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Detecting, Preventing, and Mitigating Online Firestorms in Brand Communities

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Abstract

Online firestorms pose severe threats to online brand communities. Any negative electronic word of mouth (eWOM) has the potential to become an online firestorm, yet not every post does, so finding ways to detect and respond to negative eWOM constitutes a critical managerial priority. The authors develop a comprehensive framework that integrates different drivers of negative eWOM and the response approaches that firms use to engage in and disengage from online conversations with complaining customers. A text-mining study of negative eWOM demonstrates distinct impacts of high- and low-arousal emotions, structural tie strength, and linguistic style match (between sender and brand community) on firestorm potential. The firm's response must be tailored to the intensity of arousal in the negative eWOM to limit the virality of potential online firestorms. The impact of initiated firestorms can be mitigated by distinct firm responses over time, and the effectiveness of different disengagement approaches also varies with their timing. For managers, these insights provide guidance on how to detect and reduce the virality of online firestorms.

Keywords

message dynamics, online brand community, online firestorms, text mining, word of mouth

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More than 65 million firms leverage online brand communities to connect with customers and achieve known performance benefits, such as increased online reputation, brand patronage, and customer spending (Baker, Donthu, and Kumar 2016; Hollenbeck 2018, Kumar et al. 2016). However, online communities also engender significant risks of online firestorms—that is, negative electronic word of mouth (eWOM) that receives substantial support from other customers in a short period of time (Pfeffer, Zorbach, and Carley 2014). Similar to prominent online firestorm examples, such as #deleteUber and United Airlines' passenger removal incidents, less publicized negative eWOM messages by dissatisfied customers also can go viral; a single 466-word Facebook post by a disgruntled customer in Odeon Cinemas' Facebook brand community prompted more than 94,000 likes, damaging the firm's reputation and causing it to lose thousands of customers (Dunphy 2012).

Detecting, preventing, and mitigating this virality of negative eWOM in online brand communities therefore constitutes a critical managerial priority (Hewett et al. 2016), yet 72% of firms rate their preparedness for online firestorms as "below average" (Ethical Corporation 2012). Managers seem to have a limited understanding of how to respond to negative eWOM describing dissatisfactory consumption experiences (Wang and Chaudhry 2018), nor do they know how to predict the evolution of negative eWOM messages or address angered mass audiences exposed to such negative eWOM. Lacking clear guidelines, firms continue to suffer damages from negative eWOM. We aim to address this gap by identifying sources of firestorms and detailing appropriate sequences for firm responses to negative viral content.

Extant marketing research has described the spreading of word of mouth (WOM) as a contagious process, whereby receivers "catch" others' emotions through social transmission (Berger 2014). The relatively rare research that specifically investigates negative WOM suggests that its contagiousness

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primarily depends on the sender's emotions (Berger and Milkman 2012; Heath, Bell, and Sternberg 2001) and the relationship between senders and receivers (Brown and Reingen 1987; Mittal, Huppertz, and Khare 2008). Yet few studies have applied these valuable insights to an online brand community context, so we identify sender and relational aspects pertinent to firestorms of negative eWOM in online brand communities.

In addition to identifying sources of the spread of negative eWOM, firms need to pinpoint how to respond (Chevalier, Dover, and Mayzlin 2018). Services recovery research has proposed several viable approaches to negative customer experiences, including empathic and explanatory responses (e.g., Bitner, Booms, and Tetreault 1990). In contrast with traditional complaint channels, however, the online brand community makes customers' complaints and the firm's recovery efforts visible. Therefore, beyond mitigating the complaining customer's unsatisfactory consumption experience, the firm needs to craft a response that can minimize any negative effects on the wider audience of online brand community members. By investigating regulation strategies that can reduce receivers' susceptibility to negative emotions (Gross and Thompson 2007), we investigate how firms should tailor their responses to limit the virality of negative eWOM. In so doing, we do not limit our assessment to a single response, because customers in online brand communities often evaluate cross-message developments (Villarroel Ordenes et al. 2018). Therefore, in an extension of Batra and Keller's (2016) work, we consider how sequences of firm responses might mitigate the virality of online firestorms as they evolve.

With these empirical assessments of ways to detect, prevent, and mitigate the virality of negative eWOM in online brand communities, we offer three main contributions. First, we draw on negative WOM research to investigate how sender and relational aspects aid in the detection of potential firestorms, then specify how different levels of emotional arousal and the strength of the senders' structural ties and their similarity to the online brand community relate to the virality of negative eWOM. At an operational level, we establish a reliable, computerized technique to determine the similarity of language use within online brand communities. Second, our findings provide insights into firms' ability to prevent online firestorms by issuing responses designed to engage with or disengage from customers online. More explanatory responses are best for negative eWOM messages containing above-average negative high-arousal emotions; the effectiveness of disengaging approaches varies. Third, we identify structured sequences of different engaging responses across multiple firm messages as a novel, actionable approach to mitigate the impact of evolved online firestorms.

To achieve these aims, we first systematically delineate sender and relational aspects that trigger greater virality of negative eWOM. We then systematize extant knowledge on common firm responses and contrast their effectiveness with the arousal of negative eWOM and viable cross-message composition. We test our hypotheses on large-scale data, reflecting negative customer posts from the online brand communities of 89 S&P 500 firms, which constitute potential online firestorms. In the final section, we summarize the findings, discuss the implications, and list some limitations.

Conceptual Foundations and Hypotheses

Extant marketing research primarily has focused on identifying the presence and efficacy of positive eWOM (You, Vadakkepatt, and Joshi 2015), but open customer communication also bears the risk of unprecedented, rapidly discharged, large quantities of negative eWOM (Pfeffer, Zorbach, and Carley 2014). To cope with negative experiences and warn others, customers share negative consumption experiences in online brand communities. Often highly emotional, such posts may emerge, diffuse, and dissolve quickly (Hauser et al. 2017). Similar to positive eWOM, the extent to which other customers approve of and share negative eWOM determines its virality and firestorm potential. Prestudy interviews with 16 social media managers responsible for online brand communities suggest that firms regard negative customer posts as evolved online firestorms if the firm's initial response does not suffice to prevent the negative eWOM from "catching fire" among other customers. Every like or comment that follows means that another customer may be lost. At the outset, every negative post has the potential to cause an online firestorm; not every post does so. Compared with positive eWOM, negative WOM is transmitted more often and is more influential (Hewett et al. 2016), so firms must detect and adequately respond to negative posts in online brand communities to avoid potential public debacles, customer defections, and profit reductions (Pfeffer, Zorbach, and Carley 2014).

Both product- and service-related WOM evaluations are shared through a social transmission process, like emotional contagion (Berger 2014). The Web Appendix contains an overview of studies that detail drivers of and firm responses to eWOM. Various studies have indicated that eWOM contagiousness depends on the emotions conveyed, the structural ties of the sender, or the perceived similarity between the sender and receivers; however, the joint impact of these determinants on the virality of negative eWOM is unknown. Moreover, although some studies have examined the effectiveness of the presence of firm responses, they do not differentiate the circumstances in which a certain type of response is more effective. Finally, firms might need to respond to the same negative eWOM several times to resolve customers' negative experiences, and insight is lacking on how such responses should be sequenced over time. To fill these critical research gaps, we investigate ways to detect, prevent, and mitigate online firestorms arising from negative eWOM messages.

Detecting Potential Online Firestorms

Conventional wisdom suggests that customers in online brand communities first read about the cause of negative eWOM messages and then decide whether to approve and share them. However, faced with the information overload that tends to characterize communication exchanges on social media platforms, customers might not elaborate in detail on the arguments and instead could resort to heuristic processing (Hatfield et al. 2014). Accordingly, research has suggested that the relative transmission of WOM is a result of the contagiousness of heuristics related to the sender's message and the relationship aspects between the sender and receivers (Brown and Reingen 1987; Heath, Bell, and Sternberg 2001; Mittal, Huppertz, and Khare 2008).

For example, particularly expressive people seem to transmit emotions effectively (Barsade 2002). Although emotions are not verbal properties, the verbal use of emotional words makes them relatively accessible and contagious. With increased use of affective words in a post, it efficiently reveals and makes accessible the intent or simplest raw feelings underlying the posting customer (Cohen et al. 2008). At a granular, word-use level, increasing the number of negative emotion words in eWOM translates directly into stronger behavioral responses by message recipients (Ludwig et al. 2013). Even if the content is unrealistic, more negative emotional messages are shared more frequently (Blaine and Boyer 2018). However, general negativity is a broad concept, and the influence of negative emotional expressions might depend further on people's relative arousal levels (Russell and Barret 1999). For example, in their study of urban legends, Heath, Bell, and Sternberg (2001) investigate high-arousal disgust emotions rather than just general negative emotions. Similarly, online firestorms may be more likely to arise from high-arousal (e.g., "This is so frustrating") rather than low-arousal (e.g., "This is disappointing") negative eWOM. Berger and Milkman (2012) show that *New York Times* newspaper stories that include more intensive high-arousal emotions (e.g., fear/anxiety, anger) prompt emailed shares to others more frequently than stories with more intensive low-arousal emotions (e.g., sadness). Thus, rather than simply being one-dimensional, the contagiousness of emotionally charged negative eWOM in online brand communities may depend on the level of arousal. Therefore, we posit:

> **H_1:** The intensity of high-arousal emotion words in negative eWOM messages relates to greater virality in online brand communities compared with the intensity of low-arousal emotion words.

The decision to approve or share eWOM also depends on the relationship and relational cues between the sender and receiver (Berger and Schwartz 2011). Emotional contagion theorists cite the importance of interpersonal relations that enable message recipients to evaluate others and devise appropriate responses (Barsade 2002). Marketing research on WOM suggests that tie strength and perceptions of similarity are two primary relational cues that cause receivers to regard senders as more proximate (Brown and Reingen 1987).

