



Marketing Science Institute Working Paper Series 2025

Report No. 25-117

## Beyond the Spike: How Stakeholder Response Patterns Predict Retail Crises and the Impact of Retailer Reactions

Koen Pauwels, Kelly Hewett, Raoul Kuebler and Meike Eilert

“Beyond the Spike: How Stakeholder Response Patterns Predict Retail Crises and the Impact of Retailer Reactions”  
© 2025

Koen Pauwels, Kelly Hewett, Raoul Kuebler and Meike Eilert

MSI Working Papers are Distributed for the benefit of MSI corporate and academic members and the general public. Reports are not to be reproduced or published in any form or by any means, electronic or mechanical, without written permission.

**Beyond the spike: how stakeholder response patterns predict  
retail crises and the impact of retailer reactions**

**Abstract**

Retail brands increasingly face a barrage of negative incidents—ranging from service failures to legal actions—that unfold in real time across news and social media. While most incidents fade, some escalate into full-blown crises with reputational and financial consequences. This study takes an empirics-first approach to crisis detection and prediction. We identify 510 retail incidents and track their trajectories across traditional media sentiment, social media buzz, and consumer mindset metrics. Rather than assume any one event structure or communication channel, our approach is agnostic to topic, platform, and sentiment valence. Using dynamic time warping (DTW) and decision-tree models, we uncover recurring stakeholder response patterns that predict whether an incident impacts retailer firm value. This framework helps retailers distinguish routine negativity from high-risk events. It enables early intervention based on empirical trajectory patterns, reducing reactive missteps. Our findings provide a holistic, data-driven method for interpreting crisis evolution and improving decision-making in fast-moving environments.

**Keywords: brand crisis, retail, dynamic time warping, time series clustering, abnormal returns, brand metrics**

One of the biggest challenges facing retailers today is navigating the growing stream of negative events covered in the media—some of which may escalate into full-blown brand crises. The rise of social media has increased the visibility and complexity of these situations, making it harder for retailers to anticipate how incident-related buzz will evolve before they respond. Social media, alongside traditional media, forms an 'echoverse'—a communication environment where customers, stakeholders, and (citizen) journalists interact and amplify reactions in real time (Hewett et al. 2016). As a result, negative incidents in traditional media can spill over into social media and vice versa (Hennig-Thurau, Hofacker, & Bloching 2013). For example, Target was widely criticized in 2013 after a cyberattack compromised over 40 million customer accounts (McCoy 2017). A decade later, controversy over its Pride Month display triggered a boycott and its first sales decline in six years (Meyersohn 2023).

Yet tracking crisis dynamics is not straightforward. Information can spread rapidly, often without editorial gatekeepers (Conway et al. 2007). Retailers may issue press releases or stay silent, while consumers, activists, or influencers seize public discourse through social media (McQuarrie, Miller, & Phillips 2013). These forces interact unpredictably, making it hard for retailers to anticipate how events unfold. Negative incidents often spark chain reactions, where one stakeholder group's behavior influences others. This interplay across sentiment metrics, attention spikes, and platform dynamics adds noise and makes it harder to distinguish routine negativity from crises. Many incidents do not lead to brand harm, and tracked metrics obscure rather than clarify trajectories (Pauwels 2014). Conversations with senior retail managers indicated that the key differentiator between noise and crisis is the potential for negative impact on performance. This raises a critical question: how can retailers distinguish between a publicized incident that will fade and one that will escalate into a full-blown crisis?

Extant research does not yet answer these questions given its selection of incidents already established as brand crises and focus on the emergence and impact of crises in either traditional (e.g., Liu & Shankar 2015; Cleeren, van Heerde, & Dekimpe 2013) or social media environments (e.g., Hansen, Kupfer, & Hennig-Thurau 2018; Borah & Tellis 2016; Hsu & Lawrence 2016; Kübler, Langmaack, Albers, & Hoyer 2020). We take a holistic view of the interplay among components of the communications echoverse, considering the roles of traditional and social media as well as changes in brand-related sentiment surrounding negative incidents. In doing so, we aim to unbundle the chain of reactions across stakeholder groups and understand the dynamics among them and their potential impact on firm performance.

Brand crises rarely emerge fully formed; instead, they develop through sequences of shifts in attention, sentiment, and buzz that escalate, stabilize, or dissipate over time (McCombs & Reynolds 2009; Trilling & Schoenbach 2015). Understanding these dynamics requires tracking how stakeholder reactions evolve across channels, not just the presence of content. We identify incidents through media coverage and examine changes in consumer sentiment and social media activity over time. Unlike prior studies focused on known crises or specific media, we take an agnostic approach, allowing any incident to reveal meaningful patterns. We then assess whether these patterns predict firm performance. Specifically, we address these questions:

1) Based on which metrics reflecting the reactions of different stakeholder groups can retailers anticipate the likely trajectory of a negative incident?

2) Do different incident types matter more than others in terms of the reactions of different stakeholder groups?

3) Can we predict the impact of negative incidents on firm performance based on the dynamic reaction patterns of other stakeholder groups?

In addressing these questions, our study makes several contributions. First, it illuminates different retail crisis patterns reflected in changes to traditional media, social media, and consumer sentiment throughout the incident window, helping managers interpret noisy stakeholder metrics by showing how patterns, rather than spikes, can be early signals of impact. While social listening tools (Kübler, Colicev, & Pauwels 2017) can be helpful, they often induce false alarms. Our approach offers a structure to identify meaningful, recurring patterns that serve as indicators of market outcomes. In doing so, we help managers focus on the right signals rather than reacting to anecdotal noise (McGovern et al. 2012; Pauwels & Joshi 2016).

Second, we introduce to the marketing literature DTW as a method of time series clustering, given the temporal dependencies and fluctuations exhibited in our data. The evolution and configuration of consumer responses to an incident may also be influenced by prior periods' consumer reactions. DTW allows us to group time series that share similarities in shape and timing. By doing so, we are among the first studies to identify archetypes of reaction patterns.

Finally, we assess the impact of the different trajectories identified using DTW on firm performance. In doing so we produce a decision tree distinguishing the forks in the road, and how the performance impact depends both on the firm's actions (such as the number of press releases) and the reaction patterns of multiple stakeholder groups. As a consequence managers can better foresee how patterns observable from common social media listening tools or marketing dashboards evolve into a crisis or if an incident does not impact firm value.

### **Review of relevant literature**

In Table 1, we present a summary of prior empirical research investigating the reactions of consumers, traditional media, social media, and the market surrounding negative brand- or firm-related incidents. We highlight whether each paper identifies a negative incident as a key

focus, the sources used, and the focal industry(ies) examined. We also summarize each study's key findings. While we read widely across disciplines to identify relevant findings and gaps, we restrict our summary to empirical studies with field data published in Marketing journals within the last 10 years. Where relevant, we discuss other studies to showcase our contributions.

No prior studies, to our knowledge, have begun with a range of incidents that could become crises to predict which ones do. Instead, most focus on a few crises identified after the fact, often from a single firm or industry, limiting their relevance to the environments retail managers face. We start from a base of more than 500 incidents across multiple firms, allowing us to examine incident trajectories as they unfold rather than selecting them in hindsight. By taking an empirically grounded approach we reflect the complexity of the environment—marked by uncertainty, noise, and overlapping events. This lens helps overcome selection bias, support generalizable insights, and surface patterns obscured in studies focused on isolated cases.

Second, much of the research on negative brand incidents has focused on the reactions of one or a few sources mentioned above. For example, studies examining the reactions of a single stakeholder group include those focusing on investors (Chen, Ganesan, & Liu 2009; Eilert et al. 2017; Gao et al. 2015; Kang, Germann, & Grewal 2016; Liu, Shankar, & Yun 2017; Rasouljan et al. 2017; Shiu & Yang 2017; Thirumalai & Sinha 2011; Wiles et al. 2010). Other studies focus exclusively on the reactions of consumers (Gijsenberg, van Heerde, & Verhoef 2015; Lin et al. 2011; Puzakova, Kwak, & Rocereto 2013; Srinivasan & Sarial-Abi 2021; Swait, Erdem, & Peters 2014). Finally, studies focusing on a single source also examine the reactions of traditional media (Lungeanu, Paruchuri, & Tsai 2017; Zavyalova et al. 2012).

**Table 1: Review of empirical investigations of investor, consumer, and media reactions surrounding negative events**

Cite	Relevant Issues Examined	Industries Examined	Reactions by:					Event types	Approach to Identifying Events
			Market	Consumers	Traditional media	Social media	Firms/ Retailers		
<i>This study</i>	<i>what metrics allow retailers to anticipate the trajectory of a negative incident and its potential impact on firm performance</i>	<i>Retailing</i>	X	X	X	X	X	<i>multiple negative events</i>	<i>proactive identification of all retailer days with abnormal negative news volume</i>
Mosley, Schweidel & Zhang (2024)	how consumer-brand relationship and crisis type moderate the impact of language on social media	multiple industries		X	X	X		multiple negative events	reactive identification of known crises
Yu, Huang, Qing, & Chen (2022)	how humor reduces negative feedback's impact on social media	search engine, shoes		X		X	X	multiple negative events	reactive identification of known negative events; product reviews
Kübler, Langmaack, Albers, & Hoyer (2020)	difference in impact of corporate unethical behaviour and product harm crisis on consumer outrage	banking, automotive, electronics		X		X		corporate unethical behavior and product recalls	reactive identification of known product harm crises
Stäbler & Fischer (2020)	drivers of media coverage of corporate social irresponsibility events	multiple industries	X		X	X		corporate social irresponsibility events	reactive identification of known CSI events
Hansen, Kupfer, & Hennig-Thurau (2018)	negative effects of firestorms on brand perceptions	multiple industries		X	X	X		social media firestorms	reactive identification of known social media firestorms
Eilert, Jayachandran, Kaliganam, & Swartz (2017)	impact of time to recall on stock market returns	automotive	X					product recalls	reactive identification of known safety investigations
Liu, Shankar & Yun (2017)	effect of recall volume and crisis management strategies for firm value	automotive	X				X	product recalls	reactive identification of known product recalls
Rasoulia, Grégoire, Legoux & Sénécal (2017)	impact of recovery efforts on firm performance after service failure	service industries	X				X	service failures	reactive identification of known information breach events
Borah & Tellis (2016)	effect of product recalls on online chatter	automotive	X			X		product recalls	reactive identification of known product recall events
Hsu & Lawrence (2016)	impact of social media on shareholder value	multiple industries	X			X	X	product recalls	reactive identification of known produce recall events
Kang, Germann & Grewal (2016)	CSR as a penance for corporate social irresponsibility	multiple industries	X					corporate social irresponsibility events	reactive identification of concerns regarding social issues
Gao, Xie, Wang & Wilbur (2015)	adjusting pre-recall ad spending can moderate financial damage	dairy	X				X	product recalls	reactive identification of known product recalls
Gijzenberg, van Heerde, & Verhoef (2015)	how service crises affect perceived service quality	railway		X				service failures	reactive identification of known service failures

We found far fewer studies examining two or more elements of a firm's communications echoverse, which is surprising given the likelihood that multiple sources react to negative incidents. A second limitation of prior studies is the type of negative incidents examined, with many focusing on a single type. For example, product recalls account for a large share of prior research (Borah & Tellis 2016; Chen, Ganesan, & Liu 2009; Eilert et al. 2017; Gao et al. 2015; Hsu & Lawrence 2016; Liu, Shankar, & Yun 2017; Swait, Erdem, & Peters 2014; Thirumalai & Sinha 2011). Other studies focus specifically on service failures (Gijsenberg, van Heerde, & Verhoef 2015; Rasouljan et al. 2017), product wrongdoing or harm crises (Kübler, Langmaach, Albers, & Hoyer 2020; Lin et al. 2011; Puzakova, Kwak, & Rocereto 2013), corporate social irresponsibility (Kang, Germann, & Grewal 2016; Kübler et al. 2020; Stäbler & Fischer 2020), or misconduct related to financial reporting (Lungeanu, Paruchuri, & Tsai 2017) or misleading advertising (Wiles et al. 2010). Studies examining a wider range of incident types tend to focus narrowly on investor reactions (Shiu & Yang 2017), traditional media only (Zavyalova et al. 2012), investors and traditional media only (Wei, Ouyang, & Chen 2017), or omit investor reactions entirely (Hansen, Kupfer, & Hennig-Thurau 2018; Mosley, Schweidel, & Zhang 2024; Yu, Huang, Qing, & Chen 2022).

A final observation from our review of relevant literature is the lack of studies examining negative incidents in the retail sector specifically. This is surprising given that global retail sales will reach \$32.4 trillion in 2025 (Oberlo 2024)—and the increasing prevalence of incidents such as data breaches that capture attention in both traditional and social media. The Target examples are among many that have garnered significant attention over the past decade. On average, data breaches alone cost U.S. retailers \$4.45 million. Moreover, retail crises span many types, including supply chain incidents (e.g., Chipotle's decision to stop serving carnitas), human

resources incidents (e.g., McDonald’s CEO being ousted after admitting to an intimate relationship with an employee), and legal incidents (e.g., lawsuits over retail pharmacies’ roles in the opioid epidemic)<sup>1</sup>.

