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THE SOCIAL CONSTRUCTION OF ORGANIZATIONAL MISCONDUCT:

A SOCIAL EVALUATIONS PERSPECTIVE

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ABSTRACT

This dissertation consists of two studies on the influence of different social evaluations in stakeholders' sensemaking of organizational misconduct. The first study examines how the distinctive sociocognitive content of reputation and celebrity differently shapes decisions regarding media coverage of misconduct. Although high-reputation and celebrity transgressors attract greater media attention due to the high relevance of misconduct in both rational and emotional evaluations of firms, reputation and celebrity result in different levels of publicity by altering the perceived relevance of misconduct characteristics. The second study examines how investors utilize the interpretive frames provided by perpetrators' and bystanders' status and celebrity to determine whether to generalize culpability to bystanders (i.e., negative spillovers) or appreciate bystanders for being perceived as immune to the same problem (i.e., positive spillovers). High-status perpetrators create negative spillovers by epitomizing the failure of the norms and practices stakeholders thought they stood for, whereas celebrity perpetrators trigger positive spillovers due to their atypical nature among peers. Furthermore, matching social evaluations amplify negative spillovers by highlighting commonalities between perpetrators and bystanders, and mismatching social evaluations strengthen positive spillovers by priming stakeholders to focus on their dissimilarities. Both studies reveal the role of stakeholders' sensemaking processes in the scandalization of and the spillovers from misconduct, in the wake of data breaches, one of the most critical social issues today. This dissertation highlights the importance of social evaluations, particularly their sociocognitive content, in the social construction of organizational misconduct.

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ACKNOWLEDGEMENTS

"The Unexpected Virtue of Ignorance," which is also the subtitle of my favorite movie, is perhaps the phrase that best describes how I ended up here writing the acknowledgements section of my dissertation. I pursued this career without a clue of what it takes to be a researcher. Years have passed, and now my decades-long life as a student is coming to an end—in fact, I have been nothing but a student throughout my entire life so far. The word "researcher" still seems somewhat too heavy for me, but I have managed to conclude the first chapter of an enduring journey of becoming a decent one. I would not have reached this important milestone without help from many people.

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Chapter 1

INTRODUCTION

Commensurate with the essential roles organizations play in modern society, organizational misconduct often leaves indelible remembrances of moral panics and sufferings. The fallen names like Enron, WorldCom, and Lehman Brothers remain vivid even though they were involved in scandals decades ago, and new organizational wrongdoings continue to dominate the public and academic discourse. One recent example is the 2018 Facebook scandal involving a breach of users' personal information by Cambridge Analytica. The public was shocked by the unexpected degeneracy of one of the most trusted, revered, and beloved firms, and feelings of betrayal as well as fears regarding data security spread rapidly. The media began to provide ongoing coverage of the incident, arousing suspicions that other firms might have been engaging in similar misconduct.

The dramatic nature and the profound impacts of organizational misconduct have attracted serious scholarly attention in management research (Greve, Palmer, & Pozner, 2010; Bundy, Pfarrer, Short, & Coombs, 2017). Scholars generally agree that organizational misconduct is deeply embedded in the social context surrounding the transgressors (Graffin, Bundy, Porac, Wade, & Quinn, 2013; Jensen, 2006; Jonsson, Greve, & Fujiwara-Greve, 2009; Mishina, Dykes, Block, & Pollock, 2010; Paruchuri & Misangyi, 2015; Wiersema & Zhang, 2013; Wiesenfeld, Wurthmann, & Hambrick, 2008). That is, organizations engage in misconduct in response to exigent social pressure (Greve et al., 2010; Mishina et al., 2010) or a sense of entitlement stemming from widespread social approval (Krishnan & Kozhikode, 2015; Pahnke, McDonald, Wang, & Hallen, 2015). When organizational misconduct suddenly comes to light, stakeholders' processing of this information tends to be socially constructed, guided by their own prior knowledge and beliefs about the transgressors, which often distort and even eclipse actual facts about the misconduct (Bundy & Pfarrer, 2015; Lange & Washburn, 2012; Wiesenfeld et al., 2008). In fact, the very definition of misconduct is in the eyes of stakeholders: any behaviors that are perceived as transgressing the ethical, legal, and/or normative borderlines defined by the public or the societal subgroups could qualify as misconduct (Greve et al., 2010; Pollock, Mishina, & Seo, 2016).

Consequently, stakeholders' punitive reactions to organizational misconduct tend to be exaggerated, even exceeding the magnitude mandated by the legal system (Alexander, 2008; Greve et al., 2010), notwithstanding the fact that rulings and verdicts are also susceptible to the biases from social influences (McDonnell & King, 2018). Alternatively, stakeholders can assume the role of arbiters and forgive the transgressors based on "reservoirs of goodwill" or prior positive impressions (Bundy & Pfarrer, 2015; Zavyalova, Pfarrer, Reger, & Hubbard, 2016). This unpredictable nature of stakeholders' processing of and responses to misconduct results in both unexpectedly stringent and lenient penalties, even for similar magnitudes of misconduct (Graffin et al., 2013; Rhee & Haunschild, 2006; Shiu & Yang, 2017). Understanding how stakeholders process organizational misconduct is particularly important, because their conclusions can be consequential for firms (Bundy et al., 2017; Desai, 2011).

Due to its socially constructed nature, stakeholders' processing of organizational misconduct often results in counterintuitive and unpredictable outcomes. For instance, despite having caused similar levels of disruption to stakeholders and society, only some misconduct cases involving certain actors become scandals (Adut, 2005; Barnett, 2014; Piazza & Jourdan, 2018). Particularly when considering numerous findings that publicity (i.e., media coverage) significantly aggravates the penalties associated with misconduct (Bednar, Love, & Kraatz, 2015; Graffin et al., 2013; Kölbel, Busch, & Jancso, 2017; Liu & Shankar, 2015; Wiersema & Zhang, 2013), understanding why stakeholders and the media devote disproportionate attention to and publicize certain acts of misconduct matters both theoretically and practically. Moreover, in the misconduct literature, scholars have long acknowledged that stakeholders generalize the perpetrator's culpability to a wide range of innocent others when coping with the uncertainty created by misconduct (Barnett & King, 2008; Jensen, 2006; Jonsson et al., 2009; Paruchuri & Misangyi, 2015). Nonetheless, the scrutiny and penalties directed towards the implicated organizations might also create opportunities for rivals in the form of defecting customers and renewed appreciation for ethical behavior (Martin, Borah, & Palmatier, 2017; Paruchuri, Pollock, & Kumar, 2019; Piazza & Jourdan, 2018; Roehm & Tybout, 2006). In summary, the main questions to be addressed through this dissertation are:

1. Why are some instances of misconduct readily publicized and scandalized while others go largely unnoticed?
2. Why do some innocent bystanders suffer from undeserved penalties in the wake of others' misconduct while other bystanders enjoy unexpected gains?

In so doing, I focus on the role of social evaluations accorded to the transgressors and surrounding others, defined as "socially constructed, collective perceptions of firms such as status, reputation, celebrity" (Pollock, Lashley, Rindova, & Han, 2019: 444).

Upon facing the uncertainty regarding the actual cause of misconduct and its aftermath, stakeholders engage in intuitive and heuristic-based evaluations (Bundy & Pfarrer, 2015; Tversky & Kahneman, 1974; Lange & Washburn, 2012). That is, when making sense of a misconduct-stricken environment, stakeholders tend to direct their attention towards the most visible and cognitively accessible firms (Hubbard, Pollock, Pfarrer, & Rindova, 2018; Lange, Lee, & Dai, 2011; Pollock & Gulati, 2007). Most researchers who have adopted a social evaluations approach to misconduct have focused primarily on the effects of positive social evaluations in attracting public attention and causing expectancy violations (Graffin et al., 2013; Rhee & Haunschild, 2006).

However, recent advancements in the social evaluations literature suggest that the effects of social evaluations can be more nuanced (Pollock et al., 2019). Because different social evaluations embody different expectations, stakeholders may use them as interpretive frames. These "principles of organizing and assigning meaning" that result from "social construction" and lead to a "common cognitive understanding" (Cornelissen & Werner, 2014: 197, as cited in Hubbard et al., 2018: 1978) can be used by stakeholders to make sense of a firm's behavior (Hubbard et al., 2018; Pfarrer, Pollock, & Rindova, 2010). In addressing the questions raised above, I focus on how social evaluations shape stakeholders' processing of misconduct and lead to divergent outcomes for different firms.

In the first study, I examine the first question of why some acts of misconduct are publicized while others go unnoticed (Barnett, 2014; Margolis & Walsh, 2003). In so doing, I argue that prior theorization on the role of social evaluations in imparting publicity to misconduct (Adut, 2005; Graffin et al., 2013) only partially captures the scandalization process. That is, as much as the evaluations attract attention and cause expectancy violations (Rhee & Haunschild, 2006), they may have an offsetting effect that inhibits the publicization of misconduct, as suggested by the equivocal role of social evaluations as both a benefit and a burden (Bundy et al., 2017; Wei, Ouyang, & Chen, 2017; Zavyalova et al., 2016). In essence, I suggest that differences in the sociocognitive content of reputation and celebrity influence stakeholders' receptiveness to the specific types of information about an act of misconduct (i.e., its severity and recency to similar misconduct in the past). Together, these characteristics and the interpretive frames provided by reputation and celebrity determine the extent to which stakeholders perceive an act of misconduct as worth publicizing, and in turn, the extent to which media outlets perceive it as newsworthy.

In the second study, I examine how the social evaluations of perpetrators and bystanders and the associated interpretive frames influence the direction and magnitude of spillovers to bystanders in the wake of misconduct. Focusing on the problematic theoretical status of (dis)similarities across perpetrators and bystanders as driving both undeserved losses (i.e., negative spillovers) and unexpected gains (i.e., positive spillovers) to innocent bystander firms, I suggest that (mis)matches between perpetrators' and bystanders' social evaluations prime stakeholders to view the firms as (dis)similar. Because status embodies a strong sense of conformity to industry norms, high-status firms' misconduct likely generates negative spillovers due to other firms being perceived as similarly fallible, whereas misconduct by celebrity firms' is likely to be treated as an independent deviation and incur positive spillovers to other firms due to the atypical and nonconforming nature of celebrity. Moreover, I argue that for bystanders, possessing the same type of social approval assets as the perpetrators likely amplifies negative spillovers and limits positive spillovers, and that the inverse is true when bystanders' social approval assets differ from those of the perpetrators.

In both studies, the acts of organizational misconduct are data breaches, which are increasingly becoming a crucial social issue (Angst, Block, D'Arcy, & Kelley, 2017; Gwebu, Wang, & Wang, 2018; Martin et al., 2017). Indeed, breaches of sensitive information by firms are viewed as transgressing the societal norms shared among stakeholders (Greve et al., 2010; Pollock et al., 2016) thereby violating both emotional and cognitive trust towards the firms (Martin et al., 2017). By theorizing and examining how various stakeholders, including the media and investors, process data breach incidents, I expect my dissertation to provide some useful insights into how one of the most critical emerging social issues is affecting both the corporate world and society.

Chapter 2

REPUTATION, CELEBRITY, AND SCANDALIZATION OF MISCONDUCT

On September 25, 2018, the public learned that nearly 50 million Facebook users' personal information had been exposed in a data breach. In the following days, the breach received massive media attention, including extensive coverage by major outlets such as *The New York Times*, *The Wall Street Journal*, and *The Washington Post* (Fung, 2018; Isaac & Frenkel, 2018; Schechner, 2018). The same day, a Securities and Exchange Commission (SEC) filing was released announcing that Chegg—a technology giant specializing in educational services—had been hacked, exposing the private information of approximately 40 million users. Although of similar magnitude to the Facebook breach, Chegg's data breach was only covered by specialist media in the technology and security industries (Lutke, 2018). Why were two incidents that occurred at the same time and caused a similar degree of loss publicized to different extents? In other words, why was the Facebook incident *scandalized* while the Chegg incident was not?

Scandals, defined as "the disruptive publicity of transgression" (Adut, 2005: 222), can be best conceived as a unique status accorded to misconduct that incurs the public's displeasure with actions that defy established norms (Graffin et al., 2013; Piazza & Jourdan, 2018). Thus, although misconduct is necessary for a scandal to occur, it is not sufficient; it must also be publicized so that the public knows about it and can react to it (Adut, 2005). Publicized misconduct leads to a wide variety of undesirable outcomes, such as managerial turnover (Wiersema & Zhang, 2013), decreased market share (Rhee & Haunschild, 2006) and revenue (Liu & Shankar, 2015), increased financial risks

(Kölbel et al., 2017), and reputational loss (Bednar et al., 2015). Despite these formidable costs from the publicity of misconduct, the literature has remained surprisingly silent about why only some misconduct is publicized, and thus becomes scandalized (Barnett, 2014; Margolis & Walsh, 2003). This has significant practical importance, given firms' substantial efforts to avoid bad press (Desai, 2011; Lungeanu, Paruchuri, & Tsai, 2018; Westphal & Deephouse, 2011).

Prior research has considered transgressors' social evaluations, defined as "socially constructed, collective perceptions of firms such as status, reputation, [and] celebrity" (Pollock et al., 2019: 444), to be potential antecedents of publicity with regard to misconduct (Graffin et al., 2013; Rhee & Haunschild, 2006). Indeed, the intense attention given to highly regarded firms (Lange et al., 2011; Rindova, Hayward, & Pollock, 2006) and expectancy violations their evaluations create (Burgoon, 1993) can make misconduct by such firms highly disruptive and newsworthy to the media, the most influential drivers of scandalization (Wiesenfeld et al., 2008). However, high visibility among and appreciation from stakeholders are common across firms with all types of "social approval assets" (Pollock et al., 2019)—or the stock of positive social evaluations accorded to a firm (Pfarrer et al., 2010). Current theory cannot explain why some assets provide buffers upon misconduct while others become burdens (Bundy & Pfarrer, 2015), let alone why a given asset is sometimes a buffer and sometimes a burden (Dewan & Jensen, 2019; Zavyalova et al., 2016).

In this study, I focus on the social approval assets of reputation and celebrity and the role of their "sociocognitive content"—defined as the dominant evaluative scheme(s) evoked when assessing an actor and the resulting behavioral expectations (Pollock et al., 2019)—in the publicizing of misconduct. Reputation is defined as “broad public recognition of the quality of a firm’s activities and outputs” (Pollock, Lee, Jin, & Lashley, 2015: 484), and celebrity is defined as the “high level of attention and . . . positive emotional responses from stakeholder audiences” (Rindova et al., 2006: 51). Sociocognitive content provides the foundation from which social evaluations are made. I focus on reputation and celebrity because they differ the most in their sociocognitive content (Pollock et al., 2019). Reputation accumulates for firms that consistently demonstrate superior capabilities and performance (Lange et al., 2011; Love & Kraatz, 2009), whereas celebrity emerges from stakeholders’ positive emotional resonance with firms’ nonconforming behaviors (Rindova et al., 2006). I examine how differences in the sociocognitive content of reputation and celebrity influence the amount of media coverage a misconduct incident receives, and how characteristics of misconduct are interpreted when deciding whether or not an incident should be publicized.

Because high-reputation and celebrity firms’ actions are salient to the public, particularly when they violate expectations (Pfarrer et al., 2010), the likelihood of media attention and coverage of misconduct is high (Chandler, Polidoro, & Yang, 2019; Singer, 2007). However, reputation and celebrity can also provide “interpretive frames” that shape how much attention media outlets pay to misconduct characteristics, and how they interpret them (Hubbard et al., 2018; Pfarrer et al., 2010). I focus on the magnitude of expected harm from an incident (i.e., its severity) and its timing relative to prior misconduct of the same sort (i.e., its recency) as characteristics that are likely to attract media attention and interest (Arikan, Arikan, & Shenkar, 2019; Bundy & Pfarrer, 2015; Tversky & Kahneman, 1974). I argue that high reputation increases the salience of these characteristics because they violate expectations (Pfarrer et al., 2010), thereby increasing the burden on the firm. In contrast, I argue that because audiences' emotional connection with celebrity matters more than facts (Agrawal & Maheswaran, 2005; Rindova et al., 2006), celebrity reduces the influence of these characteristics of misconduct on the likelihood of media coverage, creating a buffer for the firm. In other words, the effects of severity and recency on the publicizing of misconduct are amplified when interpreted through the reputation lens but attenuated when interpreted through the celebrity lens.

I test my hypotheses by examining data breach incidents involving publicly traded U.S. firms between 2014 and 2018. My findings show that both reputation and celebrity are associated with increased media coverage of a firm's data breach. Surprisingly, however, reputation does not moderate the effects of severity and recency. As expected, celebrity attenuates the effect of severity, however, it amplifies rather than attenuates the effect of recency. These findings suggest that the burdens from positive social evaluations and the buffers they may create require a more nuanced theorization.

This study contributes to research on organizational misconduct by suggesting that social evaluations and the interpretive frames they provide are an overlooked antecedent to the publicity of misconduct (Adut, 2005; Piazza & Jourdan, 2018). I contribute to the social evaluations literature by contextualizing the rarely questioned "fall-from-grace" argument (Graffin et al., 2013). Specifically, my findings show how the sociocognitive content of social evaluations affects how stakeholders process different aspects of firm behavior (Pollock et al., 2019). In so doing, I join the debate over whether social evaluations are a burden or a buffer during crises (Rhee & Haunschild, 2006; Zavyalova et al., 2016) and answer calls to unpack how social evaluations drive stakeholders' processing of misconduct (Bundy & Pfarrer, 2015; Dewan & Jensen, 2019) by showing that audiences' information-searching behaviors and interpretations are contingent on the sociocognitive content of social evaluations.

2.1. Reputation, Celebrity, and Misconduct Publicity

High levels of social evaluations such as reputation and celebrity are intangible "social approval assets" (Pfarrer et al., 2010) that can create value for firms. Social approval assets also attract high levels of stakeholder attention (Lange et al., 2011; Rindova et al., 2006) to firms and their behaviors; thus, when firms engage in misconduct, their behaviors are likely to be noticed. When it is the media doing the noticing, misconduct may be publicized and become a scandal (Adut, 2005; Barnett, 2014; Dewan & Jensen, 2019; Graffin et al., 2013).

Media outlets serve as critical infomediaries that curate information flows and set the public agenda (McCombs & Shaw, 1972; Pollock & Rindova, 2003). Members of the media face significant uncertainty in discerning the newsworthiness of topics and making coverage decisions (Pollock, Rindova, & Maggitti, 2008) because they do not want to be the only ones covering a topic (Shoemaker & Reese, 1996) and/or pursuing a story that is not salient to the public (Singer, 2007). Social approval assets such as reputation and celebrity can help alleviate such uncertainty because they have high visibility among stakeholders, guaranteeing the newsworthiness of their activities (Lange et al., 2011; Zavyalova, Pfarrer, & Reger, 2017). As such, acts of misconduct by high-reputation or celebrity firms often receive extensive media coverage due to stakeholders' sense of betrayal (Pollock et al., 2016; Rhee & Haunschild, 2006).

