ARTICLE IN PRESS

IJRM-01261; No of Pages 18

International Journal of Research in Marketing xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

IJRM

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Full Length Article

Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands

Nele Hansen *, Ann-Kristin Kupfer, Thorsten Hennig-Thurau

University of Muenster, Department of Marketing & Media Research, Am Stadtgraben 13-15, 48143 Muenster, Germany

ARTICLE INFO

Article history:
First received on June 19, 2017 and was under review for 8 months
Available online xxxx

Senior Editor: Andrew Stephen

Keywords:
Firestorm
Social media
Brand crisis
Brand perception
Memory

ABSTRACT

Social media firestorms imply the sudden occurrence of many, predominantly negative social media expressions against a brand. Do such firestorms leave a mark on consumers and their brand judgments—in the short term but also over time—to a degree that deserves managerial attention? What kind of firestorms have the strongest destructive potential? This manuscript treats firestorms as a digital form of brand crisis and proposes a conceptual framework to identify which firestorms harm short- and long-term brand perceptions and become part of consumers' long-term memory. A unique data set combines secondary data about 78 real-life firestorms with daily brand perceptions obtained from the YouGov panel and survey data from 997 consumers. The results indicate that of all affected brands, 58% suffer from a decrease in short-term brand perceptions, and 40% suffer long-term negative effects, suggesting that social media firestorms can indeed harm businesses but also show that strong variations exist. Contingency analyses of the conceptual framework with regressions and generalized estimating equations indicate that social media firestorms are most impactful in terms of negative brand association changes and/or memory effects when they are initiated by a vivid trigger (e.g., video in the first firestorm tweet), linked to a product/service or social failure, characterized by a large volume of social media messages, and when they last longer.
© 2018 Elsevier B.V. All rights reserved.

1. Introduction

> Brands may spend years building their reputations, but they can go down in seconds, especially with the pace of digital media.
> [—*Marketing News Weekly* (2017)]

When New York's taxi drivers struck for an hour at Kennedy Airport, in protest of Donald Trump's so-called “Muslim travel ban,” the ride-hailing company Uber announced on Twitter, “Surge pricing has been turned off at #JFK Airport” (Cresci, 2017). Within seconds, consumers voiced their criticisms of Uber's strikebreaking behavior and apparent support for the ban, using messages such as “Congrats to @Uber_NYC on breaking a strike to profit off of refugees being consigned to Hell. Eat shit and die” (O'Sullivan, 2017). Soon the hashtag #DeleteUber spread, transforming into a vast protest marked by thousands of angry, emotional tweets (Collins, 2017; Cresci, 2017); it was the top trending topic on Twitter that night and in the days that followed. Major news media reports about the firestorm further fanned the flames throughout social media.

* Corresponding author.
E-mail addresses: nele.hansen@wiwi.uni-muenster.de, (N. Hansen), ann-kristin.kupfer@wiwi.uni-muenster.de, (A.-K. Kupfer), thorsten@hennig-thurau.de. (T. Hennig-Thurau).

https://doi.org/10.1016/j.ijresmar.2018.08.001
0167-8116/© 2018 Elsevier B.V. All rights reserved.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

ARTICLE IN PRESS

Uber is by far not the only company to have suffered such a "social media firestorm." United Airlines experienced a global firestorm following a shocking cellphone video of a security officer violently removing a passenger from an overbooked flight (Victor & Stevens, 2017), and Abercrombie & Fitch found itself subjected to waves of angry, emotional comments on Twitter after CEO Mike Jeffries said in an interview that he only wanted "cool" and "popular" kids to wear the chain's clothes (*The New York Times*, 2014).

Such social media firestorms have become standard elements of the modern marketing environment, constituting a digital form of brand crisis. Whereas in the pre-digital age, consumers were only able to express their dissatisfaction with a brand individually, either by contacting the firm or talking to a very limited number of others, without much opportunity to bundle their protests (Rauschnabel, Kammerlander, & Ivens, 2016), the rise of social media has shifted power from organizations to consumers (Hennig-Thurau et al., 2010; Labrecque, vor dem Esche, Mathwick, Novak, & Hofacker, 2013). Social media enable individual consumers to inform large numbers of other consumers in a very short time frame by co-creating and spreading brand-related content through their digital networks (Labrecque et al., 2013). This environment of social media networks sets new, digital forms of word of mouth apart from their analog predecessors, by enabling, for instance, real-time access to large numbers of friends and followers (Hennig-Thurau, Wiertz, & Feldhaus, 2015).

As a digital kind of brand crisis, social media firestorms exhibit their own characteristics, reflecting the influence of the social media environment. Whereas part of what we know about "traditional" brand crises likely applies to firestorms, other factors are likely affected by the specificities of this digital surrounding, which require new understanding. For example, social media are characterized by extreme dynamics, meaning social media firestorms can experience exponential growth in a very short time frame. As a result, social media firestorms can constitute an important threat to firms' brand assets, in line with many corporate leaders' sense that "reputation risk" is a grave threat (Deloitte, 2015). But this judgment is not undisputed; some commentators suggest these threats have been exaggerated, with little actual economic meaning for firms (e.g., McKinsey, 2012), especially in the long run (i.e., "memory fades," Knowledge@Wharton, 2015).

We aim to contribute to this debate by investigating the specific negative effects of social media firestorms on consumers' perceptions of a brand. This approach anticipates that the power of social media firestorms will not be "strong" or "weak" in general but rather will vary, according to certain contingencies. We derive contingencies from general research on brand crises (e.g., the reason for the firestorm), but also from the digital characteristics of social media firestorms (e.g., amount of social media word of mouth). With the empirical insights gained from this study, we seek to help managers identify threatening social media firestorms early, so that they can allocate sufficient and appropriate resources to prevent their escalation. With firestorms having become a regular occurrence for large firms, marked by enormous and radical dynamics, we consider this insight essential for establishing effective corporate responses. In addition, our findings suggest ways to determine appropriate metrics to track the development of firestorms.

To achieve these contributions, we build on brand crisis and social media research to craft a theoretical framework of firestorm characteristics that prompt negative changes in brand perceptions in the short and long run, as well as those that cause the firestorm events to become part of consumers' long-term memory. We link firestorm factors to the elaboration likelihood model of consumer behavior (ELM; Petty & Cacioppo, 1986), which we apply to the social media environment. Leveraging the ELM, we derive factors that might influence how consumers process and remember firestorm information (i.e., based on their motivation, ability, and opportunity). The resulting framework distinguishes trigger characteristics of social media firestorms that are initially detectable (e.g., vividness of the trigger) from evolving firestorm characteristics (e.g., its length). This distinction offers brand managers both early warning indicators and important metrics to track throughout the duration of a social media firestorm.

We then test our conceptual model with two studies. First, we check the brand-related hypotheses using YouGov data about German brands affected by firestorms between January 2012 and December 2014, applying an event study approach. We analyze the effect of our ELM-based trigger and firestorm characteristics on negative abnormal changes in brand perceptions in the short- and long-term. Second, we test the consumer memory-related hypotheses by combining our data set with a survey that we used to measure consumers' memory of the respective firestorms, two years after their occurrence. With this step, we aim to assess whether changes in brand perceptions stem from a particular firestorm. Here, we use generalized estimating equations (GEE) to account for the hierarchical structure of the data.

Results show that both trigger and firestorm characteristics drive short- and long-term effects of social media firestorms on consumers and brands. Strong social media firestorms, with a high volume of social media messages (i.e., tweets), relate to negative changes of consumers' short-term brand perceptions, as well as two years later. Firestorms caused by a defective product or service have stronger consequences than those triggered by inappropriate communication strategies by a company. The length and vividness of a firestorm additionally influence consumer memory, as do firestorms caused by a social failure. We discuss the managerial implications of these findings to conclude this article.

2. Social media firestorms: brand crises in the digital age

2.1. Social media firestorms as a digital kind of brand crisis

We conceptualize social media firestorms as a new, digital form of the broader phenomenon of brand crises. Managers have long confronted brand crises; Shell's Brand Spar controversy (the company planned to dispose of an oil drilling platform in the North Sea in 1995; Nash, 1995) and the Contergan scandal (a medicine of the same name led to physical deformities of thousands of newborns in the early 1960s; Shuster, 1973) happened decades before the Internet existed. In those days, crises spread mostly by analog mass media, such as newspapers, television, and radio, and to a lesser degree by protest marches and other forms of public demonstrations.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

Marketing research has studied such crises (e.g., Hoffman, Kelley, & Rotalsky, 1995; Liu & Shankar, 2015) and produced insights that we consider helpful for understanding the digital-driven concept of social media firestorms. Among the key insights are the ideas that certain reasons create a stronger potential for a crisis to unfold than others. Traditional brand crisis research tends to focus particularly on crises that result when a product harms consumers (like in the Contergan example) (e.g., Chen, Ganesan, & Liu, 2009; Dawar & Pillutla, 2000), when there is a service failure (e.g., Hoffman et al., 1995; McCollough, Berry, & Yadav, 2000), when the firm is complicit in what is considered a social failure (as in the case of the Brand Spar platform) (e.g., Dutta & Pullig, 2011; Folkes & Kamins, 1999) or when a company fails to communicate properly (e.g., Pullig, Netemeyer, & Biswas, 2006). We anticipate that insights about the cause of a brand crisis also are relevant for social media firestorms, because they are tied to deep, underlying human patterns and less dependent on the context and modes in which the crisis unfolds.

Beyond the reasons for a brand crisis, research also has investigated the role of traditional media coverage in determining the economic impact of a crisis, with varying findings. For example, Liu and Shankar (2015) find consumers to respond more negatively to product recalls with greater media attention whereas Cleeren, van Heerde, and Dekimpe (2013) find the extent of negative publicity to have no significant main effect on brand share changes. Traditional media are closely linked to social media information in modern market environments (Hennig-Thurau, Hofacker, & Bloching, 2013; Hewett, Rand, Rust, & van Heerde, 2016), so we predict that coverage in traditional media remains a noteworthy factor, even if its role in the development of a brand crisis might be different in a digital realm.

Other main drivers identified by traditional brand crisis research are the severity of a crisis (e.g., Kalaignanam, Kushwaha, & Eilert, 2013; Liu, Liu, & Luo, 2016) and the reaction strategies by the affected company (e.g., Hoffman et al., 1995; Liu, Shankar, & Yun, 2017; Smith, Bolton, & Wagner, 1999). Our approach is one that compares different kinds of crises happening in different industries, which makes measuring a trigger's “severity” difficult; we thus focus on the type of reason and its respective varying personal relevance for consumers, as measured by the different firestorm reasons. Whereas reaction strategies' effectiveness is certainly important in the firestorm context, this research's focus is on identifying the potentially most harmful social media firestorms, which offers valuable insights for managers also.

2.2. Social media word of mouth as the underlying phenomenon

The rise of the Internet and social media in particular has created a new environment in which consumers can discuss brands' actions among each other, with such debate often taking place in conjunction with coverage by traditional mass media (Hewett et al., 2016). Scholars generally agree that digital, social media have shifted the power from “official” media sources to subjective consumer articulations, such that active and networked consumers have a more prominent role in brand crises (Labrecque et al., 2013).