While prior research often focuses on a single brand crisis or high-profile incident (e.g., product recalls, social irresponsibility), this narrow lens risks reinforcing what we term *strategic myopia*: a managerial overreliance on known, visible, or viral events at the expense of understanding the broader pattern of incident emergence and escalation. In today’s retail environment, however, crises do not arise in isolation. They occur against a backdrop of simultaneous events, stakeholder responses, and rapidly evolving digital narratives. Retailers who monitor only large spikes or familiar incident types may overreact to noise or fail to detect early warnings embedded in subtler patterns. As Pauwels (2014) warns, overinterpreting noisy metrics or momentary fluctuations can lead to costly missteps. Thus, our approach captures the broader ecosystem of incidents, recognizing the dynamic interplay among multiple signals and stakeholders over time. By analyzing trajectories rather than isolated snapshots, we help retail managers react appropriately, and demonstrate the benefits in our simulations.

### **Conceptualizing a crisis echoverse**

While we approach this study in an exploratory fashion, consistent with an “empirics first” approach (Golder et al. 2022), we nonetheless conceptualize a crisis echoverse in order to capture the complex, real-time interplay of stakeholder reactions across traditional media, social media, and consumers. We define a *retail incident* as a sharp, abnormal spike in negative traditional media coverage, identified using a statistical threshold. A *crisis*, in our operationalization, is not predefined but inferred—when stakeholder response trajectories align

---

<sup>1</sup> <https://www.nytimes.com/2022/11/15/health/walmart-opioids-settlement.html>

with performance degradation (e.g., negative Cumulative Abnormal Returns on the stock market), the incident is considered to have escalated into a crisis. This outcome-based definition avoids assumptions about content or sentiment and focuses on empirical stakeholder patterns.

While consumers, media, and social platforms amplify incident dynamics, retailers themselves are not passive observers. In fact, our analysis shows that their responses—especially in the form of press releases—can significantly shape how other stakeholders react.

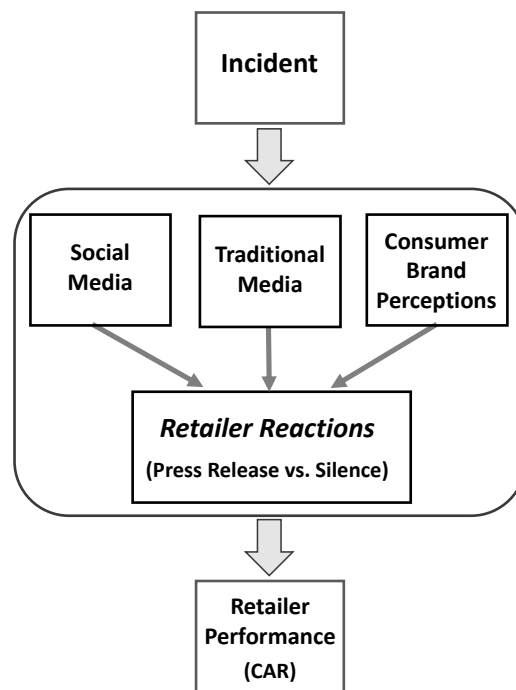
Notably, excessive retailer response may unintentionally escalate the situation, reinforcing negative sentiment and amplifying buzz, a finding that aligns with Coombs' (2007) Situational Crisis Communication Theory, which suggests that over-communicating in certain crisis types can intensify stakeholder attributions of responsibility, thereby worsening reputational harm. We therefore conceptualize retailer reactions as integral parts of stakeholder trajectory patterns, capable of either mitigating or compounding the impact of an incident.

Crises can be characterized by their strength and length (e.g., Hansen et al. 2018), both of which impact the extent to which crisis information is processed by consumers and investors and has potential to impact brand sentiment, and subsequently the firm's bottom line. Figure 1 presents a framework for understanding how retailers navigate overlapping and potentially compounding stakeholder responses. Unlike prior crisis models, this framework emphasizes pattern recognition across incidents, helping firms detect structural rather than episodic signals of risk. We argue that an event will trigger reactions by traditional media, social media, and in terms of consumers' brand perceptions. All of these sources may influence each-other, and retailers may also react and influence the reactions in social or traditional media or by consumers. We then investigate the impact of these reactions' trajectories on firm performance.

### *Stakeholder response dynamics*

In the wake of negative retail incidents, multiple stakeholder groups—including traditional media, social media users, consumers, and retailers themselves—contribute to a dynamic communication environment. Traditional media often initiate the framing of the event (Zavyalova et al. 2012), while social media can amplify, contest, or reshape the public discourse in real time (Pfeffer et al. 2014). Consumers respond with evolving sentiment and word of mouth, influenced by emotional arousal, peer diffusion, and issue salience (Berger & Milkman 2012; Berger & Iyengar 2013). In turn, firms may react with official statements or silence, influencing the evolving trajectory of stakeholder responses rather than narrating a cohesive brand story (Hewett et al. 2016).

**Figure 1: Conceptual Framework**



This dynamic interplay creates what we refer to as a *crisis echoverse*—a feedback-rich environment in which stakeholder reactions are temporally interdependent. Unlike prior studies that isolate one channel or stakeholder group, we examine how these reactions evolve over time and influence each other. Research in crisis communication and word-of-mouth diffusion has

shown that social media often facilitates faster, more emotionally intense, but also shorter-lived reactions compared to traditional media (Hansen et al. 2018; Arvidsson & Caliandro 2016).

Rather than assuming fixed narrative structures, we empirically analyze the *temporal patterns* of stakeholder response metrics using DTW. This approach allows us to detect recurring trajectory shapes across incidents, providing actionable insight into how crises escalate, stabilize, or fade—and when retailers should intervene.

### *Trajectory of a crisis*

Crises rarely erupt instantaneously; rather, they unfold through identifiable sequences of stakeholder reactions. Prior research in crisis communication has assumed that crises follow a typical arc—an initial spike in attention, a peak in visibility or controversy, and a gradual return to baseline (Coombs 1999; Howell & Miller 2006). Crisis management strategies have traditionally aimed to shorten and flatten this arc, minimizing reputational and financial damage by quickly resolving the issue or shifting attention (Gonzalez-Herrero & Pratt 1995).

However, in today’s multichannel communication environment, these temporal patterns can vary widely depending on the interplay of media sentiment, social media activity, and consumer responses. While traditional models posit a rise-and-fall trajectory (Coombs 1999; Howell & Miller 2006), empirical evidence suggests that some incidents trigger sustained or delayed stakeholder responses, while others dissipate quickly without lasting impact (Hansen et al. 2018; Arvidsson & Caliandro 2016). Our findings further reinforce this point, showing that crises can follow diverse trajectory patterns—such as oscillating sentiment (*Rollercoaster*) or late-onset attention (*Too Late*)—that diverge from linear or predictable arcs.

We move beyond theoretical assumptions by directly measuring and clustering stakeholder metrics’ empirical trajectories. Using DTW, we detect recurring temporal patterns—

such as short dips, escalators, or rollercoasters—that describe how media sentiment, consumer mindset, and online buzz evolve in response to incidents. These trajectory archetypes allow us to identify meaningful differences in stakeholder reactions across incident types and time, offering retailers a more nuanced understanding of when, how, and why an incident becomes a crisis.

### **Reactions to retailer crisis-related stories**

In this section we discuss the reactions to retailer crisis-related stories by consumers and the market, both of which are key stakeholders in the trajectory of a crisis. We furthermore consider the role of retailers themselves as they respond to negative incidents.

#### *Consumers*

Brand-related crises can influence consumers' brand perceptions, potentially leading to undesirable outcomes such as negative WOM and reduced brand purchase likelihood. Research has shown not only short-term impacts of crises on consumer perceptions but also longer-term impacts that can damage a brand (Gijzenberg, Van Heerde, & Verhoef 2015). Others view brands as signals to consumers regarding their ability to deliver on the brand's promise, and suggest that crisis-related information can serve as a "shock" to consumers' brand perceptions and consideration (Swait, Erdem, & Peters 2014). Information regarding crises can raise doubts about the brand's ability to deliver its promised benefits (Dawar & Pillutla, 2000). However, it may also increase the retailer's salience without hurting consumer consideration, for instance because consumers may not care about the incident type or scope. Thus, consumers' retailer perceptions are influenced by information flows across traditional and social media, with crisis-related events acting as shocks that disrupt and reshape the trajectory of stakeholder responses.

#### *Retailers*

A key question for retailers is whether their actions can help prevent a negative incident from becoming a full-blown crisis. While classic economics theory holds that people react based on expected utility, researchers have shown that anticipated regret engenders action bias (Patt & Zeckhauser 2000)—as observed in elite soccer coaches and goalkeepers (Zeelenberg et al. 2002; Bar-Eli et al. 2007). When faced with ambiguous and risky situations, people often feel they must act, regardless of whether doing so is wise. In our manager interviews, we heard evidence that firms feel compelled to respond to protect both their brand and customer relationships. Research shows that managers react to brand crises in several ways, such as adding to incident-related dialog in social media (Hsu & Lawrence 2016), interacting with customers through compensation or process improvements (Rasoulilian et al. 2017), or issuing press releases (Hewett et al. 2016). Because the norm is to act (Kahneman & Miller 1986), we expect retail managers to exhibit action bias, and thus capture their reactions by examining the volume of press releases issued surrounding a negative incident.

## Data

We describe next our approach for gathering our data, identifying negative incidents and selecting the variables on which to focus in understanding the trajectory of negative incidents.

### *Sample and variable selection*

We constructed our prediction model by analyzing crisis incidents within two prominent retail sectors: fashion and food service. First, we include fashion retailers due the overall size of the fashion industry, which is estimated at \$1.7 trillion as of 2023,<sup>2</sup> and its importance to the global economy.<sup>3</sup> In addition, the fashion industry has a significant social media presence and

---

<sup>2</sup> <https://www.oberlo.com/statistics/apparel-industry-statistics>

<sup>3</sup> <https://thealexcrowley.medium.com/the-role-of-fashion-in-the-global-economy-manufacturing-retail-and-luxury-brands-6a6f8c96f891>

continues to see growth in e-commerce sales.<sup>4</sup> Next, the food service industry is also among the largest retail sectors, expected to reach \$1,467.04 billion by 2028,<sup>5</sup> and the quick service food sectors in particular continue to outpace the rate of growth of other food service options such as fine dining. Furthermore, we expected that the types of negative incidents appearing in the media would differ across these industries given sensitivities about what we wear versus what we eat.

In each of these sectors, we considered a selection of major and mid-sized retailers that operate across all U.S. states, some globally, and have a substantial number of publicly reported negative incidents. We selected three of the top ten fast food retailers based on sales revenue (McDonalds, Burger King, and Dunkin' Donuts), all with a global presence (Food & Wine 2023), and selected one U.S.-only quick service food chain with a greater volume of dine-in versus takeout sales (Kona Grill)<sup>6</sup>. In the fashion industry, our focus was on three retailers: Abercrombie and Fitch and Aeropostale, both of which have a U.S. and global presence and offer fashion for both male and female consumers, and Jos. A. Bank, a retailer serving mainly male consumers and with a U.S. and online presence only.

### *Identifying negative incidents*

We isolated negative incidents by first identifying spikes in negative news volume using Ravenpack. In particular, we use Ravenpack's abnormal news volume variable to capture extra media coverage on a given day. This variable depicts how different the actual news volume over the past 24 hours is when compared to the normal (over the past 365 days) news volume for a retailer. A value of zero means the volume is the same as normal; a positive number represents the number of standard deviations the volume is above normal; and negative numbers represent

---

<sup>4</sup> <https://www.bigcommerce.com/blog/2022-fashion-apparel-report/#>

<sup>5</sup> <https://www.fortunebusinessinsights.com/fast-food-market-106482>

<sup>6</sup> <https://www.restaurantbusinessonline.com/financing/kona-grills-parent-finds-customers-are-ready-dine-out-again>

the number of standard deviations the volume is below normal. Once we identified dates on which news volume is above normal, we downloaded all news stories appearing on those dates using Factiva. We then trained four graduate assistants to read all of the news articles appearing on those days and classify the topic of each article using a coding scheme developed by two graduate assistants based on one year worth of articles across all of the retailers in our sample. (For more information on the incident codes see Appendix A and Appendix B.). Using this procedure, we identified 510 incidents across the five retailers, from January 2010 to December 2015. We further rely on managerial input to aggregate the incidents into six major categories: legal and financial, marketing, supply chain and operations, or human resources.

#### *Social media data*

Word of mouth (WOM) has been demonstrated to significantly influence consumers' perceptions of a company (Hewett et al., 2016). To capture online WOM, we use social media data. Specifically, we leverage Twitter's Academic API to extract all Tweets referencing any company within our sample during the period between January 1st 2010, and December 31st, 2015. Twitter (now X) is especially suited for our research, as it is commonly known to be among the primary complaint channels for users and customers (Ma, Sun, & Kekre 2015). Twitter furthermore brings the advantage that content posted on the platform was not hidden behind privacy curtains, so that data censorship or truncation does not create issues. For each brand represented in our sample we extracted all tweets that were either mentioning the brand or referring to a brand specific hashtag. We specifically examine the volume of social media mentions of each of the retailers during the time period of our study.