Tie strength is relevant in various information-sharing contexts; it refers to both the frequency of communication and the importance attached to the relations (Baker, Donthu, and Kumar 2016; Brown and Reingen 1987; Risselada, Verhoef, and Bijmolt 2014). Despite considerable debate about the relative advantages of weak and strong ties, researchers commonly agree that strong ties increase the likelihood that social actors will share sensitive information (Rapp et al. 2013) and engage in collective action (Obstfeld 2005). Measures of tie strength rely on a range of variables (Mittal, Huppertz, and Khare 2008; Rapp et al. 2013), including frequency of contact (Risselada, Verhoef, and Bijmolt 2014). Weak ties reflect members of a community who interact less frequently with each other, whereas strong ties describe relationships of members who interact frequently (Burt 1987). Frequent, positive encounters typically (if not always) lead to stronger structural ties (Mittal, Huppertz, and Khare 2008) and increase opportunities to transmit opinions (Frenzen and Nakamoto 1993). This assumption is also in line with Burt's (1987) suggestion that the more frequent and empathic the communication is between two users, the more likely that one user's opinion will influence the other user's opinion. Strong structural ties, as characterized by more frequent interactions, in turn increase imitative behavior within networks (McFarland, Bloodgood, and Payan 2008). Members with an exceptionally great number of ties within a community often act as opinion leaders, who influence purchase decisions and product adoptions (Katona, Zubcsek, and Sarvary 2011). Certainly, the potential of well-connected customers to influence others in a brand community is likely to be stronger than the potential of less connected members in the same community (Goldenberg et al. 2009). If the member who posts negative eWOM has stronger structural ties in the online brand community, the firestorm potential of the post thus should be greater:

> **H_2:** Stronger structural ties between the sender of negative eWOM and the receiving online brand community relate to greater virality.

In addition, perceived similarity (or homophily perceptions; Brown and Reingen 1987) between the sender and customers in online brand communities may relate to the virality of negative eWOM messages. Although perceptions of similarity are not required for contagion to occur, they can act as qualifiers of information relevance (Hatfield et al. 2014). For example, Aral, Muchnik, and Sundararajan (2009) find that perceptions of similarity between customers explain more than half of the effect of behavioral contagion on new product adoption. Although interactions in online brand communities tend to be relatively anonymous, studies drawing on psycholinguistic research suggest that perceptions of similarity in computer-mediated settings are an automatic outcome of a linguistic style match (LSM). The similar use of function words—or LSM between two or more conversation partners—represents a form of psychological synchrony that elicits perceptions of similarity, approval, and trust in receivers (Ireland and Pennebaker 2010). Just like conversation dyads, communities may develop a distinctive collective communication style (Fayard and DeSanctis 2010). An individual customer's alignment with a common, community-level communicative style may elicit similarity perceptions and in turn influence the approval likelihood by the collective (Gumperz and Levinson 1996). Ludwig et al. (2013) confirm that the congruence of a customer review with the typical linguistic style demonstrated by a product interest group on Amazon influences other customers' purchase behavior. Accordingly, negative eWOM that matches the typical linguistic style of an online brand community (i.e., evokes perceptions of similarity) should induce greater online firestorm potential:

> **H_3:** Closer LSM between the sender of negative eWOM and the receiving online brand community relates to greater virality.

Preventing Potential Online Firestorms

The growing influence of online evaluations on customer behavior has increased managerial and research interest in firm recovery strategies that can reduce the contagiousness of negative eWOM (Ma, Sun, and Kekre 2015). Recovery in the context of online brand communities is unique though, in that the customer's complaint and a firm's recovery efforts are visible to thousands or even millions of other customers. Effective recovery thus must (1) adequately restore relationship equity to the complaining customer and (2) prevent the negative eWOM message from spreading to other customers in the online brand community. The viability of common recovery approaches—offering an apology, compensation, responding empathically, or providing explanations—has been investigated mainly in bilateral firm–customer communication contexts (e.g., Hill, Roggeveen, and Grewal 2015). To gain further insight into the suitability of these approaches for reducing the contagiousness of emotions in negative eWOM, we turn to theory about emotion regulation strategies (Gross and Thompson 2007) and propose that firm responses to negative eWOM might be classified as disengaging or engaging.

A disengaging approach to emotion regulation implies reacting in ways to avoid or block elaboration, rather than preparing an adaptive response (Sheppes et al. 2011). Observations and anecdotes suggest that avoidance and nonresponse is the poorest approach to regulating the virality of negative eWOM. As an alternative, firms might try to halt an ongoing public online conversation by suggesting a communication channel change (e.g., "Please contact our service center"). Such a channel change suggestion might be effective for pushing customers to the right channels (Ansari, Mela, and Neslin 2008), but it is unclear how other online brand community react to being excluded from the continued conversation. The effectiveness of offering compensation to the complaining customer also is uncertain. Some service research has suggested that halting further elaborations is an effective recovery strategy (e.g., Bitner, Booms, and Tetreault 1990), yet Grewal, Roggeveen, and Tsiros (2008) find that compensation is not always effective and instead may depend on other response features.

Active engagement with negative eWOM messages instead might be more appropriate (Wang and Chaudhry 2018). Service recovery literature has outlined two primary response approaches that represent active firm–customer conversational elaboration (Hill, Roggeveen, and Grewal 2015): empathic or explanatory. To express empathy, a spontaneous affective response (Hoffman 1977), a firm might sympathize (e.g., "We understand that you are unhappy") or shift to a positive outlook (e.g., "We hope you have a better experience next time"). Highly empathic responses may enhance the complainant's and online brand community's perceptions of interactional justice and signal politeness and courtesy, which may reduce the virality of negative eWOM. An engaged firm response also might include substantiated explanations, and the number of reasons offered has more influence than the actual content of those reasons on decision outcomes (Seibold, Lemus, and Kang 2010). When firms provide more substantiated arguments, it may enhance perceptions of response quality and effort among brand community audiences (e.g., "We could not assist you quickly because the store was extremely busy"). By providing more explanation, firms might enhance evaluations of their recovery efforts (Bitner, Booms, and Tetreault 1990).

However, in line with cognitive appraisal theory and an affect infusion model, Homburg, Grozdanovic, and Klarmann (2007) posit that an affective approach, such as empathy, is more effective in affect-intensive environments characterized by social interactions and spontaneous decisions, such as online brand communities. In general, then, more empathic responses might be better suited to regulating the contagiousness of negative eWOM. According to the affect infusion model, the relative impact of cognitive responses, such as explanations, increases with stronger affect and higher involvement (Forgas 1995). Research on emotion regulation strategies further indicates that some stimuli may be too emotionally intense for an empathic response to suffice, and instead, receivers may seek explanations to reappraise the situation (Gross 2002). The more contagious the emotions in a negative eWOM message, the more attention customers will pay to the message and the stronger their expectations about what needs to be done to remedy the situation (Hess, Ganesan, and Klein 2003). In such situations, customers are more likely to engage in deliberate processing of negative eWOM by cognitively reappraising the situation; that is, they consider more information and perform more intricate evaluations of the explanations (Lazarus 1991). Empathic responses may help shift the attention of consumers who experience low-arousal emotions, but firms might better mitigate the virality of high-arousal emotions by offering more explanations. Thus, the relative effectiveness of firm responses for preventing online firestorms may be contingent on the intensities of the high- and low-arousal levels in the negative eWOM message:

> **H_4:** More explanation, rather than more empathy, in firm responses is better suited to contain negative eWOM with more intensive high-arousal emotions.

> **H_5:** More empathy, rather than more explanation, in firm responses is better suited to contain negative eWOM with more intensive low-arousal emotions.

Mitigating Evolved Online Firestorms

Through observational learning processes, as an online firestorm evolves, and other members support the negative eWOM, its perceived reliability should increase (Dholakia, Basuroy, and Soltysinski 2002). Thus, customers pay even more attention to the negative eWOM and form revised expectations about what needs to be done to remedy the situation. Therefore, beyond the compositional elements of individual firm responses, when negative eWOM evolves into an online firestorm, multiple firm responses become necessary to mitigate its detrimental impacts.

As Batra and Keller (2016) suggest, online messages build on one another, and thus their sequence can determine their success in terms of persuading customers, building brand equity, or driving sales. Villarroel Ordenes et al. (2018) find that posting the same (vs. mixed) consecutive brand message decreases (vs. increases) customers' engagement. Considerations of cross-message dynamics in firm responses may advance understanding of how to mitigate evolved online firestorms too. For example, by empathically sympathizing with the customer in the first reply, then issuing a second, complementary response that provides explanations, the firm might reduce the overall virality of the negative eWOM, compared with a situation in which it repeats its offer of sympathy in the second response, which might cause frustration (Kocielnik and Hsieh 2017). We predict that such cross-message sequencing should mitigate the virality of negative eWOM to a broad customer audience (Batra and Keller 2016):

> **H_6:** Consecutive firm responses with varying rather than repeated (a) empathic intensity and (b) explanatory intensity are better suited to mitigating evolved online firestorms.

Methods

Sampling Frame and Text Analysis Procedure

We used Facebook's Application Programming Interface (API) and processed detailed information on potential online firestorms from the official Facebook brand communities of all U.S. firms listed on the S&P 500 between October 1, 2011 (the introduction of the timeline feature), and January 31, 2016 (the introduction of emojis). We chose this setting for three reasons. First, it is common for customers to use Facebook to interact with firms in their brand communities and to complain through this channel. Second, unlike other rating and review sites that encourage only customers to share their views, firms actively participate in Facebook conversations and respond to customer posts (Schweidel and Moe 2014). Third, in line with previous research on online brand communities (e.g., Lee, Hosanagar, and Nair 2018; Relling et al. 2016), the count of likes and comments indicates the degree to which others approve and share a message and provides an objective measure of virality.

We selected all firms that target private customers, have an official Facebook brand community, and allow user posts in their community (see the Web Appendix). Because of our focus on negative eWOM, we analyzed text-based features to determine which posts were negative in two steps. We first applied the R Quanteda package (Benoit et al. 2018) using Linguistic Inquiry and Word Count (LIWC) text-mining dictionaries to derive the intensity of positive- and negative-emotion words in each post (for more details, see Humphreys and Wang [2018]). We then applied the Stanford Sentence and Grammatical Dependency Parser (Stanford Natural Language Processing Group 2014) to subdivide each post into sentences and identify dependencies between emotion words and negations (i.e., bigrams). The parser first identifies the presence of an emotion word and then, in cases of negation, automatically assesses whether there is a grammatical relationship (e.g., in the sentence "The service was not nice," the negation "not" is grammatically related to the adjective "nice" and therefore reverses it). Negated positive emotion words were counted toward negativity and negated negative emotions words toward positivity. If a customer post is more negative than positive overall, we count it as a potential online firestorm.