Among the findings from social media research that are of key relevance for understanding social media firestorms are changes in the nature of word of mouth. Whereas traditional brand crises were mainly driven by journalists' contributions, firestorms are essentially aggregations of consumers' digital word of mouth, which serves as the individual-level complement of firestorms. Research notes systematic differences between traditional, face-to-face word of mouth and its digital forms, such as articulations on review/retail sites (consumer reviews or electronic word of mouth) and those on social media platforms (social media or microblogging word of mouth) (Hennig-Thurau et al., 2015). The main differences include the reach of the message and the speed with which messages can diffuse. Digital word of mouth can reach an unlimited number of other consumers and media, whereas in traditional offline settings, the reach is limited to a small group of consumers. Digital messages also can be shared and picked up immediately (particularly on social media platforms), whereas they require way more time for the exchange to occur in analog environments.

A related research stream that is relevant for understanding the particularities of firestorms as digital brand crises are studies that highlight the interplay of various information sources that exist in the digital era. Hewett et al. (2016) show that brand-related consumer articulations can resonate with multiple other sources, such as traditional media, in what they call the “echoverse,” where digital messages “reverberate and echo one another” (p.18). The reach and speed of message delivery in the digital space thus increase. Related dynamics of social media messages have been noted in other contexts too, including the interplay of traditional company communication and social media messages (Stephen & Galak, 2012) and consumers' rebroadcasting behaviors on social media (Zhang, Moe, & Schweidel, 2017). This combination of the new characteristics of digital word of mouth and its amplification in the “echoverse” lays the groundwork for social media firestorms to occur and affect both consumers and brands.

2.3. Existing research on social media firestorms and related phenomena

The concept of firestorms was introduced to the academic world by Pfeffer, Zorbach, and Carley (2014), who define firestorms as “the sudden discharge of large quantities of messages containing negative WOM [word of mouth] and complaint behavior against a person, company, or group in social media networks” (p. 118). Existing research on this phenomenon is nascent, but some interesting findings have emerged.

For example, regarding the individual-level motivations of consumers, Kähr, Nyffenegger, Krohmer, and Hoyer (2016) discuss the related concept of “consumer brand sabotage,” which they define as a deliberate form of hostile, aggressive behavior to harm a brand. A similar construct are “collaborative brand attacks,” as discussed by Rauschnabel et al. (2016). Some articulations that are part of a social media firestorm match those descriptions. However, the social media firestorms that we investigate in this research are not restricted to such deliberate attacks, in which the instigators are determined to cause damage to the brand, but also include less intentional social media expressions.

ARTICLE IN PRESS

Moreover, the focus of this research is the consequences of such digital brand crises and their contingency factors, rather than their motivational drivers. Borah and Tellis (2016) analyze the effects of negative consumer online chatter during automotive product recall crises, finding that negative effects spill over to other car models in terms of poorer short-term sales and stock market performance. They do not address escalation mechanisms and study one specific facet (product recalls); their focus is on the category spillover effects of such "chatter." Hsu and Lawrence (2016) investigate social media chatter surrounding product recall announcements; they find negative effects of the volume and valence of online word of mouth on the abnormal returns directly after the event. Like Borah and Tellis (2016), they restrict their analysis to product recalls; they also do not consider individual consumer perceptions of a firestorm or any long-term impact, nor whether, and how long, they might hurt a brand's image.

Finally, some scholars have shed initial light on reaction strategies. Hsu and Lawrence (2016) do not find any mitigating effect of company involvement, whereas Hewett et al. (2016) point to the different effects that result from the ways banks address social media chatter in the particular context of financial crises. Using agent-based modeling, Hauser, Hautz, Hutter, and Füller (2017) find that the effectiveness of collaborating and accommodating reaction strategies, as well as competitive and assertive conflict management styles, depend on various contingencies, which they recommend to be taken into account.

We seek to extend existing research in four pertinent ways. First, we analyze the long-term impacts of social media firestorms and contrast them with potential short-term effects. Second, we investigate brand perceptions and memory effects, rather than sales and stock market performance, to generate new insights on how consumers process social media firestorm information. Third, we address social media firestorms comprehensively, rather than focusing on a specific type of brand crisis such as product recalls. Fourth, drawing on extant crises and social media research and using the ELM as a structuring device, we distinguish different trigger and firestorm characteristics, using a comprehensive sample of real-life social media firestorms, which allows us to generate a more contextualized understanding of firestorm effects and to analyze processual factors of firestorms and multiple information sources (e.g., traditional media), in addition to volume metrics.

Our research's relevance stems from the observation that, with few exceptions, most brand crises will enter the digital space and take the form of social media firestorms. Social media's characteristics imply that this new, digital surrounding for brand crises to occur in requires the need for novel research in this domain as it amplifies for instance, the reach and pace of consumers' protests against a brand. This paper hence helps to develop a sound understanding of social media firestorms as brand crises in a digital environment.

3. Conceptual model and hypotheses

We define social media firestorms as brand crises in the digital age that consist of multiple, publicly observable consumer articulations about a brand on social media that express strong negative emotions and spread in a highly dynamic way across and within media. In our conceptual model (Fig. 1), we categorize different social media firestorm factors into (a) trigger characteristics, which can be observed right at the beginning of the crisis, and (b) firestorm characteristics, which evolve during the crisis. The difference in their occurrence over time leads us to predict that the initial trigger characteristics (different reasons, vividness) also might influence the lagged firestorm characteristics (strength, length, and breadth). We link trigger and firestorm characteristics to the short- and long-term effects on brands, as measured by changes in brand perceptions, and on consumers, as measured by consumers' memory structures. We draw on existing crises and social media research to identify the characteristics and explain their influence on memory and brand perceptions with consumer behavior's elaboration likelihood model (Petty & Cacioppo, 1986).

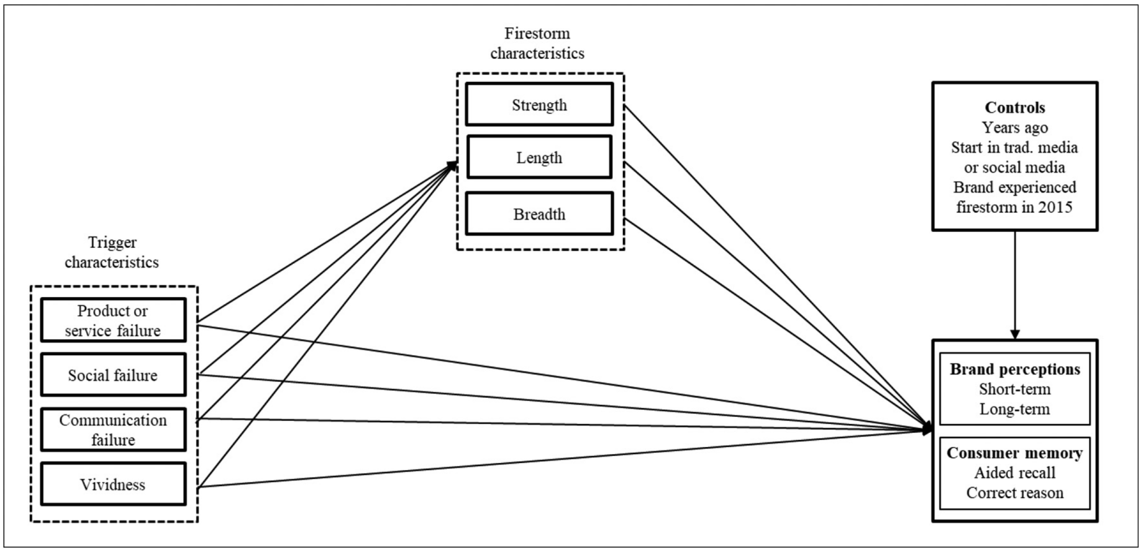

Fig. 1. Conceptual model.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

ARTICLE IN PRESS

3.1. The elaboration likelihood model (ELM) as the theoretical foundation

The ELM, along with its extensions, postulates that the likelihood of elaboration depends on consumers' motivation, ability, and opportunity to process information. Elaboration is the extent to which a person thinks carefully about an argument (Petty & Cacioppo, 1986). Whereas Petty and Cacioppo initially combined ability and opportunity, subsequent scholars cite the value of distinguishing between them (e.g., Batra & Ray, 1986; MacInnis & Jaworski, 1989; MacInnis, Moorman, & Jaworski, 1991). According to the ELM, if ability, opportunity, and motivation are high, consumers engage in central route processing of the information ("high elaboration"). If they are low, people adopt peripheral route processing ("low elaboration") instead.

On a short-term basis, information moving through both the central and peripheral routes can invoke attitude changes and thus changes in brand perceptions. However, changes caused by central route processing (i.e., deeply processed information) tend to be more enduring and stable (Cialdini, Petty, & Cacioppo, 1981; Petty, Briñol, & Priester, 2009), such that they can lead to stronger memories of key brand information, including brand names and product claims (e.g., Saegert & Young, 1982). Accordingly, we use the ELM to propose that certain firestorm characteristics will have short-term effects (i.e., negative changes in brand perception that occur directly after the firestorm) and also long-term effects (i.e., negative long-term changes in brand perceptions and consumers' enduring memory of firestorms).

3.2. Failure types as motivation-based firestorm characteristics

According to the ELM, consumers who are more motivated to engage with the stimulus exhibit a higher likelihood of message elaboration (Petty & Cacioppo, 1986). Such motivation can be triggered by the high personal relevance of the stimulus to the consumer, or the extent to which an event has intrinsic importance or personal meaning. Such relevance arises when people expect the issue to have significant consequences for their own lives (Apsler & Sears, 1968). If personal relevance increases, consumers pay more attention to the stimulus (Petty, Cacioppo, & Schumann, 1983) and think more critically when forming an opinion about it (Petty & Cacioppo, 1986). Thus, with greater personal implications, people are more motivated to elaborate cognitively on a message (Kendzierski, 1980; Petty & Cacioppo, 1986).

The various reasons that spark a social media firestorm differ in their personal relevance for consumers and should affect consumers' motivation to process the firestorm information differently. Research on traditional brand crises has identified several distinct underlying reasons for a brand crisis on which we build here, expecting that they should also be valid in the context of social media firestorms. Following previous research on traditional brand crises, we distinguish performance-related from value-related firestorms (e.g., Dawar & Pillutla, 2000; Pullig et al., 2006). Performance-related crises can be due to product failures (e.g., defective brakes in Toyota vehicles, Warner, 2010) or service failures (e.g., passenger dragged from overbooked flight, Victor & Stevens, 2017). A value-related crisis instead does not involve the product directly but pertains to social or ethical issues surrounding the brand (Dutta & Pullig, 2011). Among value-related crises, we further distinguish a social failure, such as poor working conditions at Amazon (Eddy, 2013), from a communication failure caused by offensive messages from a company (e.g., Anheuser-Busch promoted its Bud Light beer with the slogan "The perfect beer for removing 'no' from your vocabulary for the night," Strom, 2015).