#### *Consumer brand perceptions*

Our choice of variables is driven by the consumer decision-making funnel and the corresponding mindset metrics (e.g. Srinivasan et al. 2010). That is, we make use of YouGov's mindset metrics, which are updated daily and are therefore highly effective in monitoring the immediate and dynamic impact of incidents on consumer's evaluations throughout the decision-making process, particularly for short-term incidents spanning limited time periods (i.e., 5-7 days). These measures reflect how the public—not just social media users—perceive the brand before, during, and after incidents. YouGov's metrics are well established in marketing research and have been shown to accurately capture consumers' perceptions of firms (Hewett et al., 2016) and their reactions to firms' marketing actions (Colicev et al., 2018).

We illustrate the upper funnel and a consumer's awareness of the retailer with YouGov's buzz volume and buzz valence metrics. The buzz volume metric indicates the frequency of individuals who have recently heard of or discussed the respective company. On the other hand, the buzz valence metric gauges the favorability or unfavorability with which the retailer is portrayed in these discussions. Moreover, for assessing the middle and lower sections of the decision-making funnel, we depend on YouGov's company reputation score to measure how consumers generally perceive the retailer's actions in a positive or negative light.

#### *Traditional media sentiment*

Recognizing that consumers' perception of a retailer and a negative incident is also influenced by how the incident is covered in the traditional media (Stäbler & Fischer, 2020), we incorporate media coverage into our model. We use the abnormal news sentiment variable provided by Ravenpack, which captures the average sentiment strength over the previous 24 hours for a given retailer. The variable's values range from -1 (highly negative) to +1 (highly

positive) where a value of 0 is neutral. An empty value means that there was no news events and therefore no sentiment associated with the company over the past 24 hours.

### *Retailer press releases*

Understanding the role retailers' responses play in the trajectory of negative incidents, we also include data on the volume of firms' press releases. Because firms use various media platforms, including online social media (e.g., Facebook, Twitter), newspapers, television, and company websites, to publish press releases<sup>7</sup>, we account for the overall volume of press releases issued by a retailer over the past 24 hours as reported by Ravenpack. This variable's values represent a count of retailer-issued press releases during the past 24 hours.

### *Firm performance*

We assess firm performance based on financial market reactions. The market reacts to the trajectory of a crises by signaling investor support for or skepticism of the discourse from traditional or social media, or the retailer itself, in their investment decisions (Eilert et al. 2017; Flammer 2013; Liu, Shankar & Yun 2017). Studies examining the impact of crises on firm value assume that an incident reveals new information, which leads investors to adjust their company valuation perceptions. Negative incidents can signal that a retailer failed to protect customers, in cases such as the Target data breach, or in some other way let customers down, which can lead to customer churn (Eilert et al. 2017) and sales loss, as illustrated in the Target Pride Month boycott (Meyersohn 2023). Alternatively, investors may disregard the incident as a 'storm in a glass of water', or even buy more of the retailer's stock as its salience increases without hurting long-term prospects. Thus, investors respond to the retailer-related narratives, and their reactions may not necessarily be negative, but instead could be neutral or even positive.

---

<sup>7</sup> <https://oer.pressbooks.pub/mediacommunication/chapter/public-relations-basics/>

## Method

We first use dynamic time warping (DTW), a specific form of time series cluster analysis to uncover patterns of trajectories of negative incidents across the retailers in our sample using five metrics: media sentiment, buzz volume, Twitter volume, buzz valence, and retailer reputation. Next, based on these patterns, we identify 11 incident trajectory types across the five metrics. Finally, we explore the association between these trajectory types and CAR to offer valuable implications for retail managers in responding to different metrics and early patterns.

### *Dynamic time warping for negative incidents*

For every negative incident we identified, we construct time series for each of our variables. These time series encompass a seven-day window centered around the incident, encompassing three days of observations before the incident and three days of observations after the incident. This window length is similar to those of event studies in finance (e.g. Abbassi et al, 2022) and marketing (Kleine, Friederich & Paul 2023), and is selected, after assessing all incidents in the sample, to avoid interference from concurrent incidents and other confounding or omission biases (Sorescu et al 2017). Likewise, including several days before the incident's media coverage allows for leakage, i.e. market players acting with a priori knowledge (ibid).

To discern the recurring patterns in how consumers and the media engage with, evaluate, and report over time on corporate incidents, we employ a cluster analysis approach. Among the approaches to time series cluster analysis, DTW has emerged as the most adaptable and suitable approach for analyzing time series data (Paparrizos & Gravano 2017). This flexibility is especially pertinent when dealing with time series data that may encompass time shifts, such as those induced by the occurrence of an incident, and scaling effects, which can be attributed to the varying degrees of a firm's popularity or diverging levels of publicity associated with an incident.

Moreover, DTW excels in the clustering of time series that may manifest disparities in their speed or alignment (Sardá-Espinosa 2017). These differences may stem from incident type heterogeneity or other external factors, including seasonality, timing, and idiosyncratic company or incident factors. Importantly, DTW is capable of generating more interpretable clusters by grouping time series that share similarities in both shape and timing. Additionally, it provides the centroid shape for each cluster, which represents the archetypal or average trajectory. This feature can prove invaluable in fostering a comprehensive understanding of the temporal development of each metric throughout the course of an incident (see Wang et al. 2018).

Like any cluster analysis, a preliminary step involves determining the number of clusters to be identified by the algorithm. We adhere to established procedures in time-series cluster analysis and employ the two main methods for ascertaining the cluster count in each of our cluster analyses. For each variable, we utilize R's *dtwclust* package (Sardá-Espinosa & Sardá 2018) to estimate hierarchical cluster solutions, allowing for the exploration of up to ten potential clusters. Next, we scrutinize the resulting dendrograms for each cluster solution, offering insights into the separation points of clusters, cluster sizes, and their composition.

To decide on the number of clusters for each variable, we rely on cluster validation indices, as furnished by the CVI function within the *dtwclust* package (Arbelaitz et al. 2013). Table 2 provides descriptive statistics for the resulting clusters for each variable. For each variable, while the share of legal and financial incidents is greatest across all variables, there is significant variation among other types of incidents for different clusters. For media sentiment, the clusters with largest number of incidents (A2, or *short hype* with 250 and A1, or *short dip*, with 124), have marketing incidents as one of the most common and for the cluster with the

smallest number of incidents (A4, or *escalator*, with 20) human resources incidents are the most common and marketing incidents are much less common.

### *Impact of crisis trajectories on market reactions*

We aim to provide managers with actionable insights on when and which combination of media and consumer reaction trajectories leads to more positive or more negative market reactions. To this end, we estimate a regression tree model, which has four key advantages (Kübler, Wieringa, & Pauwels 2016), described below.

**Table 2: Cluster Descriptives for Each Variable**

<b>Variable</b>	<b>Number of Incidents and Percent of Each Incident Type per Cluster</b>				
	<b>Cluster 1</b>	<b>Cluster 2</b>	<b>Cluster 3</b>	<b>Cluster 4</b>	<b>Cluster 5</b>
<b>Media Sentiment</b>					
<i>Total incidents:</i>	124	250	24	20	57
Human resources	12.93	13.65	5.88	20.69	10.00
Legal and financial	41.38	40.95	47.06	41.38	41.67
Marketing	24.13	20.95	20.59	13.79	30.00
Supply chain/operations	21.55	44.44	26.47	24.14	18.33
<b>Buzz Volume</b>					
<i>Total incidents:</i>	238	101	75	70	--
Human resources	14.67	10.17	12.50	12.35	N/A
Legal and financial	43.63	39.83	39.58	39.51	N/A
Marketing	18.92	24.58	27.09	28.46	N/A
Supply chain/operations	22.78	25.42	20.83	24.13	N/A
<b>Twitter Volume</b>					
<i>Total incidents:</i>	155	282	21	14	--
Human resources	12.28	13.45	8.33	17.65	N/A
Legal and financial	39.18	41.81	54.17	41.18	N/A
Marketing	22.22	21.34	25.00	35.29	N/A
Supply chain/operations	26.31	23.39	12.50	5.88	N/A
<b>Buzz Valence</b>					
<i>Total incidents:</i>	196	85	151	47	--
Human resources	13.54	13.54	11.63	13.73	N/A
Legal and financial	41.05	46.88	40.70	35.29	N/A
Marketing	19.65	18.76	26.16	27.45	N/A
Supply chain/operations	25.77	20.84	21.50	23.53	N/A
<b>Reputation</b>					
<i>Total incidents:</i>	111	42	115	183	33
Human resources	12.30	5.71	13.39	13.79	15.79
Legal and financial	40.98	42.86	44.09	40.52	39.47
Marketing	19.67	28.57	22.84	23.28	15.79
Supply chain/operations	27.05	22.85	19.69	21.41	28.95

First, we can use the regression tree model to test the predictive power of the trajectories, while naturally accounting for non-linear relationships (see e.g. De'ath & Fabricius 2000) between independent variables (trajectories of consumer reactions and media coverage) and our dependent variable (CAR). Second, contrary to the basic Ordinary Least Squares regression model, a regression tree model automatically selects the most important variables and interactions by splitting the tree nodes based on their predictive power. We can thus account for the relationships across our variables and interactions between them, without having to make apriori assumptions (Loh 2011). Third, as our analysis involves heterogeneous incident types for retailers from different industries, each incident's effect on market reactions may vary due to differing circumstances. Regression trees excel at handling such heterogeneity because they partition the data into subsets based on incident characteristics, effectively creating different models for different incident types (c.f., Green & Kern 2012). Finally, the regression tree model output allows us to deliver actionable insights for managers (Yildirim & Kübler, pp. 246-248). The decision tree structure allows for a straightforward interpretation of the model's predictions and to deliver a roadmap, when the occurrence of a combination of trajectories across our investigated variables will lead to more negative or more positive shareholder reactions.

To allow for heterogeneity in trajectories and caused by the different types of incidents, we estimate the regression tree model depicted in equation (1) with the help of R's rpart package.

$$\begin{aligned}
 (1) \text{ CAR}_i = & \beta_0 + \beta_1 * \text{Media\_Sentiment\_Cluster}_i + \beta_2 * \text{Buzz\_Volume\_Cluster}_i + \\
 & \beta_3 * \text{Twitter\_Volume\_Cluster}_i + \beta_4 * \text{Buzz\_Valence\_Cluster}_i + \\
 & \beta_5 * \text{Reputation\_Cluster}_i + \beta_6 * \text{Finance\_and\_Legal\_Incident}_i + \\
 & \beta_7 * \text{Marketing\_Incident}_i + \beta_8 * \text{Channels\_and\_Operations\_Incident}_i + \\
 & \beta_9 * \text{Human\_Resources\_Incident}_i + \beta_{10} * \text{Number\_Press\_Releases}_i + \varepsilon_i
 \end{aligned}$$

The tree predicts *CAR* for incident *i* with the help of the incident specific patterns of the YouGov metrics and the volume of Tweets, a set of incident type dummies, and the total number of press releases per incident released by the company. Because each cluster condenses the variable's 7-day trajectory into a single incident-level pattern, the tree is specified purely cross-sectionally—explaining variation *across* incidents rather than *within* incidents over time—and therefore contains no time subscript *t*.

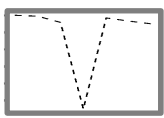
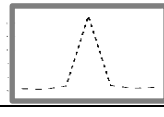
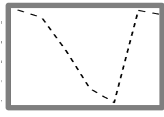
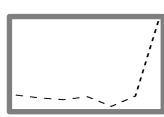
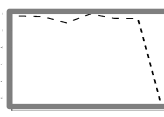
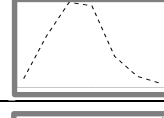
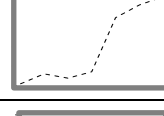
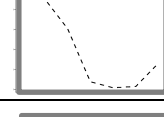
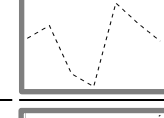
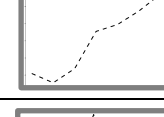
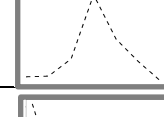
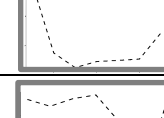
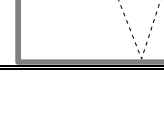
## Results

We first report on our results from the DTW analysis, describing different incident trajectories based on five different metrics: (media sentiment, buzz volume, Twitter volume, buzz valence, and retailer reputation) We then provide our findings from the decision tree analysis regarding investor reactions based on the different trajectories.

### *Crisis trajectories*

Table 3 provides the associated cluster outcomes for each of our variables along with the number of observations contained within each cluster and a description of each cluster (See Table 3). Across the brand metrics, five trajectories emerge for media sentiment, buzz valence, and retailer reputation, while four trajectories emerge for buzz volume and Twitter volume. First, media sentiment is characterized by the *Short-Dip* (1), the *Short-Hype* (2), the *Long-Dip* (3), the *Escalator* (4), and the *Too Late* (5). Concerning consumer sentiment (Buzz Valence), our analysis reveals five distinct trajectories: (1) the *Late Short Dip*, (2) *Trough*, (3) the *Rollercoaster*, (4) and the *Hero*. As to retailer reputation, the five trajectories are (1) the *Rollercoaster*, (2) the *Too late*, (3) *Trough*, (4) the *Escalator*, and (5) the *Star*. Finally, both the Buzz Volume and Twitter Volume metrics follow the trajectories of (1) the *Short-Hype*, (2) the *Escalator*, (3) the *Pre-Hype*, or (4) the *Rollercoaster*.