We excluded 48,480 posts that contained a video, picture, event, or external link, because we cannot control for this external content. Furthermore, we excluded 140 posts with fewer than three words, because every full thought requires at least a subject, verb, and object to be understandable for receivers. On Facebook, zero counts of likes and comments from other customers might occur for two reasons: (1) The post may have been viewed by other customers but prompted no reaction, or (2) the post may not have been displayed to other customers. Thus, we excluded 128,681 posts with no customer reactions, because we are interested in the inflation of virality. We also replicated our analysis with the sample including posts with no customer reactions, and we report the results in the Web Appendix.

With these restrictions, our final sample counted 472,995 negative customer posts in English across 89 online brand communities. The posts averaged 99 words (SD = 121.44, ranging from 3 to 8,121 words) and received 2.95 likes and comments on average (SD = 59.22, ranging from 1 to 37,760 likes and comments). Included in this final sample are both well-publicized incidents (e.g., customer post complaining that a police officer was prohibited from using a coffeehouse chain bathroom in September 2015) and less drastic cases in which complaints were supported by a only small number of other customers. Notably, for the well-publicized incidents, newspapers and news portals cited the original Facebook post (e.g., "A Facebook user reported that a police officer was prohibited from using a bathroom" [www.snopes.com]). Figure 1 displays illustrative examples of online firestorms and firm responses. In terms of timing, 78% of the online firestorms emerged and dissolved within a day, such that the last comment was posted within 24 hours of the initial negative post, and 93% of firm responses arrived within one hour. This short time frame is a unique feature of online firestorms that differentiates our study from previous research on product-harm crises (e.g., Cleeren, Dekimpe, and Van Heerde 2017).

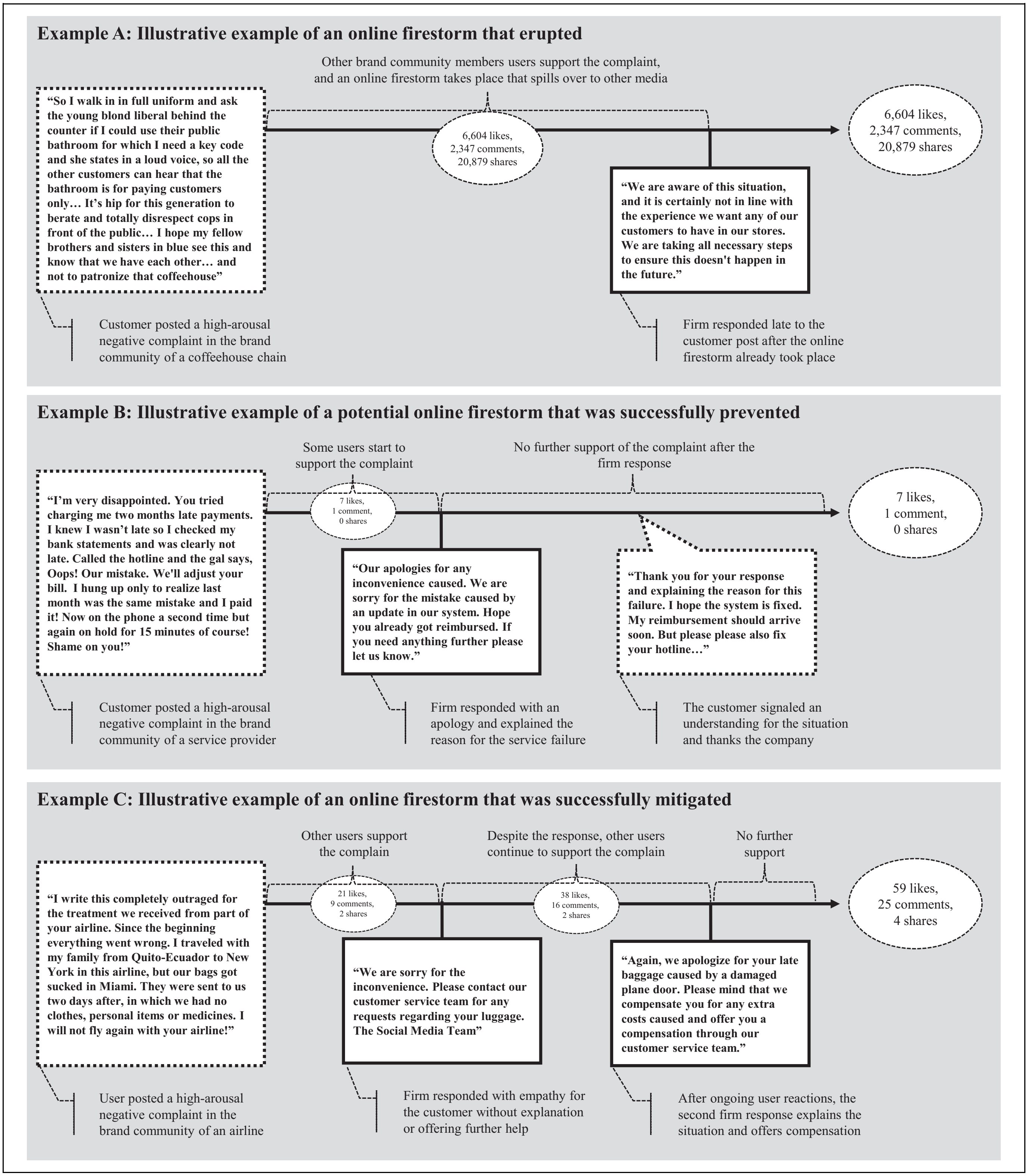


Figure 1. Illustrative examples of online firestorms and firm responses.
Notes: Posts are edited to exclude company names and customer names.

Measurement

Table 1 contains the operationalizations and sources of all variables, along with our rationale for including the control variables, and Figure 2 displays hypotheses and the measurement approach. The key variable of interest is the *virality* of negative eWOM, measured as the total number of likes and comments a post receives from other customers.[1] The total number of likes and comments correlate closely (r = .81), justifying their use as a composite variable. Because of community-level differences in virality (some online brand communities feature thousands of posts every day; others just a few), we use the deviation from the community average. Then, noting the data range and extreme values of virality (see the Web Appendix), we add a constant to have only positive values and apply a logarithmic transformation. To investigate how firms prevent and mitigate online firestorms, we include only likes and comments posted after the respective firm's response (Wang and Chaudhry 2018), which ensures that virality has been influenced by the firm response. Importantly, the API does not allow us to capture time stamps for likes. However, comments are time-stamped and known to evolve simultaneously with likes over time (Rieder et al. 2015). Therefore, we use the amount of comments following a firm response to approximate the number of likes.

We measure the intensity of high and low arousal for each negative post with computerized text analysis. In a top-down manner (Humphreys and Wang 2018), we compared each word in a message with predefined emotion word categories. We then calculated an intensity score per emotion word category: the proportion of total words that match each dictionary. In line with the main four negative emotion types in the circumplex model (Russell and Barret 1999), we classified the proportion of word use related to fear/anxiety, anger, and disgust as the intensity of high-arousal negative emotions and the proportion of sadness as the intensity of low-arousal negative emotion. We used existing LIWC dictionaries for fear/anxiety, anger, and sadness (Pennebaker et al. 2015), but we needed to develop a new dictionary to derive disgust. We provide this dictionary and details on its development in the Web Appendix. To validate the new dictionary, we compared statistical differences in arousal levels, according to an extremity measure from the Evaluative Lexicon 2.0 (EL 2.0; Rocklage, Rucker, and Nordgren 2018), between our disgust words and words classified as representing low negative arousal (i.e., sadness). We find a significant difference ($F = 7.57, p < .01$), with extremity mean scores of 3.24 and 2.89 for disgust and low arousal, respectively. This result confirms that our disgust dictionary matches the EL 2.0 measure for expression extremity.

[1] Likes and comments are more common indicators of virality than shares on Facebook. Of 472,995 negative eWOM incidences, 274,155 (52%) received at least one like, and 235,545 (50%) received at least one comment, but only 9,434 (2%) were shared at least once by other customers (see the Web Appendix). We also replicated the analyses with the number of likes, comments, and shares as separate measures of virality (see the Web Appendix).

Strength of structural ties has been measured using different variables, including subjective and objective measurements. Because we cannot collect perceptions of tie strength across the millions of brand community users, we followed Risselada, Verhoef, and Bijmolt (2014) and operationalized strength of structural ties (SST) as "the frequency of communication" (Brown and Reignen 1987, p. 356). Formally, SST for customer i posting negative eWOM at time t in community c is:

$$\begin{aligned}\mathrm{SST}_{\mathrm{ic}} = \sum_{\tau=0}^{t-1} & \text{Received Likes}^{\tau}_{\mathrm{ic}} + \text{Received Comments}^{\tau}_{\mathrm{ic}} \\ & + \text{Received Shares}^{\tau}_{\mathrm{ic}} + \sum_{\tau=0}^{t-1} \text{Likes Given}^{\tau}_{\mathrm{ic}} \\ & + \text{Comments Given}^{\tau}_{\mathrm{ic}},\end{aligned} \tag{1}$$

where $t - 1$ is the entire period prior to the post at time t, and $\mathrm{SST}_{\mathrm{ic}}$ is the sum of $\text{likes}_{\mathrm{c}}$, $\text{comments}_{\mathrm{c}}$, and $\text{shares}_{\mathrm{c}}$ that customer i received from others in the brand community c before the post at t, as well as the sum of $\text{likes}_{\mathrm{i}}$ and $\text{comments}_{\mathrm{i}}$ the customer gave to others in the brand community c prior to the post at t (all calculated based on the comment timestamp). The API does not allow us to identify customers who share a certain post, due to privacy restrictions.