These different triggers of firestorms—product or service failures, social failures, and communication failures—likely prompt different levels of personal relevance and thus should evoke different motivations to process the information. In the case of product or service failures, the performance-related crises raise doubts about the brand's ability to provide basic functional benefits (Dawar & Pillutla, 2000; Pullig et al., 2006), so consumers perceive them as serious issues (Dawar & Lei, 2009). Consumers may be more directly and personally affected by the consequences of a product failure, such as defective brakes on a car, than by sexist advertising campaigns, for example. With a social failure, companies violate existing values or social norms, which affects their brands' ability to deliver symbolic and psychological benefits (Pullig et al., 2006). Whereas in most cases, social failures do not affect consumers personally, they still suggest the potential for severe consequences for other people, such as child laborers. Finally, a communication failure should have the least effect on personal lives; people might perceive these firestorms as the least severe and least personally relevant. Morally questionable communication by a company (e.g., Bud Light slogan) might offend people but affect their personal lives less than either a product or service failure or a social failure. Therefore, we expect communication failures to have the least impact, due to the reduced motivation they create among people to process the information. This pattern should hold for both short- and long-term effects on brands, as indicated by more negative brand perceptions, and consumer memories. Thus:

H1. Social media firestorms caused by a product or service failure are processed more deeply by consumers than firestorms caused by communication failures, leading to stronger effects on (a) changes in brand perceptions and (b) consumer memory.

H2. Social media firestorms caused by a social failure are processed more deeply by consumers than firestorms caused by communication failures, leading to stronger effects on (a) changes in brand perceptions and (b) consumer memory.

3.3. Trigger vividness as an ability-based firestorm characteristic

The depth with which consumers process information also depends on ability, or consumers' skills or proficiencies for interpreting information (MacInnis et al., 1991). A lack of ability implies that the knowledge structures necessary to perform complex operations either do not exist or cannot be accessed (Alba & Hutchinson, 1987). Prior advertising research notes though that processing ability and recall can be enhanced, such as by including pictures in addition to textual content (Childers & Houston,

ARTICLE IN PRESS

1984; Lutz & Lutz, 1977). Such so-called vividness, defined as the extent to which a brand's message stimulates different senses (Steuer, 1992), can be achieved through colors, pictures, or dynamic animation (e.g., De Vries, Gensler, & Leeflang, 2012; Goldfarb & Tucker, 2011; Goodrich, 2011). Social media offer a largely visual environment, and consumers often include pictures or videos in their posts (Rauschnabel et al., 2016). This usage of visual cues in social media messages implies that vividness likely matters in the context of social media firestorms, as digital brand crises.

The degree of vividness depends on the number of senses it stimulates; a video posed on social media is more vivid than a posted picture, which in turn is more vivid than a plain text-based tweet (Coyle & Thorson, 2001). According to Smith and Shaffer (2000), vivid information creates mental images that are easier to retrieve and that interact with message content, to facilitate processing and memory of the image and message argument. For example, a posted picture or video depicting an accident caused by defective brakes should facilitate information processing and be remembered better than just a textual description. Furthermore, previous research suggests that textual information suffers more rapid decay in memory than visual information (Childers & Houston, 1984).

We therefore argue that a vivid initial tweet increases message comprehensibility and enhances consumers' ability to process the information, which should result in negative short-term but also long-term changes in brand perceptions and effects on consumers' memory. Thus:

H3. The greater the vividness of a trigger post, the deeper consumers' information processing, leading to stronger effects on (a) changes in brand perceptions and (b) consumer memory.

3.4. Firestorm strength as an opportunity-based firestorm characteristic

Repeated presentations of a message provide consumers with more opportunity to consider its content (e.g., MacInnis et al., 1991; Petty & Cacioppo, 1986). For example, repeated advertisements often are necessary to provide sufficient brand-processing opportunities (Krugman, 1972), increase memory of the brand name (Unnava & Burnkrant, 1991), and ensure message recall and purchase intentions (Batra & Ray, 1986). One exposure would be rather insufficient to support processing of a complex message or if additional information is needed, so repetition can be crucial to increase information processing (Petty & Cacioppo, 1986).

In social media environments, it is easy to repeat information, due to the high number of sent messages. For instance, consumers use this new power to voice their opinions publicly online, as indicated by 6000 tweets sent each second (Brandwatch, 2017). These messages are characterized by high reach and the speed with which they diffuse, meaning that the social media space provides consumers with ample opportunity not only to send but also to encounter information.

In our research context, more tweets pertaining to the same firestorm should increase the probability that consumers become aware of it. Being exposed to the same firestorm information, provided by repeated postings, increases consumers' opportunity to process the firestorm information. Furthermore, with more tweets, social media users add new information or insights to the topic, such as describing the poor working conditions in more detail, which also enhances people's opportunity to process the information. This should result in more negative brand perceptions and a higher recall of the firestorm and its reason. Thus:

H4. The stronger the social media firestorm, the more deeply consumers process the information, leading to stronger effects on (a) changes in brand perceptions and (b) consumer memory.

3.5. Firestorm length as an opportunity-based firestorm characteristic

It is not only the strength of the firestorm that affects consumers' processing opportunities; its duration also appears pertinent. The length of commercials, for example, has a positive impact on distinctive ad memory (Alba & Chattopadhyay, 1986; Wyer Jr & Srull, 1986). Longer commercials enhance learning effects, retrieval likelihood, and brand name recall, because they increase viewers' opportunities to attend to and process the message (Batra & Ray, 1986; Moore, Hausknecht, & Thamodaran, 1986). Contrary to traditional media channels, the social media environment is less restricted by screen time or newspaper length. Due to its unlimited capacity, messages can be repeated and discussed over days and weeks on social media; they do not need to compete for a spot in a predefined news format. The variability of the evolving length of a firestorm might hence function as an informative social media firestorm characteristic.

For a firestorm event, we expect the length of social media attention to offer consumers more opportunity to process the related information. The longer the firestorm lasts on social media, the more consumers confront the related information, which increases their opportunity to attend to and elaborate on this information. Some firestorms occur and vanish within a few days; others last for weeks, granting consumers multiple opportunities to process and remember the firestorm information, leading to more negative brand perceptions and stronger memory effects. Formally:

H5. The longer the firestorm, the more deeply consumers process the firestorm information, leading to stronger effects on (a) changes in brand perceptions and (b) consumer memory.

3.6. Breadth of news coverage as an opportunity-based firestorm characteristic

Finally, the breadth of news coverage, which we define as the number of print and online media outlets that report on the focal social media firestorm, should lead to additional repetition effects and give consumers more opportunity to process complex

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

ARTICLE IN PRESS

messages. Research on traditional brand crises has addressed the role of traditional media coverage for a crisis' impact, with varying results (Cleeren et al., 2013; Liu & Shankar, 2015). Traditional and social media echo each other in the modern social media environment (Hewett et al., 2016), so we expect traditional media to remain a factor of academic interest, yet its role might be altered by the novel use of social media as an alternative news outlet.

Posts in social media are rather short on average, which might prevent consumers from understanding the broader context surrounding a firestorm event; especially tweets contain a strictly limited number of characters. To gather further information, additional consumer action is necessary, such as clicking a link, which is relatively rare. Traditional and online news sources that cover the social media firestorm event instead allow consumers to elaborate on the topic easily and more deeply (Petty et al., 2009), because they offer background information, explanatory commentaries, or interview data. The more media are involved, the more information consumers attain, which should increase their opportunity to process and recall the firestorm information. Moreover, broader media coverage of the social media firestorm gives consumers who rarely use social media an alternative means to become informed about the event. We hence expect the additional coverage on traditional media to negatively affect brand perceptions and increase memory effects. Therefore:

H6. The greater the breadth of news coverage of a firestorm, the more deeply consumers process the information, leading to stronger effects on (a) changes in brand perceptions and (b) consumer memory.

4. Study design

4.1. Social media firestorm sample

To test our hypotheses, we combine data from multiple sources pertaining to trigger and firestorm characteristics, brand perceptions, and consumer memory for all events from January 2012–December 2014 that met our criteria to be defined as social media firestorms for major brands. We first searched all German tweets during the specified time frame for the term "shitstorm" in conjunction with a major brand. This search term is a well-established, widely used expression for social media firestorms in Germany (e.g., Chancellor Angela Merkel used it in a public discussion with former U.K. Prime Minister David Cameron [Connolly, 2013]). Therefore, we manually checked whether the word combination of "shitstorm" and the name of any of 700 major brands appeared in the same tweet; the list of brands contains all those whose perception is monitored by the global market research company YouGov.

We identified an event as a firestorm if at least one tweet combined the brand name with the term "shitstorm," and then at least ten tweets covered the same negative event on the same day. The first criterion (brand name + "shitstorm") reveals all possible social media firestorm events; the second (cut-off of ten tweets) helps ensure at least some minimum relevance of the firestorms in the final sample. By implementing this cut-off, we adhere to our definition of social media firestorms, requiring the occurrence of multiple social media messages, while also excluding cases that randomly use the word "shitstorm" with a brand name without referring to or resulting in a brand crisis. This two-step approach identified 78 valid firestorm cases, including well-known brands such as Nintendo, Sony, Google, Yahoo, Amazon, McDonald's, Burger King, Primark, Mango, Adidas, ING-DiBa, Ikea, and HTC. Appendix A provides the full list of events and affected brands.

4.2. Measures

Our measures come from different data sources. Specifically, we obtained brand perception measures from the market research firm YouGov, whereas we gathered measures of consumers' memory with a survey. Finally, we took data for the independent measures from Twitter and Lexis-Nexis. For the independent variables, we combine content and count analyses. In the following, we will provide details for each measure.

4.2.1. Brand perceptions

For our brand-related hypotheses (part (a) of the respective hypotheses), we use abnormal changes in short- and long-term brand perceptions as dependent variables, calculated with brand perceptions data from YouGov. The YouGov BrandIndex Score is calculated on the basis of 1950 daily interviews in Germany (YouGov, 2016); it aggregates six brand perception dimensions (brand quality, brand value, brand satisfaction, recommendation, identification, and overall impression; see Appendix B). Because BrandIndex Score data were not available for some of the study period for 18 of the brands, the sample for testing the brand-related hypotheses covers the 60 remaining firestorms, for each of which we obtained daily brand perception measures during 2011–2016. This long time frame ensures that we capture not only short-term brand effects but also can measure long-term brand effects, defined as reflecting an interval of at least two years after the latest firestorm event in our sample occurred (i.e., December 2014).

4.2.2. Consumers' memory

For testing the consumer memory-related hypotheses (part (b) of the respective hypotheses), we used an online survey to measure consumers' memory of the respective firestorms. Specifically, we investigate which firestorms consumers recall two years after their occurrence, as well as which ones they remembered correctly, to check if changes in brand perception can be attributed to a firestorm. The brand logos of the 78 affected brands were randomly assigned across a sample of 997 respondents.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

The survey took place over a two-week period (December 21, 2015–January 6, 2016); respondents averaged 25.3 years of age, and 66.7% were women.

To measure consumers' memory effects, we applied two dependent variables: aided recall and correct reason. To measure consumers' memory as aided recall of the firestorm, we provided respondents with a respective brand logo and asked them to state if they remembered any firestorm connected with this brand, on a five-point Likert scale. If they answered yes, they were asked to indicate the reason(s) for the firestorm next (out of eight possibilities, along with an open text field). For this evaluation, we created a binary variable, where 1 shows that respondents indicated the correct firestorm reason and 0 if not.