However, because media outlets publish what that people “want” to know as much as what people “should” know (Chandler et al., 2019; Singer, 2007), many researchers have assumed that members of the public are interested in misconduct by highly-evaluated firms. This may or may not be true when considering the long-standing debate on whether positive social evaluations are burdens or buffers (Bundy & Pfarrer, 2015; Rhee & Haunschild, 2006; Zavyalova et al., 2016). The positivity underlying social evaluations can offset the negativity implied in the misconduct, leading stakeholders to forgive and support firms (Zavyalova et al., 2016). Or, prior beliefs associated with a firm’s strong capability or atypical nature can make current misconduct less unexpected, and thus less worthy of attention, or more easily rationalized away (Pfarrer et al., 2010; Pollock et al., 2016). These buffering effects of social approval assets could factor into media coverage decisions, as members of the media are subject to the same biases from social evaluations as their audiences (Wiesenfeld et al., 2008).

In developing my theoretical arguments, I focus on differences in the sociocognitive content of reputation and celebrity. I argue that although both reputation and celebrity increase the likelihood of media coverage of a firm’s misconduct, they do so for different reasons. These reasons in turn determine how media outlets interpret the characteristics of misconduct and the extent to which these characteristics influence their decisions regarding whether or not to publicize the misconduct.

2.1.1. Reputation and celebrity as interpretive frames for misconduct events

High visibility with stakeholders is a key dimension of both high reputation and celebrity (Lange et al., 2011; Rindova et al., 2006); thus, stakeholders are likely to pay closer attention to firms with these characteristics. Beyond the high levels of baseline attention to these firms' behaviors, the nature of the behaviors and how they reflect on reputation and celebrity create differences in the magnitude of reactions (Pfarrer et al., 2010; Pollock et al., 2019). Once attained, these assets define stakeholders' future expectations such that high-reputation firms are expected to continue to perform well and at a consistent level, and celebrity firms are expected to continue engaging in nonconforming behaviors that garner approval from audience members. The question then is: How do instances of misconduct reflect or violate the sociocognitive content of reputation or celebrity?[1] I argue that misconduct is relevant to the sociocognitive content of both reputation and celebrity, but for different reasons.

Reputation leads audiences to expect and focus on the persistence of high-reputation firms' behavior and performance (Love & Kraatz, 2009; 2017). High-reputation firms' involvement in misconduct runs counter to this expectation because audiences' evaluations of firms' capabilities and performance are grounded in the assumption that the firms abide by the norms and regulations that structure the activities of legitimate entities (Mishina, Block, & Mannor, 2012; Paruchuri, Han, & Prakash, 2020; Zavyalova, Pfarrer, Reger, & Shapiro, 2012). Thus, the disclosure of high-reputation firms' misconduct has significant effects on how their capabilities are evaluated, potentially undermining previously held reputational perceptions (Mishina et al., 2012; Paruchuri et al., 2020). Furthermore, abundant findings on the negative

[1] Prior research has suggested that misconduct creates expectancy violations due to the positive nature of social approval assets (Pollock et al., 2016; Rhee & Haunschild, 2006). Although the valence of the action is a factor, what is more salient is whether the information cue is relevant to the social evaluation. For instance, if a firm is known for its innovation capability, behaviors that speak positively or negatively to this capability are more relevant than positive or negative information about less relevant behaviors, for example the firm's gains or losses from its real estate investments.

consequences of misconduct on profitability (Greve et al., 2010) suggest that audiences do not ignore information about misconduct, given their motivations to be as accurate as possible when predicting a firm's potential (Agrawal & Maheswaran, 2005; Pollock et al., 2015; 2019). That is, acts of misconduct by high-reputation firms are highly relevant, given the rational, evaluative aspect of reputation's sociocognitive content (Pollock et al., 2019). Consequently, possessing a high reputation alleviates the media's uncertainty about whether members of the public want to know about the firm's misconduct, thereby promoting media coverage (Singer, 2007).

In contrast, celebrity directs attention toward misconduct because audiences expect celebrity firms to engage in nonconforming behaviors (Lovelace, Bundy, Hambrick, & Pollock, 2018; Pollock et al., 2016). Acts that transgress societal norms surprise and befuddle stakeholders (Bundy & Pfarrer, 2015; Lange & Washburn, 2012). Thus, misconduct reflects the sociocognitive content of celebrity, because emotional reactions align with audience members' expectations that celebrity firms engage in unconventional and sometimes shocking behaviors (Hubbard et al., 2018). Although audiences may not expect or want celebrity firms' nonconformity to escalate in morally risky ways (Pollock et al., 2016), the interest in celebrity firms' nonconforming behaviors, and the potential for celebrity firms' misconduct to generate emotional responses tends to attract attention and intense interest from the public, making it newsworthy and thus more likely to be reported by the media.

In sum, acts of misconduct by high-reputation and celebrity firms are more likely to be publicized by the media than acts of misconduct by firms without these assets, because misconduct is relevant to both the rational and emotional aspects of the sociocognitive content of reputation and celebrity, respectively. Thus, I hypothesize:

Hypothesis 1. High reputation increases the likelihood of a firm's misconduct receiving media coverage.

Hypothesis 2. Celebrity increases the likelihood of a firm's misconduct receiving media coverage.

2.1.2. Reputation and celebrity as interpretive frames for misconduct characteristics

Just as reputation and celebrity can serve as interpretive frames that shape whether the media perceives a misconduct incident to be newsworthy, they can also influence how characteristics of the incident are interpreted. Interpretive frames serve as "principles of organizing and assigning meaning" that result from "social construction" and lead to a "common cognitive understanding" (Cornelissen & Werner, 2014: 197, cited in Hubbard et al., 2018: 1978). Prior research has revealed that different social evaluations create different interpretive frames that shape how audiences make sense of firms' behavior, such that the same information cue can be interpreted differently (Hubbard et al., 2018; Pfarrer et al., 2010). For instance, although both high reputation and celebrity increase the market's positive reaction to positive earnings surprises, the reaction to announcements by celebrity firms is even stronger than the reaction to announcements by high-reputation firms. Pfarrer and colleagues (2010) explained that the positive surprise is a better fit with the unexpected behaviors associated with celebrity than with the consistency and predictability expected from high-reputation firms.

Although reputation and celebrity increase the burden of misconduct on firms by attracting publicity, I argue that differences in the sociocognitive content underlying these assets also create different lenses for interpreting the characteristics of misconduct that could further amplify the burden on firms or provide a buffer that partially attenuates the likelihood of media coverage. I focus on two key characteristics considered by the media and the public when processing and publicizing misconduct: (a) the severity of or the magnitude of expected harm from the misconduct; and (b) the recency of the current misconduct relative to similar misconduct by the firm in the past (Bundy et al., 2017; Chandler et al., 2019; Pfarrer, Decelles, Smith, & Taylor, 2008). These two dimensions are intimately related to the extremity and recency dimensions that have long been acknowledged in social psychology as enhancing the salience of a stimulus (Higgins, Bargh, & Lombardi, 1985; Tversky & Kahneman, 1974) and are used by stakeholders to make sense of firms' misconduct (Mishina et al., 2012; Pfarrer et al., 2008).[2]

Because journalists, like everyone else, are constrained by limited cognitive availability, not all incidents can be equally publicized (Chandler et al., 2019; Pollock et al., 2008). In this regard, large, visible events and associated actors have been found to have greater "cognitive" centrality among audiences than smaller, less visible events (Pollock et al., 2015). The same applies at the onset of misconduct. Stakeholders actively seek information about the magnitude of expected harm to help resolve the uncertainty created by the misconduct (Lange & Washburn, 2012; Wiesenfeld et al., 2008). Misconduct that has caused massive damage, or is expected to do so, captivates the attention of stakeholders and the media, making it difficult to overlook (Chandler et al.,

[2] Along with extremity and recency, frequency is another dimension that raises the salience of cues (Tversky & Kahneman, 1974). However, recency and frequency are intimately related in stakeholders' processing of misconduct (Pfarrer et al., 2008) and in fact are highly correlated in my data ($r = 0.70$). I discuss the potential effects of frequency in the Robustness Tests section. In essence, the effects of frequency of misconduct exhibit very similar patterns as the effects of recency.

2019; Zavyalova et al., 2012). For instance, data breaches affecting a massive number of accounts have greater salience than those involving fewer potential victims (Gwebu et al., 2018; Malhotra & Malhotra, 2011; Martin et al., 2017). Thus, all else being equal, severe misconduct that is expected to cause greater harm is more likely to be publicized by the media and become a scandal.

However, as an information cue, misconduct severity can be interpreted differently depending on the transgressor's reputation and celebrity. To the extent that a social approval asset's sociocognitive content calls attention to the magnitude of expected harm from an act of misconduct, the more likely it is that the effect of the severity dimension becomes amplified. Because reputation results from deliberate processing of a firm's track record and requires constant updating (Pollock et al., 2015), stakeholders are likely to be motivated to be as accurate as possible when assessing the impacts of a misconduct incident on the firm's capabilities and prospects, and to readily incorporate information about the misconduct's severity (Agrawal & Maheswaran, 2005; Pollock et al., 2019). When misconduct is severe, stakeholders may find a firm's reputation irreconcilable with the apparent damage done, and may even feel deceived (Bundy et al., 2017; Wiesenfeld et al., 2008). This response is consistent with findings that high reputation created expectancy violations for automakers when the issued recalls potentially exposed consumers to significant hazards (Rhee & Haunschild, 2006), and for venture capitalists when the companies they took public failed (Gomulya, Jin, Lee, & Pollock, 2019). In contrast, minor acts of misconduct by high-reputation firms may not attract as much scrutiny as those of lower-reputation firms because such misconduct tends to be explained away by their successful and consistent track records (Pfarrer et al.,

2010) and/or attributed to external causes (Love & Kraatz, 2017), both of which make minor acts of misconduct less attractive to the media (Chandler et al., 2019; Rindova et al., 2006). Thus, the emphasis of stakeholders, and perhaps even media outlets, increases the influence of misconduct severity on media coverage decisions (Liu & Shankar, 2015; Wiesenfeld et al., 2008).

In contrast to reputation, celebrity is more likely to reduce the influence of misconduct severity on media coverage. Celebrity firms are the main characters in many media stories owing to the excitement and emotional resonance they generate among members of the public (Pollock et al., 2016; Rindova et al., 2006; Zavyalova et al., 2017). Thus, as discussed above, media outlets are likely to perceive any event concerning celebrity firms as newsworthy, particularly acts of misconduct, considering the media's preference for negative news (Kölbel et al., 2017; Vergne, Wernicke, & Brenner, 2018). However, once a firm gains celebrity, the driver of the firm's media coverage becomes its dramatic image and narrative, rather than actual facts (Rindova et al., 2006). Furthermore, evaluations surrounding celebrity firms are primarily emotion-laden (Pollock et al., 2019). As such, what makes misconduct interesting and newsworthy for the media is the negative emotional arousal it creates (Culnan & Armstrong, 1999; Martin et al., 2017); detailed information about misconduct plays a smaller role in the instantaneous information processing guided by emotions (Agrawal & Maheswaran, 2005; Bundy & Pfarrer, 2015).

Thus, although any misconduct by a celebrity firm warrants media coverage, its severity only marginally contributes to its publicity-worthiness, consistent with the notion that the narratives associated with celebrity firms often diverge from reality (Rindova et al., 2006). Accordingly, information about the severity of misconduct likely has less impact for celebrity firms than non-celebrity firms.

Overall, I expect that the positive effect of the severity of misconduct—for instance, data breaches affecting a massive number of accounts (Gwebu et al., 2018; Malhotra & Malhotra, 2011; Martin et al., 2017)—is amplified when the interpretive lens of reputation is employed, but is attenuated when the interpretive lens of celebrity is employed. Specifically, I hypothesize:

Hypothesis 3. High reputation strengthens the positive relationship between the severity of a firm's misconduct (i.e., the number of breached accounts) and the extent to which it is covered by the media.

Hypothesis 4. Celebrity weakens the positive relationship between the severity of a firm's misconduct and the extent to which it is covered by the media.

In addition to the severity of the focal act of misconduct, the recency of similar acts of misconduct also shapes stakeholders' responses (Pfarrer et al., 2008). Whereas events that only happen once or events that occur with substantial time between them can be explained away as aberrations, events that happen repeatedly and in close temporal proximity are perceived as suggesting a pattern (Luoma, Ruutu, King, & Tikkanen, 2017). Furthermore, individuals tend to place more weight on recent information cues (Higgins et al., 1985), rendering them more salient, and thus more easily recalled (Tversky & Kahneman, 1974). Accordingly, the media considers the recency of misconduct relative to prior misconduct of the same sort when making coverage decisions (Pollock et al., 2008). That is, when deciding whether or not to cover an incident, the existence of a recent similar incident is likely to serve as an assurance of newsworthiness.

Recency effects are of particular relevance in forming negative impressions (Denrell, 2005). Individuals exposed to negative testimony most recently are likely to render guilty verdicts (Furnham, 1986). At a more macro level, national animosity increasingly hampers cross-border corporate deals the more recently national level conflicts have taken place (Arikan et al., 2019). Thus, with prior accusations of similar misdeeds worsening stakeholders' perceptions of the accused firms' intentions and culpability (Love & Kraatz, 2017; Pfarrer et al., 2008), the recency of such accusations is likely to direct more attention to the current misconduct (Mishina et al., 2012; Pollock et al., 2008). Coupled with the media's proclivity for negative news (Kölbel et al., 2017; Vergne et al., 2018), recent similar acts of misconduct should increase the likelihood of a firm's current misconduct being publicized by the media. This effect, nonetheless, would differ in magnitude according to the interpretive frames provided by transgressors' reputation and celebrity.

Since stakeholders are primarily interested in accurately assessing a high-reputation firm's value, the recency of similar misconduct could reinforce the negative information conveyed by the current misconduct and signal a pattern of behavior (Connelly, Certo, Ireland, & Reutzel, 2011) which would be more readily incorporated into reputational judgments (Pollock et al., 2015). Furthermore, the salience of recent prior misconduct increases the likelihood of the misconduct being attributed to internal characteristics of the firm (Love & Kraatz, 2017), and eliminate any benefit of the doubt provided by reputation that would enable stakeholders to perceive the apparent failure as an aberration due to an external cause (Pfarrer et al., 2010). Thus, the recency of similar misconduct is likely to cause the media to perceive the current misconduct by a high-reputation firm as worth publicizing.

In contrast, because celebrity firms' media coverage is primarily driven by eye-catching attributes and behaviors (Rindova et al, 2006; Zavyalova et al., 2017), publicizing an act of misconduct by a celebrity firm that has recently engaged in similar acts may be less attractive to media outlets. To maintain celebrity, firms need to engage in nonconforming behaviors that differ from previous ones in their nature or extremity (Lovelace et al., 2018; Pollock et al., 2016). This implies that the fervor created by a celebrity firm's atypical behavior is rather short-lived. In this vein, the fact that a celebrity firm committed a similar misdeed in the recent past can undermine the attractiveness of the current misconduct as a news topic, because it is not surprising and simply confirms what the public already knows about the firm (Anderson, 1981; Chandler et al., 2019). As a result, information about the recency of similar misconduct may have a negative effect on media outlets' decisions to publicize a celebrity firm's misconduct.

In sum, a recent similar act of misconduct by a high-reputation firm is likely to be deemed a critical information cue in processing the firm's current misconduct; thus, a high reputation likely amplifies the recency effect. However, for a celebrity firm, the same information cue is likely to be treated as redundant, rather than corroborating, and be less likely to trigger media coverage of the firm's current misconduct; thus, celebrity likely attenuates the recency effect. Hence, I hypothesize:

Hypothesis 5. High reputation strengthens the positive relationship between the recency of similar misconduct by a firm and the extent to which a focal act of misconduct is covered by the media.

Hypothesis 6. Celebrity weakens the positive relationship between the recency of similar misconduct by a firm and the extent to which a focal act of misconduct is covered by the media.

2.2. Methods

2.2.1. Data and sample

In this study, I focus on the publicizing of data breach incidents, which are increasingly becoming a serious social problem (Accenture, 2019), as witnessed by several mega-breaches in recent years involving firms such as Facebook, Equifax, Marriott, and Yahoo. Despite the prevalence of data breach incidents, not all incidents are publicized, as illustrated in the introduction. Breaches of sensitive information held by firms are clearly a form of organizational misconduct, as they transgress societal norms shared among stakeholders (Greve et al., 2010; Pollock et al., 2016) and violate both emotional and cognitive trust in the firms (Culnan & Armstrong, 1999; Martin et al., 2017). Even victims of hacker attacks are ultimately held responsible for failing to protect private information, as witnessed by resentment over insufficient punishments inflicted on breached firms (Carter, 2019). In fact, a recent survey of more than 1,400 executives revealed that cybersecurity is among the top external concerns for top managers (Petersen, 2020).

I used the Privacy Rights Clearinghouse database to create my initial sample, which compiles data from multiple sources, including the websites of states, attorneys general, government bureaus (e.g., U.S. Securities and Exchange Commission and U.S. Department of Health and Human Services), and other consumer protection organizations regarding data breach incidents affecting government institutions, the military, schools, hospitals, other non-governmental or nonprofit organizations, and, most importantly, companies. Among the extensive list of data breach incidents, I manually identified a total of 406 incidents involving 253 publicly traded U.S. firms or their subsidiaries that were disclosed between 2014 and 2018. To ensure the accuracy of data on the date of disclosure and breach characteristics, I corroborated the data with those provided by the annual data breach reports published by the Identity Theft Resource Center. Whenever there was a discrepancy, I consulted the original data source. When the best traceable sources were the media, I tracked the dates disclosed by breached firms or government officials as referenced in the articles. After accounting for missing firm-level data and dropping three extreme outliers for the number of breached accounts, the final sample consisted of 296 breaches involving 197 firms.[3]

2.2.2. Dependent variable

To capture the extent to which a data breach incident was publicized by the media, I used the count of articles covering the focal incident during the two-week period

[3] The omitted firms with missing data did not differ significantly from the retained omitted firms in terms of breach severity and recency ($p > 0.10$). The outliers in terms of breach severity (i.e., number of breached accounts) were the incidents involving Marriott in 2018, and News Corp and Altaba (formerly Yahoo!) in 2016. These breaches affected over 300 million accounts, more than the double of the number affected in the next largest breach incidents (approximately 150 million accounts). Although the analyses including these outliers yielded similar results except for a slight increase in the p-value (0.107) for the interaction between breach severity and celebrity, I decided to drop these observations to prevent extreme values from distorting interaction patterns.

following its disclosure.[4] Only articles on the breach incident (Bednar, 2012; Chandler et al., 2019; Vergne et al., 2018), as opposed to articles on the firm in general (Zavyalova et al., 2012), were chosen to avoid mistakenly capturing the amount of media attention a high-reputation or celebrity firm would normally expect, regardless of its involvement in misconduct. In other words, I measured the extent to which a misconduct incident was publicized—and thereby scandalized—rather than general media coverage of the transgressor. I focused on articles published by the top 25 U.S. newspapers by circulation to ensure that their coverage of a data breach incident embodied some level of authority to represent the perceived disruptiveness and publicity-worthiness of the incident, rather than mere rumors or gossip (Adut, 2005), while also capturing the feelings of the general, non-expert public (Zavyalova et al., 2012). I identified a total of 718 articles covering the breach incidents in my sample; the incident that attracted the most media attention was the 2017 Equifax breach (219 articles). Confirming the problem statement of this study, 78.9 percent of breaches were neglected by the media.