We derived the degree of LSM between customer i posting negative eWOM at time t with the receiving brand community c in three steps. First, we mined the use intensity of each of the nine function word categories j separately in focal customer i's message and across all customer messages (negative and positive) in the brand community c posted in the previous three months in response to the focal negative eWOM post (moving community average). Second, the degree of similar use intensity LSM of each function word category ($\mathrm{FW_j}$) by customer i posting the negative eWOM into community c comes from the formula:

$$\mathrm{LSMj_{ic}} = 1 - \left(\frac{|\mathrm{FWj_i} - \overline{\mathrm{FWj}}_{\mathrm{ic}}|}{\mathrm{FWj_i} + \overline{\mathrm{FWj}}_{\mathrm{ic}} + .0001}\right). \tag{2}$$

Third, by aggregating all nine LSM scores with equal weights, we obtain an LSM score bound between 0 and 1, and scores closer to 1 reflect greater degree of communication style matching between customer i and the online brand community c.

We measured the intensity of empathy, or the degree of spontaneous affective response (Hoffman 1977) a firm provided, as the proportion of affect words in the response text, according to the LIWC dictionary for affect. Using the LIWC dictionary for causal expressions, we also measured the intensity of explanation in a firm's responses. We then measured variations in the response sequences as the standard deviation in empathic and explanatory intensities across all firm responses.

Following prior research, we account for multiple control variables that might influence the virality of negative eWOM (see Table 1). Firm-related aspects that influence eWOM include industry membership, brand familiarity, and brand reputation. At the online brand community level, we account for

Table 1. Operationalization and Sources of All Variables.

Variable and Time	Operationalization	Source	Rational for Inclusion (Controls) and Related Studies
Dependent Variable			
Virality	Combined sum of likes and comments the post received from other customers any time after it was posted (Virality^{t-1}; brand community-centered and log-transformed). To investigate how firms prevent and mitigate online firestorms, we only considered virality after the first firm responses (Virality^{t-2}) or after the last firm responses (Virality^{t-3}).	Facebook API	De Vries, Gensler, and Leeflang (2012); Lee, Hosanagar, and Nair (2018); Relling et al. (2016); Stephen, Sciandra, and Inman (2015)
Post Predictors			
Intensity of high arousal	LIWC dictionaries "anx" and "anger," new dictionary "disgust" for the focal post (number of matching words in the post, expressed as percentage of total words).	Text mining	Berger and Milkman (2012); Hewett et al. (2016)
Intensity of low arousal	LIWC dictionary "sad" for the focal post (number of matching words in the post, expressed as percentage of total words).	Text mining	Berger and Milkman (2012); Hewett et al. (2016)
Strength of structural ties	Frequency of communication with the online brand community before the post (see Formula 1 in the text).	Facebook API	Risselada, Verhoef, and Bijmolt (2014)
LSM	Degree of communication style matching with the online brand community before the post (see Formula 2 in the text).	Text mining	Ireland and Pennebaker (2010); Ludwig et al. (2013)
Firm Response			
Intensity of empathy	LIWC dictionary "affect" for firm responses (number of matching words in the response, expressed as percentage of total words).	Text mining	Fehr, Gelfand, and Nag (2010)
Intensity of explanation	LIWC dictionary "cogproc" for firm responses (number of matching words in the response, expressed as percentage of total words).	Text mining	Seibold and Meyers (2007)
Variation in firm responses	Variance in the proportion of empathic and explanatory words across all firm responses.	Text mining	Villarroel Ordenes et al. (2018)
Firm Controls			
GICS	Global Industry Classification Standard: consumer discretionary (49%) and consumer staples (21%) versus other (30%).	Standard & Poor's	The amount of negative eWOM may depend on the industry (Stephen, Sciandra, and Inman 2015).
Brand familiarity	Familiarity of each firm (on a scale from 0% to 100%).	Reputation Institute	Low brand familiarity may lead to less engagement with negative eWOM (Baker, Donthu, and Kumar 2016).
Brand reputation	Reputation perceptions of each firm (on a scale from 0% to 100%).	Reputation Institute	Support for negative eWOM may depend on the firm's reputation (Baker, Donthu, and Kumar 2016).
Brand Community Controls			
Brand community size	Number of page likes for the online brand community (in millions of page likes).	Facebook API	Greater brand community size gives negative eWOM a larger audience.
Brand community attentiveness	Average number of likes and comments per customer post in each online brand community (for both positive and negative posts).	Facebook API	More attentive members may be more susceptible to negative eWOM (Hatfield, Cacioppo, and Rapson 1994).
Brand community expressiveness	Average of LIWC dictionary "affect" for all posts in the online brand community (percentage of total words).	Text mining	More expressive members may be more susceptible to negative eWOM (Hatfield, Cacioppo, and Rapson 1994).
Average firm engagement	Average number of firm responses per customer post in each online brand community (for both positive and negative posts).	Facebook API	Firm engagement may stimulate negative eWOM (Homburg, Ehm, and Artz 2015).
Average tie strengths	Average tie strength of each customer who posted, commented, or liked within the online brand community.	Facebook API	Average tie strengths may increase the effectiveness of negative eWOM (Katona, Zubcsek, and Sarvary 2011).

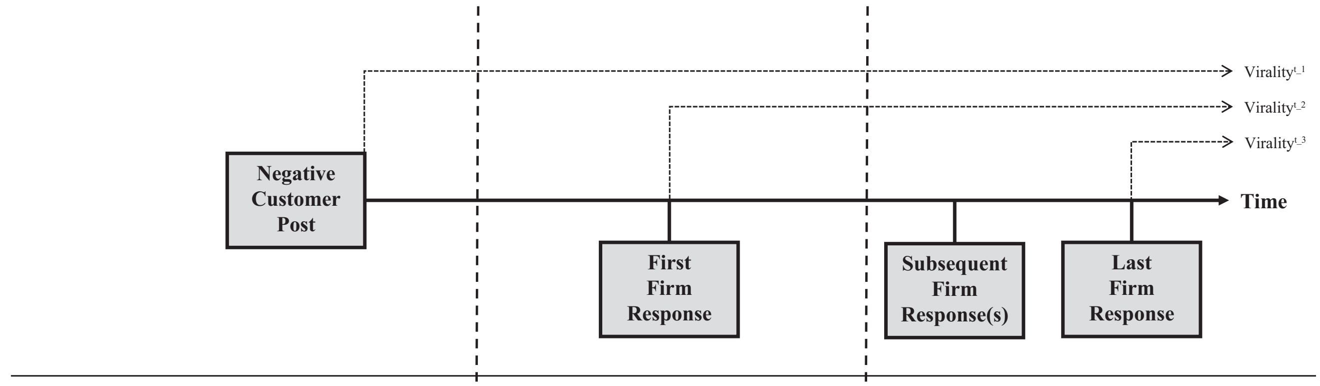
(continued)

Table 1. (continued)

Variable and Time	Operationalization	Source	Rational for Inclusion (Controls) and Related Studies
Variance in linguistic style	Variance in LSM of all customer posts in each online brand community (for both positive and negative posts).	Text mining	Variance in linguistic style may decrease the effectiveness of negative eWOM (Ludwig et al. 2014).
Post Controls			
Competing inputs	Number of other posts in the online brand community on the day of the focal negative customer post (both customer and firm posts).	Facebook API	Exposure to competing stimuli may decrease the virality of emotions (Coenen and Broekens 2012).
Sentiment previous post	LIWC dictionaries "posemo" minus "negemo" for the previous customer post in the online brand community.	Text mining	A preexisting mood state may increase the virality of emotions (Coenen and Broekens 2012).
Post length	Average words per sentence.	Text mining	Longer posts may convey more information and thus increase virality (Berger and Milkman 2012).
Post complexity	Average words with more than six letters per sentence.	Text mining	Posts that are more complex suggest eloquence in writing which may increase virality (Vásquez 2014).
Negation in post	LIWC dictionary "negate" (in percentage of total words).	Text mining	Posts with negation may be more difficult to understand and thus decrease virality.
Previous complaints	Number of negative posts from the same customer prior to the focal negative post.	Facebook API	A high frequency of complaints from the same customer may decrease virality (Ma, Sun, and Kekre 2015).
No firm response	No firm response on the negative customer post (dummy coded).	Facebook API	Virality may increase if members believe the firm is ignoring them (Homburg, Ehm, and Artz 2015).
Firm response time	Time stamp of negative customer post minus time stamp of first firm response (converted to hours).	Facebook API	A faster response should be beneficial for firms and thus may decrease virality (Homburg, Ehm, and Artz 2015).
Firm Response Controls			
Compensation	Newly developed dictionary; see the Web Appendix (dummy coded).	Text mining	Offering compensation may satisfy the complaining customer and decrease virality (Bitner, Booms, and Tetreault 1990).
Apology	Newly developed dictionary; see the Web Appendix (dummy coded).	Text mining	Apologizing may please the complaining customer and decrease virality (Bitner, Booms, and Tetreault 1990).
Channel change	Newly developed dictionary; see the Web Appendix (dummy coded).	Text mining	Evoking a channel change may take the conversation away from the brand community and decrease virality (Ansari, Mela, and Neslin 2008).

Notes: We use time dummies to control for year, month, weekend, and time of day.

community size, member attentiveness and expressiveness, firm engagement frequency, average structural tie strength among members, and variance in linguistic style. Post-related aspects include the number of competing inputs at the time of the post, the sentiment of the previous post, post length, post complexity, and the frequency with which the customer had complained on Facebook in the past. Furthermore, firm response–related aspects include whether a firm responds or not and the firm response time. We used dummy variables to account for whether a firm offered an apology, offered compensation, or suggested a communication channel change; a firm can use more than one response approach in the same message for this measure (e.g., combining apology and compensation). Finally, as fixed effects, we account for the year and month to control for seasonality in user activity and policy changes (see the Web Appendix). We also include fixed effects for weekends and time of day (Kanuri, Chen, and Sridhar 2018). The Web Appendix reports correlations and descriptive statistics. Firms responded at least once to 331,370 out of 472,995 negative posts, yielding an average response rate of 70%. Across all firm responses, suggesting a channel change (61%) and apologizing (53%) were most commonly used, while compensation was used less often (3%). The degree to which explanations were offered (8% of the time) was slightly more than the use of empathy (6%). We found that 15,762 negative posts achieved above-average virality and got multiple firm responses, suggesting that 3% of potential online firestorms evolved during the period of observation. The Web Appendix reveals the evolution of the number of potential firestorms, average virality, and average firm response rates over time. While the number of potential online firestorms increased during the study period (and we control for this increase with time-related fixed-effect), both the average virality and the average percentage of firm responses are rather stable over time.