**Table 3: Crisis Trajectory Characteristics**

Metric	Trajectory (# of incidents)	Trajectory Characteristics	Prominent Incident Types	Average CARs	Shape
<b>A. Media Sentiment</b>	A1. Short Dip (124)	<ul style="list-style-type: none"> <li>Brief decline in sentiment on incident day, followed by an immediate return to the average pre-incident level.</li> <li>Media pays only fleeting attention to the incident, portraying it negatively.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Negative	
	A2. Short Hype (250)	<ul style="list-style-type: none"> <li>Media coverage exhibits abnormally positive sentiments on the day of the incident, only to revert to the initial average the following day.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Positive	
	A3. Long Dip (24)	<ul style="list-style-type: none"> <li>Decline in media sentiment starting on second day and reaching its lowest point on the day after the incident.</li> <li>Initial and critical news coverage intensifies on incident day, normalizing shortly thereafter.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Negative	
	A4. Escalator (20)	<ul style="list-style-type: none"> <li>Consistent negative media coverage turning markedly positive on day 7.</li> <li>Sustained negative company coverage becomes positive by day 7, possibly due to corrective actions.</li> </ul>	<ul style="list-style-type: none"> <li>Human resources</li> <li>Supply chain</li> </ul>	Modest, positive	
	A5. Too late (57)	<ul style="list-style-type: none"> <li>Consistently positive throughout 7 days, then a sharp decrease on day 7.</li> <li>Media appears hesitant to cover related incidents negatively, adopting a highly critical and negative stance.</li> </ul>	<ul style="list-style-type: none"> <li>Finance</li> <li>Marketing</li> </ul>	Positive	
<b>B. Buzz Volume</b>	B1. Short Hype (238)	<ul style="list-style-type: none"> <li>Attention gradually increases until incident day, then a gradual decline to pre-incident level on day 7.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Negative	
	B2. Escalator (101)	<ul style="list-style-type: none"> <li>Pattern of building hype, with public attention steadily increasing, then exponentially growing after incident day, reaching a peak by day 7.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Marginal, positive	
	B3. Pre-Hype (75)	<ul style="list-style-type: none"> <li>Buzz starts at its highest level, declines to the lowest point on incident day, then gradually recovers by day 7.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Negative	
	B4. Rollercoaster (70)	<ul style="list-style-type: none"> <li>Buzz fluctuates - rising until day 2, falling to lowest point on incident day; then peaking on day 4 before falling to pre-incident level.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Slightly negative	
<b>C. Twitter Volume</b>	C1. Escalator (155)	<ul style="list-style-type: none"> <li>Pattern of building hype, with UGC volume fiercely growing until event day, then (slower) growth until peak on day 7.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> </ul>	Slightly positive	
	C2. Short Hype (282)	<ul style="list-style-type: none"> <li>UGC volume quickly increases shortly before the event day and then immediately declines to pre-incident level.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> <li>Human resources</li> </ul>	Negative	
	C3. Pre-Hype (21)	<ul style="list-style-type: none"> <li>UGC volume high prior to event but substantially decreases until event day and remains afterwards on a low level.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> </ul>	Marginal, negative	
	C4. Late short dip (14)	<ul style="list-style-type: none"> <li>UGC volume remains at a high level until event day, then takes a dip and recovers post-incident quickly to pre-event level.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> </ul>	Negative	

**Table 3: Crisis Trajectory Characteristics, continued**

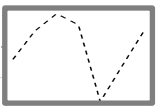
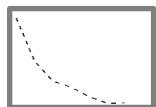
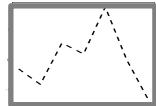
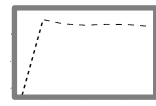
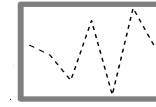

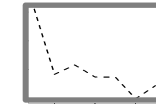
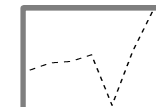
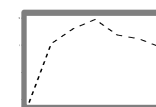
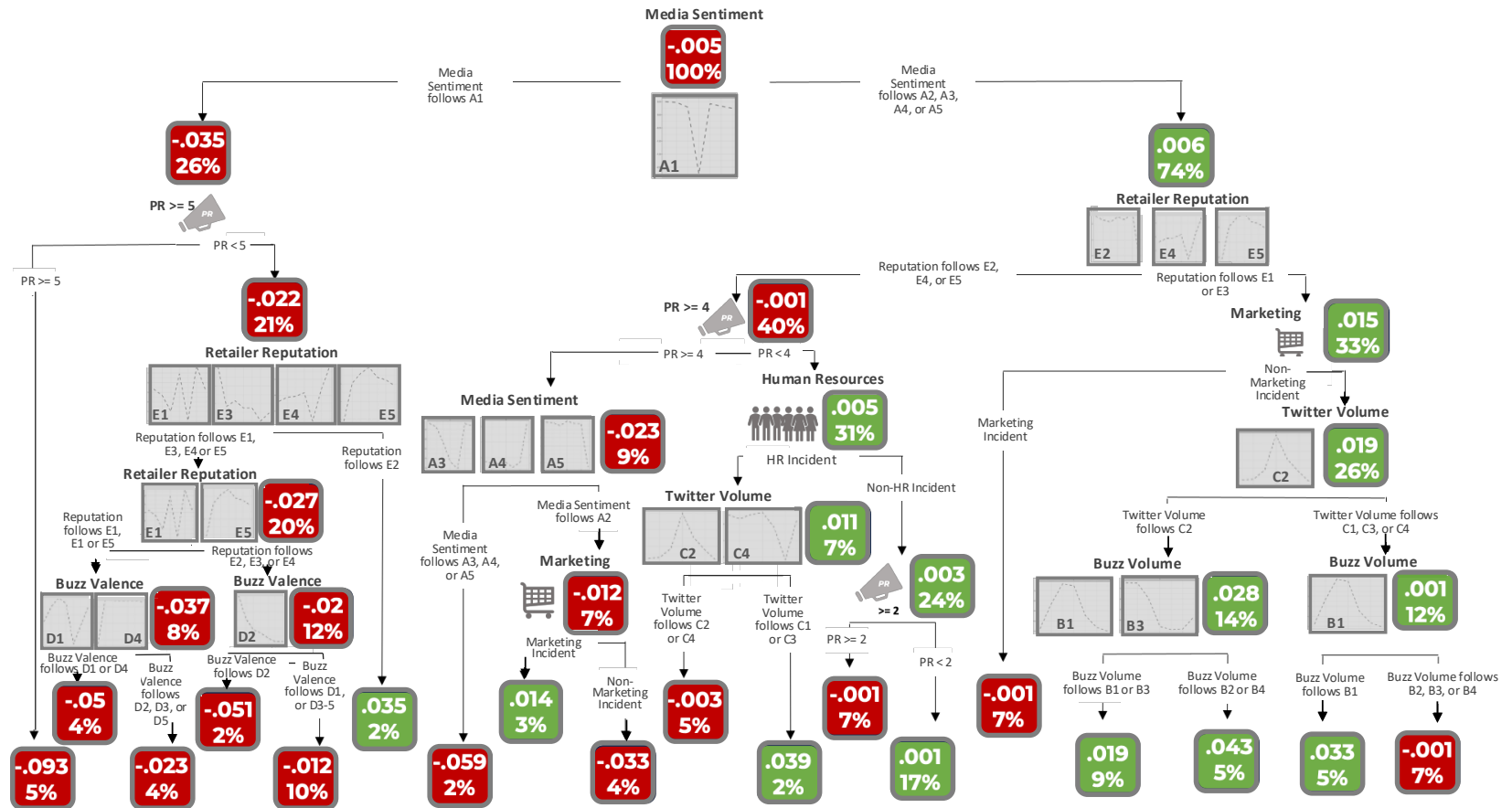
Metric	Trajectory (# of incidents)	Trajectory Characteristics	Prominent Incident Types	Average CARs	Shape
<b>D. Buzz Valence</b>	D1. Late short dip (196)	<ul style="list-style-type: none"> <li>Consumer buzz starts positive, then declines to lowest point on incident day, recovering to initial level thereafter.</li> <li>Suggests intense meandering debate involving brand enthusiasts and critics.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> <li>Human resources</li> </ul>	Marginal, negative	
	D2. Trough (85)	<ul style="list-style-type: none"> <li>Steady decline over entire 7 days.</li> <li>Consumers appear to drive the debate, initiating incidents by alerting the company and other users to an issue.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> <li>Human resources</li> </ul>	Negative	
	D3. Rollercoaster (151)	<ul style="list-style-type: none"> <li>Initial increase in positive sentiment, then rapid decrease in the 3 days post-incident.</li> <li>Consumers appear to develop expectations toward the brand that are unmet, leading to a decline.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Supply chain</li> <li>Marketing</li> </ul>	Negative	
	D4. Hero (47)	<ul style="list-style-type: none"> <li>Ascends early on to peak, remaining there throughout the observed 7 days.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> </ul>	Marginal, average	
<b>E. Retailer Reputation</b>	E1. Rollercoaster (111)	<ul style="list-style-type: none"> <li>Initiates with a brief decrease, recovers towards the mid of the observation window, experiences a second dip followed by a recovery, and concludes with a shorter dip.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Supply chain</li> </ul>	Positive	
	E2. Too late (42)	<ul style="list-style-type: none"> <li>Prolonged positive perception that declines towards the end of the observation period, hitting rock bottom on day 7.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> </ul>	Positive	
	E3. Trough (115)	<ul style="list-style-type: none"> <li>Swift and sustained downfall continuing throughout the 7 days, with no subsequent recovery.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> <li>Human resources</li> </ul>	Negative	
	E4. Escalator (183)	<ul style="list-style-type: none"> <li>Short increase in reputation, that declines sharply on incident day and then quickly recovers to reach a peak towards day 7.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Marketing</li> <li>Supply chain</li> <li>Human resources</li> </ul>	Marginal, negative	
	E5. Star (33)	<ul style="list-style-type: none"> <li>Climb up from the beginning while remaining high throughout the 7 days.</li> </ul>	<ul style="list-style-type: none"> <li>Legal/financial</li> <li>Supply chain</li> </ul>	Negative	

Figure 2: Regression tree with prediction of shareholder reactions



### *Market reactions*

Figure 2 displays the results of the regression tree model. We test the predictive power of our tree with the help of a holdout validation approach, setting aside 20% of our sample as test data (see Kübler, Wieringa, & Pauwels 2017). The resulting Root Mean Square Error (RMSE) of .0755 indicates a good fit. The resulting tree first splits at media sentiment, indicating that incidents that are covered by a *short dip* in media sentiment (trajectory A1) lead to more negative investor reactions than the other trajectories. This A1 trajectory covers 26% of incidents in our sample, yielding on average a negative CAR (-.035). Within this group, only one path leads to positive investor reactions: when retailer reputation follows a *too late* trajectory (A5), we find that investor react on average more positively (CAR .035). As detailed in Table 3, media sentiment remains positive throughout the first 7 days of the incident, plausible given journalistic reluctance to criticize the retailer, and only dips after a week. In these cases, media appears to favor the retailer, and only substantial pressure from other stakeholders seems to force it to something negative after a week. However, this path is reserved to only 2% of our observations.

*The magnitude of negative investor reactions depends largely on how the retailer handles the case.* Our tree model indicates that especially increasing public attention by sending out five or more press releases during our observation window results in more negative CAR (-.093) on average. Thus, while retailers may attempt to protect their brands using their own narratives (Mills & Robson 2019), our results suggest that they may be best served by tempering these efforts. Meanwhile, when retailers address the issue publicly but rely only on a few press releases (fewer than five) we find that investor reactions again depend on the trajectories of retailer reputation as well as how public attention (YouGov Buzz) develops. More negative reactions (-.05 and -.051) result from a combination of reputation following a *rollercoaster* (E1)

or a *Star* trajectory (E5), with buzz valence following either the *late short dip* (D1) or *hero* (D4) trajectory. Milder, but still negative investor reactions, require buzz valence to follow a *trough* (D2), *rollercoaster* (D3) or *escalator* (D5) trajectory which results in average CAR around  $-.023$ .

In the 74% of cases in which media is covering an incident by not following the *short dip* trajectory (A1), investor reactions are on average positive but rather weak ( $+0.006$ ). Our tree model suggest that investors largely focus on how retailer reputation changes throughout the incident period. In case reputation follows the *downfall* (E2), *escalator* (E4), and *star* (E5) trajectories, we find investor reactions to be on average negative ( $-0.001$ ). Again this negative effect can get amplified. Our tree indicates that when retailers communicate too often by sending out more than four press releases surrounding an incident and media actively covers the incident (with trajectories A3 – *long dip*, A4 – *escalator*, and A5 – *too late*), investor investor reactions become by average negative ( $-0.059$ ). Our tree model indicates only one exception for this branch: In case of marketing incidents, we find that investors tend to react positively ( $+0.014$ ). If retailers communicate less frequently through press releases, we find on average weak but positive investor reactions ( $+0.001$ ). However the same branch also indicates another incident type specific finding: In case of human resources related incidents, with strong public attention (Twitter Volume trajectories C2 - *short hype* and C4 –*rollercoaster*) incidents culminate on average in mild negative abnormal returns ( $-0.003$ ).