4.2.3. Trigger characteristics

To identify the reason for each firestorm, we used content analyses of tweets and news articles collected from the Lexis-Nexis archive. Two independent coders categorized these firestorms as product or service failures, social failures, or communication failures, with three binary variables. Coders agreed in 90% of the cases. Communication failure provided the base category. Using the differentiation proposed by De Vries et al. (2012), we also identify three vividness levels (low, medium, high) of the social media firestorm trigger. Low vividness indicates that the first firestorm-related tweet only consists of text; triggers with medium vividness include a picture; and triggers with a high vividness include a video.

4.2.4. Firestorm characteristics

Using Twitter data about the respective firestorm brands (January 1, 2012–December 31, 2014), we identified the date of the first and last tweet containing the word "shitstorm" and the respective brand name. By gathering the most popular tweets (i.e., so-called "Top Tweets") for the first firestorm day, we identified relevant keywords that referred to the firestorm topic. Those keywords covered firestorm-related hashtags and various terms describing the critical incident that started the firestorm; together they formed firestorm-specific dictionaries. All tweets that contained the respective brand name then were collected throughout the identified time frame, as well as one week before and after, to ensure comprehensiveness. This procedure helped ensure that relevant tweets were included in the sample, because not all users mention the term "shitstorm" in their tweets to refer to a firestorm; it further was instrumental to ensure that tweets were correctly assigned to a specific firestorm, rather than having multiple independent firestorms in a short time frame being misclassified as one large firestorm.

Using those firestorm-specific dictionaries, we filtered the collected tweets to distinguish relevant firestorm tweets from unrelated ones, such as tweets that appeared several times or that contained discussions of new product introductions that clearly were not related to the firestorm topic. Then we checked whether the filtering was successful, using a human coder who looked for misclassifications in random selections of tweets and confirmed their fit with the respective topic. The suitability of keywords was checked and modified, if necessary. Tweets from commercial robots with no relation to the firestorm topic were excluded. We thus obtained a final set of firestorm-related tweets for each social media firestorm, which we used to measure the strength and length of the firestorm.

For the strength variable, we accumulated all tweets that mentioned the brand name together with a firestorm-related keyword during the specified time frame. For the length variable, we relied on two criteria: the first and last day a firestorm-related tweet appeared on Twitter, as well as whether at least ten firestorm-related tweets had appeared on the first day. We set the beginning of the firestorm to "day 1" if at least 10 tweets covered the firestorm topic. To determine the end of a firestorm, we tracked if no new firestorm-related tweets appeared for more than three days. It is deliberately set to a short, conservative cut-off criterion to adhere to the dynamic nature of the social media environment. This procedure ensures that the length measure is not artificially inflated by long periods with no firestorm activity. If these two criteria were fulfilled, we counted the number of days. Then for breadth, we searched Lexis-Nexis and Google News databases between 2012 and 2014. We collected all articles in newspapers (print and online) that contained the term "shitstorm" in combination with the brand name. The sum of all online and print articles dealing with the firestorm provides our breadth variable.

We further account for possible time-based interdependencies between the measures due to the lagged occurrence of the two different categories of independent variables. As already discussed, the firestorm characteristics (strength, length, and breadth) might depend on the initial trigger characteristics (reason and vividness), implying a hierarchical structure. To address this interdependency, we follow Hausman (1978) and use the residuals of an auxiliary regression for the firestorm characteristics, instead of their raw values. Specifically, we performed three auxiliary regressions in which strength, length, and breadth serve as the dependent variable, respectively, and the different reasons and vividness serve as the independent variable. Formally,

$$LN\left(Y_{kj}\right) = \alpha + \beta_1 ProdSerFail_j + \beta_2 SocFail_j + \beta_3 LN\left(Vivid_j\right) + u_j, \tag{1}$$

where Y_k depicts the strength, length, or breadth for firestorm *j* respectively; ProdSerFail is a dummy variable that indicates whether the firestorm is caused by a product or service failure; and SocFail is a dummy variable that indicates the firestorm is caused by a social failure (baseline category is communication failure). Consistent with our main model, we apply a log-log specification; we add constants where necessary to avoid taking a log of 0. The Vividness variable is the logarithm of the values ranging from 1 to 3, u depicts the error term. Appendix C displays the results of the different auxiliary regressions.

4.2.5. Control variables

We further include three control variables: a binary variable indicating whether a firestorm started in traditional or social media (Start TM_SM), the number of years since the firestorm event occurred (Years_Ago), and a binary variable accounting for whether the brand experienced an additional firestorm in the period between our firestorm sample and the online survey (FST_2015). The first control was used in both the short-term and long-term analyses, whereas the latter two were used only in the long-term analyses. Table 1 summarizes the final measures and their respective data sources.

4.3. Methods

To test the brand- and consumer memory-related hypotheses, we used two sets of analyses. We first tested the brand-related hypotheses with an event study approach (Hsu & Lawrence, 2016) in combination with regression analyses, which enabled us to determine the impact of a singular event (i.e., social media firestorm) on brand performance (i.e., abnormal change in brand perceptions). Identifying abnormal changes in brand perceptions requires an initial prediction, for each firestorm brand, about how brand perceptions might have developed in the absence of the firestorm event (Hennig-Thurau, Houston, & Heitjans, 2009). Using daily YouGov data for each of the brands, 365 days prior to its firestorm event, we fit a regression function that predicts the development of brand perceptions without the firestorm event. For each brand, we tested alternative regression functions, with brand perceptions serving as the dependent variable and the respective days as the independent variable, then selected the one that fit the data best.

Using this best-fitting regression function, we predict daily brand perception values for a seven-day window following the firestorm event for each affected brand. We use the mean of the predicted values in the subsequent calculation step. To determine the short-term effect of the abnormal change in brand perceptions, we calculated the difference between the mean of the predicted brand perceptions and the mean of the actually observed brand perceptions, measured in the seven days after the beginning of the firestorm event. Eq. (2) specifies the model for firestorm brand j:

$$\Delta BP_j[t_1,t_2] = \frac{\sum_{t=t1}^{t2} BP_{jt}}{N_{t1,t2}} - \frac{\sum_{t=t1}^{t2} E\left(BP_{jt}\right)}{N_{t1,t2}} = \frac{\sum_{t=t1}^{t2} BP_{jt}}{N_{t1,t2}} - \frac{\sum_{t=t1}^{t2}\left(\hat{\alpha}_j + \hat{\beta}_j t_j\right)}{N_{t1,t2}}, \quad (2)$$

where ΔBP is the abnormal change in brand perceptions for the brand of firestorm j over the estimation window $[t_1,t_2]$, $N_{t1,\ t2}$ is the number of days in the estimation window, and $\hat{\alpha}_{j,}\hat{\beta}_j$ are the estimated parameters obtained from the regression function.

To measure the long-term effects on brand perceptions, we again adopt an event study approach, but with a longer time frame. The chosen period of two years after the end of the firestorm event is consistent with previous research (e.g., Cleeren et al., 2013; Luo, 2009), which often analyzes long-term effects over one to two years. The best-fitting regression functions again enable us to predict the development of brand perceptions, using a two-year window after the firestorm event, in a three-month estimation window to calculate the mean. It is important to examine the cumulative abnormal scores over a longer interval, to control for external influences that might skew the score, such as special events, advertising campaigns, or new product introductions. We calculate the mean of the actual brand perception values for each of the firestorm brands and determine the difference in the predicted and actual values.

Because we expect the different trigger and firestorm characteristics to influence the outcome measures in a multiplicative, rather than additive, way, we follow Hofmann, Clement, Völckner, and Hennig-Thurau (2017) and specify our model as a nonlinear log-log model. The multiplicative model incorporates trigger variables and firestorm characteristics as independent variables and

Table 1
Variable descriptions.

Variable	Description	Source
Product or service failure	Dummy variable equal to 1 if the firestorm was caused by a product or service failure	Twitter, Lexis-Nexis
Social failure	Dummy variable equal to 1 if the firestorm was caused by a social failure	Twitter, Lexis-Nexis
Communication failure	Dummy variable equal to 1 if the firestorm was caused by a communication failure	Twitter, Lexis-Nexis
Vividness of trigger	Degree of vividness of the first firestorm-related tweet, ranging from 1 to 3	Twitter
Strength	Number of firestorm tweets, adjusted by auxiliary regressions to account for the pre-occurrence of trigger characteristics	Twitter
Length	Length of the firestorm in days, adjusted by auxiliary regressions to account for the pre-occurrence of trigger characteristics	Twitter
Breadth	Number of print and online articles covering a respective firestorm (i.e., refer to the term "shitstorm"), adjusted by auxiliary regressions to account for the pre-occurrence of trigger characteristics	Lexis-Nexis, Google News
Start TM_SM	Control dummy variable equal to 1 if the firestorm started in social media and 0 if it started in traditional media	Twitter, Lexis-Nexis, Google News
Years_Ago	Control variable indicating the number of years that passed since the firestorm event	Twitter
FST_2015	Control dummy variable equal to 1 if the brand experienced a firestorm in 2015	Twitter
Abnormal short-term change in brand perceptions	Difference between predicted BrandIndex Score and actual BrandIndex Score seven days after the firestorm event	YouGov
Abnormal long-term change in brand perceptions	Difference between predicted BrandIndex Score and actual BrandIndex Score two years after the firestorm event	YouGov
Aided recall	Strength of memory measured on a five-point scale	Online survey
Correct reason	Binary variable equal to 1 if the reason for a firestorm was remembered correctly	Online survey

the change in brand perceptions caused by the firestorm as the dependent variable. Formally, the model for short-term abnormal brand perception changes for firestorm j is specified in Eq. (3), and the model for long-term abnormal brand perception changes is in Eq. (4).

$$y_{STBj} = e^{\alpha} \times e^{\beta 1 ProdSerFail_j} \times e^{\beta 2 SocFail_j} \times Vivid_j^{\beta 3} \times Strength_j^{\beta 4} \times Length_j^{\beta 5} \times Breadth_j^{\beta 6} \times e^{\beta 7 Start\ TM\_SM_j} \times e^{u_j} \quad (3)$$

$$y_{LTBj} = e^{\alpha} \times e^{\beta 1 ProdSerFail_j} \times e^{\beta 2 SocFail_j} \times Vivid_j^{\beta 3} \times Strength_j^{\beta 4} \times Length_j^{\beta 5} \times Breadth_j^{\beta 6} \times e^{\beta 7 Start\ TM\_SM_j} \times Years\_Ago_j^{\beta 8} \times e^{\beta 9\ FST\_15_j} \times e^{u_j} \quad (4)$$

where y_{STBj} depicts the abnormal short-term change in brand perceptions for firestorm j, and y_{LTBj} is the abnormal long-term brand perception change for firestorm j. Strength captures the number of firestorm tweets, Length denotes the length of the firestorm in days, Breadth refers to the number of print and online articles covering a respective firestorm, and u is the error term (see Table 1 for variable descriptions). Start TM_SM, Years_Ago, and FST_15 are the controls.