Stage	*Detecting Potential Online Firestorms*	*Preventing Potential Online Firestorms*	*Mitigating Evolved Online Firestorms*
Virality	Virality^{t_1} = total number of likes and comments from other customers at any time after posting at t	Virality^{t_2} = the number of likes and comments from other customers at any time after the first firm response	Virality^{t_3} = the number of likes and comments from other customers at any time after the last firm response
Sample	All posts with and without firm response (472,995 negative posts)	All posts with at least one firm response (331,370 negative posts)	All posts with more than one firm response and above-average virality (15,762 negative posts)
Hypotheses	**H$_1$:** The intensity of high-arousal-emotion words in negative eWOM messages relates to greater virality in online brand communities, compared with the intensity of low arousal emotion words. **H$_2$:** Stronger structural ties between the sender of negative eWOM and the receiving online brand community relate to greater virality. **H$_3$:** Closer LSM between the sender of negative eWOM and the receiving online brand community relates to greater virality.	**H$_4$:** More explanation, rather than more empathy, in firm responses is better suited to contain negative eWOM with more intensive high-arousal emotions. **H$_5$:** More empathy, rather than more explanation, in firm responses is better suited to contain negative eWOM with more intensive low-arousal emotions.	**H$_6$:** Consecutive firm responses with varying rather than repeated (a) empathic intensity and (b) explanatory intensity are better suited to mitigating evolved online firestorms.
Results	Table 2	Table 3	Table 4

Figure 2. Hypotheses and measurement approach.

Modeling Approach

The incidences of negative eWOM are nested within the online brand communities, and thus the negative posts and firm responses might be interdependent. To determine whether a multilevel approach is warranted, we first conducted a one-way analysis of variance with random effects to reveal any systematic between-group variance in the virality of negative eWOM. We find significant between-group variance ($\chi^2(88) = 818{,}729$, $p < .01$). In addition, the design effect of 36.74 suggests that a multilevel structure is possible (Múthen and Satorra 1995). The maximum variance inflation factor score across all models is 3, indicating no potential threat of multicollinearity.

We specified a series of separate hierarchical models, with parameters at the post and the firm/brand community level, using full information maximum likelihood estimation and grand mean-centering. Virality, our focal outcome measure, is operationalized differently across these models along three time periods. Virality^{t_1} is the total number of likes and comments from other customers any time after posting at t. Virality^{t_2} is the number of likes and comments from other customers any time after the first firm response, and Virality^{t_3} is the number of likes and comments from other customers any time after the last firm response. We provide more detailed explanations for each variable in Table 1. Thus, we assess the predictors of virality for all 472,995 negative posts across the 89 brand communities as follows:

$$\begin{aligned}\text{Virality}_{ic}^{t-1} = {} & \gamma_{00} + \gamma_{01-04}\text{Firm Controls}_c \\ & + \gamma_{05-10}\text{Brand Community Controls}_c \\ & + \gamma_{11-17}\text{Post Controls}_{ic} \\ & + \gamma_{18}\text{Dum No Firm Response}_{ic} \\ & + \gamma_{19-23}\text{Post Predictors}_{ic} \\ & + \gamma_{24-43}\text{Dum Timing}_{ic} + u_{0c} + r_{ic},\end{aligned} \tag{3}$$

where t_1 is the time period after the time t of customer i's post in brand community c;

Virality$_{ic}^{t-1}$ = the combined sum of likes and comments post i receives from other customers in community c any time after it was posted (brand community-centered and log-transformed);

Firm Controls$_c$ = community-specific controls using the Global Industry Classification Standard: GICS Consumer Discretionary$_c$, GICS Consumer Staples$_c$, Brand Familiarity$_c$, and Brand Reputation$_c$;

Brand CommunityControls$_c$ = Brand Community Size$_c$, Brand Community Attentiveness$_c$, Brand Community Expressiveness$_c$, Firm Engagement$_c$, Average Tie Strengths$_c$, and Variance in Linguistic Style$_c$;

Post Controls$_{ic}$ = Competing Inputs$_{ic}$, Sentiment Previous Post$_{ic}$, Post Length$_{ic}$, Post Complexity$_{ic}$, Negation in Post$_{ic}$, and Previous Complains$_{ic}$;

Dum No Firm Response$_{ic}$ = 1 if there is no firm response at any time, and 0 otherwise;
Post Predictors$_{ic}$ = Intensity of High Arousal$_{ic}$, Intensity of Low Arousal$_{ic}$, SST$_{ic}$, and LSM$_{ic}$;
Dum Timing$_{ic}$ = dummy variables for years (baseline is 2015), month (baseline is December), weekend day (baseline is week day), and time of the day (baseline is night time, EST);
u_{0c} = brand community–specific error term; and
r_{ic} = post-specific error term.

Next, to determine how firms can prevent viral online firestorms, we examine 331,370 negative posts that received at least one firm response according to the following equation:

$$\begin{aligned}\text{Virality}_{ic}^{t\text{–}2} = {} & \gamma_{00} + \gamma_{01-04}\text{Firm Controls}_c \\ & + \gamma_{05-10}\text{Brand Community Controls}_c \\ & + \gamma_{11-17}\text{Post Controls}_{ic} \\ & + \gamma_{18}\text{Firm Response Time}_{ic} \\ & + \gamma_{19-23}\text{Post Predictors}_{ic} \\ & + \gamma_{24-43}\text{Dum Timing}_{ic} \\ & + \gamma_{44-48}\text{First Firm Response}_{ic} \\ & + \gamma_{49-52}\text{Interactions}_{ic} + u_{0c} + r_{ic},\end{aligned} \tag{4}$$

where t_2 is the time period after the first firm response;

Virality$_{ic}^{t\text{–}2}$ = the combined sum of likes and comments post i received from other customers in community c any time after the first firm response (brand community-centered and log-transformed);
Firm Response Time = time until the first firm response;
First Firm Response = Compensation$_{ic}$, Apology$_{ic}$, Channel Change$_{ic}$, Intensity of Empathy$_{ic}$, and Intensity of Explanation$_{ic}$; and
Interactions$_{ic}$ = Intensity of High Arousal$_{ic}$ × Intensity of Empathy$_{ic}$, Intensity of High Arousal$_{ic}$ × Intensity of Explanation$_{ic}$, Intensity of Low Arousal$_{ic}$ × Intensity of Empathy$_{ic}$, and Intensity of Low Arousal$_{ic}$ × Intensity of Empathy$_{ic}$.

Finally, we investigate how firms can mitigate the evolved online firestorms represented by 15,762 negative posts that achieved above-average virality and to which firms responded multiple times:

$$\begin{aligned}\text{Virality}_{ic}^{t\text{–}3} = {} & \gamma_{00} + \gamma_{01-04}\text{Firm Controls}_c \\ & + \gamma_{05-10}\text{Brand Community Controls}_c \\ & + \gamma_{11-17}\text{Post Controls}_{ic} \\ & + \gamma_{18}\text{Firm Response Time}_{ic} \\ & + \gamma_{19-23}\text{Post Predictors}_{ic} \\ & + \gamma_{24-43}\text{Dum Timing}_{ic} \\ & + \gamma_{44-48}\text{First Firm Response}_{ic} \\ & + \gamma_{49-51}\text{Subsequent Firm Responses}_{ci} \\ & + \gamma_{52-53}\text{Variance in Firm Responses}_{ci} + u_{0c} + r_{ic},\end{aligned} \tag{5}$$

where t_3, . . . , T is the time period after the last firm response;

Virality$_{ic}^{t\text{–}3}$ = the combined sum of likes and comments post i received from other customers in community c any time after the last firm response (brand community-centered and log-transformed);
Subsequent Firm Responses$_{ic}$ = include all firm responses after the first firm response, Compensation$_{ic}$, Apology$_{ic}$, Channel Change$_{ic}$, Intensity of Empathy$_{ic}$, and Intensity of Explanation$_{ic}$; and
Variance in Firm Responses$_{ci}$ = Variance in Empathy$_{ic}$ and Variance in Explanation$_{ic}$ (across all Firm Responses$_{ic}$).

Results

Detecting Potential Online Firestorms

The results provide support for our hypotheses that the intensity of high-arousal emotions (vs. low-arousal emotions), SST, and LSM relate to the virality of negative eWOM (Table 2, Model 3).[2] Both intensities of high arousal (γ = .186, p < .01) and low arousal (γ = .026, p < .01) relate positively to virality. However, a t-test reveals that the intensity of high arousal is more strongly related to virality than the intensity of low arousal (t = 35.15, p < .01), in support of H_1. In addition, SST (γ = 1.432, p < .01) and LSM (γ = .025, p < .01) relate positively to virality, in support of H_2 and H_3. Considering the relative influence of the drivers, we find that SST exerts the strongest impact on virality (all t ≥ 77.97, p < .01).

Regarding brand community controls, we find that average tie strength relates negatively to virality (γ = −.247, p < .05), and greater variance in linguistic style relates positively to virality (γ = 5.550, p < .10). Online firestorms thus appear to occur less in brand communities in which members have stronger connections with one another and are more similar. Regarding the post controls, we find that competing inputs (γ = −.001, p < .01) and previous complaints (γ = −.213, p < .01) relate negatively to virality. Conversely, post length (γ = .005, p < .01) and post complexity (γ = .017, p < .01) relate positively to virality. Finally, a lack of firm response is significantly related to increased virality (γ = .029, p < .01), clearly indicating the importance of actively managing negative eWOM in online brand communities.

