squared and/or cubed terms quantifying how long an article spent in each of seven home page regions; (2) adding dummies indicating whether an article ever appeared in a given home page region; (3) splitting the home page region control variables into time spent in each region during the day (6 A.M.–6 P.M. eastern standard time) and night (6 P.M.–6 A.M. eastern standard time); (4) controlling for the day of the week when an article was published in the physical newspaper (instead of online); (5) Winsorizing the top and bottom 1% of outliers for each control variable in our regression; (6) controlling for the first home page region in which an article was featured on the *New York Times*' site; (7) replacing day fixed effects with controls for the average rating of practical utility, awe, anger, anxiety, sadness, surprise, positivity and emotionality in the day's published news stories; and (8) including interaction terms for each our primary predictor variables with dummies for each of the 20 topic areas classified by the *New York Times*.

Alternate Dependent Measures

Making the 24-hour most e-mailed list is a binary variable (an article either makes it or it does not), and while we do not have access to the actual number of times articles are e-mailed, we know the highest rank an article achieves on the most e-mailed list. Drawing strong conclusions from an analysis of this outcome measure is problematic, however, for several reasons. First, when an article earns a position on the most e-mailed list, it receives considerably more "advertising" than other stories. Some people look to the most e-mailed list every day to determine what articles to read. It is unclear, however, exactly how to properly control for this issue. For example, the top ten most e-mailed stories over 24 hours are featured prominently on the *New York Times*' home page, but readers must then click on a link to see the rest of the most e-mailed list (articles 11–25). This suggests that it may be inappropriate to assume that the same model predicts performance from rank 11–25 as rank 1–10. Second, any model assuming equal spacing between ranked categories is problematic because the difference in virality between stories ranked 22 and 23 may be very small compared with the difference in virality between stories ranked 4 and 5, thus reducing the ease of interpretation of any results involving rank as an outcome variable. That said, using an ordered logit model and coding articles that never make the most e-mailed list as earning a rank of 26 (leaving these articles out of the analysis introduces additional selection problems), we find nearly identical results to our primary analyses presented in Table 5 (Table A3).

Another question is persistence, or how long articles continue to be shared. This is an interesting issue, but unfortunately it cannot be easily addressed with our data. We do not have information about when articles were shared over time, only how long they spent on the most e-mailed list. Analyzing time spent on the most e-mailed list shows that both more affect-laden and more interesting content spends longer on the list (Table A3). However, this alternative outcome variable also has several problems. First, there is a selection problem: Only articles that make the most e-mailed list have an opportunity to spend time on the list. This both restricts the number of articles available for analysis and ensures that all articles studied contain highly viral content. Second, as we discussed previously, articles that make the most e-mailed list receive different amounts of additional "advertising" on the *New York Times* home page, depending on what rank they achieve (top ten articles are displayed prominently). Consequently, although it is difficult to infer too much from these ancillary results, they highlight an opportunity for further research.

Table WA1

HOME PAGE LOCATION ARTICLE SUMMARY STATISTICS

		For Articles That Ever Occupy Location		
	% of Articles That Ever Occupy This Location	*% That Make List*	*Mean Hours*	*Hours Standard Deviation*
Top feature	28%	33%	2.61	2.94
Near top feature	32%	31%	5.05	5.11
Right column	22%	31%	3.85	5.11
Middle feature bar	25%	32%	11.65	11.63
Bulleted subfeature	29%	26%	3.14	3.91
More news	31%	24%	3.69	4.18
Bottom list	88%	20%	23.31	28.40

Notes: The average article in our data set appeared somewhere on the *New York Times*' home page for a total of 29 hours (SD = 30 hours).

Table WA2

PHYSICAL NEWSPAPER ARTICLE LOCATION SUMMARY STATISTICS

		For Articles That Ever Occupy Location		
	% of Articles That Ever Occupy This Location	*% That Make List*	*Mean Page Hours*	*Mean Page Number for Articles That Make List*
Section A	39%	25%	15.84	10.64
Section B	15%	10%	6.59	5.76
Section C	10%	16%	4.12	5.38
Section D	7%	17%	3.05	2.27
Section E	4%	22%	4.78	7.62
Section F	2%	42%	3.28	3.43
Other section	13%	24%	9.59	14.87
Never in paper	10%	11%	—	—

Table WA3

AN ARTICLE'S HIGHEST RANK AND LONGEVITY ON THE *NEW YORK TIMES'* MOST E-MAILED LIST AS A FUNCTION OF ITS CONTENT CHARACTERISTICS

Outcome Variable	*Highest Rank (7)*	*Hours on List (8)*
Emotion Predictors		
Emotionality	.22***	2.25**
	(.04)	(.85)
Positivity	.15***	.72
	(.04)	(.81)
Specific Emotions		
Awe	.25***	–1.47
	(.05)	(1.11)
Anger	.35***	.35
	(.08)	(1.14)
Anxiety	.19**	.36
	(.06)	(.95)
Sadness	–.16**	–.77
	(.06)	(.93)
Content Controls		
Practical utility	.31***	.38
	(.05)	(1.07)
Interest	.27***	1.85†
	(.06)	(1.00)
Surprise	.17***	1.04
	(.05)	(.85)
Homepage Location Control Variables		
Top feature	.11***	–.18
	(.02)	(.18)
Near top feature	.11***	.21†
	(.01)	(.13)
Right column	.15***	.88***
	(.01)	(.17)
Middle feature bar	.05***	–.01
	(.00)	(.06)
Bulleted subfeature	.03*	–.21
	(.01)	(.22)
More news	.01	.32
	(.01)	(.24)
Bottom list × 10	.04*	.07
	(.02)	(.22)
Other Control Variables		
Word count × 10^{-3}	.37***	4.67*
	(.08)	(1.99)
Complexity	.01	–1.10
	(.03)	(.95)
First author fame	.21***	1.89***
	(.02)	(.55)
Female first author	.37***	4.07**
	(.07)	(1.35)
Uncredited	.74***	13.29†
	(.26)	(7.53)
Newspaper location and web timing controls	Yes	Yes
Article section dummies (e.g., arts, books)	No	No
Observations	6956	1391
Regression modeling approach	Ordered Logit	Ordinary Least Squares
Pseudo-R^2/R^2	.13	.23
Log-pseudo-likelihood	–6929.97	N.A.

†Significant at the 10% level.
*Significant at 5% level.
**Significant at 1% level.
***Significant at the .1% level.

Notes: The regressions models examine the content characteristics of an article associated with its highest rank achieved on the *New York Times*' most e-mailed list (reverse-scored such that 25 = the top of the list and 0 = never on the list) and its longevity on the list. Both models rely on our primary specification (see Table 5, Model 4) and include day fixed effects. N.A. = not applicable.