When media *does not negatively cover an incident* and where company reputation follows a *rollercoaster* (E1) or *trough* (E3) pattern, we find weakly negative CARs in the case of marketing related incidents ( $-0.001$ ). In the case of non-marketing related incidents, we find that short peaks in public attention (trajectory C2 – *short hype*) commonly lead to more positive investor reactions ( $+0.019$ ). Hereby avoiding large changes in buzz valence (D3 – *rollercoaster* as

well as D2 - *trough*) leads to even higher CARs (.043). Finally, when a non-marketing incident receives only short awareness on social media, but follows a *rollercoaster* (D3) buzz valence trajectory, abnormal returns culminate on average at a mildly positive levels (.033), but otherwise turn culminate in a mildly negative level (-.001).

In synthesizing the key findings of our study, it becomes apparent that the timing and nature of a retailer's public communication, particularly in response to negative press, significantly influence investors' reactions. A delayed negative press reaction appears to be advantageous for CAR, suggesting that retailers who strategically manage their brand narrative, even in the face of criticism, can mitigate potential damage. This finding underscores the importance of elements within the retailer's control, such as the frequency of press releases, as we demonstrate further below in an illustration using two retailers in our sample - Dunkin' and McDonald's. While our analysis is predictive and intended to guide retailer decision-making based on observable patterns, it raises intriguing questions regarding the underlying mechanisms, which we propose be examined in future research that delves deeper into these processes. Next, we summarize our findings and discuss important implications for theory and for retailers.

## **Discussion**

Our findings offer strong evidence that retailers' abilities to detect and contribute to the narrative related to different types of negative incidents in the media can impact firm performance. In this section, we discuss managerial implications of our findings and the contributions of our paper to marketing theory. Before discussing implications, however, we summarize our main findings in terms of our research questions and then provide a brief illustration using two of the retailers in our sample – Dunkin' and McDonald's.

### *Summary of findings*

*RQ1) Based on which metrics reflecting the reactions of different stakeholder groups can retailers anticipate the likely trajectory of a negative incident?* Our findings suggest that certain metrics are more important than others in influencing investor reactions to negative retail incidents. Monitoring media sentiment is critical, and if it follows any trajectory other than a *short dip* (A1), there is a greater chance of a positive reaction by investors (14 out of 23 possible outcomes result in positive CAR), with the greatest likelihood of positive CAR occurring if the retailer's reputation score then follows a *rollercoaster* or *trough* (E1 or E3, respectively) trajectory. In those cases, the only negative CAR we observed resulted when both Twitter volume and buzz volume follow any other trajectory than a *short hype* (C2 and B1, respectively). While buzz volume and buzz valence are also important in determining investor reactions, their influence appears to depend on the trajectories of other metrics including media sentiment and Twitter volume as well as incident type. Thus, the trajectory of a retail crisis appears to be heavily influenced by the narratives in both traditional and social media.

*RQ2) Do different incident types matter more than others in terms of the reactions of different stakeholder groups?* Incident types indeed matter, though less than the trajectories we identified. This finding highlights that the dynamic configuration of stakeholder reactions plays a larger role in crisis escalation than the incident category itself. We find that marketing- and human resources-related incidents appear as factors determining the split in the regression tree in various places. Marketing incidents emerge as important branches in the regression tree in two cases. The first case occurs when media sentiment follows any other trajectory than a *short dip* (i.e., follows A2-5) and retailer reputation follows either a *rollercoaster* (E1) or *trough* (E3) trajectory, both of which occur when reputation is already somewhat or very positive, again suggesting an important role for retailer reputation in reducing investor skepticism regarding the

brand's narrative in the wake of negative media sentiment. The second case is if the retailer issues four or more press releases and retailer sentiment experiences a *short hype* (A2), which may combine to help control the brand-related narrative and combat any negative sentiment regarding marketing-related incidents. In this latter case, CAR is positive only for marketing incidents, suggesting that media coverage of the retailer's own voice can indeed boost investors' positive perceptions of marketing incidents.

When media sentiment follows any trajectory other than a *short dip*, human resources incidents also appear as an important branch in the regression tree if retailer reputation follows either an E2, E4, or E5 trajectory, characterized by a positive reputation that either gradually trends negative (E2 or E5) or dips on the incident day but eventually trends positive (E4). Interestingly, the volume of press releases also matters in this case, with fewer press releases leading to human resources incidents emerging as important in determining investor reactions. For human resources incidents, if Twitter volume follows an *escalator* or *pre-hype* (C1 or C3) trajectory, investors respond positively, suggesting that social media can support a positive brand narrative if volume follows more of a steady pattern as opposed to experiencing both ups and downs, as with a C2 or C4 trajectory (*short hype* or *late short dip*, respectively). Finally, if media sentiment follows a *short dip* (A1) trajectory, incident type appears to have no significant role in determining the influence on CAR.

*RQ3) Can we predict the impact of negative incidents on firm performance based on the dynamic reaction patterns of other stakeholder groups?* Our findings shown in the regression tree offer evidence that retail managers may be able predict market reactions to incidents based on how other stakeholders react. We find considerable differences in the impact on CAR based on different trajectories in stakeholder reactions. For example, after media sentiment is observed

following any trajectory other than a *short dip* (following A2-5), investors are likely to react positively if retailer reputation is following either an E1 or E3 trajectory, characterized by a moderate to highly positive reputation that dips relatively early in the event window. Such investor signaling their support for the brand's narrative, is especially likely if the incident is related to issues other than marketing (customer facing), i.e. HR, financial/legal or supply chain/operations issues. If media sentiment does exhibit a *short dip*, retailer reputation again becomes an important factor in determining investor reactions if the retailer issues a smaller number of press releases. Thus, not only can retailers influence the trajectory of a crisis with their own press releases, retailer reputation appears to reduce investors' potential skepticism regarding the brand's narrative in the wake of negative media sentiment.

*An illustrative example*

To illustrate the results shown in Figure 2 and highlight implications for retailers, we contrast Dunkin' and McDonald's in their reaction to negative marketing incidents. Marketing incidents could pertain to advertising campaigns, new products, sales promotions, price changes, or customer experience issues (see Appendix A and Appendix B for details). We choose to examine Dunkin' and McDonald's due to their significant differences in press release volume surrounding incidents—Dunkin' averages 4.82 press releases per incident, whereas McDonald's averages 1.05. Both companies are in the food service industry.

If both Dunkin' and McDonald's experience a *short dip* in media sentiment (A1), the next step is to decide on the number of press releases to issue. According to our data, Dunkin' would issue approximately five press releases, while McDonald's would issue one, suggesting that Dunkin' may favor a more active role in crafting its brand narrative while McDonald's favors a more passive role at least in terms of the volume of press releases. Following the regression tree

in Figure 1, Dunkin' would move to the left branch, resulting in a net decrease in CAR of  $-.093$ . To avoid this fate, we would advise Dunkin' to issue fewer press releases.

For McDonald's, issuing only one press release would then lead to the need to monitor its reputation score. If the score follows a *too late* trajectory (E2), McDonald's can expect a CAR increase of  $.35$  during the seven-day window surrounding the incident. However, if the reputation score follows other trajectories (E1, E3, E4, or E5), the CAR for McDonald's could decrease, ranging from  $-.012$  to  $-.093$ .

These examples underscore the importance of monitoring media sentiment and the critical role of retailer reputation in effectively managing negative incidents. Importantly, managing their ongoing reputation appears to be one way in which retailers can help establish a foundation for telling their own stories in the wake of negative incidents. In addition, the significant role of press release volume, a critical tool retailers can use in crafting their stories, in determining the course of investor reactions becomes clear. Next, we offer managerial guidance based on these illustrations and our findings.

### *Managerial implications*

Our findings equip retail managers with tools to better prioritize response strategies based on evolving stakeholder dynamics rather than isolated incident attributes. Importantly, our findings suggest that retailers need not panic at the first sign of a crisis. Indeed, in seven out of 18 possible outcomes, CAR is positive. As we will highlight below, in addition to the need to monitor key metrics such as media sentiment and retailer reputation, our results highlight the important role retailers themselves play in determining investors' reactions based on their own contributions to the narratives surrounding their brands. We thus highlight the importance of

proactive crisis monitoring and strategic communication responses by retailers in the face of negative incidents.

*Proactive crisis monitoring:* Our findings reveal that when media sentiment follows non-linear trajectories (e.g., A2, A3, A4, or A5), particularly in cases where sentiment either starts low or takes longer to dip, the outcome for the brand can vary significantly depending on the subsequent actions taken. Managers should invest in advanced sentiment analysis tools that can detect these complex trajectories early. For instance, if media sentiment around a brand dips slowly or oscillates (as in the *rollercoaster* trajectory E1), managers should be prepared to act swiftly to stabilize sentiment before it worsens. Tools like DTW can identify early warning signals by analyzing these patterns. Recognizing trajectories such as the short dip or rollercoaster enables managers to anticipate a crisis's course and devise effective responses. By recognizing distinct trajectories such as the *short dip* or *rollercoaster*, managers can anticipate the likely course of a crisis, which can allow them to devise and implement an effective response, contributing to the narrative before it escalates and negatively impacts firm performance.

*Strategic communication responses:* Our results show that the volume of press releases following a marketing incident is critical in shaping investor reactions. Specifically, issuing a high number of press releases (four or more) in response to a marketing incident when media sentiment follows an A2 trajectory can lead to more negative CAR. One implication of this is that managers should focus on quality over quantity in their communications, especially press releases. While doing so would essentially reduce the volume of firms' own voices among others in the narrative of negative incidents, there is evidence from prior research that the content of firms' messages may be an important factor in their effectiveness in weathering crises. For example, Kübler and Albers (2010) show that companies strategically adapt the content of

product recall related press releases, contingent of the type of product issues and the targeted customer group. Furthermore, while Hewett et al. (2016) find that a greater volume of press releases can be useful, these authors similarly find that their effectiveness depends on their content, with more neutral or positive tone having a positive effect on firm performance.

Aside from the tone of firms' messages, there is also evidence that emphasizing particular content in their own brand narratives can help buffer the potential impact of such negative incidents in the media. For instance, prior research suggests that firms with a strong history of CSR activities are perceived more favorably by stakeholders during a crisis, which can mitigate negative reactions (Coombs and Holladay 2006; Dutta and Pullig 2011). To understand potential receptiveness of customers to different messages, we encourage retailers to implement effective stakeholder engagement practices and leverage customer insights to understand their priorities. According to Fombrun and van Riel (2004), maintaining open lines of communication with key stakeholders can foster a supportive network that helps the firm navigate through crises more effectively. Engaging stakeholders through transparent communication can build trust and reduce the likelihood of negative sentiment escalating. This approach is supported by the findings of Luo (2007), who demonstrated that timely and sincere communication during crises can significantly improve a firm's reputation and mitigate financial losses.

*Leveraging retailer reputation:* Our research highlights the importance of retailer reputation in crisis outcomes. For instance, when a retailer's reputation is already somewhat or very positive (following a *rollercoaster* E1 or *trough* E3 trajectory), the impact of subsequent press releases on CAR can be influenced by the type of incident and the trajectory of media sentiment. Retailers with a strong reputation should leverage this asset by ensuring that any public communication reinforces their established brand values (Chun, Da Silva, Davies &

Roper 2005). Managers should also be aware that a positive reputation can act as a buffer, allowing for a more measured response to crises. However, this reputation should be actively managed, as it can quickly deteriorate if not properly maintained during a crisis.

*Avoiding strategic myopia.* A key managerial implication of our findings is that decision-making based on isolated incidents or reactive spikes in media attention may result in poor outcomes. Managers who treat each incident as unique may overlook emerging patterns or divert resources toward events with little long-term impact. This risk is especially acute in retail, where brand exposure is frequent, public-facing, and highly scrutinized—conditions that foster faster action bias in crisis response. The urgency to act quickly can lead to overreaction, particularly when managers rely on volume-based indicators without understanding trajectory patterns. Our results show that the shape and evolution of stakeholder responses—rather than their volume alone—are more predictive of performance outcomes. Monitoring these aggregate trajectories and cross-metric dynamics may help managers better prioritize response efforts, avoid overreach, and support more strategic, evidence-based crisis decisions.

#### *Theoretical implications*

Our findings contribute to research on crisis communication, stakeholder dynamics, and market signaling by introducing an empirically grounded framework for understanding how stakeholder reactions unfold. Unlike prior studies relying on one-off crisis events or content interpretations, we identify recurring temporal trajectory patterns across media sentiment, consumer mindset, and social media buzz—each reflecting how crises evolve and escalate (Hansen et al. 2018; Pfeffer et al. 2014; Zavyalova et al. 2012). This approach extends prior work on information flows (Berger and Milkman 2012), multichannel brand communication (Hewett et al. 2016), and digital discourse dynamics (Arvidsson & Caliandro 2016) by

emphasizing timing, interaction, and signal integration as key explanatory dimensions. In doing so, we provide a dynamic, multi-stakeholder lens for understanding brand crises.