Preventing Potential Online Firestorms

When considering the main effects of the intensities of empathy and explanation in firm responses in Model 5 (Table 3), we find that the increased use of empathy (γ = −.069, p < .01) leads to significantly lower virality than the increased use of explanation (γ = −.011, p < .01; t = 14.42, p < .01). Regarding other firm responses that reflect disengaging from

[2] The fixed effects for year, month, weekend, and time of day for all models appear in the Web Appendix.

Table 2. Predictors of Potential Online Firestorms.

	DV = Total Virality of Negative Customer Post Sample = All Posts with and Without Firm Response					
	Model 1		Model 2		Model 3	
	γ	t/r	γ	t/r	γ	t/r
Level 2: Firm/Brand Community						
Firm controls						
GICS consumer discretionary	−.185	−1.48	−.190	−1.56	−.190	−1.56
GICS consumer staples	−.100	−.62	−.100	−.63	−.100	−.64
Brand familiarity	.149	.57	.139	.55	.139	.55
Brand reputation	−.640	−.69	−.664	−.74	−.665	−.74
Brand community controls						
Brand community size	.002	.18	.002	.20	.002	.20
Brand community attentiveness	.009	.15	.011	.20	.011	.20
Brand community expressiveness	5.641	1.33	5.736	1.38	5.726	1.38
Average firm engagement	.287	1.60	.290	1.66	.291	1.66
Average tie strengths	−.230†	−1.87	−.247*	−2.06	−.247*	−2.06
Variance in linguistic style	5.363†	1.80	5.498†	1.89	5.500†	1.89
Level 1: Customer Post						
Post controls						
Competing inputs	−.001**	.03	−.001**	.03	−.001**	.03
Sentiment previous post	−.001	.00	−.001	.00	−.002	.00
Post length	.005**	.07	.005**	.07	.005**	.06
Post complexity	.018**	.02	.012**	.01	.017**	.01
Negation in post	.021**	.01	−.022	.01	.004	.00
Previous complaints	.017**	.00	−.212**	.05	−.213**	.05
No firm response	.030**	.14	.030**	.14	.029**	.14
Post predictors						
Negative emotions			.133**	.06		
Intensity of high arousal (H_1)					.186**	.07
Intensity of low arousal (H_1)					.026**	.01
Strength of structural ties (H_2)			1.435**	.13	1.432**	.13
LSM (H_3)			.032**	.05	.025**	.04
Log-likelihood	−1,019,495		−1,030,248		−1,031,025	
Change in log-likelihood			10,752**		11,530**	
$N_{Level\ 2}$			89 brand communities			
$N_{Level\ 1}$			472,995 negative posts			

†$p < .10$.
*$p < .05$.
**$p < .01$.
Notes: Significance is based on two-tailed tests. We report t-values for Level 2 and effect size r for Level 1. Change in fit in comparison with the model with control variables only. We test GICS consumer discretionary and GICS consumer staples against GICS other. Fixed effects for year, month, weekend, and time of day are included in the model and reported in the Web Appendix. Slopes of high-arousal and low-arousal emotions are different at $p < .01$ and t = 35.15. An additional model that compared the effects of different high-arousal emotions (fear/anxiety, anger, disgust) with the low-arousal emotion (sadness) revealed that fear/anxiety (t = 10.75, $p < .01$), anger (t = 37.52, $p < .01$), and disgust (t = 1.74, $p < .10$) are all more strongly related to virality than sadness. The small difference between disgust and sadness is in line with Berger and Milkman's (2012) finding and can be attributed to the relative scarcity of disgust in the negative eWOM messages. We also find that anger relates more strongly to virality then other high-arousal emotions (all ts ≥ 21.34, $p < .01$).

the conversation, we find that responses that contain an apology ($\gamma = -.004$, $p < .01$) or a suggestion for a channel change ($\gamma = -.005$, $p < .01$) relate negatively to virality. However, immediately offering compensation fosters the virality of negative eWOM ($\gamma = .003$, $p < .01$).

When considering the interaction effects in Model 6 (Table 3), we find a positive interaction between the intensity of high arousal and the increased use of empathy in the firm response ($\gamma = 2.678$, $p < .01$). The increased use of empathy in a response to a post with a high intensity of high arousal thus increases, rather than decreases, virality. Conversely, we find a significant negative interaction between the increased intensity of high arousal and the increased use of explanation in the firm response ($\gamma = -1.437$, $p < .01$). Therefore, the increased use of explanation in a response to a post with a high intensity of high arousal significantly reduces its virality, as depicted in Figure 3. A t-test further reveals significant differences between providing more empathy versus more explanation in buffering the effect of high arousal (more empathy: $\gamma = .386$, $p < .01$; more explanation: $\gamma = .180$, $p < .01$; t = 23.43,

Table 3. Preventing Potential Online Firestorms.

	DV = Virality After the First Firm Response Sample = All Posts with at Least One Firm Response					
	Model 4		Model 5		Model 6	
	γ	t/r	γ	t/r	γ	t/r
Level 2: Firm/Brand Community						
Firm controls						
GICS consumer discretionary	−.206	−1.45	−.206	−1.44	−.206	−1.44
GICS consumer staples	−.104	−.57	−.105	−.57	−.104	−.57
Brand familiarity	.119	.40	.118	.40	.117	.40
Brand reputation	−.842	−.80	−.833	−.79	−.834	−.79
Brand community controls						
Brand community size	.003	.24	.003	.24	.003	.24
Brand community attentiveness	.019	.28	.018	.28	.019	.28
Brand community expressiveness	5.971	1.23	5.968	1.23	5.960	1.23
Average firm engagement	.323	1.57	.323	1.58	.323	1.58
Average tie strengths	−.310*	−2.20	−.309*	−2.20	−.310*	−2.20
Variance in linguistic style	5.996†	1.76	5.995†	1.76	5.993†	1.76
Level 1: Customer Post						
Post controls						
Competing inputs	.003**	.03	.003**	.03	.003**	.03
Sentiment previous post	−.005**	.01	−.005**	.01	−.005**	.01
Post length	.005**	.08	.006**	.08	.006**	.08
Post complexity	.017**	.01	.018**	.02	.018**	.02
Negation in post	.005	.00	.002	.00	.002	.00
Previous complaints	−.171**	.03	−.179**	.03	−.178**	.03
Firm response time	.001**	.02	.001**	.02	.001**	.02
Post predictors						
Intensity of high arousal	.220**	.08	.217**	.08	.252**	.09
Intensity of low arousal	.025**	.01	.025**	.01	.027**	.02
Strength of structural ties	1.047**	.08	1.044**	.08	1.038**	.08
LSM	.022**	.04	.024**	.04	.023**	.04
First firm response						
Compensation			.003**	.01	.003**	.01
Apology			−.004**	.02	−.004**	.02
Channel change			−.005**	.03	−.006**	.03
Intensity of empathy (EMP)			−.069**	.04	−.065**	.04
Intensity of explanation (EXP)			−.011**	.01	−.006*	.00
Intensity of high arousal × EMP (H_4)					2.678**	.05
Intensity of high arousal × EXP (H_4)					−1.437**	.04
Intensity of low arousal × EMP (H_5)					−.042	.00
Intensity of low arousal × EXP (H_5)					−.206**	.01
Log-likelihood	−770,911		−771,760		−773,267	
Change in log-likelihood			849**		1,508**	
$N_{\text{Level 2}}$			89 brand communities			
$N_{\text{Level 1}}$			331,370 negative posts			

$^{\dagger}p < .10$.
$^{*}p < .05$.
$^{**}p < .01$.
Notes: Significance is based on two-tailed tests. We report t-values for Level 2 and effect size r for Level 1. Fixed effects for year, month, weekend, and time of day are included in the model and reported in the Web Appendix.

$p < .01$). Overall, these results support H_4 and indicate that intensive high arousal is better contained with more explanation.

Contrary to our expectations, we find no negative interaction between the intensity of low arousal and the increased use of empathy in the firm response at conventional significance levels ($\gamma = -.042$, $p = .30$) and a negative interaction between the intensity of low-arousal emotions and the increased use of explanation in the firm response ($\gamma = -.206$, $p < .01$). A t-test reveals no significant differences between providing more empathy versus more explanation in buffering intensive low-arousal emotions (more empathy: $\gamma = .025$, $p < .01$; more explanation: $\gamma = .016$, $p < .01$; t = 1.63, $p = .10$). Thus, H_5 is not supported.

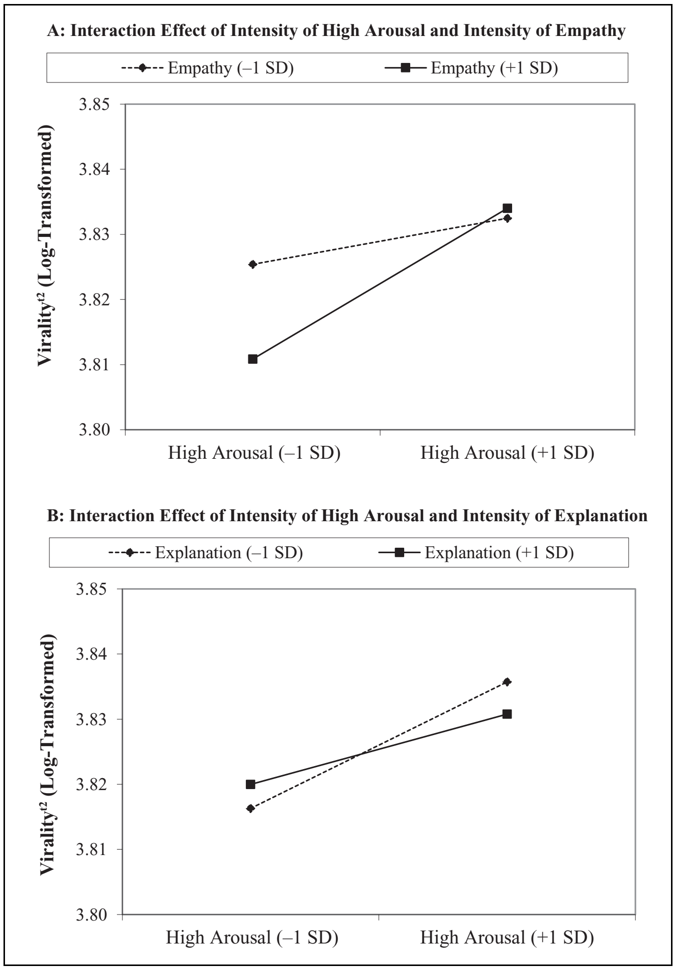


Figure 3. Firm response strategies moderate the effect of high-arousal emotions on virality.
Notes: Virality^{t_2} is measured after the first firm response.