2.2.3. Independent variables

Following prior research, I used the *Fortune* "Most Admired Companies" (FMA) list and the *Wall Street Journal/Harris Interactive* (WSJ) "Reputation Quotient" to operationalize corporate reputation (Gwebu et al., 2018; Haleblian, Pfarrer, & Kiley, 2017; Love & Kraatz, 2009; Pfarrer et al., 2010). Each year, *Fortune* publishes a ranking of firms based on a survey of executives, directors, and analysts that captures various

[4] Search terms used were "data breach," "hack*," "cyber security (cybersecurity)," "cyber attack (cyberattack)," "privacy issue/concern," "security concern," and "phishing." I used the company search function in Factiva to ensure that the articles were about the breached firms.

aspects of capabilities and performance (e.g., innovation, use of corporate assets, long-term investment value, management and product quality, and social responsibility). This ranking reflects industry experts' expectations about the firms' future performance and capabilities—in other words, their reputations (Pollock et al., 2019). In line with my theoretical focus on how audiences interpret high-reputation firms' misconduct, I created a binary variable, *reputation*, coded 1 if a firm was included among the top 50 firms in the FMA or WSJ rankings (Lungeanu et al., 2018; Pfarrer et al., 2010; Pollock et al., 2019), and 0 otherwise.

The high levels of attention and positive emotional resonance represented by media coverage are the core components of celebrity (Pollock et al., 2019; Rindova et al., 2006). I identified celebrity firms by comparing them against their competitors rather than other firms in the dataset, because the distribution of media attention and emotional resonance among breached firms was unlikely to yield meaningful comparisons. In prior empirical studies on firm celebrity, researchers sampled firms that are referents to each other, such as FMA firms and firms of similar size and profitability (Pfarrer et al., 2010), and IPO cohorts (Hubbard et al., 2018). I used the Text-Based Network Industries (TNIC) database (Hoberg & Phillips, 2010; 2016) to identify each breached firm's 10 closest competitors, which resulted in 2,996 firm-years in total, and then identified celebrity firms among this larger group of comparable firms. The database utilizes the mandatory product description section in all 10-K statements filed with the SEC and defines competitors in terms of the similarities in their product descriptions.[5] Studies

[5] To build their database, Hoberg and Phillips (2010; 2016) first downloaded all 10-K statements filed with the SEC each year. They then identified the set of unique words firms used to describe their products in the business description sections in the filings, which are legally mandated to be accurate. Using the words, pairwise similarity scores were computed across all firms where scores closer to zero indicate lower levels

using the TNIC database have demonstrated that rivalries defined by the database significantly predict firms' acquisition behavior (Shi, Zhang, & Hoskisson, 2017), acquisition outcomes (Hoberg & Phillips, 2010), and innovation strategies (Kim, Gopal, & Hoberg, 2016).

Once the larger set of firms with similar offerings was defined, I collected articles about the breached firms and their competitors that were published by the top 25 U.S. newspapers during the previous year. Using these 116,667 articles, I created two ad hoc variables: *volume of public attention* (i.e., number of articles covering a firm) and *intensity of positive emotional resonance*. To operationalize positive emotional resonance, I used the Linguistic Inquiry and Word Count (LIWC) 2015 software program, which counts the number of words in a text associated with pre-validated categories or themes (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Following prior research (Hubbard et al., 2018), I counted the number of words from the positive and negative emotions categories in the LIWC dictionary and computed the ratios of positive emotional words to total emotional words (i.e., both positive and negative) for each article. I then averaged these scores across all articles about a firm to calculate overall emotional positivity.

In prior studies, researchers have measured celebrity by creating discrete variables for both the attentional and emotional components, using the top quartiles for the cut-off

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of product overlap and larger scores indicate stronger competition between the paired firms. Their operationalization of interfirm competition better reflects reality compared to more conventional methods, such as using SIC or NAICS industry codes, by allowing yearly changes in competition and nontransitive memberships in competitive groups: that is, the fact that companies A and B and companies B and C have high levels of product similarity and are competitors does not automatically mean that A and C are competitors. Their study (Hoberg & Phillips, 2016) shows that their measurement better predicts the likelihood that firms discuss high competition in their annual statements as well as their self-identified rivals than SIC and NAICS codes. For more detailed information about their measurement, refer to their articles (Hoberg & Phillips, 2010; 2016) and the website (http://hobergphillips.tuck.dartmouth.edu/).

points, and identifying firms with scores of 1 for both variables as celebrity firms (Hubbard et al., 2018; Pfarrer et al., 2010). However, using the same approach in this study would classify too few observations as involving celebrity firms (21 observations; approximately 7 percent). Furthermore, the list of celebrity firms identified by the conventional approach lacked face validity, as it included firms such as WellCare Health Plans which was featured in only 14 articles in 2016 across the top 25 U.S. newspapers, 12 of which were positive (i.e., at least 66 percent of the emotional content was positive). This reflects a potential problem of using the conventional approach to analyze my data: firms that receive less media attention could systematically score higher on the positive emotions component. Although this may be a theoretical phenomenon whereby celebrity firms with increased visibility subsequently attract unfavorable evaluations (Zavyalova et al., 2017), it is reasonable to say that Google, which had 1,250 positive articles out of 1,760 total articles in 2016, is far more likely to be a celebrity firm than WellCare.

To address this issue, I multiplied the two components to prevent the systematic discounting of the attention component. In so doing, I standardized the scores for both components and transformed them into positive values. Based on the multiplied values, I defined celebrity firms as those scoring higher than one standard deviation above the mean.[6] As a result, a total of 56 breach incidents were operationalized as involving celebrity firms. The celebrity firms in my sample were covered by 839 articles in the previous year on average, which better reflects the highly visible nature of celebrity firms compared to using the conventional approach, where the firms identified as celebrities

[6] Using different cut-off points such as the 75th or 90th percentiles results in more than a quarter of my observations being classified as involving celebrity firms, which contradicts the exclusive nature of social approval assets (Pollock et al., 2019).

were covered by 62 articles on average, with a maximum of 115 articles for Yum! Brands in 2016. This number is even smaller than the celebrity firms in my sample with the minimum amount of coverage: News Corp featured in 127 articles in 2013.[7]

As a measure of misconduct severity, I used the number of accounts affected (in thousands), which has been found to significantly amplify investor reactions to data breaches (Gwebu et al., 2018; Malhotra & Malhotra, 2011; Martin et al., 2017). Because the variable has a significant rightward skew, I used the natural logarithm to prevent extreme values from driving the results. Note, however, that data are not available for some incidents because the number of affected accounts was indeterminate at the time of disclosure (i.e., a system breaches had been identified, but whether or how many accounts were affected was unknown). Although it has been reported in prior research that there is no significant relationship between investor reactions to data breach events and the availability of information about the number of affected accounts (Malhotra & Malhotra, 2011), I controlled for this aspect by creating a binary variable, *unknown impact*, coded as 1 if the number of affected accounts was not available, and 0 otherwise. I assigned the mean value of these observations to the *breach severity* variable. Assigning different values such as the median or the 75th percentile did not affect the results.

[7] To further elaborate on the difference between the original measurement and mine, when the conventional approach is used, the correlation between celebrity and reputation is 0.01. Although celebrity and reputation are theoretically distinct constructs (Pollock et al., 2019) and have been shown to be weakly correlated (Pfarrer et al., 2010), almost no correlation between the two variables in my sample seems nonsensical. Using the current measure, the correlation is 0.43. Some firms identified as both reputable and celebrities are Apple, Facebook, Google, Starbucks, and the Walt Disney Company, seemingly reflecting reality. Celebrity firms not identified as high-reputation include Chipotle Mexican Grill, Twitter, Verizon, News Corp, and Time Warner. Whereas the correlation between reputation and celebrity may seem problematic, nonlinear models such as the negative binomial regressions used in this study require all non-theoretical variables to be held at certain values to interpret marginal effects and plot interactions (Hubbard et al., 2018). I held reputation at 0 when interpreting the results related to celebrity and celebrity at 0 when interpreting the results related to reputation. Thus, overlaps between high-reputation and celebrity firms should not affect interpretations of my findings. This is confirmed by an additional analysis in the Robustness Tests section.

As a measure of the recency of similar misconduct (i.e., *breach recency*), I counted the number of months since the latest reported breach involving a focal firm, up to two years prior to the beginning of my observation period (i.e., January 1, 2012). For observations where firms had not been involved in data breaches between the beginning of 2012 and the focal breach incident, I counted the number of months since January 1, 2012. To facilitate interpretation, I reverse-coded this variable by subtracting the maximum value and multiplying by -1. This way, larger values indicate greater recency of prior breach incidents.[8]

2.2.4 Control variables

I controlled for several firm characteristics that may affect firms' visibility to stakeholders and thus increase the likelihood of breach incidents involving these firms receiving media coverage. In addition to *firm size* (log-transformed total assets) and *firm age* (Lungeanu et al., 2018), I controlled for *firm return on assets* (ROA) to account for the effect of performance on media coverage (Vergne et al., 2018). Although the media-reported reputation rankings are based on surveys of external experts, I derived my measures of both celebrity and reputation from media outlets; thus, media coverage of high-reputation and celebrity firms' data breach incidents might reflect the amount of coverage the firms would normally receive (Vergne et al., 2018). Although this possibility is to some extent accounted for in my dependent variable measure, which is based only on articles pertaining to breach incidents (Bednar, 2012; Vergne et al., 2018)

[8] Variable transformations in nonlinear models can be problematic because altering the values of a variable can influence the effects of other variables. However, in my data, using the original variable (i.e., not reverse-coded) yielded the same results as those reported here except for the opposite sign of the recency variable.

rather than the firms in general (Zavyalova et al., 2012), I controlled for the volume of media coverage a firm received during the one-month period prior to the breach incident with a one-week gap (i.e., *firm media visibility*) (Dewan & Jensen, 2019; Vergne et al., 2018). As this variable was highly skewed, I used the natural logarithm. Lastly, firms may have different propensities to seek or avoid media coverage (Pollock et al., 2008; Pollock & Rindova, 2003). To control for this aspect, I included a log-transformed count of press releases issued by a firm and disseminated by PR Newswire and Business Wire, the two leading outlets in the corporate world (Zavyalova et al., 2012), during the previous year (i.e., *firm press releases*).

The second set of control variables accounts for the impacts of breach characteristics. First, whether or not a breach exposed sensitive information can affect stakeholders' reactions and increase the likelihood of the event being publicized (Campbell, Gordon, Loeb, & Zhou, 2003; Gwebu et al., 2018). Thus, I included three binary variables indicating whether a breach exposed personal identification information such as Social Security or driver's license numbers (i.e., *ID information*), *financial information* such as bank account or credit card numbers, and/or *medical information* such as prescriptions, diagnoses, and Medicaid or Medicare ID numbers. Second, a firm's perceived culpability can be affected by whether data were mishandled by the firm itself or by an external contractor (Lange & Washburn, 2012). Thus, I included a binary variable, *breached through contractor*, coded 1 if a breach occurred through a contracted entity, and 0 otherwise. Third, I included a dichotomous variable, *breached through subsidiary*, because information cues from diversified entities tend to have weaker impacts on stakeholders' evaluations of the parent firm (Connelly et al., 2011) and thus have a weaker influence on media outlets' decisions to publicize breach incidents. Fourth, I controlled for whether a breach occurred through a *hacker attack* because such attacks accounted for more than half of my sample and may have been deemed more newsworthy by the media. Finally, as mentioned above, I included a binary variable indicating *unknown impact*.

The remaining set of variables relates to environmental factors that could affect media coverage decisions. To account for the effect of the prevalence of data breach incidents within an industry (Zavyalova et al., 2012), I included the number of data breaches involving firms with the same two-digit SIC code during the 12-month period preceding a focal breach. I took the natural log of this variable, *industry breach prevalence*, to account for its skewed distribution. Also, the salience of data breaches as a newsworthy issue can differ over time, thus affecting the likelihood of a breach event being covered by the media (Desai, 2011). To control for this, I accessed the Google Trends database, which indexes search terms related to various topics and provides periodic data on the volume of topic-related searches (Choi & Varian, 2012; Vosen & Schmidt, 2011). To measure *issue salience*, I log-transformed the number of searches related to the "data breach" topic during the one-month period prior to each focal breach incident, with a one-week gap.

I also included year dummies with 2014 as the excluded variable. Because I had a relatively small sample of 296 incidents, I could not include industry fixed effects across all 44 two-digit SIC codes. Thus, I included four industry dummies for the most frequently breached industries, which accounted for about 44 percent of observations: *communications* (2-SIC: 48), *miscellaneous retail* (2-SIC: 59), *business services* (2-SIC:

73), and *health services* (2-SIC: 80)

2.3. Analysis and Results

Because my dependent variable is a count variable, I used negative binomial regression with robust standard errors clustered by each firm (Hubbard et al., 2018; Park & Rogan, 2019). Table 2.1 presents descriptive statistics and correlations. Although most variables are only moderately correlated with each other, *reputation* is highly correlated with *firm media visibility* (0.61), *size* (0.55), and *press releases* (0.50). Similarly, *celebrity* is highly correlated with *firm media visibility* (0.73), *size* (0.50), and *press releases* (0.57). Moreover, *firm size* is highly correlated with *media visibility* (0.72) and *press releases* (0.76), and *firm media visibility* is highly correlated with *press releases* (0.74). Thus, I regressed *firm media visibility* on *reputation*, *celebrity*, *firm size*, and *firm press releases* to obtain residuals and used them as the instrument for *firm media visibility* (Dewan & Jensen, 2019). Then, in a similar fashion, I regressed *firm size* on *reputation*, *celebrity*, and *firm press releases* to generate the residualized version of firm size, and regressed *firm press releases* on *reputation* and *celebrity* to create the residualized version of *firm press releases*.

Table 2.1. Descriptive Statistics and Correlations

Variables	**Mean**	***SD***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1. Breach media coverage	2.13	13.75											
2. Reputation	0.18	0.38	0.10										
3. Celebrity	0.18	0.39	0.08	0.43									
4. Breach severity	2.88	2.73	0.29	0.11	0.21								
5. Breach recency	48.07	24.23	0.14	0.21	0.26	0.04							
6. Firm ROA	0.18	0.29	0.13	0.15	0.11	-0.01	0.13						
7. Firm size	7.98	1.89	0.05	0.55	0.50	0.11	0.46	0.17					
8. Firm age	55.15	39.17	0.07	0.10	-0.04	-0.07	0.07	-0.03	0.18				
9. Firm media visibility	1.50	1.54	0.13	0.61	0.73	0.29	0.39	0.16	0.72	0.02			
10. Firm press releases	4.38	1.26	0.11	0.50	0.57	0.16	0.41	0.21	0.76	0.09	0.74		
11. Unknown impact	0.29	0.45	-0.02	-0.10	-0.03	-0.15	-0.07	0.07	-0.10	-0.17	0.00	-0.05	
12. ID information	0.33	0.47	0.02	-0.04	-0.18	-0.15	-0.13	0.06	-0.18	0.06	-0.24	-0.21	0.04
13. Financial information	0.29	0.45	0.09	-0.10	-0.15	-0.01	-0.15	0.08	-0.18	0.02	-0.09	-0.12	-0.02
14. Medical information	0.24	0.43	-0.08	-0.01	-0.06	-0.23	0.15	-0.09	0.06	0.06	-0.05	-0.03	-0.32
15. Hacker attack	0.55	0.50	0.12	-0.05	0.09	0.26	-0.22	0.04	-0.11	-0.09	0.09	0.01	0.17
16. Breached through contractor	0.11	0.32	-0.05	-0.05	-0.03	-0.06	0.02	-0.09	0.03	0.05	-0.05	0.01	-0.01
17. Breached through subsidiary	0.28	0.45	-0.07	-0.25	-0.06	-0.10	-0.15	0.09	-0.05	0.05	-0.18	-0.07	-0.02
18. Industry breach prevalence	1.59	0.95	0.10	0.00	0.16	0.21	0.31	-0.01	0.11	-0.16	0.18	0.18	-0.13
19. Issue salience	2.79	0.58	-0.07	0.03	-0.17	-0.01	-0.07	0.08	-0.04	0.01	-0.05	-0.02	0.01
Variables	**12**	**13**	**14**	**15**	**16**	**17**	**18**						
13. Financial information	-0.17												
14. Medical information	0.01	-0.30											
15. Hacker attack	-0.17	0.32	-0.44										
16. Breached through contractor	0.02	-0.13	0.06	-0.39									
17. Breached through subsidiary	-0.01	0.01	0.06	0.00	-0.03								
18. Industry breach prevalence	-0.12	-0.23	0.10	-0.04	-0.04	-0.02							
19. Issue salience	0.00	0.11	-0.04	0.03	-0.03	-0.01	-0.06						

N = 296

This procedure mitigated potential collinearity concerns, as the condition numbers computed across all models presented in Table 2.2 are below 30, a widely accepted threshold, with the maximum being 17.68 (Belsley, Kuh, & Welsch, 2005). The mean variance inflation factor (VIF) values for all models do not exceed the commonly used threshold of 10, with the maximum being 3.16. However, the VIFs computed for *celebrity* (12.17 in Model 6 and 13.33 in Model 7) and its interaction term with *breach recency* (10.90 in Model 6 and 13.27 in Model 7) slightly exceed 10. Nonetheless, when using the mean-centered value for *breach recency* in the interactions with *celebrity* and *reputation* in Model 7, the interaction terms yield exactly the same *p*-values, suggesting that the high VIFs in the original models are not problematic.