For the consumer memory-related hypotheses, we used generalized estimating equations (GEE), in which the dependent variables were consumers' aided recall of a firestorm and its correct reason. The individual brand logos of the 78 firestorm brands were randomly assigned to the sample of 997 respondents, so our data have a hierarchical structure. Using standard ordinary least square regressions would violate several assumptions of linear regression, such as the normal distribution of residuals, such that the standard errors could be under- or overestimated (e.g., Ghisletta & Spini, 2004). In contrast, GEE provide unbiased estimations of the regression coefficients (Liang & Zeger, 1986). Among the different correlation matrices, an independent matrix fits the data best. The analytical model to explain our dependent variable Aided recall (y_{AR}) for respondent i related to firestorm j is formally expressed in Eq. (5):

$$y_{ARij} = e^{\alpha} \times e^{\beta 1 ProdSerFail_j} \times e^{\beta 2 SocFail_j} \times Vivid_j^{\beta 3} \times Strength_j^{\beta 4} \times Length_j^{\beta 5} \times Breadth_j^{\beta 6} \times e^{\beta 7 Start\ TM\_SM_j} \times Years\_Ago_j^{\beta 8} \times e^{\beta 9\ FST\_15_j} \times e^{u_{ij}} \quad (5)$$

To explain our binary dependent variable Correct reason within the hierarchically structured dataset, we chose a GEE logit model that is formally expressed in Eq. (6):[1]

$$LN\left(\frac{\left(\pi\left(y_{CRij}=1\right)\right)}{\left(1-\pi\left(y_{CRij}=1\right)\right)}\right) = \alpha + \beta_1 ProdSerFail_j + \beta_2 SocFail_j + \beta_3 LN\left(Vivid_j\right) + \beta_4 LN\left(Strength_j\right) + \beta_5 LN\left(Length_j\right) + \beta_6 LN\left(Breadth_j\right) + \beta_7 Start\ TM\_SM_j + \beta_8 LN\left(Years\_Ago_j\right) + \beta_9 FST\_15_j + u_{ij} \quad (6)$$

where y_{CRij} indicates a correct reason given by consumer i for firestorm j, so it equals 1 (consumer i remembers the firestorm reason correctly) with a probability of π or 0 (consumer i does not remember the firestorm reason correctly) with a probability of 1 − π.

5. Results

5.1. Average effects of social media firestorms on brand perceptions and consumer memory

The data set reveals that of all affected firestorm brands in our sample, 58.3% suffer from a decrease in short-term brand perceptions, and 40.0% face long-term negative effects. Those brands suffer from an average abnormal short-term decrease in brand perceptions of 3.4% and an average abnormal long-term decrease of 6.9%. In addition, 23.0% of the brands with a short-term decrease recover quickly, revealing no long-term damage to their brand perceptions. Almost all the brands that suffer a long-term decrease previously experienced a short-term decrease in brand perceptions (but not vice versa).[2] Noting also that 23.7% of the respondents remembered the respective firestorm two years after is occurrence and 10.2% remembered the correct reason, we can conclude that social media firestorms are a relevant phenomenon in the digital age but exhibit strong variations. Thus, we already gain preliminary support for the importance of differentiating firestorms; explaining which firestorms are linked with more negative brand perceptions and stronger memory effects is the goal of the main analyses. A model-free comparison of changes in brand associations across firestorm types gives a first indication that firestorms with (a) more tweets, (b) longer

[1] Since we are interested in the probabilities of the occurrence of an event (correct reason as a binary variable) in a hierarchically structured dataset, we estimate a GEE logit model (instead of a multiplicative log-log model as in the case of our dependent metric variables). The estimated coefficients displayed in the results are estimated using the logit values; we provide odds ratios as well.

[2] Only 5% of the brands that experienced a long-term decrease did not show a short-term effect; those rare exceptions also experienced only very small changes in the long run.

ARTICLE IN PRESS

Table 2
Summary statistics.

Variable	Frequency	Mean	Standard deviation
Aided recall		2.21	1.47
Correct reason (value = 1)	102		
Product or service failure	31		
Social failure	23		
Communication failure	24		
Vividness of trigger		1.73	0.81
Strength		5.92	1.60
Length		2.34	0.74
Breadth		4.04	5.10

Notes: This table contains logged values before conducting auxiliary regressions.

durations, (c) broader media coverage, (d) higher vividness, and (e) a reason rooted in a product or service failure tend to suffer more in terms of immediate negative changes in brand perceptions than their respective counterparts. More elaborate analyses are required to make reliable judgments. Table 2 displays the summary statistics for the variables in our study.

5.2. Results for brand-related hypotheses

The estimation results for the brand-related hypotheses are in Table 3. The model for the short-term change in brand perceptions (Eq. (3)) explains the variance of the dependent variable well ($R^2 = 0.38$, adj. $R^2 = 0.29$). The model for long-term changes in brand perceptions (Eq. (4)) also achieves a reasonable fit, though it explains somewhat less variance ($R^2 = 0.31$, adj. $R^2 = 0.19$). Both models – and both trigger and firestorm characteristics – significantly explain changes in brand perceptions. The variance inflation factors peak at 2.23, which indicates that multicollinearity is no reason to be concerned.[3]

5.2.1. Brand-related results for trigger characteristics

Compared with a communication failure, a product or service failure influences both short- and long-term abnormal changes in brand perceptions more negatively ($b_{short} = -0.374$, $p < .05$; $b_{long} = -0.630$, $p < .05$), so this type of firestorm results in more negative brand perceptions, in support of H1a. A social failure (compared to a communication failure) instead does not relate significantly to either short- or long-term changes in brand perceptions, such that we must reject H2a. The vividness of the social media firestorm trigger has a significant impact on short-term, negative changes in brand perceptions ($b_{short} = -0.302$, $p < .05$), but it is not related to the change in brand perceptions two years after the firestorm. We treat this result as partial support for H3a.

5.2.2. Brand-related results for firestorm characteristics

Strength relates significantly to the negative change in brand perceptions within seven days of the beginning of the firestorm ($b_{short} = -0.149$, $p < .01$) and also exerts an impact on the negative change in brand perceptions two years after the firestorm-event ($b_{long} = -0.155$, $p < .05$), in support of H4a. Because we uncover no effects of length or breadth, we have to reject both H5a and H6a.[4]

5.2.3. Results for control variables and post-hoc tests

We find no differences related to the type of media where the crises started, the time passed since the firestorm took place, or the number of other firestorms the brand experienced in the year of data collection. To check the robustness of our results, we reran the regression analyses but excluded the control variables. The reduced models yield similar results, affirming the robustness of our findings. We further tested post-hoc for effects of a ratio of number of retweets per firestorm-related tweet as an additional firestorm characteristic, residual-corrected for trigger characteristics. However, no significant effects could be detected ($b_{short} = 0.245$, $p > .10$; $b_{long} = 0.163$, $p > .10$).

5.3. Results for consumer memory-related hypotheses

The GEE results for consumers' general memory (aided recall) of social media firestorms and consumers' memory of the correct reason are in Table 4. As was the case for brand perceptions, we find that both trigger and firestorm characteristics have significant associations with the memory outcome variables.

[3] When performing the auxiliary regressions to correct the firestorm variables for the previous occurrence of the trigger variables, we did not find any significant effects. For robustness, we reran the model without the auxiliary regressions; similar results point to the robustness of our findings.

[4] We investigated whether interaction effects might arise between the firestorm reasons and firestorm characteristics but did not detect any significant effects.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

Table 3
Regression results for brand-related hypotheses.

	Abnormal short-term change in brand perceptions				Abnormal long-term change in brand perceptions			
	b	Beta	*p*	VIF	b	Beta	*p*	VIF
Constant	3.262		.000		3.138		.000	
Product or service failure	−0.374	−0.420	.011	2.141	−0.630	−0.456	.012	2.226
Social failure	−0.077	−0.081	.562	1.604	−0.128	−0.086	.587	1.823
Vividness	−0.302	−0.320	.018	1.418	−0.110	−0.075	.597	1.444
Strength	−0.149	−0.516	.001	1.751	−0.155	−0.347	.032	1.791
Length	0.047	0.065	.669	1.898	0.033	0.030	.860	2.044
Breadth	0.011	0.020	.879	1.476	−0.072	−0.087	.561	1.620
Start TM_SM	0.127	0.117	.339	1.220	0.040	0.023	.865	1.372
Years_Ago					0.244	0.155	.251	1.306
FST_2015					0.040	0.030	.814	1.139
F value	4.496				2.544			
R^2 (adj.R^2)	0.378 (0.294)				0.314 (0.191)			

Notes: N = 60. VIF = variance inflation factor.

5.3.1. Consumer memory-related results for trigger characteristics

A product or service failure is significantly and positively related to aided recall and memory of the correct reason for the firestorm ($b_{recall} = 0.258$, $p < .05$; $b_{reason} = 0.657$, $p < .10$), in support of H1b. Whereas we do not find any significant effects for a social failure on aided recall, we find a positive effect on memory of the correct reason ($b_{reason} = 1.259$, $p < .01$), in partial confirmation of H2b. The vividness of the trigger has a significant effect on memory of the correct reason ($b_{reason} = 0.735$, $p < .01$), such that an increase in vividness of the initial firestorm-related tweet increases the probability of recalling the reason for the firestorm, in partial support of H3b.

5.3.2. Consumer memory-related results for firestorm characteristics

The strength of a firestorm significantly increases both aided recall ($b_{recall} = 0.088$, $p < .01$) and the probability of remembering the correct reason ($b_{reason} = 0.202$, $p < .05$), as predicted in H4b. For length, we find a significant effect only for the memory of the correct reason ($b_{reason} = 0.959$, $p < .05$). That is, a longer firestorm increases the probability that consumers recall its reason correctly, in partial support of H5b. However, we do not find any significant effect of breadth, and thus H6b cannot be supported.

5.3.3. Results for control variables and post-hoc tests

Again, we do not find any significant effects for the control variables or the post-hoc analysis of the ratio of retweets per firestorm tweet ($b_{recall} = -0.090$, $p > .10$; $b_{reason} = -0.217$, $p > .10$).

Table 4
GEE results for consumer memory-related hypotheses.

	Aided recall		Correct reason		
	b	*p*	b	Exp(B)	*p*
Constant	0.423	.011	−3.279	0.038	.000
Product or service failure	0.258	.015	0.657	1.930	.052
Social failure	0.082	.473	1.259	3.523	.005
Vividness	0.025	.768	0.735	2.086	.005
Strength	0.088	.004	0.202	1.224	.032
Length	0.084	.223	0.959	2.610	.013
Breadth	−0.092	.130	−0.280	0.756	.280
Start TM_SM	−0.013	.940	−0.232	0.793	.555
Years_Ago	−0.060	.532	−0.227	0.797	.424
FST_2015	0.127	.145	−0.017	0.983	.959
QIC	451.108		590.796		

Notes: N = 997. Aided recall is a metric variable and correct reason is a binary variable. QIC = quasi-likelihood under the independence model criterion. For the GEE models, fit criteria exist only for the working correlation matrix; there are no overall fit criteria (Cui & Qian, 2007).

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

6. Conclusion

6.1. Discussion of results

This study investigates social media firestorms as a digital kind of brand crisis in which consumers' negative word of mouth shared via social media plays a central role. After conceptually establishing their characteristics, we empirically describe the influence of social media firestorms on consumers and brands, with a purposeful dependence on several theory-based contingency factors. Trigger and firestorm characteristics—which both can be associated with varying degrees of consumers' motivation, ability, and opportunity to process information—result in more negative consequences for brand perceptions. These consequences arise in both the short and long run for brand perceptions, as well as in consumers' memory effects.