Our theoretical contribution centers on the concept of strategic myopia, extending the foundational logic of marketing myopia (Levitt 1960) into crisis detection and response. While traditional models emphasize what firms say during a crisis, we emphasize when and how stakeholders respond—and show that trajectory patterns in sentiment, attention, and consumer mindset predict outcomes. Managers who focus solely on isolated spikes or high-visibility events may misallocate attention and resources. Recognizing structured patterns across stakeholder groups offers a way to interpret ambiguous signals, reduce uncertainty, and prevent overreaction (Pauwels 2014; Hewett et al. 2016). Our findings enrich theory on managerial decision-making under uncertainty, offering a temporal, multi-source corrective to reactive crisis management.

More broadly, our approach invites future theory to account for trajectory-based dynamics in stakeholder communication and organizational response. While prior work has theorized about the roles of individual channels (e.g., social media, traditional press) or specific stakeholder voices (e.g., customers, investors), our model emphasizes their interdependence over time. Introducing trajectory-based crisis patterns and clustering stakeholder reactions over time, our findings extend prior work on dynamic stakeholder behavior (Hewett et al. 2016; Zavyalova et al. 2012) and digital media dynamics (Berger & Milkman 2012; Hansen et al. 2018; Pfeffer et al. 2014), offering a multichannel framework that advances theory on organizational resilience, crisis evolution, and decision-making under uncertainty.

### ***Limitations and future research directions***

Our study is not without limitations. First, we have focused on a limited set of industries and firms, specifically within the retail sector. While this provides a concentrated view of crisis

management in this particular context, it may limit the generalizability of our findings to other industries. Future research could expand the scope to include a broader range of industries, such as technology, healthcare, or finance, to examine whether the identified patterns and managerial implications hold across different sectors.

Second, our analysis focuses on U.S. retailers during the 2010–2015 period, and future work should validate the generalizability of trajectory patterns across other retail categories, geographic markets, and time periods. In particular, the social media landscape has evolved significantly, and replicating this analysis on newer platforms (e.g., TikTok or Instagram) could further test the robustness of stakeholder dynamics identified here.

Third, our analysis primarily adopts an external view, concentrating on media sentiment, social media buzz, and consumer perceptions without delving into internal actions firms take beyond press release volume. Changes in advertising spend, internal communications, and operational adjustments are crucial factors influencing the trajectory and impact of a crisis. Future studies should incorporate a broader set of internal firm responses to better understand their role in mitigating negative incidents. For example, prior research has examined firms' use of empathy (Herhausen et al. 2023), private versus monolog responses (Argyris et al. 2021), and tailored responses based on arousal levels (Herhausen et al. 2019) in social media, as well as service interventions (Sun, Gao, and Rui 2021). While retailers can act on the "what" in managing brand narratives based on knowledge that strategic communication timing yields benefits, future research is needed to better understand the "why" behind our observations.

Fourth, the time period examined in this study may not capture the evolving dynamics of social media use and its impact on crisis management. Future research should consider

longitudinal studies that track these dynamics over a longer period, incorporating more recent data to account for the latest trends and platform developments.

Additionally, while our study employs DTW to identify patterns in media sentiment and consumer reactions, this method has its limitations. DTW is effective for time series clustering, but it may not fully capture the complexity and nuances of crisis narratives. Future research could explore the use of advanced machine learning techniques and natural language processing to analyze the sentiment and content of media and social media posts more granularly.

Furthermore, our study does not account for potential moderating effects of firm-specific characteristics, such as retailer size, market position, and prior reputation. These factors could significantly influence how a crisis is managed and perceived. Future research should examine these variables to provide a more nuanced understanding of retailers' crisis management strategies. We encourage research to assess the role of firm-related boundary conditions on investor reactions to negative incidents. For example, we found support for the critical role of retailer reputation trajectories in investors' reactions. Future studies should examine whether the impact of such trajectories depends on the retailer's reputation prior to the incident.

Finally, there is a need for further investigation into the long-term effects of crisis management strategies on firm performance. While our study focuses on the immediate aftermath of negative incidents, understanding the sustained impact on brand reputation and financial performance is crucial for developing effective crisis management frameworks. Future research should examine longer-term impacts of negative incidents on retailer or brand reputation. Similarly, a longer-term view of retailer responses, such as press releases, would help inform retailers' strategies for detecting and mitigating the impact of negative incidents.

## References

- Abbassi, W., Kumari, V., & Pandey, D. K. (2022), "What makes firms vulnerable to the Russia–Ukraine crisis?," *The Journal of Risk Finance*, 24 (1), 24-39.
- Arbelaitz, Olatz, Ibai Gurrutxaga, Javier Muguerza, Jesús M. Pérez, and Iñigo Perona (2013), "An Extensive Comparative Study of Cluster Validity Indices," *Pattern Recognition* 46 (1), 243-256.
- Argyris, Young Anna, Kafui Monu, Yongsuk Kim, Yilu Zhou, Zuhui Wang, and Zhaozheng Yin (2021), "Using Speech Acts to Elicit Positive Emotions for Complainants on Social Media," *Journal of Interactive Marketing*, 55 (1), 67-80.
- Arvidsson, Adam, and Alessandro Caliandro (2016), "Brand Public: How Brands Create Value in Social Media," *Journal of Consumer Research*, 42 (5), 727-748.
- Ashby-King, Drew T. and Ashley N. Aragón (2022), "Reinforcing and Challenging Whiteness through Crisis Communication: Proposing a Discourse of Community Repair," *Public Relations Review*, 48 (1), 102139.
- Bar-Eli, Michael, Ofer H. Azar, Ilana Ritov, Yael Keidar-Levin, and Galit Schein (2007), "Action Bias among Elite Soccer Goalkeepers: The Case of Penalty Kicks," *Journal of Economic Psychology*, 28(5), 606-621.
- Berger, Jonah, and Katherine L. Milkman (2012), "What Makes Online Content Viral?," *Journal of Marketing Research*, 49 (2), 192-205.
- Berger, Jonah, and Raghuram Iyengar (2013), "Communication Channels and Word of Mouth: How the Medium Shapes the Message," *Journal of Consumer Research*, 40 (3), 567-579.
- Bickart, Barbara, and Robert M. Schindler (2001), "Internet Forums as Influential Sources of Consumer Information," *Journal of Interactive Marketing*, 15 (3), 31-40.
- Borah, Abhishek, and Gerard J. Tellis (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.
- Chen, Yubo, Shankar Ganesan, and Yong Liu (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.
- Chun, Rosa, Rui Da Silva, Gary Davies, and Stuart Roper. *Corporate Reputation and Competitiveness*. Routledge, 2005.
- Cleeren, Kathleen, Harald J. van Heerde, and Marnik G. Dekimpe (2013), "Rising from the Ashes: How Brands and Categories Can Overcome Product-Harm Crises," *Journal of Marketing*, 77 (2), 58-77.
- Colicev, Anatoli, Ashwin Malshe, Koen Pauwels, and Peter O'Connor (2018), "Improving Consumer Mindset Metrics and Shareholder Value through Social Media: The Different Roles of Owned and Earned Media," *Journal of Marketing*, 82 (1), 37-56.

- Conway, Tony, Mike Ward, Gerard Lewis, and Anke Bernhardt (2007), "Internet Crisis Potential: The Role of the Internet in Disseminating Information During Crises," In *Public Relations Issues and Crisis Management* (213-214). Cape Town: Juta.
- Coombs, W. Timothy, and Sherry J. Holladay (2006), "Unpacking the halo effect: Reputation and crisis management." *Journal of Communication Management*, 10 (2), 123-137.
- Coombs, W. Timothy (2007), "Protecting Organization Reputations During a Crisis: The Development and Application of Situational Crisis Communication Theory," *Corporate Reputation Review*, 10 (3), 163–176.
- Coombs, W. Timothy, and J. Sherry Holladay (2012), "The Paracrisis: The Challenges Created by Publicly Managing Crisis Prevention," *Public Relations Review*, 38 (3), 408-41
- Dawar, Niray and Madan M. Pillutla (2000), "Impact of Product Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (2), 215–226.
- De'ath, Glenn, and Katharina E. Fabricius (2000), "Classification and Regression Trees: A Powerful yet Simple Technique for Ecological Data Analysis," *Ecology*, 81 (11), 3178-3192
- De Vries, Lisette, Sonja Gensler, and Peter S.H. Leeflang (2017), "Effects of Traditional Advertising and Social Messages on Brand-Building Metrics and Customer Acquisition," *Journal of Marketing*, 81 (5), 1-15.
- Dholakia, Utpal M., and Kerry Soltysinski (2001), "Coveted or Overlooked? The Psychology of Bidding for Comparable Listings in Digital Auctions," *Marketing Letters*, 12 (3), 225-237.
- Dutta, Sujay, and Chris Pullig (2011), "Effectiveness of Corporate Responses to Brand Crises: The Role of Crisis Type and Response Strategies," *Journal of Business Research* 64 (12), 1281-1287.
- Egan, Matt (2018), "Wells Fargo customers are fed up. They Could Yank Billions of Dollars in Deposits," CNN Business, October 10. Retrieved April 4, 2020 at: <https://www.cnn.com/2018/10/10/business/wells-fargo-bank-customers-scandal/index.html>
- Eilert, Meike, Satish Jayachandran, Kartik Kalaiganam, and Tracey A. Swartz (2017), "Does It Pay to Recall Your Product Early? An Empirical Investigation in the U.S. Automobile Industry," *Journal of Marketing*, 81 (3), 111-129.
- Escalas, Jennifer Edson (2004), "Narrative Processing: Building Consumer Connections to Brands," *Journal of Consumer Psychology*, 14 (1-2), 168–180.
- Feiereisen, Stephanie, Dina Rasolofoarison, Cristel Antonia Russell, and Hope Jensen Schau (2021), "One Brand, Many Trajectories: Narrative Navigation in Transmedia," *Journal of Consumer Research*, 48 (4), 651-681.
- Food & Wine (2023), "World's Largest Fast Food Chains," June 20: <https://www.foodandwine.com/lifestyle/worlds-largest-fast-food-chains>

- Fombrun, Charles J., and Cees B.M. van Riel (2004). *Fame & Fortune: How Successful Companies Build Winning Reputations*. Financial Times Prentice Hall.
- Gao, Yang, Xiaoquan Zhang, Xun Wang, and Weizeng Wang (2015), "The Impact of Brand Crises on Brand Trust and Brand Loyalty: An Empirical Analysis of the Automobile Industry," *Journal of Business Research*, 68 (3), 452-460.
- Gelper, Sarah, Renana Peres, and Jehoshua Eliashberg (2018), "Talk Bursts: The Role of Spikes in Prerelease Word-of-Mouth Dynamics," *Journal of Marketing Research*, 55 (6), 801-817.
- Gijzenberg, Maarten J., Harald J. van Heerde, and Peter C. Verhoef (2015), "Losses Loom Longer than Gains: Modeling the Impact of Service Crises on Perceived Quality over Time," *Journal of Marketing Research*, 52 (5), 642-656.
- Goffman, E. (1974), *Frame analysis: An Essay on the Organization of Experience*. Cambridge, MA: Harvard University Press.
- Goffman, E. (1976), "Replies and Responses," *Language in Society*, 5, 257-313.
- Golder, Peter N., Marnik G. Dekimpe, Jake T. An, Harald J. van Heerde, Joseph W. Alba (2022), "Learning from Data: An Empirics-First Approach to Knowledge Generation in Marketing," *Journal of Marketing*, 87 (3), 319-336.
- Goldstein, Morris, Graciela Laura Kaminsky, and Carmen M. Reinhart (2000). *Assessing Financial Vulnerability: An Early Warning System for Emerging Markets*. Peterson Institute.
- Green, Donald P., and Holger L. Kern (2012), "Modeling Heterogeneous Treatment Effects in Survey Experiments with Bayesian Additive Regression Trees," *Public Opinion Quarterly*, 76 (3), 491-511.
- Gruen, Thomas W., Talai Osmonbekov, and Andrew J. Czaplewski (2006), "eWOM: The Impact of Customer-to-Customer Online Know-How Exchange on Customer Value and Loyalty," *Journal of Business Research*, 59 (4), 449-456.
- Hansen, Nele, Ann-Kristin Kupfer, and Thorsten Hennig-Thurau (2018), "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*, 35 (4), 557-574.
- Hennig-Thurau, Thorsten, Kevin P. Gwinner, Gianfranco Walsh, and Dwayne D. Gremler (2004), "Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet," *Journal of Interactive Marketing*, 18 (1), 38-52.
- Herhausen, Dennis, Lauren Grewal, Krista Hill Cummings, Anne L. Roggeveen, Francisco, Villaroel Ordenes, and Dhruv Grewal (2023), "Complaint De-escalation Strategies on Social Media," *Journal of Marketing*, 87 (2), 210-231.
- Herhausen, Dennis, Stephan Ludwig, Dhruv Grewal, Jochen Wulf, and Marcus Schoegel (2019), "Detecting, Preventing, and Mitigating Online Firestorms in Brand Communities," *Journal of Marketing*, 83 (3), 1-21.