Table 2.2. Results Predicting Media Coverage of Data Breaches

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
constant	-0.422	-4.917**	-4.923**	-5.256***	-4.927**	-4.403**	-4.735**
	(1.645)	(1.512)	(1.509)	(1.488)	(1.524)	(1.579)	(1.579)
Unknown impact	-0.611*	0.653†	0.653†	0.564	0.664†	0.572	0.507
	(0.311)	(0.378)	(0.379)	(0.390)	(0.375)	(0.368)	(0.366)
Hacker attack	1.474**	1.950***	1.948***	1.825**	2.229***	2.037***	2.023**
	(0.540)	(0.570)	(0.572)	(0.569)	(0.636)	(0.595)	(0.634)
ID information	-1.476***	-0.106	-0.108	-0.254	0.020	0.040	-0.045
	(0.387)	(0.425)	(0.422)	(0.441)	(0.415)	(0.399)	(0.407)
Financial information	0.025	0.987**	0.992**	0.867*	0.908*	1.066**	0.873*
	(0.414)	(0.352)	(0.364)	(0.354)	(0.359)	(0.351)	(0.382)
Medical information	-2.617***	-1.613*	-1.613*	-1.818*	-1.661*	-1.583*	-1.828*
	(0.781)	(0.651)	(0.651)	(0.714)	(0.665)	(0.654)	(0.737)
Breached through contractor	-0.295	0.724	0.721	0.561	1.013	0.652	0.610
	(0.967)	(0.910)	(0.910)	(0.946)	(0.946)	(0.933)	(1.022)
Breached through subsidiary	-1.835***	-0.650	-0.648	-0.797†	-0.659	-0.664	-0.866†
	(0.495)	(0.449)	(0.452)	(0.465)	(0.445)	(0.447)	(0.465)
Firm ROA	2.517***	0.795	0.788	0.836	0.851	0.917†	1.046†
	(0.690)	(0.566)	(0.588)	(0.585)	(0.563)	(0.558)	(0.589)
Firm size	-0.089	-0.244	-0.243	-0.245	-0.226	-0.238	-0.236
	(0.166)	(0.160)	(0.160)	(0.167)	(0.155)	(0.152)	(0.151)
Firm age	0.007	0.005	0.005	0.007†	0.006	0.008†	0.011*
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Firm media visibility	1.106***	0.888***	0.889***	0.930***	0.960***	0.948***	1.021***
	(0.297)	(0.239)	(0.239)	(0.252)	(0.236)	(0.239)	(0.241)
Firm press releases	0.282	0.504*	0.502*	0.490*	0.473*	0.485*	0.467*
	(0.186)	(0.226)	(0.227)	(0.229)	(0.214)	(0.204)	(0.202)
Ind. breach prevalence	0.019	-0.146	-0.141	-0.232	-0.117	0.031	-0.099
	(0.312)	(0.301)	(0.310)	(0.314)	(0.299)	(0.299)	(0.326)
Issue salience	-0.325	-0.223	-0.224	-0.168	-0.254	-0.342	-0.274
	(0.381)	(0.302)	(0.303)	(0.302)	(0.297)	(0.322)	(0.313)
Reputation		1.160***	1.201*	0.985**	0.079	0.979**	-0.087
		(0.333)	(0.540)	(0.350)	(0.947)	(0.330)	(0.941)
Celebrity		1.963***	1.958***	3.081***	1.863***	0.192	1.585†
		(0.338)	(0.343)	(0.432)	(0.340)	(0.861)	(0.900)
Breach severity		0.239***	0.242***	0.293***	0.230***	0.247***	0.288***
		(0.052)	(0.061)	(0.053)	(0.052)	(0.049)	(0.054)
Breach recency		0.021*	0.021*	0.023**	0.016†	0.008	0.006
		(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.011)
Breach severity x Reputation			-0.010				0.072
			(0.095)				(0.094)
Breach severity x Celebrity				-0.287***			-0.332***
				(0.083)			(0.092)
Breach recency x Reputation					0.021		0.011
					(0.016)		(0.012)
Breach recency x Celebrity						0.037*	0.035*
						(0.017)	(0.016)
Industry dummies				Included			
Year dummies				Included			
Log pseudo-likelihood	-277.11	-253.92	-253.92	-251.38	-253.28	-252.41	-249.00
Likelihood-ratio tests		46.39***	0.01	5.07*	1.28	3.01†	9.85*

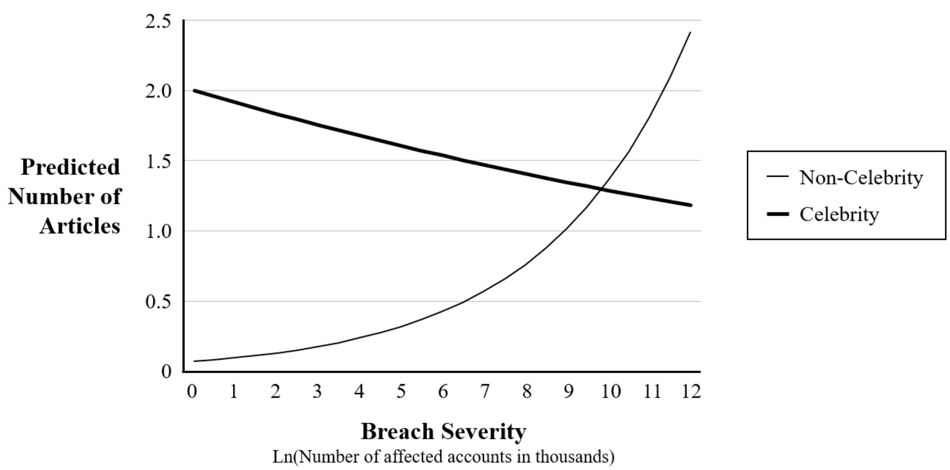
† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $N = 296$ (197 clusters).
Likelihood-ratio tests are based on Model 1 for Model 2, and on Model 2 for Models 3, 4, 5, 6, and 7.

Table 2.2 presents the results of the negative binomial regression predicting the volume of media coverage on data breaches. Model 1 includes only the control variables, Model 2 introduces the battery of independent variables, Models 3–6 introduce the interaction terms one at a time, and Model 7 is the saturated model. The likelihood-ratio tests suggest that including the main effects of reputation and celebrity, as well as those of the breach characteristics in Model 2 significantly improves model fit. Model fits significantly improve relative to the main effects model when the interaction terms involving celebrity are included (i.e., Models 4, 6, and 7) but not when the interaction terms involving reputation are included in isolation (i.e., Models 3 and 5). The saturated model demonstrates a significantly better fit than all of the interaction models except for Model 4 (p = 0.189).

Hypotheses 1 and 2 state that reputation and celebrity lead to a higher likelihood of a firm's misconduct being publicized. Results in Model 2 indicate that the transgressors' reputation (b = 1.159, p = 0.000) and celebrity (b = 1.962, p = 0.000) have a positive and significant effect on the number of articles covering their data breaches. When a data breach involves a high-reputation firm, the number of articles increases by approximately 3.262 on average; when a breach involves a celebrity firm, the number of articles increases by approximately 5.520, on average. Given the mean of 2.215 articles, reputation leads to almost a 50 percent increase and celebrity leads to approximately a 150 percent increase in media coverage. Hypotheses 3 and 4 predict that reputation amplifies and celebrity attenuates the positive effect of misconduct severity. These hypotheses assume the positive main effect of severity as the baseline, which is confirmed across all models at $p < 0.001$. The interaction between breach severity and reputation is not significant ($p > 0.10$) in Models 2 and 7. Thus, Hypothesis 3 is not supported.

The interaction between breach severity and celebrity is negative and significant in Models 3 and 7 ($p < 0.001$ in both), as hypothesized. The interaction is plotted in Figure 2.1 based on the results for Model 7. All variables other than the theoretical variables are held at their means if continuous, and modes if discrete (Hubbard et al., 2018). Figure 2.1 shows that breach severity drastically increases the predicted number of articles for non-celebrity firms from almost no articles to approximately 2.4 articles, but the predicted number of articles gradually decreases for celebrity firms from 2 articles to 1.18 articles. Hypothesis 4 is therefore supported.

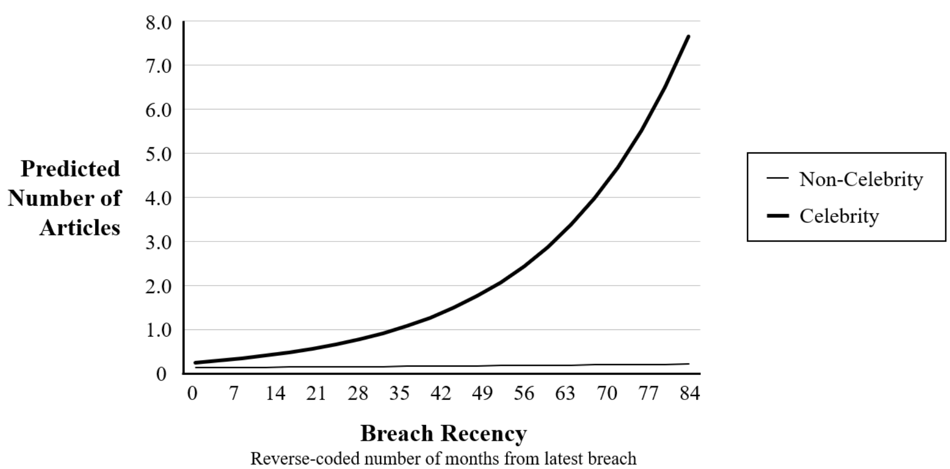
Figure 2.1. Interaction between Breach Severity and Celebrity



Hypotheses 5 and 6 predict that reputation amplifies and celebrity attenuates the effect of breach recency. The baseline prediction that the recency of similar misconduct by a firm increases the likelihood of the media publicizing a focal act of misconduct is significant in Model 2 ($p = 0.011$). However, the interaction effect between reputation and recency is not significant ($p > 0.10$) in Models 3 and 7. Thus, Hypothesis 5 is not supported.

The interaction between breach recency and celebrity, perhaps the most surprising finding in this study, is significant in Models 6 ($p = 0.033$) and 7 ($p = 0.026$), but in the opposite direction from what I hypothesized. That is, celebrity amplifies the recency effect on media coverage. The interaction plot presented in Figure 2.2 is based on the results in Model 7. The plot shows that the predicted number of articles drastically increases for celebrity firms from 0.13 to 7.65 articles as recency increases, whereas the predicted number of articles for non-celebrity firms stays virtually constant around 0. Hence, Hypothesis 6 is not supported, but in a surprising way, leaving room for potential explanations. I discuss this unexpected finding, as well as the lack of significant interactions between breach characteristics and reputation in the Discussion section.

Figure 2.2. Interaction between Breach Recency and Celebrity



2.3.1. Robustness Tests

Although reputation and celebrity have different sociocognitive content (Pfarrer et al., 2010; Pollock et al., 2019), their correlation is 0.43, indicating that slightly less than half of the high-reputation firms in the sample also happen to be celebrity firms. Although I held reputation at 0 when interpreting the interaction effects of celebrity, the conflation of reputation and celebrity could introduce potential empirical and conceptual problems. Hence, I reran the analysis after orthogonalizing reputation and celebrity to remove the common variance from the variables, using a Gram-Schmidt procedure through the *orthog* command in STATA (Piazza & Jourdan, 2018; Pollock & Rindova, 2003). The results were virtually the same regarding the signs and significances of the findings, except that the interaction between breach recency and reputation became marginally significant ($p < 0.10$) in the saturated model, even though it remained nonsignificant when included separately. Thus, it seems reasonable to conclude that the covariance of reputation and celebrity did not affect my original findings.

Frequency, as captured by the number of prior acts of misconduct in which a firm was involved, may also affect the processing of misconduct (Pfarrer et al., 2008; Love & Kraatz, 2017). Indeed, frequency also contributes to the salience of a stimulus, along with its extremity and recency (Tversky & Kahneman, 1974). Hence, I created a count variable of the number of breaches involving a firm during the five years preceding the focal breach incident. Because this variable was highly skewed, I log-transformed it. However, recency and frequency were highly correlated at 0.70 reflecting the close relationship between the two constructs.

The results in Table 2.3 show that using breach frequency instead of recency yields substantially the same results. The main effects of reputation and celebrity are both positive and significant at $p < 0.01$ and $p < 0.001$, respectively, in Model 9. Celebrity significantly attenuates the effect of breach severity ($p < 0.001$) in Model 11 and amplifies the effect of breach frequency ($p < 0.01$) in Model 13. The interactions between reputation and both breach severity and breach frequency are not significant. However, the main effect of breach frequency itself is not significant ($p > 0.10$) across all models, suggesting that frequency might be a more ambiguous information cue than recency. Overall, these results suggest that the frequency and recency dimensions capture similar aspects of misconduct and thus are processed in similar ways in light of the interpretive frames provided by reputation and celebrity.

Table 2.3. Robustness Test Exploring the Effect of Breach Frequency

Variables	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
constant	-0.248	-3.692**	-3.687**	-3.922**	-3.797**	-3.492**	-3.937**
	(1.552)	(1.322)	(1.321)	(1.326)	(1.334)	(1.226)	(1.230)
Unknown impact	-0.632*	0.627	0.625	0.552	0.633	0.407	0.324
	(0.312)	(0.390)	(0.389)	(0.400)	(0.388)	(0.395)	(0.395)
Hacker attack	1.517**	1.961**	1.970***	1.833**	2.146***	2.135***	2.109**
	(0.538)	(0.596)	(0.597)	(0.603)	(0.643)	(0.630)	(0.668)
ID information	-1.481***	-0.139	-0.133	-0.300	-0.074	-0.046	-0.172
	(0.391)	(0.428)	(0.424)	(0.446)	(0.424)	(0.396)	(0.406)
Financial information	-0.121	1.060**	1.048**	0.971*	0.971*	0.914*	0.682
	(0.415)	(0.377)	(0.394)	(0.381)	(0.388)	(0.386)	(0.420)
Medical information	-2.788***	-1.649*	-1.654*	-1.820*	-1.633*	-1.607*	-1.863*
	(0.734)	(0.678)	(0.684)	(0.736)	(0.676)	(0.656)	(0.766)
Breached through contractor	-0.266	0.795	0.805	0.640	0.999	0.797	0.730
	(0.949)	(0.917)	(0.912)	(0.942)	(0.946)	(0.905)	(0.985)
Breached through subsidiary	-1.730***	-0.800†	-0.804†	-0.984*	-0.769†	-0.720	-0.997†
	(0.489)	(0.467)	(0.468)	(0.499)	(0.462)	(0.470)	(0.517)
Firm ROA	2.310***	0.983†	0.995†	1.027†	1.022†	1.194*	1.360*
	(0.675)	(0.544)	(0.557)	(0.547)	(0.554)	(0.543)	(0.580)
Firm size	-0.298	-0.216	-0.219	-0.208	-0.181	-0.201	-0.167
	(0.185)	(0.170)	(0.168)	(0.173)	(0.174)	(0.165)	(0.173)
Firm age	0.007	0.005	0.005	0.007	0.006	0.007†	0.011*
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Firm media visibility	1.137***	0.913***	0.908***	0.945***	0.936***	1.034***	1.094***
	(0.290)	(0.252)	(0.251)	(0.268)	(0.246)	(0.247)	(0.249)
Firm press releases	0.311	0.533*	0.536*	0.520*	0.532*	0.577**	0.585**
	(0.199)	(0.231)	(0.232)	(0.234)	(0.223)	(0.218)	(0.215)
Ind. breach prevalence	-0.019	-0.122	-0.131	-0.206	-0.096	0.060	-0.058
	(0.310)	(0.314)	(0.323)	(0.332)	(0.314)	(0.304)	(0.347)
Issue salience	-0.335	-0.301	-0.299	-0.259	-0.320	-0.424	-0.362
	(0.369)	(0.292)	(0.292)	(0.297)	(0.288)	(0.280)	(0.281)
Reputation		1.068**	0.983†	0.887*	0.605	1.060**	0.146
		(0.352)	(0.542)	(0.366)	(0.564)	(0.351)	(0.666)
Celebrity		2.089***	2.093***	3.171***	2.103***	0.853†	2.278***
		(0.405)	(0.406)	(0.503)	(0.411)	(0.516)	(0.574)
Breach severity		0.235***	0.230***	0.287***	0.240***	0.231***	0.298***
		(0.055)	(0.065)	(0.057)	(0.054)	(0.053)	(0.058)
Breach frequency		0.295	0.294	0.329	0.105	-0.230	-0.441
		(0.243)	(0.245)	(0.255)	(0.301)	(0.259)	(0.319)
Breach severity x Reputation			0.021				0.060
			(0.095)				(0.085)
Breach severity x Celebrity				-0.280***			-0.381***
				(0.085)			(0.099)
Breach frequency x Reputation					0.502		0.415
					(0.403)		(0.376)
Breach frequency x Celebrity						1.464**	1.595***
						(0.480)	(0.448)
Industry dummies				Included			
Year dummies				Included			
Log pseudo-likelihood	-276.44	-255.08	-255.06	-252.77	-254.64	-252.13	-247.73

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $N = 296$ (197 clusters).

Because the majority of data breaches in my sample did not receive any media coverage (approximately 79 percent), I also examined whether my findings extend to alternative specifications.[9] Specifically, I dichotomized the dependent variable by assigning a value of 1 if a breach incident was covered by the media, and 0 otherwise. The results using probit regression are similar to the original results, as presented in Table 2.4. The effects of both reputation and celebrity are significantly positive ($p < 0.01$) in Model 16. In Model 18, celebrity attenuates the effect of breach severity ($p < 0.01$); however, in Model 20, celebrity no longer amplifies the effect of breach recency ($p < 0.10$). Although the probit specification replicates most but not all of my findings, I believe the negative binomial regression best represents my data. More importantly, my theoretical inquiry regarding the scandalization of misconduct necessitates measures reflecting the magnitude of media coverage of an act of misconduct.

[9] Zero-inflated negative binomial regression can be an alternative approach to test my hypotheses. However, since I have a relatively small sample (*N* = 296), I cannot properly model the inflation equation. The model does not converge, even with only year and industry dummies to predict the inflation factor. Allison (2012a; 2012b) provided a useful guideline: (a) standard negative binomial regression can handle an excessive number of observations with a count of zero; and (b) zero-inflated models should be used only when strong enough reasons exist for not assigning non-zero values to zero-count observations based on theory or common sense.

Table 2.4. Robustness Test Using the Probit Specification

Variables	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21
constant	-0.985	-1.987*	-2.061*	-2.341*	-1.952*	-1.940*	-2.280*
	(0.711)	(0.861)	(0.871)	(0.910)	(0.881)	(0.904)	(0.963)
Unknown impact	-0.451*	0.042	0.045	-0.035	0.062	0.039	-0.018
	(0.206)	(0.253)	(0.259)	(0.281)	(0.254)	(0.253)	(0.286)
Hacker attack	0.744*	0.817*	0.845*	0.923**	0.938**	0.819*	1.050**
	(0.327)	(0.337)	(0.337)	(0.348)	(0.338)	(0.335)	(0.341)
ID information	-0.528*	-0.143	-0.149	-0.110	-0.074	-0.142	-0.040
	(0.243)	(0.253)	(0.259)	(0.271)	(0.248)	(0.253)	(0.263)
Financial information	0.127	0.552*	0.550*	0.506*	0.545*	0.560*	0.508†
	(0.222)	(0.240)	(0.241)	(0.250)	(0.244)	(0.247)	(0.259)
Medical information	-1.160***	-0.898**	-0.906*	-1.028**	-0.938**	-0.905*	-1.066**
	(0.332)	(0.345)	(0.355)	(0.381)	(0.359)	(0.352)	(0.397)
Breached through contractor	0.284	0.563	0.566	0.614	0.690	0.563	0.746
	(0.405)	(0.424)	(0.433)	(0.462)	(0.420)	(0.424)	(0.458)
Breached through subsidiary	-0.779**	-0.471†	-0.477†	-0.501†	-0.472†	-0.475†	-0.520†
	(0.241)	(0.267)	(0.267)	(0.278)	(0.270)	(0.268)	(0.285)
Firm ROA	0.329	0.022	0.023	-0.063	0.066	0.039	0.003
	(0.342)	(0.403)	(0.407)	(0.404)	(0.397)	(0.407)	(0.407)
Firm size	-0.055	-0.035	-0.031	-0.030	-0.042	-0.036	-0.035
	(0.083)	(0.101)	(0.102)	(0.107)	(0.101)	(0.102)	(0.106)
Firm age	0.002	0.000	0.000	0.000	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Firm media visibility	0.363**	0.328*	0.330*	0.402**	0.382*	0.330*	0.463**
	(0.126)	(0.138)	(0.140)	(0.142)	(0.149)	(0.139)	(0.152)
Firm press releases	0.101	0.203	0.197	0.216	0.203	0.204	0.217
	(0.108)	(0.148)	(0.149)	(0.151)	(0.143)	(0.147)	(0.145)
Ind. breach prevalence	0.149	0.344†	0.352†	0.302	0.375†	0.354†	0.344
	(0.176)	(0.203)	(0.203)	(0.210)	(0.208)	(0.205)	(0.222)
Issue salience	-0.071	-0.068	-0.077	-0.060	-0.091	-0.074	-0.082
	(0.181)	(0.189)	(0.190)	(0.198)	(0.189)	(0.191)	(0.200)
Reputation		0.866**	1.120**	0.818**	0.102	0.849**	0.027
		(0.293)	(0.375)	(0.304)	(0.718)	(0.300)	(0.703)
Celebrity		1.092**	1.092**	1.964***	1.047**	0.895	1.794*
		(0.351)	(0.353)	(0.411)	(0.357)	(0.749)	(0.744)
Breach severity		0.152***	0.164***	0.210***	0.154***	0.153***	0.215***
		(0.043)	(0.049)	(0.049)	(0.042)	(0.043)	(0.049)
Breach recency		-0.005	-0.005	-0.003	-0.009	-0.006	-0.008
		(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Breach severity x Reputation			-0.069				0.001
			(0.069)				(0.083)
Breach severity x Celebrity				-0.203**			-0.213**
				(0.070)			(0.080)
Breach recency x Reputation					0.015		0.015
					(0.013)		(0.011)
Breach recency x Celebrity						0.004	0.004
						(0.014)	(0.012)
Industry dummies				Included			
Year dummies				Included			
Log pseudo-likelihood	-112.99	-92.47	-92.16	-89.16	-91.55	-92.42	-88.10

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $N = 296$ (197 clusters).