In terms of trigger characteristics, social media firestorms whose triggers involve a product or service failure, such that they have greater potential personal relevance to consumers, apparently increase people's motivation to process the firestorm information when forming their brand perceptions. They are not just vaguely remembered but deeply rooted in consumers' memory, as reflected by the long-term changes in brand perceptions, which likely stem from their strong relation to consumers' personal lives and strong resulting motivation to process the information. Firestorms caused by a social failure instead have no stronger evident impact on brand perceptions or general memory compared to communication failures as the reference category, though they increase the likelihood that consumers remember the reason for the event. We posit that performance-related failures might occur more regularly and in a more comparable fashion, whereas cases of social failures might be more distinct, so that in some cases, they maintain a more persistent presence in society and political debates.

Vividly triggered firestorms that offer a visual stimulus to consumers in the initial tweets also enhance their ability to process the firestorm information, so they are associated with negative consequences for brand perceptions. In the long term though, these vividly triggered firestorms lose their influence on the change in brand perceptions. That is, a visual representation in the initial firestorm-related tweet is associated with more negative brand perceptions immediately after the firestorm, but they dissolve in the long run, even as correct recall of the reason persists. A picture or video in the first tweet likely helps people store the details; triggers with such visual material appear to enhance consumers' ability to process the information so deeply that the reason sticks with them.

With regard to firestorm characteristics, which evolve after the social media firestorm initially has been triggered, we show that strong social media firestorms, accompanied by a high volume of tweets, particularly influence consumers' brand perceptions in both the short and long term. With more tweets, which repeat and extend the social media firestorm, consumers have more opportunity to process the information, as reflected in their more negative brand perceptions. Similar effects arise for both types of memory effects. The length of the social media firestorm emerges as an additional influence on recall of the correct reason: Short firestorms tend to be remembered only vaguely, but long ones are more likely to be remembered in detail. Perhaps, considering that the majority of social media firestorm events are limited to rather short intervals, their unique length makes these firestorm topics more memorable than other, more vaguely remembered cases—similar to the influence of social failures.

The breadth of the social media firestorm, as reflected in broader news media coverage on the social media firestorm, does not have any effect on the change in brand perceptions or consumers' memory in our empirical study. This finding might reflect an overall decrease in attention to traditional news media, as signaled by decreasing circulations and advertising revenues (Ember, 2016), combined with the simultaneous increase of social media functioning as news providers (e.g., more than 50% of Internet users cite social media as their primary news sources; Reuters Institute, 2016).

Thus, some factors elicited from traditional brand crisis literature remain strong (different firestorm reasons), showing the persistent importance of these findings. However, another variable rooted and ambiguously discussed in traditional brand crisis research exhibits no influence (breadth of the firestorm, captured by traditional news coverage of the social media firestorm), hence stressing the need to pay special attention when applying traditional brand crises factors to the social media context. The strong effects of drivers of social media firestorms that arise from the social media environment like firestorm strength (i.e., number of tweets) highlight the importance of our new additions to the brand crisis literature.

In addition to these theory-based characteristics, we probed whether the starting point of the social media firestorm (social media or traditional media) helps clarify the particularities of social media firestorms as digital brand crises. We did not find any significant effect across models though, which we cautiously explain by referring to the complexity of the "echoverse" (Hewett et al., 2016) in which firestorms evolve; the "pinball" metaphor of social media marketing (Hennig-Thurau et al., 2010) offers a similar perspective. If consumers react strongly in social media, traditional media pick up on the topic and echo it. If traditional media report on the crisis and it raises some interest, consumers also will pick up on it and reverberate it by discussing the topic on social media. That is, independent of its starting point, firestorm information can spread on social media and impact brand perceptions and memory.

6.2. Managerial implications

It typically takes years to build a brand with positive brand perceptions, so gaining information about not only immediate consequences but also long-term effects of social media firestorms on consumers and brands is crucial. With this study, we show that the consequences of social media firestorms can last years after their occurrence. Even if the event itself is limited to a few days or weeks, firestorms represent a managerially relevant phenomenon in the digital age.

Beyond affirming the harmful potential of social media firestorms, our study provides actionable insights into *which* social media firestorms threaten brand perceptions most. Our descriptive average effects suggests that a strong variability exists in the effects of social media firestorms, with some showing strong negative impacts, but many others remaining without such harm. Managers can make

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

ARTICLE IN PRESS

Table 5
Ranking of potentially most harmful firestorms.

	Short-term brand perceptions			Long-term brand perceptions	
	Strength	Vividness	Reason	Strength	Reason
1.	High	Video	Product or service failure	High	Product or service failure
2.	High	Picture	Product or service failure	High	Social failure
3.	Medium	Video	Product or service failure	High	Communication failure
4.	High	Video	Social failure	Medium	Product or service failure
5.	High	Only text	Product or service failure	Medium	Social failure

Notes: A ranking reflecting the memory effects also is available on request.

the important distinction between those potentially harmful firestorms and less threatening ones, using our findings about the conditions in which firestorms hurt brand perceptions and affect consumers' memory. The key characteristics that enable managers to predict the developments and consequences of a firestorm span both trigger characteristics, which they can evaluate at the moment the very first tweet or post appears, and firestorm characteristics, which unfold over time. The reason for the firestorm, the vividness of its trigger, the strength of the firestorm, and its length can all help for classifying firestorms as harmful or not. Social media firestorms generally are associated with a decrease in brand perceptions and/or increase in memory effects when they (1) are caused by a product/service or social failure, (2) start with a vivid trigger, (3) prompt many tweets, and (4) persist for a long duration.

Whereas the first two indicators stem from the category of initial trigger characteristics, the last two indicators belong to the set of evolving firestorm characteristics. Specifically, both the reason for the social media firestorm and the vividness of its trigger can be determined immediately, making them suitable early warning measures. Using their assessment (e.g., high alert for product or service failures), it is possible to establish an instant classification of each new social media firestorm and derive an appropriate reaction. The strength and length of a firestorm instead require consideration over the duration of the firestorm and after its occurrence, so they represent important metrics for ongoing management efforts. For instance, if consumers continue to encounter high numbers of firestorm-related tweets, managers are advised to take the ongoing firestorm seriously and act accordingly.

To provide substantial value for managers and offer them actionable implications, we undertook an illustrative ranking of the potentially most harmful social media firestorms. That is, we calculated the estimated outcomes for all combinations of trigger and firestorm characteristics, then ranked their estimated outcomes to arrive at a hierarchy for the most dangerous firestorms that require managers' priority attention. In each case, for each of our focal metric variables, we included (1) the mean value, (2) the mean value plus the standard deviation, and (3) the mean value minus the standard deviation in the equation. We kept the values for the dummy variables at 0 and 1, for the trigger variable at 1–3, and for the insignificant variables at their mean values. Table 5 lists the top five firestorm combinations that we predict, based on our research findings, would be most harmful for brand perceptions. For both short-term and long-term effects, we use only the respective significant predictors to describe firestorm types.[5]

Managers can develop warning systems based on the illustrative summary of our findings in this ranking. With such warnings, they can allocate resources to handle the most threatening social media firestorms more efficiently. For example, if the firm sparks social media outrage by making a communication error, the firestorm likely would earn a rather low threat score, because its consequences tend to be less severe than those of firestorms sparked by performance or social failures. But if managers face a firestorm prompted by a service failure, captured with an uploaded video, which sparks a high number of firestorm-related tweets, they will be well-advised to react promptly and proactively, because it is likely to have severe immediate and potentially also long-term consequences for their brands.

6.3. Limitations and further research

Some limitations of this study suggest avenues for further research. First of all, we focus with our sample on digital brand crises that lead to social media firestorms of varying sizes; giving us the possibility to analyze which crises evolved in impactful firestorms and which did not. However, we are limited in making such statements about which incidents do not lead to any type of social media firestorm, neither big nor small. We welcome further research to address this interesting research question with a differently structured dataset.

With our findings, we offer some indicators that can be judged early on, namely the reason and vividness of the firestorm, whereas our other indicators are more suitable for the ongoing firestorm management efforts. As especially the early stage is crucial for managers dealing with firestorms, we emphasize the need for additional research uncovering more early indicators as a next step for this emerging research stream. The emotionality of the trigger, its sender, and the fact whether the underlying misbehavior can be attributed to a deliberate mistake of the company or external sources could be fruitful starting points.

Whereas our analyses are mostly located on an aggregate level on one platform, more in-depth analyses of consumer-driven dynamics within and between platforms are encouraged. In a post-hoc analysis, we could not detect an additional significant effect of consumers' retweets of firestorm-related tweets over and above the characteristics we already account for. Digging deeper into consumers' rebroadcasting behaviors, as a way to exert power in social networks, is an exciting option for further research. Maybe time-dependent effects or the identification of particularly influential rebroadcasters could yield interesting insights (see e.g., Zhang et al., 2017). Who are those individuals whose activities fan the spread of a firestorm?

[5] Note that vividness is only significant in the short-term model, so we do not use it to describe the most harmful firestorm types for the long-term model.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

Furthermore, we deliberately focus on negative changes in brand perceptions and on consumers' memory structures, which offer important metrics of consumer behavior and long-term brand success. Applying our conceptual model and empirical design to awareness measures and behavioral sales data might generate other interesting insights into the patterns of social media firestorm effects and the importance of different metrics. Some commentators debate whether positive effects of social media firestorm occur, due to higher awareness levels (Knowledge@Wharton, 2015). Do such effects regularly occur and if yes, under which condition? Also, considering changes in brand sales as another important outcome metric, it is possible that the sales pattern might recover faster than the more enduring decrease in brand perceptions. Such a gap might be dangerous, as it could give managers a false sense of security and leave them ignorant of their consumers' true brand perceptions. We encourage continued research to shed light on these other outcomes of social media firestorms.

Lastly, we studied firestorms during 2012–2014 to capture long-term effects, together with short-term impacts. Analyses of more recent firestorms can provide further insights, considering the rapid evolution of social media. Nowadays, some sort of firestorm occurs almost daily (*The Slate*, 2014), and the critical firestorm drivers we have identified might have grown even more important. Consumers' general motivation, opportunity, and ability to process them might have decreased, compared with their reactions at the start of our study time frame. It would be exciting to investigate if the impact of firestorms shift over time. Do firestorms become omnipresent "background noise" in social media, or do they continue to receive people's close attention? These questions offer directions for further research, among both academics and practitioners.

Funding

This work was supported by the German Research Foundation, Germany (DFG) research unit 1452, "Marketing of Hedonic Media Products in the Age of Digital Social Media", HE-3437/11-1.

Acknowledgments

We thank Eva Kurz for her help in collecting the extensive data and her contributions to the theoretical considerations. We thank Silvia Halbing for further data collection efforts. We acknowledge support from the DFG research group "Marketing of Hedonic Media Products in the Age of Digital Social Media", especially Franziska Völckner, Henrik Sattler, and Marius Johnen, and constructive comments from participants of the special session, "Weathering a Social Media Firestorm: Strategies for Protecting and Creating Brand Value," at Winter AMA 2017.