Mitigating Evolved Online Firestorms

Variations in the intensity of empathy ($\gamma = -.185$, $p < .05$) and intensity of explanation ($\gamma = -.205$, $p < .01$) relate negatively to virality in Model 9 (Table 4), in support of H_{6a} and H_{6b}. These findings suggest that firms should vary their response formulation to decrease the virality of evolved online firestorms. We further find that an increased use of explanation in subsequent responses increases virality ($\gamma = .083$, $p < .01$). To mitigate the virality of negative eWOM, firms should vary their response, focusing on more empathy in later responses. Notably, at an evolved stage of an online firestorm, firm responses that contain an apology ($\gamma = .031$, $p < .01$) or a channel change ($\gamma = .038$, $p < .01$) positively relate to virality. These findings reveal that such response strategies not only are ineffective in mitigating evolved online firestorms but even fuel the fire. In contrast, offering compensation in a subsequent response negatively relates to virality ($\gamma = -.045$, $p < .01$).

Additional Analyses

Addressing potential endogeneity. In our research design, endogeneity might arise out of reverse causality, omitted variables, or a learning effect. First, the timestamps provided allow us to avoid reverse causality by considering only customer comments that occur after the respective firm response. Second, we address omitted variables stemming from the 89 firms with firm-fixed-effects regressions to account for the unobservable heterogeneity of each brand community (Allison 2009). All results are fully in line with the main analyses, as displayed in the Web Appendix. Third, we account for a learning effect in an analysis in which we include a continuous time variable that captures the 52 months of our study period (1 = October 2011 to 52 = January 2016). If endogeneity from a learning effect biases our results, this time variable would reduce the virality of negative posts and/or increase the effectiveness of the response strategies. Instead, when we include the time variable in our prevention model, we find a nonsignificant main effect on virality ($p = .98$). The positive interaction effects of the time variable with empathy ($\gamma = .010$, $p < .01$) and explanation ($\gamma = .002$, $p < .08$) indicate that both response strategies become less effective over time. Taken together, these additional analyses suggest it is unlikely that endogeneity biases our results.

Additional interaction effects. Recent research has suggested that different drivers of virality may reinforce one another (Ludwig et al. 2013). Thus, we tested for potential interaction effects among the four drivers of online firestorms in Model 3. We find that both SST ($\gamma = 28.840$, $p < .01$) and LSM ($\gamma = .743$, $p < .01$) increase the effect of high-arousal emotions. In addition, LSM increases the effect of low-arousal emotions ($\gamma = .107$, $p < .01$), and SST and LSM reinforce each other ($\gamma = 2.079$, $p < .01$). When we tested whether SST influences the effectiveness of empathy and explanation, we find that both empathy ($\gamma = -4.00$, $p < .01$) and explanation ($\gamma = -5.83$, $p < .01$) are more effective in reducing the virality of negative eWOM from customers with strong structural ties in the brand community.

Alternative measures of virality. In line with previous research (e.g., Relling et al. 2016), we regard the combined number of likes and comments as the most appropriate measure for virality. For robustness, we tested our results with three separate, alternative measures of virality: likes, comments, and shares. Previous research has indicated mixed results, such that Lee, Hosanagar, and Nair (2018) find no major difference in using likes or comments as measures, but De Vries, Gensler, and Leeflang (2012) find different results using likes versus comments to measure virality. We replicate all the models with these different outcome measures and report the results in the Web Appendix; nearly all estimates for the hypothesized effects are directionally similar and significant at conventional levels.

Table 4. Mitigating Evolved Online Firestorms.

	DV = Virality After the Last Firm Response Sample = All Posts with More Than One Firm Response and Above-Average Virality					
	Model 7		Model 8		Model 9	
	γ	t/r	γ	t/r	γ	t/r
Level 2: Firm/Brand Community						
Firm controls						
GICS consumer discretionary	.021	1.34	.022	1.40	.022	1.40
GICS consumer staples	−.012	−.54	−.015	−.67	−.015	−.67
Brand familiarity	−.006	−.16	−.007	−.16	−.007	−.17
Brand reputation	−.009	−.08	−.005	−.04	−.004	−.04
Brand community controls						
Brand community size	.001	1.08	.002	1.15	.002	1.15
Brand community attentiveness	−.008	−1.24	−.007	−1.19	−.007	−1.19
Brand community expressiveness	−.304	−.50	−.295	−.48	−.296	−.49
Average firm engagement	.014	.53	.012	.46	.012	.46
Average tie strengths	−.020	−1.45	−.020	−1.45	−.020	−1.45
Variance in linguistic style	.616	1.08	.615	1.07	.616	1.07
Level 1: Customer Post						
Post controls						
Competing inputs	−.001	.00	−.001	.00	−.001	.00
Sentiment previous post	−.030	.01	−.029	.01	−.029	.01
Post length	.013**	.07	.013**	.07	.013**	.07
Post complexity	−.017	.01	−.016	.00	−.016	.00
Negation in post	−.087	.01	−.082	.01	−.082	.01
Previous complaints	−.707**	.03	−.710**	.03	−.710**	.03
Firm response time	.003**	.05	.003**	.05	.003**	.05
Post predictors						
Intensity of high arousal	.363**	.06	.364**	.06	.364**	.06
Intensity of low arousal	.122**	.03	.124**	.03	.124**	.03
Strength of structural ties	5.796**	.11	5.813**	.11	5.812**	.11
LSM	.045**	.03	.045**	.03	.045**	.03
First firm response						
Compensation	.018†	.01	.017	.01	.017	.01
Apology	−.011*	.02	−.012**	.02	−.012**	.02
Channel change	−.008†	.02	−.010*	.02	−.010*	.02
Intensity of empathy	−.084	.01	−.072	.01	−.072	.01
Intensity of explanation	−.129**	.03	−.127**	.03	−.127**	.03
Subsequent firm responses						
Compensation	−.044**	.04	−.045**	.04	−.045**	.04
Apology	.032**	.06	.031**	.06	.031**	.06
Channel change	.040**	.08	.038**	.08	.038**	.08
Intensity of empathy	−.110**	.03	−.016	.00	−.021	.00
Intensity of explanation	.042	.01	.082**	.02	.083**	.02
Variance in firm response			−.198**	.04		
Variance in empathy (H_{6a})					−.185**	.02
Variance in explanation (H_{6b})					−.205**	.03
Log-likelihood	−1,463.20		−1,480.45		−1,475.86	
Change in log-likelihood			17.25**		12.66**	
$N_{Level\ 2}$	72 brand communities					
$N_{Level\ 1}$	15,762 negative posts					

†$p < .10$.
*$p < .05$.
**$p < .01$.
Notes: Significance is based on two-tailed tests. We report t-values for Level 2 and effect size r for Level 1. Fixed effects for year, month, weekend, and time of day are included in the model and reported in the Web Appendix.

Table 5. Overview of Results.

Hypotheses		Effect on Virality of Negative eWOM	Support
H_1	High- versus low-arousal emotions	Intensity of high arousal > Intensity of low arousal	Supported (Table 2)
H_2	Strength of structural ties	Strong structural ties > Weak structural ties	Supported (Table 2)
H_3	LSM	Closer LSM > More distant LSM	Supported (Table 2)
H_4	Firm response to high-arousal emotions	For high arousal: More explanation > More empathy	Supported (Table 3)
H_5	Firm response to low-arousal emotions	For low arousal: More empathy > More explanation	Not supported (Table 3)
H_{6a}	Variation in empathy in firm responses	Variation in empathy > Similar intensity of empathy	Supported (Table 4)
H_{6b}	Variation in explanation in firm responses	Variation in explanation > Similar intensity of explanation	Supported (Table 4)

Discussion

Theoretical Implications and Extensions

Extensive literature has addressed the benefits of eWOM (e.g., Baker, Donthu, and Kumar 2016), but theoretical and empirical work devoted to negative eWOM in brand communities is scarce. Drawing on research on negative WOM (e.g., Brown and Reingen 1987; Heath, Bell, and Sternberg 2001), we combine multiple sender and relational aspects that likely increase the virality of negative eWOM in online brand communities. We then empirically assess their role in driving virality across 472,995 potential online firestorms in 89 online brand communities of S&P 500 firms. Integrating common recovery approaches from service literature (Hill, Roggeveen, and Grewal 2015) with emotion regulation strategies (Gross and Thompson 2007), we also highlight the relative effectiveness of different firm response approaches and cross-response variations to prevent and mitigate online firestorms. Thereby, our study makes three primary contributions to extant marketing research (for a summary of the results, see Table 5).

First, we advance research on how to detect the online firestorm potential of negative eWOM with an empirical investigation of prototypical conceptions of different drivers of virality and their interrelations. In line with prior marketing research on negative WOM (Brown and Reingen 1987; Heath, Bell, and Sternberg 2001, Mittal, Huppertz, and Khare 2008), we show that the virality of negative eWOM in online brand communities varies depending on sender and relational aspects. As an extension of Berger and Milkman's (2012) findings about sharing newspaper articles, we find that in online brand communities, the use of more high-arousal-emotion words in negative eWOM increases its virality and makes it relatively more contagious than the use of low-arousal-emotion words. We also find that stronger structural ties between the complaining customer and the receiving online brand community relate to greater virality of negative eWOM. Thus, Brown and Reingen's (1987) conclusions, gathered from a small offline community, hold in large digital communities. Notably, owing to data limitations, we were only able to use the frequency of communication as tie strength indicator, not the importance attached to the relationship. Moreover, in this otherwise anonymous context, we use the degree of LSM as an indicator of interpersonal similarity between senders and receivers. In line with Ludwig et al. (2013), we find that closer LSM between the complaining customer and the receiving online brand community relates to greater virality of negative eWOM. In contrast with previous studies, we consider a broader set of drivers of virality and test their relative importance and interrelationships. Structural ties are the strongest driver of virality. Furthermore, strong structural ties and a close LSM amplify the virality effect of high-arousal emotions in negative eWOM. To put our estimated effects into perspective with related research, we calculate effect sizes r using the formula from Rosenthal and Rosnow (2007). The identified drivers show effect sizes ranging from .04 to .13. Taken together, our study thus advances negative eWOM research with a theoretically grounded framework of sender and relational aspects, useful for detecting potential online firestorms in brand communities.