Reputation and celebrity may influence whether a firm appears in my sample by increasing the likelihood of being breached. Moreover, there may be an omitted variable that affects both my independent variables and the magnitude of media attention. Thus, to eliminate endogeneity concerns, I conducted an impact threshold of a confounding variable (ITCV) analysis on the main effects model (Table 2.2, Model 2) (Frank, 2000). This method, which is attracting increased attention in management research (Busenbark, Lange, & Certo, 2017; Harrison, Boivie, Sharp, & Gentry, 2018; Hubbard, Christensen, & Graffin, 2017), enables researchers to determine how strong the effect of a hypothetical confounding variable should be in order to overturn current findings. To conduct the analysis, I applied the *konfound* command in Stata with the nonlinear option specified, which uses the average partial effects for computation. The results suggest that in order to invalidate the findings for reputation and celebrity, 29.14 percent (86 cases) and 30.64 percent (91 cases) of the estimate, respectively, would have to be due to bias. This is highly unlikely; thus, it seems reasonable to conclude that my findings are not subject to bias.

To better understand the potential impact of the omitted variable bias, I specified a linear regression model with my original dependent variable (i.e., number of articles about a breach) and log-transformed values to reflect its skewed distribution. Both reputation and celebrity show significant and positive effects ($p < 0.01$), mirroring the original results. The results of the ITCV analysis are substantially the same: 44.22 percent and 42.42 percent of the estimate would have to be due to bias to invalidate the results regarding reputation and celebrity, respectively. Furthermore, the analysis suggested that a hypothetical omitted variable should have a minimum correlation of 0.29

with both reputation and the outcome, and 0.28 with both celebrity and the outcome to have an impact on the results. None of the current variables have such high correlations with reputation and celebrity except for firm size, media visibility, and press releases, and I already control for the effects of these variables. Thus, again, endogeneity is not likely to be an issue.

2.3.2. Post Hoc Analysis

My theoretical framework and hypotheses imply that the magnitude of media attention sufficiently captures the publicizing of organizational misconduct which in turn can lead to scandal. Given that media outlets tend to maintain a neutral tone in their reporting (Pollock et al., 2008) and that corporate misconduct itself conveys negative information (Mishina et al., 2012; Paruchuri et al., 2020), it seems reasonable that the mere disclosure of a firm's misconduct to the public can lead to scandal even when media coverage does not have negative tone. However, to further explore the role of social evaluations in the scandalization process, I conducted a set of analyses focused on the tenor of articles about firm misconduct.

First, I coded the tenor of each article covering a focal data breach incident.[10] In so doing, I computed the ratio of negative emotional words to total emotional words in each article and classified an article as negative if the ratio exceeded 50 percent.[11] Then, I

[10] Another way to examine my hypothesized effects on the tenor of media coverage would be to use the overall tenor of all articles on the breach incidents (Vergne et al., 2018). However, the small number of observations that received media coverage in my sample (61 observations) deterred me from using this approach as the fitting of my current model would reduce the statistical power of my results (Howell, 1992).

[11] Other studies have used cut-off points of 60 percent (Pfarrer et al., 2010) or 66 percent (Zavyalova et al., 2012) to determine negative articles. Using the same thresholds would result in only 21 observations being classified as negatively publicized by the media. However, since negative information often carries greater weight than positive information (Vergne et al., 2018; Zavyalova et al., 2012), audiences are likely to form

created a new dependent variable, *negative media coverage of breach*. Because the number of negative media articles is highly correlated with the total amount of media coverage (0.83 in my sample), I used the predicted number of articles on breach incidents from Model 7 in Table 2.2 and included it as a variable, *likelihood of publicizing* (Shi et al., 2017), which has a weaker correlation with negative media coverage of breaches at 0.51. Subsequently, I replicated my hypothesis tests using negative binomial regression to predict the number of negative articles about breach incidents. I did not include *firm press releases* in this regression, as information provided by the firms themselves may not necessarily influence the evaluative judgments of stakeholder audiences. That is, although the media may pay more attention to firms that actively issue press releases and seek coverage (Pollock et al., 2008), such attention-seeking tendencies may not incur more positive or negative coverage due to the dubious credibility of firm-provided information (Pollock & Rindova, 2003). Accordingly, whereas firm press releases has significantly positive effects across Models 2–7 in Table 2.2 ($p < 0.05$), it has a nonsignificant effect across all models predicting negative media coverage. Also, the results reported in Table 2.5 remain the same without the variable.

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stronger negative impressions even when reading an article containing equal amounts of positive and negative words.

Table 2.5. Post Hoc Analysis Predicting Negative Coverage of Data Breaches

Variables	Model 22	Model 23	Model 24	Model 25	Model 26	Model 27	Model 28
constant	0.396	-4.190*	-4.297*	-5.742*	-5.239**	-3.790*	-7.070**
	(1.282)	(1.738)	(1.765)	(2.371)	(1.882)	(1.715)	(2.543)
Unknown impact	0.179	0.871†	0.887†	0.812	0.996†	0.894†	0.999*
	(0.327)	(0.501)	(0.488)	(0.525)	(0.525)	(0.486)	(0.476)
Hacker attack	0.522	1.295†	1.233†	1.319	2.219*	1.382†	2.553*
	(0.591)	(0.721)	(0.747)	(0.903)	(0.930)	(0.725)	(1.147)
ID information	-0.808†	0.332	0.329	0.412	0.758	0.538	1.158*
	(0.473)	(0.496)	(0.509)	(0.588)	(0.515)	(0.504)	(0.579)
Financial information	-0.553	0.302	0.379	0.187	0.350	0.545	0.654
	(0.423)	(0.437)	(0.410)	(0.428)	(0.470)	(0.490)	(0.503)
Medical information	-15.318***	-16.960***	-14.557***	-16.798***	-16.002***	-14.944***	-16.465***
	(0.609)	(0.692)	(0.714)	(0.901)	(0.617)	(0.863)	(0.684)
Breached through contractor	-0.790	0.231	0.233	0.385	1.234	0.077	1.291
	(0.853)	(0.991)	(1.010)	(1.089)	(1.212)	(1.039)	(1.348)
Breached through subsidiary	-1.525**	-0.760	-0.658	-0.756	-0.708	-0.843	-0.963
	(0.465)	(0.567)	(0.594)	(0.561)	(0.559)	(0.544)	(0.605)
Firm ROA	1.145	0.778	0.608	0.643	1.018	0.926	1.310†
	(0.823)	(0.787)	(0.820)	(0.768)	(0.700)	(0.752)	(0.712)
Firm size	-0.020	-0.100	-0.071	-0.075	-0.219	-0.111	-0.174
	(0.175)	(0.208)	(0.211)	(0.242)	(0.232)	(0.202)	(0.246)
Firm age	-0.003	-0.002	-0.003	0.001	0.003	0.002	0.014*
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)
Firm media visibility	0.459*	0.514**	0.528*	0.591**	0.827***	0.599**	1.177***
	(0.199)	(0.197)	(0.211)	(0.224)	(0.216)	(0.203)	(0.317)
Ind. breach prevalence	-0.220	-0.190	-0.140	-0.508	-0.278	0.055	-0.399
	(0.348)	(0.410)	(0.409)	(0.570)	(0.417)	(0.456)	(0.591)
Issue salience	-0.653*	-0.570†	-0.565†	-0.358	-0.681*	-0.754*	-0.668*
	(0.290)	(0.314)	(0.323)	(0.315)	(0.294)	(0.324)	(0.331)
Likelihood of publicizing	0.046*	-0.006	-0.002	-0.004	-0.028	-0.016	-0.043*
	(0.023)	(0.025)	(0.025)	(0.021)	(0.027)	(0.026)	(0.019)
Reputation		1.210**	1.680**	0.995*	-1.181	1.071*	-2.139*
		(0.455)	(0.546)	(0.497)	(0.999)	(0.457)	(1.005)
Celebrity		1.677***	1.640***	3.487***	1.373***	-0.308	1.213
		(0.459)	(0.474)	(0.718)	(0.405)	(1.267)	(1.349)
Breach severity		0.210*	0.235*	0.326**	0.229*	0.250*	0.414***
		(0.103)	(0.101)	(0.107)	(0.093)	(0.101)	(0.078)
Breach recency		0.025†	0.025†	0.031†	0.019†	0.013	0.008
		(0.013)	(0.013)	(0.017)	(0.012)	(0.014)	(0.018)
Breach severity x Reputation			-0.103				0.045
			(0.088)				(0.095)
Breach severity x Celebrity				-0.391***			-0.554***
				(0.080)			(0.087)
Breach recency x Reputation					0.054**		0.063*
					(0.020)		(0.024)
Breach recency x Celebrity						0.040†	0.054*
						(0.024)	(0.026)
Industry dummies				Included			
Year dummies				Included			
Log pseudo-likelihood	-138.55	-126.53	-126.20	-121.50	-124.16	-125.49	-115.56

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $N = 296$ (197 clusters).

Model 23 shows that the main effects of reputation ($p < 0.01$) and celebrity ($p < 0.001$) are positive and significant. Also, celebrity attenuates the effect of breach severity ($p < 0.001$) in Model 25 and amplifies the effect of breach recency ($p < 0.10$) in Model 27. The significance of interaction between celebrity and breach is stronger ($p < 0.05$) in Model 28. Although these results are all consistent with the analysis predicting overall media attention, the interaction between breach recency and reputation is significant and positive in Models 26 ($p < 0.01$) and 28 ($p < 0.05$), as predicted in Hypothesis 5.

Although the results of this post hoc analysis mirror my theory and hypotheses, they should only be interpreted as confirming the effects of reputation and celebrity on the processing of misconduct and its characteristics, rather than supporting specific hypotheses. Without a more adequate way to directly examine the hypothesized effects on the tenor of articles covering the breaches, whether reputation and celebrity shape the media's processing of misconduct-related information in their decisions to render negative opinions remains an open question.

2.4. Discussion

In this study, I have theorized how firms' acts of misconduct become scandalized by attracting public interest and generating media coverage. Building on the well-established role of transgressors' social evaluations in shaping stakeholders' perceptions of the publicity-worthiness of misconduct (Adut, 2005; Graffin et al., 2013), I have shown that the sociocognitive content of transgressors' reputation and celebrity affect the likelihood of scandalization beyond the direct effects of these social assets.

Reflecting stakeholders' elevated need for accuracy when evaluating high-reputation firms (Agrawal & Maheswaran, 2005; Pollock et al., 2019), and the diagnosticity of misconduct in social evaluations (Mishina et al., 2012; Paruchuri et al., 2020), acts of misconduct involving high-reputation firms can be deemed especially newsworthy by the media (Wiesenfeld et al., 2008). The nonsignificant interactions between reputation and misconduct characteristics mean that the involvement of a high-reputation firm in misconduct has considerable diagnosticity in and of itself (Mishina et al., 2012), and the specific information about the misconduct is assessed separately, regardless of the firm's reputation. This may be due in part to the use of severity and recency to assess both misconduct and firm reputation. Thus, my findings suggest that, at least with respect to publicizing misconduct, reputation does not burden firms in the wake of severe or repeated misconduct to the extent suggested by prior research (Bundy et al., 2017; Pfarrer et al., 2008; Rhee & Haunschild, 2006), at least not beyond the higher level of attention it attracts to the firms' actions in general. The flip side is that reputation does not buffer firms from the effects of minor or unrepeated acts of misconduct, either.

Conversely, celebrity attracts significant media attention to transgressors' misconduct, as any surprising behavior by celebrity firms is newsworthy, and misconduct cases are indeed highly surprising (Bundy & Pfarrer, 2015). However, the relationships between celebrity and characteristics of misconduct are more complex than I had theorized. Celebrity attenuates the effect of misconduct severity, as hypothesized, providing evidence that emotion-laden evaluations lead to downplaying or overlooking relevant facts in the processing of misconduct (Agrawal & Maheswaran, 2005; Pollock et al., 2019). However, celebrity amplifies the recency effect, rather than attenuating it. This means that although audiences are typically attracted to novel, nonconforming behaviors from celebrity firms (Pfarrer et al., 2010; Rindova et al. 2006), they do not necessarily tolerate morally risky conduct (Pollock et al., 2016). Thus, whereas a single instance of misconduct might be excused, multiple instances of the same sort that occur in close succession may signal a pattern of behavior (Connelly et al., 2011) that speaks to the character of the celebrity transgressor (Zavyalova et al., 2017). Rather than being treated as redundant information (Anderson, 1981; Chandler et al., 2019), the temporal adjacency of similar misconduct provides additional information about the celebrity transgressor's character, increasing its newsworthiness.

2.4.1. Research implications

Despite the devastating outcomes scandals can have for firms (Adut, 2005; Wiersema & Zhang, 2013), there is only a limited understanding of how scandals emerge, or more precisely, why only some instances of misconduct are publicized, and thus become scandalized (Barnett, 2014; Margolis & Walsh, 2003). That is, although research on misconduct has generated numerous insights into the antecedents and consequences of organizational misconduct (Greve et al., 2010; Mishina et al., 2010), and findings have revealed that the consequences are especially negative when acts of misconduct are publicized (Liu & Shankar, 2015; Rhee & Haunschild, 2006; Wiersema & Zhang, 2013), scholars have overlooked determinants of publicity, which is what transforms a misconduct case into a scandal. This dearth of research is surprising, considering firms' substantial efforts to avoid negative media coverage (Desai, 2011; Lungeanu et al., 2018; Westphal & Deephouse, 2011).

In attempts to understand the antecedents of publicity surrounding misconduct, scholars have suggested that the positive social evaluations accorded to transgressors are the key driver of scandalization (Adut, 2005; Graffin et al., 2013). Although researchers' theoretical emphasis on the role of social evaluations in attracting public attention to misconduct and creating a sense of betrayal is useful, it is crucial to note that not all social evaluations amplify stakeholders' responses to misconduct (Bundy & Pfarrer, 2015). Moreover, even when they do, they do so for different reasons (Pfarrer et al., 2010; Pollock et al., 2019). My findings with respect to celebrity are consistent with prior research suggesting that social evaluations can serve as buffers against negative surprises, even when the potential severity of the events is great (Pfarrer et al., 2010). This neglected aspect of social evaluations points to an important, yet overlooked condition in the theory of scandalization: although high social evaluations can raise the profile of misconduct, countervailing forces might be simultaneously at play due to the idiosyncratic expectations and biases associated with the sociocognitive content of different types of social evaluations. That is, the perceived disruption caused by firm misconduct and the perceived need to publicize it are jointly determined by the burdens and buffers provided by a firm's social approval assets (i.e., reputation, celebrity). This insight also contributes to resolving the longstanding debate on the role of social approval assets during organizational crises in the social evaluations literature, as discussed below.

The question of whether social approval assets amplify or attenuate stakeholders' punishment of firms' misconduct has led to a related and active debate in the social evaluations literature (Bundy & Pfarrer, 2015; Park & Rogan, 2019; Rhee & Haunschild, 2006; Zavyalova et al., 2017). In attempting to resolve the debate, several recent studies have identified the boundary conditions of the burdening and buffering effects of reputation. Some researchers have focused on the specified dimensions of reputation as determining the relative buffer or burden (e.g., Chandler et al., 2019; Park & Rogan, 2019), while other researchers have suggested that stakeholders' level of identification buffers the otherwise burdensome effect of high reputation (Zavyalova et al., 2016). While acknowledging the insights provided by these studies, I suggest that the determinants of relative burdens and buffers—that is, the fit between the nature of misconduct and the sociocognitive content of social approval assets—affect social evaluations.

Because stakeholders expect consistent and predictable behaviors from high-reputation firms, misconduct by these firms is worthy of public attention, regardless of whether specific acts result in significant harm or are repeated within a short period of time. However, the severity and recency of the misconduct can be diagnostic for evaluating reputation itself (Mishina et al., 2012; Paruchuri et al., 2020), which is assessed rationally, as well as for evaluating the newsworthiness of the event; thus, their influence on the likelihood of media coverage appears to be unaffected by the firm's reputation. Taken together, these findings suggest that high reputation is a burden rather than a buffer with regard to media coverage of a firm's misconduct (Park & Rogan, 2019; Zavyalova et al., 2016).

Whether celebrity burdens or buffers firms when misconduct is revealed is more nuanced, and depends more on the characteristics of the misconduct. Due to audiences' expectations about celebrity firms' atypical behaviors (Pollock et al., 2016), the revelation of celebrity firms' misconduct increases its newsworthiness. However, when it comes to interpreting misconduct characteristics, firm celebrity serves as both a burden and a buffer. In line with the insight that facts and details matter less in media portrayals and audience appraisals of celebrity firms (Rindova et al., 2006), and that emotion-laden evaluations result in a discounting of relevant information cues (Bundy & Pfarrer, 2015), celebrity reduces the importance of the severity of the misconduct in decisions about media coverage. However, as Figure 2.1 reveals, the higher baseline publicity rate for celebrity firms still results in a greater likelihood of their misconduct attracting media coverage, except at the very highest levels of severity. Thus, celebrity firms are still more susceptible to the risk of scandalization due to minor acts of misconduct, given the considerably high baseline publicity their social approval asset incurs.

Contrary to my expectation that the influence of similar recent misconduct on media coverage would also be attenuated (Chandler et al., 2019), my findings show that celebrity firms' misconduct is more likely to be publicized when they have engaged in similar misconduct recently. Indeed, Figure 2.2 shows that recency has little effect on the likelihood of non-celebrity firms' misconduct being publicized, but has a significant effect for celebrity firms. One potential distinction is that severity provides facts about the potential damage misconduct can cause, whereas recency may speak more to the firm's character, reducing potential uncertainties (Denrell, 2005; Furnham, 1984). The basis of the media's and stakeholders' interest in celebrity firms is the formation of a persona imbued with positive emotion-laden narratives and images (Pollock et al., 2016; Rindova et al., 2006). Thus, although sporadic occurrence of the same type of misconduct can be rationalized away, repeated instances of similar misconduct in a short period of time can affect perceptions of the celebrity firm's character, creating negative emotions that can lead to another dramatic storyline—the celebrity's fall from grace (Pollock et al., 2016; Zavyalova et al., 2017). Thus, recency becomes an information cue that is highly relevant to the emotional aspect of celebrity, amplifying its importance in assessing the newsworthiness of the misconduct.