Appendix A. Overview of identified social media firestorms

Brand_Name	StartDate	Stated reasons
Deutsche Bahn	Dec 14	Rumor of abolishing discount system
Apple	Dec 14	Displaced front camera from smartphone
KaDeWe	Dec 14	Luxury department store fired Santa Claus
Sony	Nov 14	Sexist advertising campaign
Reformhaus	Nov 14	Homophobic article in customer magazine
Drogeriemarkt dm	Nov 14	Sale of bags associated with child labor
Sparkasse	Nov 14	Advertising campaign with Nazi-like symbol
WhatsApp	Nov 14	Introduction of product feature that was perceived as threatening privacy
Apple	Oct 14	Quality issue of new product
Kleiderkreisel	Oct 14	Increase in price
Sky	Oct 14	Product app does not work/system failure
Mango	Oct 14	Nazi-like symbols on product
Microsoft	Oct 14	Sexist statement of CEO against gender equal payment
H&M	Oct 14	Sale of overalls that look like battledress
Apple	Sept 14	Quality issue of new product software
Netflix	Sept 14	Sexist reply to customer by streaming platform
Apple	Sept 14	Automatic download of record as gift
Vorwerk	Sept 14	Customers not informed of upcoming release of newer product version
Zara	Aug 14	Anti-Semitic–looking symbols on product
Facebook	Aug 14	Customers forced to use additional product
O2	July 14	Planned capacity throttling of Internet flat rates
Abercrombie & Fitch	June 14	Introduction of new smaller clothing size (size 000)
Primark	June 14	Calls for help from employees and indicators of bad working conditions in textiles
Amazon	June 14	Customers questioning motives to act more environmentally friendly
IKEA	June 14	Injunction suit against fan blog
Adidas	June 14	Advertising campaign using real animal hearts
Airberlin	May 14	Popular steward is admonished
Nintendo	May 14	Homophobic product
Ariel	May 14	Use of digits in commercial associated with racism

(continued on next page)

Appendix A (*continued*)

Brand_Name	StartDate	Stated reasons
Shell	May 14	Unavailability of loyalty program gift 3 h after start of promotion
Burger King	Apr 14	Poor hygiene and working conditions
Lidl	Apr 14	Sexist advertising campaign
Zalando	Apr 14	Poor working conditions
Sky	Mar 14	Product app does not work/system failure
HypoVereinsbank	Mar 14	Stoppage of online banking
WhatsApp	Feb 14	Software failure
IKEA	Feb 14	Halted sales of popular shelf
Drogerie Müller	Feb 14	Refusal to sell new record by a rapper
ADAC	Jan 14	Automobile club manipulating readers' awards
Tom Tailor	Jan 14	Alleged faux fur in clothing is unveiled as cat fur
Nivea	Dec 13	Sexist advertising campaign
Sony	Dec 13	Special treatment of celebrity
Ritter Sport	Nov 13	Dispute over hidden usage of chemical aroma revealed by quality test institution
Google	Nov 13	Privacy issues
Yahoo!	Oct 13	New app design of product
Maggi	Oct 13	Launch of new product containing many flavor enhancers
Hipp	Oct 13	Product quality issues and genetically manipulated vegetables
Congstar	Sept13	Planned capacity throttling of fixed landline Internet connections
Barilla	Sept 13	Food company unwilling to depict homosexuality in advertisements
Google	Aug 13	Privacy issues of mailing service
Sixt	Aug 13	Advertising campaign
Tchibo	Aug 13	Nazi-like symbols on product
HTC	July 13	Failure to provide software update for product
PayPal	July 13	Erroneous notification about winning a price draw
Microsoft	June 13	Features of new product with more defaults and conditions
Lidl	May 13	Customer loyalty program fail because gifts ran out of stock
Dextro Energy	May 13	High proposed consumption frequency and portions by glucose producer
Abercrombie & Fitch	May 13	Discrimination against homeless people
Bionade	May 13	Homophobic advertising campaign
Deutsche Telekom	Apr 13	Announcement of changing usage conditions
Nordsee	Apr 13	Sexist advertising campaign
KiK	Apr 13	Child labor
Jack Wolfskin	Mar 13	Injunction suit against use of supposed brand logo in movie
Otto	Mar 13	Sexist product
Yahoo!	Feb 13	Change of working model
McDonald's	Feb 13	Launch of new product
Amazon	Feb 13	Bad working conditions
Otto	Nov 12	Coupon error
Apple	Sept 12	Quality issues of new product software
Sparda-Bank	Sept 12	Recruiting campaign
Ernsting's family	Aug 12	Advertising campaign with animal cruelty
McDonald's	Aug 12	Price increase
Zalando	July 12	Public television criticizes working conditions
Lufthansa	June 12	Sexist advertising campaign
Fressnapf	May 12	Advertising campaign was discussed in the context of animal cruelty
Maredo	Mar 12	Homophobic advertising campaign
E wie einfach	Mar 12	Advertising campaign glorifies domestic violence
ING-DiBa	Jan 12	Advertising campaign with sausage

Source: Twitter/Lexis-Nexis. Specific references are available on request.

Appendix B. YouGov BrandIndex Score

The aggregate raw brand perception measure is calculated by counting the number of respondents who agree with the six positive items subtracted by the number of respondents who agree with the six negative items, divided by the total number of respondents, multiplied by 100. Thus, the YouGov BrandIndex measure is a ratio-scaled variable that lies within the range of −100 to +100 (YouGov, 2016; see also Luo, Raithel, & Wiles, 2013).

Items:	
Perceived brand quality	“Which of the brands in the sector do you associate with high or poor quality?”
Perceived brand value	“Which of the brands do you associate with good or poor value-for-money?”
Perceived brand satisfaction	“Would you identify yourself as a recently satisfied or an unsatisfied customer of any of these brands?”
Perceived brand recommendation	“Which brands would you recommend to a friend or suggest avoiding?”
Perceived brand impression	“For which brands do you have a ‘generally positive’ or ‘generally negative’ feeling?”
Perceived brand workplace reputation	“Which of the brands would you be proud/embarrassed to work for?”

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

ARTICLE IN PRESS

Appendix C. Auxiliary regression for brand perception and consumer memory models

	Strength		Length		Breadth	
	b	*p*	b	*p*	b	*p*
Constant	5.405	.000	2.255	.000	0.882	.003
Product or service failure	0.916	.106	0.134	.551	0.129	.671
Social failure	0.103	.845	−0.077	.719	0.438	.131
Vividness	0.127	.803	0.038	.852	0.244	.378

Notes: Log-log specified, calculated with OLS regression.

	Strength		Length		Breadth	
	b	*p*	b	*p*	b	*p*
Constant	5.734	.000	2.364	.000	1.115	.000
Product or service failure	0.563	.301	0.024	.906	−0.087	.759
Social failure	0.265	.543	−0.005	.981	0.502	.074
Vividness	−0.253	.656	0.046	.810	−0.022	.937

Notes: Log-log specified, calculated with GEE.

References

Alba, J. W., & Chattopadhyay, A. (1986). Salience effects in brand recall. *Journal of Marketing Research*, *23*(4), 363–369.

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research*, *13*(4), 411–454.

Apsler, R., & Sears, D. O. (1968). Warning, personal involvement, and attitude change. *Journal of Personality and Social Psychology*, *9*(2), 162–166.

Batra, R., & Ray, M. L. (1986). Situational effects of advertising repetition: The moderating influence of motivation, ability, and opportunity to respond. *Journal of Consumer Research*, *12*(4), 432–445.

Borah, A., & Tellis, G. J. (2016). Halo (spillover) effects in social media: Do product recalls of one brand hurt or help rival brands? *Journal of Marketing Research*, *53*(2), 143–160.

Brandwatch (2017). 44 incredible and interesting twitter statistics. https://www.brandwatch.com/blog/44-twitter-stats/, Accessed date: 2 February 2018.

Chen, Y., Ganesan, S., & Liu, Y. (2009). Does a firm's product-recall strategy affect its financial value? An examination of strategic alternatives during product-harm crises. *Journal of Marketing*, *73*(6), 214–226.

Childers, T. L., & Houston, M. J. (1984). Conditions for a picture-superiority effect on consumer memory. *Journal of Consumer Research*, *11*(2), 643–654.

Cialdini, R. B., Petty, R. E., & Cacioppo, J. T. (1981). Attitude and attitude change. *Annual Review of Psychology*, *32*(1), 357–404.

Cleeren, K., van Heerde, H. J., & Dekimpe, M. G. (2013). Rising from the ashes: How brands and categories can overcome product-harm crises. *Journal of Marketing*, *77*(2), 58–77.

Collins, B. (2017). *#DeleteUber's creator: Resist trump or 'pay a price'*. The Daily Beast. http://www.thedailybeast.com/articles/2017/01/29/deleteuber-s-creator-resist-trump-or-pay-a-price.html, Accessed date: 20 March 2017.

Connolly, K. (2013). Shitstorm arrives in German dictionary. *The Guardian*. https://www.theguardian.com/books/booksblog/2013/jul/04/shitstorm-german-dictionary-duden-shitschturm, Accessed date: 20 January 2017.

Coyle, J. R., & Thorson, E. (2001). The effects of progressive levels of interactivity and vividness in web marketing sites. *Journal of Advertising*, *30*(3), 65–77.

Cresci, E. (2017). #DeleteUber: How social media turned on Uber. *The Guardian*. https://www.theguardian.com/technology/2017/jan/30/deleteuber-how-social-media-turned-on-uber, Accessed date: 20 February 2017.

Cui, J., & Qian, G. (2007). Selection of working correlation structure and best model in GEE analyses of longitudinal data. *Communications in Statistics: Simulation and Computation*, *36*(5), 987–996.

Dawar, N., & Lei, J. (2009). Brand crises: The roles of brand familiarity and crisis relevance in determining the impact on brand evaluations. *Journal of Business Research*, *62*(4), 509–516.

Dawar, N., & Pillutla, M. M. (2000). Impact of product-harm crises on brand equity: The moderating role of consumer expectations. *Journal of Marketing Research*, *37*(2), 215–226.

De Vries, L., Gensler, S., & Leeflang, P. S. H. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing*, *26*(2), 83–91.

Deloitte (2015). Exploring strategic risk. https://www2.deloitte.com/us/en/pages/risk/articles/exploring-strategic-risk-survey-report.html, Accessed date: 10 February 2017.

Dutta, S., & Pullig, C. (2011). Effectiveness of corporate responses to brand crises: The role of crisis type and response strategies. *Journal of Business Research*, *64*(12), 1281–1287.

Eddy, M. (2013). Amazon to investigate claims of worker intimidation at distributor in Germany. *The New York Times*. http://www.nytimes.com/2013/02/16/world/europe/amazon-to-investigate-claims-of-worker-intimidation-at-german-centers.html, Accessed date: 10 March 2017.

Ember, S. (2016). More wretched news for newspapers as advertising woes drive anxiety. *The New York Times*. https://www.nytimes.com/2016/10/28/business/media/buyouts-wall-street-journal-bad-news-for-newspapers.html, Accessed date: 5 May 2017.

Folkes, V. S., & Kamins, M. A. (1999). Effects of information about firms' ethical and unethical actions on consumers' attitudes. *Journal of Consumer Psychology*, *8*(3), 243–259.