- Hewett, Kelly, William Rand, Roland T. Rust, and Harald J. van Heerde (2016), "Brand Buzz in the Echoverse," *Journal of Marketing*, 80 (3), 1-24.
- Hölzle, Katharina, Harry Boer, and Jennie Björk (2020), "Crisis Management through Creativity and Innovation: Storytelling, Moral Organizational Creativity, and Open Innovation as Creative Means to Spark Innovation," *Creativity & Innovation Management*, 29 (2), 195-197.
- Howell, Gordon A., and Ronald L. Miller (2006), "The Importance of Sound Crisis Communication in Reputation Management," *Journal of Public Relations Research*, 18 (2), 123-145.
- Hsu, Liwu, and Benjamin Lawrence (2016), "The Role of Social Media and Brand Equity During a Product Recall Crisis: A Shareholder Value Approach," *International Journal of Research in Marketing*, 33 (1), 59-77.
- Kamleitner, Bernadette, Carina Thurrndl, and Brett A.S. Martin (2019), "A Cinderella Story: How Past Identity Salience Boosts Demand for Repurposed Products," *Journal of Marketing*, 83 (6), 76-92.
- Kang, Charles, Frank Germann, and Rajdeep Grewal (2016), "Washing Away Your Sins? Corporate Social Responsibility, Corporate Social Irresponsibility, and Firm Performance," *Journal of Marketing*, 80 (2), 59-79.
- Khamitov, Mansur, Yany Grégoire, and Anshu Suri (2020), "A Systematic Review of Brand Transgression, Service Failure Recovery and Product-Harm Crisis: Integration and Guiding Insights," *Journal of the Academy of Marketing Science*, 48 (3), 519–542.
- Kleine, Janina, Nico Friederich, N., and Michael Paul (2023), "Celebrity Endorser Scandals and Competitor Firm Value," *Journal of Advertising*, 1-16.
- Krush, Michael T., Raj Agnihotri, Kevin J. Trainor, and Edward L. Nowlin (2013), "Enhancing Organizational Sensemaking: An Examination of the Interactive Effects of Sales Capabilities and Marketing Dashboards," *Industrial Marketing Management*, 42 (5), 824-835.
- Krush, Michael T., Raj Agnihotri, and Kevin J. Trainor (2016), "A Contingency Model of Marketing Dashboards and Their Influence on Marketing Strategy Implementation Speed and Market Information Management Capability," *European Journal of Marketing*, 50 (12), 2077-2102.
- Kübler, Raoul V., and Sönke Albers (2010), "Communication Behavior of Companies in Product Recalls without Customer Identification Information," *Marketing-Journal of Research and Management*, 6(1), 19-30.
- Kübler, Raoul V., Michael Langmaack, Sönke Albers, and Wayne D. Hoyer (2020), "The Impact of Value-related Crises on Price and Product-performance Elasticities," *Journal of the Academy of Marketing Science*, 48, 776-794.
- Laufer, Daniel, and W. Timothy Coombs (2006), "How Should a Company Respond to a Product Harm Crisis? The Role of Corporate Reputation and Consumer-Based Cues," *Business Horizons*, 49 (5), 379–385.

- Levitt, Theodore (1960), "Marketing Myopia," *Harvard Business Review*, 38(4), 45–56.
- Lin, Xialing, Jason Crowe, and Mylene Pierre (2011), "The Role of Brand Equity in Corporate Social Responsibility: Evidence from the U.S. Market," *Journal of Marketing*, 75(3), 123-135.
- Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing*, 70 (3), 74-89.
- Liu, Yan and Venkatesh Shankar (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, Yan, Venkatesh Shankar, and Wonjoon Yun (2017), "Crisis Management Strategies and the Long-Term Effects of Product Recalls on Firm Value," *Journal of Marketing*, 81 (5), 30-48.
- Loh, Wei-Yin (2011), "Classification and Regression Trees," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 1 (1), 14-23.
- Lungeanu, Razvan, Srikanth Paruchuri, and Wenpin Tsai (2017), "Stepping Across for Social Approval: Ties to Independent Foundations' Boards After Financial Restatements," *Strategic Management Journal*, 39 (4), 1163-1187.
- Luo, Xueming (2007), "Consumer Negative Voice and Firm-Idiosyncratic Stock Returns," *Journal of Marketing*, 71 (3), 75-88.
- Luo, Xueming, Sascha Raithel, and Michael A. Wiles (2013), "The Impact of Brand Rating Dispersion on Firm Value," *Journal of Marketing Research*, 50 (3), 399-415.
- Ma, Liye, Baohong Sun, and Sunder Kekre (2015), "The Squeaky Wheel Gets the Grease: An Empirical Analysis of Customer Voice and Firm Intervention on Twitter," *Marketing Science*, 34 (5), 627-645.
- McAlister, Leigh, Garrett Sonnier, and Tom Shively (2012), "The Relationship Between Online Chatter and Firm Value," *Marketing Letters*, 23 (1), 1-12.
- McCombs, Maxwell E., and Donald L. Shaw (1972), "The Agenda-Setting Function of Mass Media," *Public Opinion Quarterly*, 36 (2), 176–187.
- McCoy, Kevin. (2017), "Target to Pay \$18.5M for 2013 Data Breach that Affected 41 million Consumers," USA Today, May 23:  
<https://www.usatoday.com/story/money/2017/05/23/target-pay-185m-2013-data-breach-affected-consumers/102063932/>
- McCullough, Daryl (2018), "What Does It Take To Control A Brand Crisis Today?," Forbes.com: <https://www.forbes.com/sites/forbesagencycouncil/2018/03/15/what-does-it-take-to-control-a-crisis-today/#2c003ddd23dd>
- McGovern, Gail, David Court, John A. Quelch, and Blair Crawford. (2004), "Bringing Customers into the Boardroom," *Harvard Business Review*, 82 (11), 70-81.

- McQuarrie, Edward F., Jessica Miller, and Barbara J. Phillips (2012), "The Megaphone Effect: Taste and Audience in Fashion Blogging," *Journal of Consumer Research*, 40 (1), 136-158.
- Meire, Matthijs, Kelly Hewett, Michel Ballings, V. Kumar, and Dirk Van den Poel, (2019), "The Role of Marketer-Generated Content in Customer Engagement Marketing," *Journal of Marketing*, 83 (6), 21-42.
- Meyersohn, Nathaniel (2023), "Pride Month backlash hurt Target's sales. They fell for the first time in six years", *CNN News*, August 16, <https://www.cnn.com/2023/08/16/investing/target-stock-earnings/index.html>
- Miller, Arthur (1949), "Tragedy and the Common Man," *The New York Times*, February 27: [https://archive.nytimes.com/www.nytimes.com/books/00/11/12/specials/miller-common.html?\\_r=1&oref=slogin](https://archive.nytimes.com/www.nytimes.com/books/00/11/12/specials/miller-common.html?_r=1&oref=slogin)
- Mills, Adam J., and Karen Robson (2019), "Brand Management in the Era of Fake News: Narrative Response as a Strategy to Insulate Brand Value," *Journal of Product & Brand Management*, 29 (2), 159-167.
- Mitchell, Ronald K., Bradley R. Agle, and Donna J. Wood (1997), "Toward a Theory of Stakeholder Identification and Salience: Defining the Principle of Who and What Really Counts," *Academy of Management Review*, 22 (4), 853–86.
- Mosley, Buffy, David A. Schweidel, and Kunpeng Zhang (2024), "When Connection Turns to Anger: How Consumer–brand Relationship and Crisis Type Moderate Language on Social Media," *Journal of Consumer Research*, 50 (5), 907-922.
- Oberlo. (2024). Global Retail Sales (2018–2024). Retrieved from <https://www.oberlo.com/statistics/global-retail-sales>
- O'Sullivan, Don, and Andrew V. Abela (2007), "Marketing Performance Measurement Ability and Firm Performance," *Journal of Marketing*, 71 (2), 79-93.
- Paparrizos, John, and Luis Gravano (2017), "Fast and Accurate Time-series Clustering," *ACM Transactions on Database Systems (TODS)* 42 (2), 1-49.
- Patt, Anthony, and Richard Zeckhauser (2000), "Action Bias and Environmental Decisions," *Journal of Risk and Uncertainty*, 21, 45-72.
- Pauwels, Koen (2014). *It's Not the Size of the Data--it's how You Use it: Smarter Marketing with Analytics and Dashboards*. Amacom.
- Pauwels, Koen, and Amit Joshi (2016), "Selecting Predictive Metrics for Marketing Dashboards: An Analytical Approach," *Journal of Marketing Behavior*, 2 (2–3), 195–224
- Pauwels, Koen, Tim Ambler, Bruce H. Clark, Pat LaPointe, David Reibstein, Bernd Skiera, Berend Wierenga, and Thorsten Wiesel (2009), "Dashboards as a Service: Why, What, How, and What Research is Needed?," *Journal of Service Research*, 12 (2), 175-89.
- Pauwels, Koen, and Bernadette van Ewijk (2020), "Enduring Attitudes and Contextual Interest: When and Why Attitude Surveys Still Matter in the Online Consumer Decision Journey," *Journal of Interactive Marketing*, 52 (1), 20-34.

- Pfeffer, Jürgen, Thomas Zorbach, and Kathleen M. Carley (2014), "Understanding Online Firestorms: Negative Word-of-Mouth Dynamics in Social Media Networks," *Journal of Marketing Communications*, 20 (3-4), 117-128.
- Puzakova, Marina, Hyokjin Kwak, and Joseph F. Rocereto (2013), "When Humanizing Brands Goes Wrong: The Detrimental Effect of Brand Anthropomorphization Amid Product Wrongdoings," *Journal of Marketing*, 77 (3), 81-100
- Rasoulilian, Shiva, Yujie Xie, and Christian Homburg (2017), "The Effects of Service Crises and Recovery Resources on Market Reactions," *Journal of Service Research*, 20 (2), 154-171.
- Reid, Emma, and Katherine Duffy (2018), "A Netnographic Sensibility: Developing the Netnographic/Social Listening Boundaries," *Journal of Marketing Management*, 34 (3-4), 263-286.
- Sardá-Espinosa, Alexis (2017), "Comparing Time-series Clustering Algorithms in r Using the dtwclust Package," *R package vignette*, 12, 41.
- Sarda-Espinosa, Alexis, Maintainer Alexis Sarda, and T. R. U. E. LazyData (2018), "Package 'dtwclust'." *Pobrane z: <http://cran.ma.imperial.ac.uk/web/packages/dtwclust/dtwclust.Pdf>*.
- Scholz, Joachim and Andrew M. Smith (2019), "Branding in the Age of Social Media Firestorms: How to Create Brand Value by Fighting Back Online," *Journal of Marketing Management*, 35 (11-12), 1100-1134.
- Shiu, Yung-Ming and Shou-Lin Yang (2017), "Does Engagement in Corporate Social Responsibility Provide Strategic Insurance-like Effects?," *Strategic Management Journal*, 38 (2), 455-470.
- Singh, Sangeeta, and Stephan Sonnenburg (2012), "Brand Performances in Social Media," *Journal of Interactive Marketing*, 26, 189-197.
- Sonnier, Garrett P., Leigh McAlister, and Oliver J. Rutz (2011), "A Dynamic Model of the Effect of Online Communications on Firm Sales," *Marketing Science*, 30 (4), 702-716.
- Sorescu, Alina, Nooshen Warren, and Larissa Ertekin (2017), "Event Study Methodology in the Marketing Literature: An Overview," *Journal of the Academy of Marketing Science*, 45 (2), 186-207.
- Srinivasan, Shuba, Marc Vanhuele, and Koen Pauwels (2010), "Mind-Set Metrics in Market Response Models: An Integrative Approach," *Journal of Marketing Research*, 47 (4), 672-84.
- Srinivasan, Raji, and Gülen Sarial-Abi (2021), "When Algorithms Fail: Consumers' Responses to Brand Harm Crises Caused by Algorithm Errors," *Journal of Marketing*, 85 (5), 74-91.
- Stäbler, Samuel, and Marc Fischer (2020), "When Does Corporate Social Irresponsibility Become News? Evidence from More Than 1,000 Brand Transgressions Across Five Countries," *Journal of Marketing*, 84 (3), 46-67.