2.4.2. Practical implications

My theory and findings suggest several important implications for practice. The likelihood of misconduct being publicized is influenced by transgressing firms' social approval assets. Whether these assets serve as a buffer or a burden depends on the type of asset and the extremity of the misconduct.

My findings suggest that because stakeholders expect high-reputation firms to behave in consistent and predictable ways, reputation becomes an overwhelming burden when misconduct is revealed. Even minor infractions or one-time mistakes may turn into scandals for high-reputation firms, suggesting that such firms must take all acts of misconduct, even minor aberrations, seriously. They also need to have clear and well-developed crisis communications and management plans in place, so that in the event of a data breach or other act of misconduct, they are prepared to manage the publicity that is likely to result.

My findings also show that celebrity firms, which are perhaps at a greater risk of scandalization due to misconduct, also need to be aware of the challenges they face, and be prepared to respond when misconduct occurs, because the likelihood of media coverage is much greater. Finally, my results suggest that if a celebrity firm has recently engaged in misconduct, it should make every effort to avoid a repeat event in the near future, because subsequent misconduct is even more consequential than for the firm.

2.4.3. Limitations and future research directions

As is the case with most studies, this one has limitations that create future research opportunities. First, this study focuses on firms' data breach incidents. Although data breaches are quickly becoming one of the most serious social issues today (Accenture, 2019), some may question whether they qualify as organizational misconduct because they could result from external parties' hacking activities, making the firms themselves the victims. However, consumers entrust their private information to firms based on the implicit promise that the firms will protect it; failing to do so amounts to a significant breach of trust (Culnan & Armstrong, 1999; Martin et al., 2017), and the public places responsibility for data breaches squarely on the firms entrusted with their information (Carter, 2019). In fact, lawmakers and the federal government are attempting to make data breaches illegal and to hold firms entrusted with the data accountable (Fung, 2014; Holmes, 2019). Therefore, data breaches can indeed be considered a form of organizational misconduct that are perceived as transgressing accepted norms held by the general public or certain subgroups (Greve et al., 2010; Pollock et al., 2016). Nevertheless, replicating and extending my theory and findings using more clearly illicit corporate activities could be useful (Mishina et al., 2010).

I focus on the social approval assets of reputation and celebrity in this study because they have clearly contrasting evaluative dimensions with respect to the accuracy of information and the predictability of behaviors. In the future, researchers might examine how other assets such as status affect the likelihood of scandal in the wake of misconduct. Status has some similarities to reputation in that the sociocognitive content of both assets have a rational aspect (Pollock et al., 2019). However, the moral aspect plays a more significant role in evaluating high-status firms (Pollock et al., 2019), and influences could differ those of the rational and emotional aspects that dominate reputation and celebrity. In support of this speculation, Graffin and colleagues (2013) found that high-status actors' deviations attract greater publicity, leading to higher rates of turnover and greater accountability for high-status actors than for lower-status actors, even given the same level of misconduct. Delving further into the sociocognitive content of status (Hubbard et al., 2018) can help unpack the role of status in scandals (Dewan & Jensen, 2019) and enrich the social evaluations literature (Pollock et al., 2019).

Additionally, organizations can possess "social disapproval liabilities" (Chandler et al., 2019; Pollock et al., 2019). Specifically, a bad reputation is not analogous to possessing fewer of the attributes possessed by firms with good reputations (Mishina & Devers, 2012). A bad reputation indicates that an actor is widely known for having demonstrated consistently negative or unacceptable behaviors and outcomes (Lange et al., 2011). Organizations can similarly accumulate infamy—the antithesis of celebrity—by attracting high levels of attention but evoking strong negative emotions (Zavyalova et al., 2017). Although both of these liabilities entail a part of the necessary condition for scandalization (i.e., high public visibility), whether they follow the same mechanisms as their positive counterparts remains unresolved. On the one hand, the elevated need for accuracy and novel stimuli similarly applies to bad reputation and infamy. Nonetheless, misconduct may confirm, rather than violate expectations surrounding transgressors with these liabilities (Chandler et al., 2019). Exploring these aspects would yield useful insights into the recently suggested positive effects of social disapproval (Helms &

Patterson, 2014; Tracey & Phillips, 2016).

Finally, examining whether the magnitudes of media coverage of misconduct adjusted by the sociocognitive content of reputation and celebrity actually manifest as different levels of material losses following scandals could further strengthen this study's argument regarding the burden versus buffer debate in the social evaluations literature. Replicating the interactive effects of social approval assets and misconduct characteristics on the reactions of stakeholders other than the media (e.g., investors, customers, affiliated organizations) would be useful. Overall, understanding the role of social approval assets as interpretive frames requires more empirical studies (Hubbard et al., 2018; Pfarrer et al., 2010; Pollock et al., 2019).

2.4.4. Conclusion

Conventional wisdom in research on misconduct and scandals suggests that acts of misconduct by highly regarded firms attract a significant amount of attention, followed by dramatic falls from grace (Adut, 2005). This study, however, sheds light on yet another aspect to be considered. Specifically, how the transgressors have arrived at their current highly regarded positions matters because it dictates the specific content of stakeholders' expectations about their behaviors, and thus the relevance of specific dimensions of their misconduct to the likelihood of publicity. Whereas any behaviors, particularly those that transgress societal norms, of highly regarded firms inevitably attract attention from the media and stakeholders, the foundations of these audiences' evaluations can make the attention relatively more or less onerous depending on what and how the firms have done wrong.

Chapter 3

STATUS, CELEBRITY, AND MISCONDUCT SPILLOVERS

On July 29, 2019, Capital One, the fifth-largest U.S. credit-card issuer, was disclosed as having exposed nearly 140,000 Social Security numbers and 80,000 bank account numbers of approximately 106 million card customers and applicants, along with their credit scores and transaction data. The news immediately raised concerns over information security practices in general, and the public was advised that more breaches can be expected in the future (Andriole, 2019). The rankings of the largest corporate data breaches are constantly being updated (Holmes, 2019), and public concerns about data security are increasing each year (Goldberg, 2018). With virtually all firms today collecting private information from their stakeholders (Martin et al., 2017), the outbreak of data breaches stimulates stakeholders' curiosity about which firms are more susceptible to information security lapses and which can be trusted (O'Flaherty, 2018).

The observation that penalties for misconduct extend beyond the implicated firms has long captivated the attention of researchers (Jensen, 2006; Jonsson et al., 2009; Paruchuri & Misangyi, 2015). Facing the turmoil created by misconduct, stakeholders become increasingly wary of the possibility that culpability is generalizable beyond the perpetrator, and thus similar misconduct could reoccur (Barnett & King, 2008; Paruchuri & Misangyi, 2015). Consequently, stakeholders often punish innocent bystanders due to the suspicion that they might engage in the same or similar questionable behaviors. These negative spillovers can be quite undeserved: bystander firms are punished for merely using the same inputs (Barnett & King, 2008), sharing similar characteristics (Jonsson et al., 2009), operating in the same industries (Paruchuri & Misangyi, 2015), or even sharing the same country of origin (Huang, Rui, Shen, & Tian, 2017).

However, the possibility that some bystanders may in fact benefit from a firm's misconduct in the form of positive spillovers has begun to be explored only recently. Piazza and Jourdan (2018) found that following the sexual abuse scandal in the U.S. Catholic Church, non-Catholic churches with religious practices similar to those of the Catholic Church experienced growth in their memberships. Similarly, Paruchuri and colleagues' (2019) finding that Mexican restaurants located near Chipotle locations in Seattle gained temporary reputational benefits following Chipotle's E. coli crisis in 2015. These findings suggest that stakeholders engage in a complicated process whereby they determine the boundary to which the culpability can be generalized while identifying firms that can still be trusted.

Despite the plausibility of both negative and positive spillovers, delineating the conditions that determine spillover valence becomes infeasible due to the emphasis on attributes that perpetrators and bystanders have in common. This intensive focus on attribute-based similarities is problematic for several reasons. First, simply delineating the boundaries of associable bystanders cannot explain why shared attributes sometimes result in penalties and sometimes result in rewards. Second, as audiences can form almost infinite combinations of cognitive groupings based on organizational attributes (Cattani, Porac, & Thomas, 2017), efforts to configure a meaningful spillover boundary inevitably end up being context-specific (Paruchuri et al., 2019). Third, by emphasizing similarities, scholars have overlooked the role of dissimilarities (Paruchuri et al., 2019; Roehm & Tybout, 2006), which is surprising because bystanders must be perceived as different from perpetrators in some way to receive positive spillovers. Lastly, and specifically when considering the emphasis by prior research on overlapping product offerings (Barnett & King, 2008; Jonsson et al., 2009; Zavyalova et al., 2012), the causes and consequences of some types of misconduct may not be germane to any specific group of firms, as implied in my introductory example. Even a single data breach as severe as the 2013 Target incident can have a profound impact on the entire business world, instigating legislative movements to oversee all corporate data practices (Fung, 2014). Imposing a particular market category can result in arbitrarily limiting the range of spillovers.

Instead, I suggest that social evaluations—particularly the distinctive interpretive frames provided by different evaluations (Hubbard et al., 2018; Pollock et al., 2019; Pfarrer et al., 2010)—determine the valence of misconduct spillovers. Specifically, I focus on the effects of status and celebrity because they serve as cognitive heuristics to alleviate post-misconduct turmoil (Bundy & Pfarrer, 2015; Wiesenfeld et al., 2008), and more importantly, differ the most in terms of implications for stakeholders' social comparisons. Status is bestowed on firms considered to be ideal among their peers, and thus high-status firms are regarded as exemplars (Han & Pollock, 2020; Washington & Zajac, 2005). Celebrity, on the other hand, accrues to firms that distinguish themselves from peers in emotionally appealing ways (Rindova et al., 2006; Zavyalova et al., 2017).

These different origins can "prime" stakeholders to focus on bystanders' commonalities with or distinctiveness from perpetrators, and induce them to penalize or favor the bystanders (Roehm & Tybout, 2006). High status leads to the generalization of culpability by highlighting the prototypical nature of firms and attributes shared by the majority (Han & Pollock, 2020). In contrast, celebrity leads to isolated rather than generalized culpability, because celebrity firms are atypical relative to their peers (Zavyalova et al., 2017). Once stakeholders are primed to generalize or isolate culpability, social evaluations shape the perceived similarities and dissimilarities of bystanders relative to perpetrators, because their status and celebrity also informs stakeholders about their (a)typicality among peers. A bystander may be viewed as similarly risky if they are in the same status class as the perpetrator, but as different when either the perpetrator or bystander is a celebrity.

I test my hypotheses using all data breach incidents involving publicly traded U.S. companies in 2018. I examine the positive and negative abnormal stock returns accruing to the unimplicated S&P 500 firms when the breach is disclosed, because spillovers can involve both tangible (e.g., market performance) and intangible outcomes (e.g., reputational losses and gains), and investors factor both aspects into their valuations of firms (Barnett & King, 2008; Martin et al., 2017; Paruchuri & Misangyi, 2015). My findings show that perpetrators' status and celebrity, respectively, are associated with negative and positive spillovers to bystanders. However, the hypotheses regarding the interactions between perpetrators' status and celebrity and bystanders' status and celebrity receive limited support, warranting further investigation on how stakeholders use their social evaluations of both parties when determining the valence and boundaries of misconduct spillovers.

Despite the sustained notion innocent firms may be undeservedly penalized for other firms' misconduct, by emphasizing similarities as the basis for such negative spillovers, scholars have failed to address the possibility that such similarities could instead lead stakeholders to appreciate similar, but guiltless firms. Positive spillovers have only recently begun to be studied (Paruchuri et al., 2019; Piazza & Jourdan, 2018). By focusing on social evaluations as driving the perceived (dis)similarities across perpetrators and bystanders, I suggest that positive and negative spillovers can coexist without envisioning stakeholders as imparting capricious meanings to organizational similarities (Roehm & Tybout, 2006). This study is among the first to examine both types of spillovers from misconduct.

In addition, the foundation for all social evaluations is their relational nature—status cannot be conferred without a defined hierarchy (Sauder, Lynn, & Podolny, 2012), and celebrity cannot be accorded without reference to a categorical norm to gauge unconventionality (Pollock et al., 2016). Nevertheless, prior studies have primarily focused on the effects of perpetrators' social evaluations (Graffin et al., 2013; Pontikes, Negro, & Rao, 2010). I suggest a novel possibility that audiences combine different types of social evaluations accorded to different firms when forming their evaluations. In so doing, I join the budding stream of research on the effect of social evaluations as interpretive frames (Hubbard et al., 2018; Pfarrer et al., 2010; Pollock et al., 2019), and demonstrate that the frames provided by perpetrators and bystanders could jointly determine stakeholders' processing of misconduct.

3.1. Status, Celebrity, and Misconduct Spillovers to Bystander Firms

Beyond the devasting outcomes of misconduct for perpetrators (see Greve et al., 2010 for a review), scholars have also devoted attention to how misconduct affects innocent bystanders (Barnett & King, 2008; Goffman, 1963; Jonsson et al., 2009). In the wake of turmoil created by a misconduct event, stakeholders face significant uncertainty regarding why it happened, how much damage is expected, and who should be held responsible, and thus engage in intensive sensemaking efforts (Bundy & Pfarrer, 2015; Lange & Washburn, 2012). During the process, stakeholders become increasingly concerned about the extent to which the root cause of the misconduct is endemic to the entire industry or a category of firms to determine whether firms are in fact institutionally flawed and assess the likelihood of the same type of misconduct reoccurring (Barnett & King, 2008; Cleeren, van Heerde, & Dekimpe, 2013; Paruchuri & Misangyi, 2015).

Nonetheless, due to the acute nature of misconduct, stakeholders' processing of misconduct events tends to be immediate and intuitive, thus their responses are more akin to "moral panic" than thorough investigation (Lange & Washburn, 2012; Pontikes et al., 2010). As a result, innocent firms often come to be devalued upon their rivals' misconduct merely because they use the same inputs (Barnett & King, 2008), offer similar products (Borah & Tellis, 2016) and services (Jonsson et al. 2009), operate in the same industry (Paruchuri & Misangyi, 2015), or originate from the same country (Huang et al., 2017).

Undeserved losses have been incurred by bystanders in response to various types of misconduct, including chemical accidents (Barnett & King, 2008), product recalls (Jarrell & Peltzman, 1985; Zavyalova et al., 2012), financial misconduct (Paruchuri & Misangyi, 2015), and data breaches (Martin et al., 2017), as well as across various types of stakeholders, including customers (Jonsson et al., 2009), social media users (Borah & Tellis, 2016), the media (Zavyalova et al., 2012), and investors (Paruchuri & Misangyi, 2015). Compared to strong evidence of negative spillovers, however, the possibility that a firm's misdeed creates opportunities for bystanders has been largely overlooked until recently (Paruchuri et al., 2019; Piazza & Jourdan, 2018). This lack of consideration is indeed surprising, considering findings regarding the defection of stakeholders such as customers (Jensen, 2006), supporters (Zavyalova et al., 2016), and partners (Sullivan, Haunschild, & Page, 2007) upon the revelation of misconduct. Accordingly, a few studies have revealed that misconduct can benefit bystanders through increased market share (Piazza & Jourdan, 2018), reputational bumps (Paruchuri et al., 2019), and higher stock market valuations (Martin et al., 2017).[12]

The issue of whether bystanders experience undeserved losses or unexpected gains is further complicated when considering the overlapping criteria for both negative and positive spillovers (i.e., the perceived similarities between the implicated and affected firms). When generalizing culpability, stakeholders focus on commonalities between the perpetrator and bystanders (Barnett & King, 2008; Paruchuri & Misangyi, 2015); for example, transactions at innocent firms dropped following the Skandia AB scandals just because they all provided "mutual funds" (Jonsson et al., 2009). However, the operating mechanism of positive spillovers also requires similarities to perpetrators, as well as differentiating factors. Restaurants in Seattle benefited from Chipotle's failure not just because they did things differently, but more profoundly because they provided substitutes based on cuisine and geographic proximity (Paruchuri et al., 2019). Similarly, non-Catholic churches were able to attract members who were disappointed at the depravity of the Catholic Church not simply because they were non-Catholic, but because their practices were similar to those of the Catholic Church (Piazza & Jourdan, 2018).

[12] Martin and colleagues (2017) found support for both negative and positive spillovers. The disclosure of a firm's data breach negatively affected its rival firm's market valuation, but the effect turned positive when the breach was severe in terms of the number of accounts affected.

The confusing ways in which stakeholders deal with the similarities and dissimilarities can be resolved by considering yet another possibility: stakeholders can be “primed” to think about commonalities or differences when evaluating firms (Roehm & Tybout, 2006). Given that social comparisons are often devoid of actual organizational attributes (Kim & Tsai, 2012), stakeholders can remain to some extent unaware of whether the bystanders actually share similar problems or possess safeguards, particularly when considering the spontaneity of stakeholders’ responses to misconduct before facts about the cause and responsibility are even disclosed (Bundy & Pfarrer, 2015; Lange & Washburn, 2012). I turn to this aspect next by elaborating on the role of social evaluations as priming devices.

3.1.1. The effect of perpetrators’ status

Not all misconduct spurs enough public concern to initiate industry-level attribution processes, let alone punish the perpetrators themselves (Hoffman & Ocasio, 2001). In this regard, acts of misconduct by highly regarded firms often become high profile events, given that such firms already attract a considerable amount of stakeholder attention (Adut, 2005; Graffin et al., 2013; Zavyalova et al., 2017). Accordingly, Paruchuri and Misangyi (2015) found that upon the revelation of financial misconduct, investors devalued bystanders within the same industry to a greater extent when they were more familiar with both the perpetrators and the bystanders. Although familiarity and high social evaluations are not directly interchangeable, firms with high evaluations are indeed likely to be familiar to stakeholders. Yet, firms can be accorded high social evaluations and thus become familiar to stakeholders on different grounds.

Status denotes an actor's position within "a socially constructed, intersubjectively agreed-upon and accepted ordering" (Washington & Zajac, 2005: 1147). In other words, status is conferred on actors that possess more of the attributes that are unanimously valued by their peers within the hierarchy and external audiences. As a result, high-status actors in a social system are often viewed as prototypes of the norms and values governing the system (Han & Pollock, 2020; Rao, Monin, & Durand, 2005).

Whereas moral aspects are not a prerequisite for obtaining high status, stakeholders often apply exigent ethical standards to high-status actors (Adut, 2005; Hahl & Zuckerman, 2014; Pollock et al., 2019). Thus, the misdeeds of high-status actors incur particularly fierce responses from stakeholders (Graffin et al., 2013), and their apparent disloyalty generates feelings of betrayal (Phillips, Turco, & Zuckerman, 2013). This bitterness could trickle down to lower-status actors. The fact that status hierarchies emerge out of voluntary deferential relationships informs audiences that high-status firms are indeed esteemed by their peers (Gould, 2002). What is also implied, however, is that the deferring firms hold similar belief systems which enable them to establish a unified deference rule among themselves (Washington & Zajac, 2005). Hence, stakeholders would perceive high-status firms as epitomizing what the entire category of firms aspire to become (Han & Pollock, 2020). Beyond the perceptual aspects, lower-status firms are likely to adopt similar ways of doing business because they are inclined to imitate high-status firms (Haunschild & Miner, 1997).