Ghisletta, P., & Spini, D. (2004). An introduction to generalized estimating equations and an application to assess selectivity effects in a longitudinal study on very old individuals. *Journal of Educational and Behavioral Statistics*, *29*(4), 421–437.

Goldfarb, A., & Tucker, C. (2011). Online display advertising: Targeting and obtrusiveness. *Marketing Science*, *30*(3), 389–404.

Goodrich, K. (2011). Anarchy of effects? Exploring attention to online advertising and multiple outcomes. *Psychology and Marketing*, *28*(4), 417–440.

Hauser, F., Hautz, J., Hutter, K., & Füller, J. (2017). Firestorms: Modeling conflict diffusion and management strategies in online communities. *Journal of Strategic Information Systems*, *26*(4), 285–321.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, *46*(6), 1251–1271.

Hennig-Thurau, T., Hofacker, C. F., & Bloching, B. (2013). Marketing the pinball way: Understanding how social media change the generation of value for consumers and companies. *Journal of Interactive Marketing*, *27*(4), 237–241.

Hennig-Thurau, T., Houston, M. B., & Heitjans, T. (2009). Conceptualizing and measuring the monetary value of brand extensions: The case of motion pictures. *Journal of Marketing*, *73*(6), 167–183.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001

ARTICLE IN PRESS

Hennig-Thurau, T., Malthouse, E. C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The impact of new media on customer relationships. *Journal of Service Research*, *13*(3), 311–330.

Hennig-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). Does twitter matter? The impact of microblogging word of mouth on consumers' adoption of new movies. *Journal of the Academy of Marketing Science*, *43*(3), 375–394.

Hewett, K., Rand, W., Rust, R. T., & van Heerde, H. J. (2016). Brand buzz in the echoverse. *Journal of Marketing*, *80*(3), 1–24.

Hoffman, K. D., Kelley, S. W., & Rotalsky, H. M. (1995). Tracking service failures and employee recovery efforts. *Journal of Services Marketing*, *9*(2), 49–61.

Hofmann, J., Clement, M., Völckner, F., & Hennig-Thurau, T. (2017). Empirical generalizations on the impact of stars on the economic success of movies. *International Journal of Research in Marketing*, *34*(2), 442–461.

Hsu, L., & Lawrence, B. (2016). The role of social media and brand equity during a product recall crisis: A shareholder value perspective. *International Journal of Research in Marketing*, *33*(1), 59–77.

Kähr, A., Nyffenegger, B., Krohmer, H., & Hoyer, W. D. (2016). When hostile consumers wreak havoc on your brand: The phenomenon of consumer brand sabotage. *Journal of Marketing*, *80*(3), 25–41.

Kalaignanam, K., Kushwaha, T., & Eilert, M. (2013). The impact of product recalls on future product reliability and future accidents: Evidence from the automobile industry. *Journal of Marketing*, *77*(2), 41–57.

Kendzierski, D. (1980). Self-schemata and scripts: The recall of self-referent and scriptal information. *Personality and Social Psychology Bulletin*, *6*(1), 23–29.

Knowledge@Wharton (2015). Social media shaming: Can outrage be effective? http://knowledge.wharton.upenn.edu/article/social-media-shaming-can-outrage-be-effective/, Accessed date: 1 February 2018.

Krugman, H. E. (1972). Why three exposures may be enough. *Journal of Advertising Research*, *12*(6), 11–14.

Labrecque, L. I., vor dem Esche, J., Mathwick, C., Novak, T. P., & Hofacker, C. F. (2013). Consumer power: Evolution in the digital age. *Journal of Interactive Marketing*, *27*(4), 257–269.

Liang, K. -Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*(1), 13–22.

Liu, A. X., Liu, Y., & Luo, T. (2016). What drives a firm's choice of product recall remedy? The impact of remedy cost, product hazard, and the CEO. *Journal of Marketing*, *80*(3), 79–95.

Liu, Y., & Shankar, V. (2015). The dynamic impact of product-harm crises on brand preference and advertising effectiveness: An empirical analysis of the automobile industry. *Management Science*, *61*(10), 2514–2535.

Liu, Y., Shankar, V., & Yun, W. (2017). Crisis management strategies and the long-term effects of product recalls on firm value. *Journal of Marketing*, *81*(5), 30–48.

Luo, X. (2009). Quantifying the long-term impact of negative word of mouth on cash flows and stock prices. *Marketing Science*, *28*(1), 148–165.

Luo, X., Raithel, S., & Wiles, M. A. (2013). The impact of brand rating dispersion on firm value. *Journal of Marketing Research*, *50*(3), 399–415.

Lutz, K. A., & Lutz, R. J. (1977). The effects of interactive imagery on learning: Application to advertising. *Journal of Applied Psychology*, *62*(4), 493–498.

MacInnis, D. J., & Jaworski, B. J. (1989). Information processing from advertisements: Toward an integrative framework. *Journal of Marketing*, *53*(4), 1–23.

MacInnis, D. J., Moorman, C., & Jaworski, B. J. (1991). Enhancing and measuring consumers' motivation, opportunity, and ability to process brand information from ads. *Journal of Marketing*, *55*(4), 32–53.

Marketing News Weekly (2017). United Airlines social sentiment drops 160%. https://www.ama.org/publications/eNewsletters/Marketing-News-Weekly/Pages/united-airlines-social-sentiment-dropped-160-percent.aspx, Accessed date: 4 May 2017.

McCollough, M. A., Berry, L. L., & Yadav, M. S. (2000). An empirical investigation of customer satisfaction after service failure and recovery. *Journal of Service Research*, *3*(2), 121–137.

McKinsey (2012). Turning buzz into gold. https://www.mckinsey.de/files/Social_Media_Brochure_Turning_buzz_into_gold.pdf, Accessed date: 20 March 2017.

Moore, D. L., Hausknecht, D., & Thamodaran, K. (1986). Time compression, response opportunity and persuasion. *Journal of Consumer Research*, *13*(1), 85–99.

Nash, N. C. (1995). Oil companies face boycott over sinking of rig. *The New York Times*. http://www.nytimes.com/1995/06/17/world/oil-companies-face-boycott-over-sinking-of-rig.html, Accessed date: 2 February 2018.

O'Sullivan, D. (2017). Congrats to @Uber_NYC. https://twitter.com/bro_pair/status/825518408682860544?lang=de, Accessed date: 1 May 2017.

Petty, R. E., Briñol, P., & Priester, J. R. (2009). Mass media attitude change: Implications of the elaboration likelihood model of persuasion. In J. Bryant, & M. B. Oliver (Eds.), *Media effects: Advances in theory and research* (pp. 125–164). New York: Routledge.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology*, *19*, 123–205.

Petty, R. E., Cacioppo, J. T., & Schumann, D. (1983). Central and peripheral routes to advertising effectiveness: The moderating role of involvement. *Journal of Consumer Research*, *10*(2), 135–146.

Pfeffer, J., Zorbach, T., & Carley, K. M. (2014). Understanding online firestorms: Negative word-of-mouth dynamics in social media networks. *Journal of Marketing Communications*, *20*(2), 117–128.

Pullig, C., Netemeyer, R. G., & Biswas, A. (2006). Attitude basis, certainty, and challenge alignment: A case of negative brand publicity. *Journal of the Academy of Marketing Science*, *34*(4), 528–542.

Rauschnabel, P. A., Kammerlander, N., & Ivens, B. S. (2016). Collaborative brand attacks in social media: Exploring the antecedents, characteristics, and consequences of a new form of brand crises. *Journal of Marketing Theory and Practice*, *24*(4), 381–410.

Reuters Institute (2016). Reuters Institute digital news report 2016. http://reutersinstitute.politics.ox.ac.uk/sites/default/files/Digital-News-Report-2016.pdf?utm_source=digitalnewsreport.org&utm_medium=referral, Accessed date: 10 May 2017.

Saegert, J., & Young, R. K. (1982). Comparison of effects of repetition and levels of processing in memory for advertisements. *Advances in Consumer Research*, *9*, 431–434.

Shuster, A. (1973). The thalidomide babies are growing up. *The New York Times*. http://www.nytimes.com/1973/04/29/archives/better-as-is-than-not-at-all-the-thalidomide-babies-are-growing-up.html, Accessed date: 2 February 2018.

Smith, A. K., Bolton, R. N., & Wagner, J. (1999). A model of customer satisfaction with service encounters involving failure and recovery. *Journal of Marketing Research*, *36*(3), 356–372.

Smith, S. M., & Shaffer, D. R. (2000). Vividness can undermine or enhance message processing: The moderating role of vividness congruency. *Personality and Social Psychology Bulletin*, *26*(7), 769–779.

Stephen, A. T., & Galak, J. (2012). The effects of traditional and social earned media on sales: A study of a microlending marketplace. *Journal of Marketing Research*, *49*(5), 624–639.

Steuer, J. (1992). Defining virtual reality: Dimensions determining telepresence. *Journal of Communication*, *42*(4), 73–93.

Strom, S. (2015). Bud light withdraws slogan after it draws ire online. *The New York Times*. https://www.nytimes.com/2015/04/29/business/bud-light-withdraws-slogan-after-it-draws-ire-online.html?_r=0, Accessed date: 10 December 2016.

The New York Times (2014). Chief of Abercrombie & Fitch is stripped of chairman title. http://nyti.ms/1k3S4Xx, Accessed date: 10 December 2016.

The Slate (2014). The Outrage project. http://www.slate.com/articles/life/culturebox/2014/12/the_year_of_outrage_2014_behind_the_scenes_of_everything_you_were_angry.html, Accessed date: 20 February 2017.

Unnava, H. R., & Burnkrant, R. E. (1991). Effects of repeating varied ad executions on brand name memory. *Journal of Marketing Research*, *28*(4), 406–416.

Victor, D., & Stevens, M. (2017). United airlines passenger is dragged from an overbooked flight. *The New York Times*. https://www.nytimes.com/2017/04/10/business/united-flight-passenger-dragged.html, Accessed date: 5 May 2017.

Warner, B. (2010). Big brands can be inept at defusing blog storms over recalls. *Washington Post*. http://www.washingtonpost.com/wp-dyn/content/article/2010/03/06/AR2010030602481.html, Accessed date: 8 May 2017.

Wyer, R. S., Jr., & Srull, T. K. (1986). Human cognition in its social context. *Psychological Review*, *93*(3), 322–359.

YouGov (2016). YouGovBrandIndex: Your brand's perception changes every day. https://doc-10-5g-docs.googleusercontent.com/docs/securesc/ha0ro937gcuc7l7deffksulhg5h7mbp1/kodjmkrb77oagmhaqtqpbvniel8v3bhi/1488981600000/15404878037040702269/*/0B1zND3ca7RW3S2Z0ZW1lekdibHM, Accessed date: 15 December 2016.

Zhang, Y., Moe, W. W., & Schweidel, D. A. (2017). Modeling the role of message content and influencers in social media rebroadcasting. *International Journal of Research in Marketing*, *34*(1), 100–119.

Please cite this article as: Hansen, N., et al., Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands, *International Journal of Research in Marketing* (2018), https://doi.org/10.1016/j.ijresmar.2018.08.001