- Stephen, Andrew T., and Jeff Galak (2012), "The Effects of Traditional and Social Earned Media on Sales: A Study of a Microlending Marketplace," *Journal of Marketing Research*, 49 (5), 624-39.
- Suler, John (2004), "The Online Disinhibition Effect," *Cyberpsychology & Behavior*, 7 (3), 321-326.
- Sun, Shujing, Yang Gao, and Huaxia Rui (2021), "Does Active Service Intervention Drive More Complaints on Social Media? The Roles of Service Quality and Awareness," *Journal of Management Information Systems*, 38 (3), 579-611.
- Swait, Joffre, Tulin Erdem, and Tom Peters (2014), "Shocks to Brand Equity: An Information Economics Perspective on the US Auto Industry 2006-2011," *Customer Needs and Solutions*, 1 (4), 317-32.
- Tang, Tanya (Ya), Eric (Er) Fang, and Feng Wang (2014), "Is Neutral Really Neutral? The Effects of Neutral User-Generated Content on Product Sales," *Journal of Marketing*, 78 (4), 41-58.
- Thirumalai, Sriram and Kingshuk K. Sinha (2011), "Product Recalls in the Medical Device Industry: An Empirical Exploration of the Sources and Financial Consequences," *Management Science*, 57 (2), 376-392.
- Tirunillai, Seshadri, and Gerard J. Tellis (2012), "Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance," *Marketing Science*, 31 (2), 198-215.
- Tripodi, Joe (2011), "Coca-Cola Marketing Shifts from Impressions to Expressions," *Harvard Business Review*, April 27. Retrieved July 18, 2023 at: <https://hbr.org/2011/04/coca-colas-marketing-shift-fro>
- Trusov, Michael, Randolph E. Bucklin, and Koen Pauwels (2009), "Effects of Word-of-Mouth versus Traditional Marketing: Findings from an Internet Social Networking Site," *Journal of Marketing*, 73 (5), 90-102.
- Tyler, Lisa (2005), "Towards a Postmodern Understanding of Crisis Communication," *Public Relations Review*, 31 (4), 566-571.
- Villaroel Ordenes, Francisco, Dhruv Grewal, Stephan Ludwig, Ko de Ruyter, Dominik Mahr, and Martin Wetzels (2018), "Cutting through Content Clutter: How Speech and Image Acts Drive Consumer Sharing of Social Media Brand Messages," *Journal of Consumer Research*, 45 (5), 988-1012.
- Vogler, Christopher (2007). *The Writer's Journey: Mythic Structure for Writers* (3rd ed.). Michael Wiese Productions.
- Wang, Weizeng, Gaofan Lyu, Yuliang Shi, and Xun Liang (2018), "Time Series Clustering Based on Dynamic Time Warping," In *2018 IEEE 9th international conference on software engineering and service science (ICSESS)*, 487-490.
- Wiles, Michael A., Neil A. Morgan, and Lopo L. Rego (2010), "Brand Investment, Brand Performance, and Stock Returns," *Journal of Marketing*, 74 (6), 44-66.

- Wei, Jiuchang, Zhe Ouyang, Haipeng (Allan) Chen, (2017), "Well-Known or Well-Liked? The Effects of Corporate Reputation on Firm Value at the Onset of a Corporate Crisis," *Strategic Management Journal*, 38 (10), 2103-2120.
- Weick, Karl E. (1995). *Sensemaking in Organizations*. Sage.
- Yang, Ming, Melody Kiang, and Wei Shang (2015), "Filtering Big Data from Social Media – Building an Early Warning System for Adverse Drug Reactions," *Journal of Biomedical Informatics*, 54, 230-240.
- Yildirim, Gökhan, and Raoul V. Kübler (2023). *Applied Marketing Analytics Using R*. Sage Publications Ltd.
- Yu, Ying, Li Huang, Ping Qing, and Tong Chen (2022), "How Humor Reduces the Impact of Negative Feedback on Social Media," *Journal of Interactive Marketing*, 57 (4), 601-613.
- Zeelenberg, Marcel, Kees Van den Bos, Eric Van Dijk, and Rik Pieters (2002), "The Inaction Effect in the Psychology of Regret," *Journal of Personality and Social Psychology*, 82 (3), 314-327.
- Zavyalova, Anastasiya, Michael D. Pfarrer, Rhonda K. Reger, and Debra L Shapiro, (2012), "Managing the Message: The Effects of Firm Actions and Industry Spillovers on Media Coverage Following Wrongdoing," *Academy of Management Journal*, 55 (5), 1079-1101.

## Appendix

### Appendix A: Full set of codes for news events with key words

<p><u>Company Performance (PERF)</u></p> <ul style="list-style-type: none"> <li>• Declaration of distributions</li> <li>• New account awarded</li> <li>• Growth</li> <li>• Financial results, dividends</li> <li>• Stock repurchase or performance</li> <li>• Sales/profit report</li> <li>• Quarterly report</li> <li>• 8K – current report, other events</li> <li>• 8K – regulation fd</li> <li>• 8K – operations/financial cond.</li> <li>• 10K report</li> <li>• Conference call/meeting</li> <li>• Stock split/reverse split</li> <li>• Earnings report</li> <li>• Market share</li> <li>• Cost cutting program</li> </ul>	<p><u>Executive/Board Member Issues (EXEC)</u></p> <ul style="list-style-type: none"> <li>• Board member</li> <li>• Appointment, new leader</li> <li>• Resignation, retired</li> <li>• Retirement</li> <li>• Compensation</li> <li>• Benefits</li> <li>• Executive performance</li> <li>• Executive scandal</li> <li>• Executive/board non-work activities</li> <li>• Executive stock disposition/acquisition</li> <li>• Executive change in interest</li> <li>• Executive transactions</li> <li>• Promotion</li> <li>• Founder</li> <li>• Company scandal</li> <li>• Director’s dealings</li> </ul>	<p><u>Personnel Issues (PERS)</u></p> <ul style="list-style-type: none"> <li>• Non-executive</li> <li>• Personnel</li> <li>• Employee benefit/program</li> <li>• New hires</li> <li>• Talent</li> <li>• Compensation</li> <li>• Benefits</li> <li>• Lay-offs, job cuts</li> <li>• Labor strike</li> <li>• Labor union issues</li> <li>• Labor contract negotiations</li> <li>• Overtime</li> <li>• Contract labor</li> <li>• Agents</li> <li>• Staffing decisions</li> <li>• Personnel scandal</li> <li>• Pension deficit</li> </ul>
<p><u>Analyst/Economist Reports (ECON)</u></p> <ul style="list-style-type: none"> <li>• Recession</li> <li>• Trading</li> <li>• Economic growth</li> <li>• Analyst forecast/opinion of performance</li> <li>• Buy rating</li> <li>• International relations</li> <li>• Political issues, election</li> <li>• Government committees</li> </ul>	<p><u>Award/Recognition (RECO)</u></p> <ul style="list-style-type: none"> <li>• Presentation</li> <li>• Industry meeting</li> <li>• Ranking</li> <li>• Top U.S.</li> <li>• Certifications</li> <li>• Conference</li> <li>• Ring stock market opening/closing bell</li> </ul>	<p><u>Customer Service – (CSVC)</u></p> <ul style="list-style-type: none"> <li>• Customer experiences</li> <li>• Customer reviews</li> <li>• Bad customer service</li> <li>• Good customer service</li> <li>• Decrease in rating</li> <li>• Increase in rating</li> <li>• Customer accommodations</li> <li>• Customer convenience</li> </ul>
<p><u>Mergers/Acquisitions/Partnerships (MERG)</u></p> <ul style="list-style-type: none"> <li>• Agreement</li> <li>• Partnership</li> <li>• Joint venture</li> <li>• Licensing agreement</li> <li>• Strategic relationship</li> <li>• Collaboration</li> <li>• Restructuring</li> <li>• Company buy-out</li> <li>• Alliance</li> <li>• Franchise sale</li> <li>• Management statement</li> <li>• Divestment/divestiture</li> </ul>	<p><u>Supplier Issues (SUPP)</u></p> <ul style="list-style-type: none"> <li>• Supply chain management software provider</li> <li>• Transportation software provider</li> <li>• Raw material supplier</li> <li>• Packaging supplier</li> <li>• Outsourcing</li> <li>• Supplier quality control</li> <li>• Manufacturer</li> <li>• Parts supplier</li> <li>• Equipment maintenance service</li> <li>• Supplier bid/contract</li> <li>• Consulting firm</li> <li>• Service contract</li> <li>• Enterprise resource planning provider</li> <li>• Mobile commerce provider</li> </ul>	<p><u>Philanthropic Activities – (PHIL)</u></p> <ul style="list-style-type: none"> <li>• Community involvement</li> <li>• Disaster relief</li> <li>• Charitable donation</li> <li>• University partnerships (non-affinity)</li> <li>• Donate</li> <li>• Disabled veterans</li> <li>• Grant</li> <li>• Art</li> <li>• Exhibition</li> <li>• Museum</li> <li>• Victims</li> <li>• Contributions</li> <li>• Match donations</li> <li>• Scholarship</li> <li>• Humanitarian efforts</li> </ul>

**Appendix A: Full set of codes for news events with key words, continued**

<p><u>Legal (LEGL)</u></p> <ul style="list-style-type: none"> <li>• Investigation</li> <li>• Prosecution</li> <li>• Obligations</li> <li>• Settlement</li> <li>• Testimony</li> <li>• Testified</li> <li>• Labor violation</li> <li>• Intellectual property infringement</li> <li>• Class-action lawsuit</li> <li>• Regulation</li> <li>• Ban</li> <li>• Petition</li> <li>• Patents</li> <li>• Trademarks</li> <li>• Intellectual property</li> </ul>	<p><u>Product/Service Issues (PROD)</u></p> <ul style="list-style-type: none"> <li>• New product feature/technology</li> <li>• Customer experience enhancement</li> <li>• Patents</li> <li>• Educational resources</li> <li>• New or increased security measures</li> <li>• Simplification</li> <li>• Buyers express product appreciation</li> <li>• Savings program</li> <li>• Customer benefits</li> <li>• Competitive benefits</li> <li>• New product/service/offerings</li> <li>• Recalls, product safety issues</li> <li>• Discontinuation of product/service</li> <li>• Product functionality issues</li> <li>• Previews</li> <li>• Product/service quality</li> <li>• Service capacity increase</li> <li>• Product/service feature</li> <li>• Ambiance/atmosphere</li> </ul>	<p><u>Advertising/Promotion Campaign (ADVS)</u></p> <ul style="list-style-type: none"> <li>• Ads</li> <li>• Branding</li> <li>• Logo</li> <li>• Promotion announcement</li> <li>• Agency change</li> <li>• Television commercial</li> <li>• Campaign</li> <li>• Limited time offer</li> <li>• Agency</li> <li>• Celebrity endorsements</li> <li>• Holiday sale</li> <li>• Advertising platforms</li> <li>• Rewards card</li> <li>• Loyalty program</li> </ul>
<p><u>Environmental Factors (ENVI)</u></p> <ul style="list-style-type: none"> <li>• Hurricane</li> <li>• Superstorm</li> <li>• Flood</li> <li>• Earthquake</li> <li>• Tsunami</li> <li>• Fire</li> <li>• Explosion</li> <li>• Carbon footprint</li> <li>• Sustainability</li> <li>• Land, waste cleanup</li> <li>• Composting</li> <li>• Recycle</li> <li>• Resource conservation</li> </ul>	<p><u>Crime (CRIM)</u></p> <ul style="list-style-type: none"> <li>• Crime scene</li> <li>• Death</li> <li>• Arrest</li> <li>• Assault</li> <li>• Theft</li> <li>• Robbery</li> <li>• Hold-up</li> <li>• Brawl, fight</li> <li>• Car wreck</li> <li>• Litter</li> <li>• Drunk driving</li> <li>• Attack, shooting</li> <li>• Terrorist attack</li> </ul>	<p><u>Sponsorship (SPON)</u></p> <ul style="list-style-type: none"> <li>• Non-philanthropic cultural and sport events</li> <li>• Marathon</li> <li>• Championship</li> <li>• Golf</li> <li>• Tournament</li> <li>• PGA tour</li> <li>• NASCAR</li> <li>• Festivities</li> <li>• Baseball</li> </ul>
<p><u>Changes in Physical Channel/Global Market (GMKT)</u></p> <ul style="list-style-type: none"> <li>• Add/open stores</li> <li>• Reduce/close stores</li> <li>• Grand openings</li> <li>• Expansion into new markets</li> <li>• Existing products for sale in global markets</li> <li>• Building permit</li> <li>• Increase/decrease traffic region</li> <li>• Increase/decrease global network</li> <li>• Extension permit</li> <li>• Building lease/rent</li> <li>• List of locations</li> </ul>	<p><u>Changes in Virtual/E-Channel (VIRT)</u></p> <ul style="list-style-type: none"> <li>• Expansion of online/mobile channels (not branches/stores)</li> <li>• Elimination of online/mobile channels (not branches/stores)</li> <li>• Omnichannel</li> <li>• Adding online sales option</li> <li>• New app release</li> <li>• 8K – other events</li> <li>• Mobile platform</li> </ul>	<p><u>Price change (higher/lower) (PRIC)</u></p> <ul style="list-style-type: none"> <li>• Terms of accounts being changed</li> <li>• Price increase for products</li> <li>• Price decrease for products</li> </ul> <hr/> <p><u>Other/Miscellaneous (MISC)</u></p> <ul style="list-style-type: none"> <li>• Weather closures/Holiday hours</li> <li>• Building repair</li> <li>• Building renovation</li> <li>• Fictitious story</li> <li>• Company name is street name</li> </ul>

## **Appendix B: Collapsed incident categories**

Codes from Appendix A that constitute each grouping are provided in parentheses

- Finance and Legal (ECON, PERF, LEGL, CRIM, MERG)
- Marketing (ADVS, PRIC, PROD, SPON, CSVS, PHIL, RECO)
- Supply Chain and Operations (GMKT, SUPP, VIRT, ENVI, MISC)
- Human Resources (EXEC, PERS)