Overall, acts of misconduct by high-status firms are not likely to be viewed by stakeholders as individual deviations, but as contaminating what their status represents. The finding that product crises involving dominant brands negatively affect less-dominant brands, but not vice versa supports this argument (Borah & Tellis, 2016). The symbolic value accorded to the tainted high-status actors inevitably leads to disapproval of the entire status hierarchy and other firms within it.

It is worth noting that a strand of research in the status literature holds that high- and low-status actors are relatively better able to deviate from norms with less risk, whereas middle-status actors are under the strongest conformity pressure, a phenomenon dubbed “middle-status conformity” (Pahnke et al., 2015; Phillips & Zuckerman, 2001). Although the effect of different status levels as the antecedent of misconduct is beyond the scope of this study, the key reasoning underlying the theory is informative: audiences grant substantial security to high-status actors so as to tolerate their deviations from accepted norms, and do not expect low-status actors to comply because they are already excluded from the consideration set (Phillips & Zuckerman, 2001). If so, there is little reason to believe that culpability for misconduct by high-status firms would be generalized to other firms. High-status firms’ deviations can be buffered by the exclusive leeway conferred to them and are not perceived as embodying the whole status system’s failure. Even if the culpability trickles down to some extent, middle-status firms are more likely to suffer than low-status firms, which may still be exempt from punitive spillovers.

However, I argue that middle-status conformity does not hold in my context. The nonconformity in Phillips and Zuckerman’s (2001) original theorization did not involve morally questionable conduct, although some later works insinuated as such (e.g., Krishnan & Kozhikode, 2015; Pahnke et al., 2015). Recent studies suggest that high-status actors’ positions are not as robust as to allow them to easily deviate from accepted norms (Bothner, Smith, & White, 2010; Prato, Kypraios, Ertug, & Lee, 2019), and that high-status firms are just as susceptible to "falls from grace," particularly when considering the gravity of integrity violations (Adut, 2005; Graffin et al., 2013; Hahl & Zuckerman, 2014). Moreover, even when assuming that low-status firms are outside the audiences' consideration set and actually have idiosyncratic offerings, this may not safeguard the firms from the downward generalization of culpability because the processes involved in sensemaking with regard to misconduct (Bundy & Pfarrer, 2015; Lange & Washburn, 2012) that are used to compare firms are often devoid of actual attribute-based reasoning (Kim & Tsai, 2012). Rather, the mere fact that low-status firms are ranked at the bottom of the same hierarchy can be more onerous for firms, because the perceived and/or actual differences between low-status firms and high-status perpetrators would lead stakeholders to perceive the firms not as exempt from generalized culpability, but as inferior versions of other similarly culpable firms (Borah & Tellis, 2016; Jonsson et al., 2009).

Therefore, the aftermath of high-status firms' misconduct for bystanders is likely to be negative in general, although the magnitudes may differ according to the bystanders' own social evaluations, as I argue below. In the context of data breaches, established and central organizations are under more exigent pressure to adopt substantive data management practices due to increasing awareness of data security issues (Angst et al., 2017). Whereas the effectiveness of the data security investments in reducing breaches remains open to debate (Angst et al., 2017; Straub, 1990), stakeholders who evaluate high-status firms' data breaches are likely to attribute such failures to the entire system because the failures of the firms that were supposed to apply extra caution in data security could instigate the suspicion that all other firms are similarly susceptible

(Jensen, 2006; Paruchuri & Misangyi, 2015). Hence, upon the disclosure of a high-status firm's data breach incident, investors are likely to devalue bystanders because they suspect that security problems are endemic to general corporate data practices. Formally stated:

Hypothesis 1. Perpetrators' status negatively affects bystanders' market valuations upon the revelation of misconduct.

3.1.2. The effect of perpetrators' celebrity

Whereas status is conferred on those who best represent the foundations of the status system, audiences also confer a significant amount of social approval on firms that stand out from their peers in ways that attract the acclaim of stakeholders. Non-conforming characteristics and behaviors often get firms cast as the main characters in the media's dramatized reality, leading to the emergence of celebrities (Rindova et al., 2006; Zavyalova et al., 2017). As a result, celebrity firms attract significant attention and strongly positive emotional responses from stakeholders (Hubbard et al., 2018; Pfarrer et al., 2010). Thus, the key to the emergence and appreciation of celebrity firms is their defiance of conventional and dominant ways of doing things.

Due to celebrity firms' atypical nature, stakeholders attribute such behavior to the firms themselves, making celebrity an individuating frame (Bundy & Pfarrer, 2015; Hayward, Rindova, & Pollock, 2004), as opposed to the overarching frame provided by status whereby high-status firms are perceived as representing the attributes valued by themselves and others. Thus, in assessing whether culpability for misconduct is generalizable to bystanders, stakeholders who evaluate misconduct by celebrity perpetrators may be primed to think about the differentiating factors of perpetrator firms, thereby limiting negative spillovers (Roehm & Tybout, 2006). Once culpability is isolated to the perpetrators, stakeholders are likely to appreciate the innocent and norm-conforming (i.e., non-celebrity) bystanders, because their typicality contrasts with the celebrity perpetrators' tendency to engage in risky conduct to "stay true to their type" and maintain their celebrity (Lovelace et al., 2018; Pollock et al., 2016). With the most salient feature of celebrity perpetrators being atypical behaviors, stakeholders are likely to favor more conventional alternatives, just as former Catholics favored stricter denominations after the Catholic Church sex scandal (Piazza & Jourdan, 2018).

It should be noted, however, that celebrity firms' nonconformity can imply both under- and over-conforming to accepted norms (Pollock et al., 2016). Whereas under-conforming can be easily associated with shadier security practices, over-conforming can be associated with innovative and masterful information technologies that no other firms possess. Also, due to their high visibility to stakeholders, celebrity firms might also be susceptible to strong external pressure to adopt data security practices due to the legitimacy concerns associated with data breach issues, similar to high-status firms (Angst et al., 2017). Nonetheless, stakeholders' emotional resonance with celebrity firms does not necessarily involve legitimacy concerns, and thus stakeholders need not expect firms to have conformed to such pressures (Rindova et al., 2006; Zavyalova et al., 2017). Furthermore, even when a celebrity perpetrator has been renowned for its over-conformity to accepted norms (e.g., regarding data security) the individuating nature of celebrity would still hamper the generalization of culpability (Bundy & Pfarrer, 2015). That is, the mere fact that a celebrity perpetrator had demonstrated stringent standards or distinctive capabilities is insufficient to spark suspicions that other firms with normal levels of conformity (and probably less advanced capabilities) might also be fallible, because stakeholders are primed to think that celebrity firms are different from the rest (Roehm & Tybout, 2006). For instance, stakeholders could think that the celebrity perpetrator went too far, albeit positively, so as to adopt innovative yet unproven practices (Deephouse, 1999; Semadeni & Anderson, 2010).

Hence, upon the disclosure of a celebrity firm's data breach, investors would appreciate the value of non-celebrity bystanders, although to different extents depending on the bystanders' characteristics. First, there is no definitive reason to believe that bystanders are similarly culpable, and second, the heightened importance of conformity leads stakeholders to view non-celebrity firms as more trustworthy. Thus, I predict:

Hypothesis 2. Perpetrators' celebrity positively affects bystanders' market valuations upon the revelation of misconduct.

3.1.3. The effect of bystanders' status

Bystanders' social evaluations are also likely to influence stakeholders' decisions on whether to view bystanders as trustworthy exceptions or assumed accomplices. The basic premise is that bystanders' social evaluations serve as useful heuristics when navigating the significant uncertainty created by misconduct (Bundy & Pfarrer, 2015) and comparing the plethora of firms within the consideration set (Pollock & Gulati, 2007). However, bystanders' evaluations also provide interpretive frames for making sense of misconduct by high-status and celebrity firms that may lead to different conclusions (Hubbard et al., 2018; Pfarrer et al., 2010). I begin with the effects of bystanders' status.

The prerequisite for the advantages provided by high status is that membership in the highest status level is exclusive (Sauder et al., 2012). Status concerns govern social actors' behaviors and affiliative choices, thereby stabilizing status hierarchies (Gould, 2002; Magee & Galinsky, 2008). As a result, stakeholders tend to perceive firms within the same status class as possessing similar attributes, and group them into the same consideration sets (Jensen & Roy, 2008). Thus, when high-status perpetrators engage in misconduct, similarly high-status bystanders are likely to be implicated.

However, misconduct by another high-status firm does not result in relative appreciation of high-status bystanders, because misconduct by elites often triggers antipathy and a vague sense of corruption regarding the elite group as a whole (Adut, 2005; Graffin et al., 2013). Moreover, exclusive interactions among high-status firms increase the likelihood that firms actually share similar practices and business models (Lounsbury, 2001; Piazza & Castellucci, 2014). Thus, regardless of whether or not shared attributes within the high-status group are the actual root cause of misconduct or firms even share the same attributes, the mere observation that a bystander belongs to the same elite group as the perpetrator is enough to spark suspicions that the bystander may be similarly fallible (Jonsson et al., 2009; Lange & Washburn, 2012). Therefore, although bystanders' status would normally make them an attractive alternative to other high-status firms, their status instead primes stakeholders to focus on their similarities with high-status perpetrators (Roehm & Tybout, 2006).

Thus, even if all bystanders are likely to suffer from industry-wide generalization of culpability due to high-status firms' misconduct, high-status bystanders are likely to suffer the most because they are perceived as more similar to the perpetrating firm. In my context, upon witnessing a data breach incident involving a high-status firm, investors are likely to be particularly aware of the potential culpability of other high-status firms due to substantive or perceived similarities. Hence:

Hypothesis 3. Bystanders' status strengthens the negative effect of perpetrators' status on their market valuations upon the revelation of misconduct.

As mentioned above, stakeholders likely attribute celebrity firms' misconduct to their atypical characteristics (Hayward et al., 2004) and look for alternatives that demonstrate stronger conformity to normal and safer ways of doing things (Piazza & Jourdan, 2018). In the search for such alternatives, high-status firms are likely to be most readily accessible, owing to their salience (Pollock & Gulati, 2007). With ease of access providing a substantial advantage in receiving relative appreciation in the wake of others' misconduct (Paruchuri et al., 2019), high-status bystanders are likely to be a particularly attractive option due to their exemplary stature (Han & Pollock, 2020; Rao et al., 2005). Status represents stability and is often used as a proxy for quality in the face of uncertainty and when quality is otherwise difficult to observe (as in the case of a firm's cyber security measures) (Hubbard et al., 2018; Pollock et al., 2015; Sauder et al., 2012).

Therefore, whereas stakeholders may respond to misconduct by celebrity perpetrators by evaluating other firms relatively positively, those of high status likely benefit the most from positive spillovers. That is, upon the disclosure of a celebrity firm's data breach, investors are likely to recognize the value of high-status bystanders because they stand in stark contrast to the atypical perpetrator by being exemplars among other normal firms. Hence:

Hypothesis 4. Bystanders' status strengthens the positive effect of perpetrators' celebrity on their market valuations upon the revelation of misconduct.

3.1.4. The effect of bystanders' celebrity

I argued above that when high-status firms engage in misconduct, culpability spreads to other firms because such events demonstrate that even the most prototypical organization can make a serious mistake (Rindova et al., 2006). However, celebrity bystanders may be insulated from spillovers due to the individuating nature of celebrity (Bundy & Pfarrer, 2015). That is, the belief that celebrity firms do things differently from other firms—which may not be based in reality (Rindova et al., 2006; Zavyalova et al., 2017)—can effectively differentiate them from others, including high-status bystanders, which are likely to be perceived as similar to the perpetrators (Roehm & Tybout, 2006). Moreover, the high level of attention and affinity towards celebrity firms makes them stand out in stakeholders' fields of vision, even among untainted alternatives (Hubbard et al., 2018). Thus, stakeholders' beliefs that celebrity firms do things differently than most can make the firms' atypical nature particularly valuable when other firms are considered implicit accomplices following a high-status firm's misconduct. In other words, because the perception that a firm does things differently from the perpetrator is key to the relative appreciation the firm could receive (Paruchuri et al., 2019), celebrity bystanders can avoid and even benefit from the generalization process. As a result, upon the revelation of a high-status firm's data breach, celebrity bystanders likely experience less negative, and perhaps even positive spillover effects. Thus, I hypothesize:

Hypothesis 5. Bystanders' celebrity weakens the negative effect of perpetrators' status on their market valuations upon the revelation of misconduct.

Given the individuating nature of celebrity (Bundy & Pfarrer, 2015), no two celebrity firms are likely to be similar to each other, even though neither firm conforms to conventional norms. Thus, although stakeholders are likely to favor more conforming and less risky bystanders when evaluating celebrity firms' misconduct, celebrity bystanders may differ from both celebrity perpetrators and non-celebrity bystanders.

Stakeholders would nonetheless perceive celebrity bystanders as somewhat similar to the celebrity perpetrators. This is because social actors employ flexible categorization rules that best fit their evaluative task and the goal at hand (Durand & Paolella, 2013). The revelation of misconduct increases stakeholders' scrutiny of all firms within the same industry (Barnett & King, 2008; Desai, 2011). Thus, what would become increasingly salient to stakeholders is the fact that a firm that has demonstrated atypical behaviors has transgressed societal norms (Pollock et al., 2016). Given the elevated awareness about the potential risks associated with atypical firms, stakeholders are likely to extend their categorization rule to group firms based on their (a)typicality, and as a result, even celebrity bystanders—which may have become celebrities for different reasons—may be grouped into the same category. This crude categorization can instigate negative spillovers because the perceived similarities of bystanders to perpetrators need not be based on an exact match in the two parties' characteristics nor on the causal relationship between their similarities and the misconduct (Jonsson et al., 2009). Furthermore, stakeholders often make logical fallacies in their sensemaking processes upon misconduct (Bundy & Pfarrer, 2015; Lange & Washburn, 2012). Accordingly, if the perpetrator is a celebrity, stakeholders may associate the misconduct with being a celebrity per se, rather than specific differences among different celebrity firms.

Thus, when a celebrity firm has a data breach, stakeholders' disinclination towards freewheeling firm behaviors and the resulting depreciation of all atypical celebrity firms would be reflected in investors' valuations of celebrity bystanders. Consequently, the positive spillover effects from the celebrity perpetrators' misconduct are likely to be attenuated, if not reversed to negative spillovers, for the celebrity bystanders. Hence, I hypothesize:

Hypothesis 6. Bystanders' celebrity weakens the positive effect of perpetrators' celebrity on their market valuations upon the revelation of misconduct.

Figure 3.1 summarizes my hypotheses. Whereas misconduct by high-status firms generally produces negative spillovers for bystanders, bystanders' status amplifies the magnitude of negative spillovers and bystanders' celebrity mitigates the magnitude of negative spillovers or reverses their valence, making them positive. Perpetrators' celebrity, on the other hand, generally incurs positive spillovers to bystanders, which become amplified by bystanders' status and attenuated by bystanders' celebrity. A different way to look at the hypotheses is that a match between perpetrators' and bystanders' social evaluations results in negative (or less positive) spillovers and a mismatch results in positive (or less negative) spillovers.

Figure 3.1. Summary of Hypotheses

		Bystanders' Social Evaluation		
		Non-high-status Non-celebrity	High-Status	Celebrity
Perpetrators' Social Evaluation	High-Status	**Negative** Spillover (Hypothesis 1)	**Amplified** Negative Spillover (Hypothesis 3)	**Attenuated** Negative / **Positive** Spillover (Hypothesis 4)
	Celebrity	**Positive** Spillover (Hypothesis 2)	**Amplified** Positive Spillover (Hypothesis 5)	**Attenuated** Positive / **Negative** Spillover (Hypothesis 6)

3.2. Methods

3.2.1. Data and sample

In this study, I focused on data breach incidents as acts of misconduct that could result in negative or positive spillovers for innocent bystander firms. Recurrent data breaches by companies, including the recent mega-breaches by Equifax, Facebook, Target, Marriott, and Yahoo, have raised serious privacy concerns among members of the public (Goldberg, 2018; Holmes, 2019), to the point where the U.S. Congress declared January 28 to be National Data Privacy Day. Considering the seriousness of privacy violations and the pervasiveness of corporate data breaches, a single data breach incident can potentially affect stakeholders' evaluations of the entire corporate community, as collecting individuals' private information is an essential task in contemporary business (Martin et al., 2017).

Same as the previous chapter, I used the database provided by Privacy Rights Clearinghouse to first identify the sample of data breach incidents. I identified a total of

62 incidents involving 56 publicly traded U.S. companies in 2018. To ensure the accuracy of the breach details, I corroborated the data with annual reports published by the Identity Theft Resource Center. Whenever a discrepancy arose, I tracked the original data source.

I identified 526 firms that belonged to the S&P 500 in 2017 as bystanders to be matched with the data breach incidents. After eliminating firms with missing data on firm characteristics (e.g., size, ROA, total shareholder returns [TSRs]), my sample included 27,928 breach-bystander pairs involving 451 bystander firms. After excluding observations where cumulative abnormal returns (CARs) to bystanders were not available, my final sample consisted of 27,069 breach-bystander pairs involving 441 bystander firms.

3.2.2. Dependent variable

Following prior research on stakeholder reactions to data breaches in particular (e.g., Gwebu et al., 2018; Malhotra & Malhotra, 2011; Martin et al., 2017) and corporate misconduct in general (e.g., Barnett & King, 2008; Paruchuri & Misangyi, 2015), I captured *investor reactions to bystanders* upon the disclosure of breach incidents by computing the CARs of bystander firms using the Eventus program. Investors are highly relevant stakeholders in this study because their investment decisions involve not only their own judgments about the generalizability of culpability and the relative trustworthiness of bystanders, but also the anticipated reactions of a broader set of stakeholders (Martin et al., 2017). Thus, the dependent variable of this study is the CARs of bystander firms during the period surrounding other firms' data breach events, which I measured using the Fama and French (1993) three-factor model (Haleblian et al., 2017; Savor & Wilson, 2016).[13] The event window was the period from one day prior to the announcement of the data breach to five days after the announcement (i.e., from $t - 1$ to $t + 5$) to allow enough time for spillovers to occur (Barnett & King, 2008). The "normal" period which serves as the baseline to predict abnormal returns was set to the 250-day period (i.e., one year of trading days) from 295 days to 45 days prior to the breach disclosure. The mean value of CARs to bystanders was -0.06 percent and significantly smaller than 0 ($p = 0.011$), indicating that bystanders suffered from negative spillovers from others' data breaches, on average. I multiplied this variable by 100 to facilitate interpretation of the results.

3.2.3. Independent variables

Following prior studies (Dewan & Jensen, 2019; Wang & Jensen, 2019), I used the extent to which a firm is covered by analysts with high expertise in the firm's domain to operationalize *high-status perpetrators* and *high-status bystanders*. Certification by authoritative, expert third parties is a major mechanism of status conferral (Sauder et al., 2012). In this regard, attracting attention from analysts with expertise in a business sector can have a certifying effect in the eyes of stakeholders, especially for investors, the stakeholders of interest in this study (Bowers & Prato, 2018). This measure is analogous to eigenvector centrality—one of the most widely adopted measures of status in single-industry studies (Pollock et al., 2019)—in that it "proxies the centrality of the focal firm

[13] The Fama and French (1992; 1993) three-factor model accounts for the impacts of (a) market returns above the risk-free rate, (b) market outperformance of small firms relative to large firms (in terms of market capitalization), and (c) market outperformance of "value" stocks relative to "growth" stocks (in terms of book-to-market ratio).

in the security analyst coverage network" weighted by "the industry expertise of the security analysts" (Dewan & Jensen, 2019: 20). Thus, this status measure is "not simply a measure of the [firms'] popularity" (Wang & Jensen, 2019: 865) and avoids the problem of using the volume of media/analyst coverage as a status measure (Pollock et al., 2019).