Second, as suggested in prior research (e.g., Ma, Sun, and Kekre 2015), we consider the effectiveness of firm response approaches to reduce the contagiousness of negative eWOM in online brand communities. Contributing to this emergent stream of research, we reconcile research on service recovery (Hill, Roggeveen, and Grewal 2015) and emotion regulation (Gross and Thompson 2007) to delineate common, theoretically grounded firm response alternatives. We empirically confirm the common knowledge that not responding to a negative customer post is a firm's worst choice and should be avoided. In line with Homburg, Ehm, and Artz (2015), we further find that responding fast is important. When actively engaging in elaboration with the complaining customer within the online brand community, the increased use of empathy is more effective overall. However, if a negative eWOM message contains exceptionally intense high-arousal emotions, increasing the amount of explanation is more effective for preventing and mitigating its virality. Contrary to our expectations, we find that explanation rather than empathy best contains negative eWOM containing severe low-arousal emotions (e.g., sadness). Indeed, in line with Gross and Thompson (2007), customers who are experiencing severe emotions (either anger or sadness) are not able to shift attention but are always looking for explanations beyond empathy.

Initially aiming to block and disengage, rather than engage in elaborate online discussions, firms are best advised to offer an apology or suggest a channel change. At a later stage, once the negative eWOM has gathered support within the online brand community, these disengagement approaches are not only ineffective but may further increase a post's virality.

Offering to take a customer's complaint offline seems to remove at least some negative conversations before they go viral. However, at a later stage, when the support of others for the negative eWOM has increased its perceived reliability (Dholakia, Basuroy, and Soltysinski 2002), both the complaining customer and the community likely feel further encouraged by a firm's admittance of guilt (i.e., apology) and disgruntled if forcefully removed from the conversation (i.e., channel change). Moreover, the switching effect of channel change is in line with recent research from Grégoire et al. (2018), who find that for customers using indirect revenge behaviors with public exposure (e.g., complaining online in a brand community), desire for revenge increases over time. Offering compensation only mitigates the virality of the negative eWOM message when used as a later response by the firm. Some controversy exists regarding the effectiveness of compensation as a means to recover from a service failure. That is, compensation may dissipate customers' frustrations (Bitner, Booms, and Tetreault 1990), but offering it without explanation increases attributions of control and indicates an admission of guilt, evoking more negative evaluations (Bitner 1990). In line with Grewal, Roggeveen, and Tsiros (2008), we therefore suggest that compensation is most effective if it follows an offer of an explanation or empathy. With these findings on how to prevent online firestorms, we extend debates about service recovery strategies to negative eWOM in online brand communities.

Third, online firestorms that have evolved often require multiple responses. We contribute to research on social media sharing by analyzing the implications of variations in firm response sequences (Batra and Keller 2016). Several firm responses are likely to be interpreted jointly rather than in isolation (Villarroel Ordenes et al. 2018). We find that varying response approaches, rather than consistently responding in the same way, can reduce the virality of evolved online firestorms in brand communities. Firms that use the same intensity of empathy or explanation to respond to negative eWOM increase, rather than mitigate, its contagiousness to other community members. Together with our findings that the effectiveness of compensation, apology, and channel change depends on when they are used, we add new insights into how best to sequence multiple firm responses in social media. Finally, as a useful resource for research, we have developed text-mining dictionaries to derive firms' response approaches automatically using a top-down text-mining approach (see the Web Appendix). We carefully followed traditional dictionary development standards (Humphreys and Wang 2018), so researchers who want to examine written or transcribed firm responses in firm–customer exchanges may use these dictionaries as a starting point for their own investigations of firm response strategies.

Managerial Implications

By investigating how to detect, prevent, and mitigate the virality of negative eWOM in online brand communities, we offer several actionable implications for managers. We discuss them in the following subsections.

Detecting potential online firestorms. Brand community managers, who struggle to identify potentially threatening negative eWOM messages, should consider complainers' message formulations, beyond what is literally said, as well as their relationship with other members of the community. First, by using our dictionary-based, straightforward, automatic text-mining approach, managers can assess the high- and low-arousal levels of negative messages to predict their potential virality. The higher-arousal-emotion words a message contains, the more likely it is to go viral. Second, managers should assess the tie strength of the customer posting the negative message. Negative messages by customers who frequently interact with other community members are more likely to go viral than messages by customers who are relative strangers in the community. Third, text-mining tools can track the brand community's dominant communication style continuously and contrast it with the style of each negative customer post. Posts that closely match the dominant communication style are more likely to go viral. Taken together, the identified drivers explain 25% of virality across all examined brand communities. Finally, the different drivers amplify one another, so managers should be particularly cautious of complaining customers with strong structural ties who closely match the community's dominant communication style.

Preventing potential online firestorms. Unlike in a traditional service recovery setting, the success of managers' responses in preventing online firestorms critically depends on their ability to satisfy both the complainant and the brand community. Not responding is the worst choice, but the firm response also needs to be fast and tailored to the customer's message. In an initial response, empathy is generally most effective for containing negative eWOM. However, very negative messages that use an exceptional amount of high-arousal emotion words (e.g., "angry," "hate") demand more explanation. To disengage from the conversation and reduce the virality of negative eWOM upfront, managers should apologize or ask the unsatisfied customer to use another channel to raise the issue. Offering compensation immediately is not advised; it is effective only as a later response. We find that an appropriate response strategy can reduce virality of an intensive high-arousal post by up to 10%, which may equal hundreds of angry customers supporting and sharing negative eWOM.[3]

Mitigating evolved online firestorms. Some negative eWOM cannot be prevented from going viral or "catching fire" among

[3] For the calculation, we compared the expected virality of an intensive high-arousal post where firms respond with above-average empathy, below-average explanation, and with a compensation with the expected virality of an intensive high-arousal post where firms respond with below-average empathy, above-average explanation, and with apology and channel change (while keeping all other predictors constant).

other customers, and managers will need to respond multiple times. These responses are likely to be viewed collectively, rather than in isolation, so managers should consider each response as part of an overall response sequence. Rather than consistently posting the same message, managers should vary the use of empathy and explanation to mitigate the further virality of negative eWOM messages. An explanatory approach is viable as a first response to exceptionally intense high-arousal negative eWOM, and later firm responses should use increased empathy. If used at a later response stage, apologizing or suggesting a different communication channel will "feed the fire" and increase the virality of the negative eWOM. Instead, offering compensation should be the last resort for managers to prevent further elaborations and reduce the virality of negative eWOM. Using an appropriate response strategy over time can reduce subsequent virality by up to 11%.[4]

Limitations and Directions for Further Research

Our results are consistent with the proposition that firms need to manage negative eWOM in their online brand communities actively to prevent or mitigate their detrimental effects (e.g., Hewett et al. 2016; Pfeffer, Zorbach, and Carley 2014). Although we believe our findings have broad applicability, managing online firestorms is a vast and largely neglected field of research that is of critical importance to managers. Thus, it is important to recognize some limitations of our study and suggest further research. Although our large-scale study offers theoretical and empirical insights into textual aspects related to the virality of negative eWOM, using what Humphreys and Wang (2018) call a top-down approach, we also acknowledge that alternative bottom-up approaches might usefully derive specific service or product failures and their severity to test the suitability of the response approaches we outline. Similarly, in other communication contexts where heuristic processing is less prevalent, the implications of systematic content in firm responses should be assessed (e.g., size of the compensation, legitimacy of the argument).

Moreover, the scope of our study is limited to all posts visible in the communities. On Facebook, firms have the option to remove comments. Deletion criteria may include especially offensive (e.g., racist, derogatory) messages. This option may bias our results for high-arousal emotions, because we do not observe deleted posts. Managerial reports strongly discourage deleting negative customer posts on social media (e.g., Duncan 2016), but extreme posts missing from our data set could further increase the virality effect, or the effect may taper off or even reverse with an extreme use of high-arousal emotions. The consequences of deleting customer posts remain to be investigated. In addition, we could not assess perceptions of source credibility or how source credibility may interact with the use of empathy or other firm responses to make them more or less effective. Therefore, further research might seek novel ways to determine the importance of source credibility for message acceptance. Similarly, lacking an ability to account for the attitudinal importance that customers attribute to their ties in brand communities, continued research could extend our study by assessing the implications of weak and strong tie perceptions for sharing negative eWOM in brand communities. Potential measures that could be adapted for this purpose could be obtained from Umashankar, Ward, and Dahl (2017). Furthermore, we were not able to obtain data on the number of friends due to privacy restrictions in Facebook's API terms and conditions. However, in line with Peng et al. (2018), we believe that strength of structural ties (i.e., the number of encounters with other users in the brand community) influences virality regardless of the number of friends.

Interestingly, we found that customers expressing intense negative emotions, irrespective of whether they are high (e.g., anger) or low (e.g., sadness) on arousal, are looking for explanations rather than empathy. Future research should consider how the relative lack of emotionality might relate to the suitability of firm's response options. Finally, it was surprising that immediate compensation leads to more virality. Potentially, if firms offering an initial compensation that is perceived as not high enough could lead to an offense. If firms would then offer a higher compensation at a later stage this might lead to less virality. Thus, future research should investigate whether offering greater levels of compensation at later stages lead to the observed effects.

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[4] For the calculation, we compared the expected virality of a post where firms first respond with compensation, later with apology and channel change, and no variation in empathy and explanation to the expected virality of a post where firms first respond with apology and channel change, later with compensation, and with variation in empathy and explanation (all other predictors constant).

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