Based on the data obtained from the I/B/E/S database, I first counted the number of firms each analyst covered in a 3-digit SIC industry during the previous year. Then, I assigned the value of 1 to the analyst covering the largest number of firms in an industry and normalized the numbers of firms covered by other analysts relative to the largest number to calculate each analyst's expertise score in each industry. Subsequently, I added the expertise scores of the analysts covering a firm and used this aggregated score as the measure of the firm's status (Dewan & Jensen, 2019; Wang & Jensen, 2019). Following Jensen and colleagues, I assigned a value of 0 to firms with no analyst coverage. Finally, I dichotomized the status scores at one standard deviation above the mean among the perpetrators and bystanders to reflect the categorical nature of status effects (Han & Pollock, 2020; Pollock et al., 2019).

I operationalized *celebrity perpetrators* and *celebrity bystanders* by following a process similar to the one documented in Chapter 2, except I used S&P 500 firms and breached firms, as these firms comprise the comparative referent in this study. Based on the list of 554 firms, including S&P 500 bystanders and perpetrators, and non-S&P 500 perpetrators, I collected articles published by the top 25 U.S. newspapers about the firms during 2017, which totaled 41,843 articles. Then, I created the ad hoc variables *volume of public attention* and *intensity of positive emotional resonance* and multiplied them. As described above, I set one standard deviation above the mean of the multiplied scores as the cut-off point, and treated the perpetrators and bystanders above this point as celebrity perpetrators and celebrity bystanders.

3.2.4. Control variables

The first set of control variables include bystander and perpetrator characteristics. To account for the effects of investors' familiarity with the perpetrators and bystanders on the likelihood of spillovers, I measured *firm size* using the natural log of market capitalization, considering the importance of this metric to investors, the stakeholders of interest in this study (Josefy, Kuban, Ireland, & Hitt, 2015). I also controlled for *ROA* and *TSR*, as these performance indicators are known to affect investor reactions (Petrenko, Aime, Recendes, & Chandler, 2019), as well as *firm age,* which can affect investors' familiarity with firms (Paruchuri & Misangyi, 2015). Also, because my measure of firm status is a proxy variable, like most other status measures, I controlled for *analyst coverage*, which captures the number of analysts that covered a firm in the previous year (Dewan & Jensen, 2019). Finally, repeated misconduct by a firm can trigger stronger attributions to internal causes, which can aggravate stakeholders' perceptions of perpetrators (Pfarrer et al., 2008). Prior accusations of misconduct involving bystanders matter as well, because stakeholders can view these bystanders as having implicit complicity (Lange & Washburn, 2012). Thus, I included *prior breaches* measured by the number of data breach incidents a firm was involved during the previous five years. As both variables had skewed distributions, they were log-transformed.

Although all of the bystander firms in my sample belonged to the S&P 500 during the previous year, only about half of the perpetrators did. Membership in the S&P 500 index can lead to a permanent increase in stock price that sustains even after a firm is no longer included in the index (Chen, Noronha, & Singal, 2004); moreover, S&P 500 firms generally attract more attention from investors (Boivie, Graffin, & Gentry, 2016). Failure to control for this aspect could result in a potential omitted variable bias that interferes with the influence of perpetrator status. Thus, I included a binary variable, *S&P 500 perpetrator*, indicating whether a perpetrator belonged to the S&P 500 in 2017.

I also controlled for variables that capture potential relatedness between perpetrators and bystanders. First, horizontal market similarities could affect stakeholders' perceived boundaries of negative and positive spillovers (Paruchuri et al., 2019; Paruchuri & Misangyi, 2015). Thus, I accessed the TNIC database (Hoberg & Phillips, 2010; 2016) described in Chapter 2, and used the product similarity scores provided by the database to control for *product similarity* between perpetrators and bystanders, where scores closer to 0 indicate lower levels of product overlap, and larger scores indicate stronger product similarity between the paired firms. Because this variable had a skewed distribution (i.e., many bystander-perpetrator pairs had low or zero similarity), I calculated natural logarithms after multiplying the original values by 100. Also, negative spillovers from misconduct could be particularly consequential for partners and/or clients of perpetrators (Jensen, 2006; Sullivan et al., 2007). To control for this aspect, I accessed the Vertical Textual Network Industry Relatedness Classification (VTNIC) database (Frésard, Hoberg, & Phillips, 2019),[14] which provides pairwise scores

[14] This database was constructed in a similar fashion as the TNIC database described above. Frésard and colleagues (2019) matched the overlapping words used in the perpetrators' and bystanders' product descriptions in their respective 10-K statements and then matched these words to the product words and descriptions used by the U.S. Bureau of Economic Analysis's input-output tables, which firms use to report their products to the Bureau. Using these data to operationalize vertical relatedness between potential acquirers and targets, they found that R&D intensive firms are less likely to end up with vertical

of potential upstream and downstream relatedness, where scores closer to 0 indicate unrelatedness. Because the distribution of both dimensions of relatedness scores were significantly right-skewed, and the two scores were highly correlated at 0.87, I created a binary variable, *vertical relatedness*, coded 1 if an observation involved a perpetrator and a bystander with relatedness above the 90th percentile along either of the dimensions. Last, I included *analyst co-coverage*, because investors consider firms covered by the same analyst to be economically similar or related (Ali & Hirshleifer, 2020). Because more than 90 percent of perpetrator-bystander pairs did not have any analyst jointly covering the firms, I assigned a value of 1 if a perpetrator and a bystander were covered by the same analyst(s), and 0 otherwise.

The last set of control variables concerns misconduct characteristics. Following prior research, I used the number of accounts affected by a breach incident to capture the severity of data breaches (Gwebu et al., 2018; Malhotra & Malhotra, 2011), which significantly influences the magnitude and valence of spillovers from such incidents (Martin et al., 2017). Because the variable has a significant rightward skew, I dichotomized this variable at the 90th percentile (approximately 40 million accounts) to create the variable *mega breaches*. Also, whether or not a breach exposed sensitive information can affect stakeholders' reactions to the breach and increase the likelihood of spillovers (Campbell et al., 2003; Gwebu et al., 2018). Thus, I included *sensitive information breached*, coded as 1 if a breach incident exposed personal identification information such as Social Security or driver's license numbers and financial information such as bank account or credit card numbers, and 0 otherwise. I also controlled for

acquisitions, whereas firms with patented innovations are more likely to be acquired by vertically related buyers.

whether a breach resulted from a *hacker attack*, because hacker attacks accounted for more than half of my sample and may be more salient to stakeholders, facilitating the spillovers (Paruchuri et al., 2019).

Whether or not a breach incident occurred through the failure of a contracted entity's data mishandling can affect the firm's perceived culpability, which may influence stakeholders' perceptions of associated firms' complicity (Lange & Washburn, 2012). Thus, I included a binary variable *breached through contractor*, coded 1 if a breach occurred through a contracted entity, and 0 otherwise. I also included a dichotomous variable, *breached through subsidiary*, because information cues from diversified entities tend to have a weaker impact on stakeholders' evaluations of the parent firm (Connelly et al., 2011), and thus create less momentum to instigate spillovers in the first place. Last, I included a series of dummy variables indicating *perpetrator 3-digit SIC industry* to control for different reactions to data breaches in different industries (Martin et al., 2017).

3.2.5. Analytic strategy

Following prior research in which scholars used multiple regression analysis to perform event studies (e.g., Barnett & King, 2008; Gwebu et al., 2018; Martin at el., 2017; Paruchuri & Misangyi, 2015), I used the following regression equations to test my hypotheses:

$$CAR_{ij} = \alpha + \beta_1 Z_{ij} + \beta_2 BS_{ij} + \beta_3 BC_{ij} + \beta_4 PS_{ij} + \beta_5 PC_{ij} + e_{ij} \quad (1)$$

$$CAR_{ij} = \alpha + \beta_1 Z_{ij} + \beta_2 BS_{ij} + \beta_3 BC_{ij} + \beta_4 PS_{ij} + \beta_5 PC_{ij} + \beta_6 PS_{ij} * BS_{ij} + e_{ij} \quad (2)$$

$$CAR_{ij} = \alpha + \beta_1 Z_{ij} + \beta_2 BS_{ij} + \beta_3 BC_{ij} + \beta_4 PS_{ij} + \beta_5 PC_{ij} + \beta_7 PC_{ij} * BS_{ij} + e_{ij} \quad (3)$$

$$CAR_{ij} = \alpha + \beta_1 Z_{ij} + \beta_2 BS_{ij} + \beta_3 BC_{ij} + \beta_4 PS_{ij} + \beta_5 PC_{ij} + \beta_8 PS_{ij} * BC_{ij} + e_{ij} \quad (4)$$

$$CAR_{ij} = \alpha + \beta_1 Z_{ij} + \beta_2 BS_{ij} + \beta_3 BC_{ij} + \beta_4 PS_{ij} + \beta_5 PC_{ij} + \beta_9 PC_{ij} * BC_{ij} + e_{ij} \quad (5)$$

where CAR_{ij} is the CAR for bystander i upon the disclosure of data breach j, Z_{ij} is the vector of control variables, PS_{ij} and PC_{ij} are the status and celebrity of the perpetrator of the data breach j, BS_{ij} and BC_{ij} are the status and celebrity of bystander i, and e_{ij} is the residual. Hypothesis 1 is supported if β_4 is negative and significant, and Hypothesis 2 is supported if β_5 is positive and significant in equation (1). Hypothesis 3 is supported if β_6 in equation (2) is negative and significant. Hypothesis 4 is supported if β_7 in equation (3) is positive and significant. A positive and significant value for β_8 in equation (4) provides support for Hypothesis 5, and a negative and significant value for β_9 in equation (5) indicates support for Hypothesis 6.

I did not include fixed effects (i.e., bystander, perpetrator, or event) because including the fixed effects would not allow me to test my hypotheses, which involve characteristics of perpetrators and bystanders. Year fixed effects are irrelevant for this study, as all of the data breach incidents occurred in 2018. However, because each bystander appears once every breach incident, I clustered standard errors on bystander firms.

3.3. Results

Table 3.1 presents the mean, standard deviations, and correlation coefficients of the variables used in this study. Although all variables are only moderately correlated, perpetrator size, analyst coverage, S&P 500 membership, and number of prior breaches are highly correlated with each other and with perpetrators' status and celebrity. Thus, I created residualized versions of the variables that are the sources of high correlations and used them as the instruments for the original variables (Dewan & Jensen, 2019). For example, I regressed *perpetrator size* on *high-status perpetrator*, *celebrity perpetrator*, *perpetrator analyst coverage*, *S&P 500 perpetrator*, and *perpetrator prior breaches* and used the residual from this regression instead of the original perpetrator size. Similarly, I regressed *perpetrator analyst coverage* on *high-status perpetrator*, *celebrity perpetrator*, *perpetrator ROA*, *S&P 500 perpetrator*, and *perpetrator prior breaches*; *S&P 500 perpetrator* on *high-status perpetrator*; and *perpetrator prior breaches* on *high-status perpetrator* and *celebrity perpetrator* to create the residualized versions of these perpetrator characteristics.

Table 3.1. Descriptive Statistics and Correlations

Variables	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. Investor reaction to bystander	-0.06	4.02												
2. High-status perpetrator	0.24	0.43	0.00											
3. Celebrity perpetrator	0.11	0.32	-0.01	0.39										
4. High-status bystander	0.17	0.37	0.02	0.00	0.00									
5. Celebrity bystander	0.07	0.25	0.01	0.00	0.00	0.12								
6. Bystander size	10.16	1.00	-0.01	0.00	0.00	0.16	0.46							
7. Bystander ROA	0.06	0.06	-0.03	0.00	0.00	0.15	0.01	0.12						
8. Bystander TSR	0.23	0.36	-0.10	0.00	0.00	-0.06	0.00	0.09	0.07					
9. Bystander age	71.22	48.67	-0.01	0.00	0.00	-0.06	0.08	0.11	-0.12	-0.13				
10. Bystander analyst coverage	24.73	9.25	0.04	0.00	0.00	0.49	0.30	0.43	-0.02	-0.06	-0.09			
11. Bystander prior breaches	0.25	0.50	0.01	0.00	0.00	0.16	0.40	0.34	0.00	-0.02	0.01	0.26		
12. Perpetrator size	9.17	2.29	-0.02	0.54	0.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
13. Perpetrator ROA	0.04	0.09	-0.01	0.34	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.62
14. Perpetrator TSR	0.16	0.34	-0.01	0.14	0.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.42
15. Perpetrator age	56.30	40.72	-0.02	-0.08	-0.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.05
16. Perpetrator analyst coverage	21.86	14.73	-0.02	0.64	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.86
17. Perpetrator prior breaches	0.54	0.75	0.00	0.49	0.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.55
18. S&P 500 perpetrator	0.55	0.50	-0.02	0.51	0.32	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.76
19. Product similarity	0.55	0.75	-0.02	-0.05	0.00	0.05	0.02	0.00	0.06	0.01	-0.08	0.02	0.13	0.01
20. Vertical relatedness	0.16	0.37	-0.02	-0.09	0.01	-0.01	-0.04	0.00	0.03	-0.01	0.03	-0.05	-0.12	0.01
21. Analyst co-coverage	0.08	0.27	-0.01	0.09	0.07	0.09	0.04	0.04	0.06	0.00	-0.02	0.08	0.06	0.14
22. Mega breach	0.11	0.32	-0.02	0.04	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16
23. Sensitive information	0.61	0.49	0.01	-0.09	-0.34	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.19
24. Hacker attack	0.60	0.49	-0.01	0.00	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.02
25. Breached through contractor	0.10	0.30	0.00	0.07	-0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.04
26. Breached through subsidiary	0.26	0.44	0.02	-0.08	-0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.21

Variables	13	14	15	16	17	18	19	20	21	22	23	24	25
14. Perpetrator TSR	0.28												
15. Perpetrator age	-0.18	-0.20											
16. Perpetrator analyst coverage	0.51	0.27	-0.12										
17. Perpetrator prior breaches	0.37	-0.10	-0.01	0.50									
18. S&P 500 perpetrator	0.46	0.24	0.22	0.72	0.31								
19. Product similarity	0.00	0.03	-0.02	-0.03	-0.02	0.00							
20. Vertical relatedness	0.04	0.01	0.07	-0.01	-0.08	0.01	0.04						
21. Analyst co-coverage	0.10	0.04	0.00	0.15	0.08	0.14	0.30	0.05					
22. Mega breach	0.05	0.27	-0.25	0.27	0.06	0.02	-0.01	-0.05	0.03				
23. Sensitive information	0.09	-0.21	0.17	-0.13	-0.18	0.08	-0.01	0.02	0.00	-0.34			
24. Hacker attack	0.01	0.20	-0.03	0.10	-0.21	0.11	-0.03	0.00	0.02	0.08	0.16		
25. Breached through contractor	0.10	-0.03	0.17	-0.11	-0.10	-0.03	0.00	0.12	-0.01	-0.12	0.04	-0.40	
26. Breached through subsidiary	-0.06	-0.08	-0.10	-0.15	-0.23	-0.06	0.02	0.03	-0.04	-0.09	0.17	-0.12	-0.07

N = 27,069

The above procedure mitigated collinearity concerns. The mean VIFs of all models were below 5, with the maximum being 3.10; the maximum individual VIF was 6.83 for *perpetrator TSR*, and the condition numbers of all models were below 30 with the maximum being 24.38. All of these diagnostics were well below the widely accepted thresholds (Belsley et al., 2005). Thus, multicollinearity is not likely to be an issue.

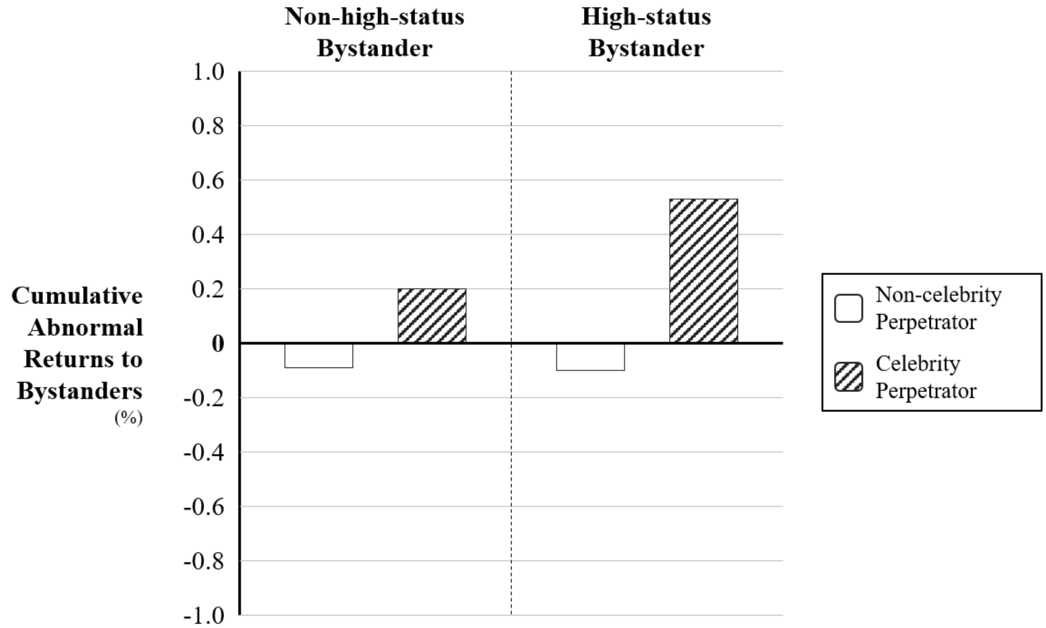
Table 3.2 presents the regression results predicting investor reactions to bystanders upon the disclosure of data breaches. Model 1 introduces the control variables, and Model 2 introduces *high-status perpetrator* and *celebrity perpetrator*. Hypothesis 1 predicts that misconduct by high-status perpetrators results in negative spillovers for bystanders, and Hypothesis 2 predicts that misconduct by celebrity perpetrators results in positive spillovers for bystanders. The results for Model 2 show that *high-status perpetrator* is associated with a -0.40 percent decrease in CARs to bystanders (p = 0.002), whereas *celebrity perpetrator* is associated with a 0.35 percent increase in CARs to bystanders (p = 0.021). Moreover, the effects of *high-status perpetrator* and *celebrity perpetrator* differ significantly from each other (p = 0.004). Thus, Hypotheses 1 and 2 are supported. Models 3–6 sequentially introduce the interactions to test Hypotheses 3–6. The interaction between *high-status perpetrator* and *high-status bystander* is not significant ($p < 0.10$), failing to support Hypothesis 3 that bystanders' status amplifies the negative effect of perpetrators' status. Model 4 shows that *high-status bystander* strengthens the positive effect of *celebrity perpetrator* (p = 0.060), supporting Hypothesis 4. Figure 3.2 illustrates this interaction effect. The increase in CARs to bystanders owing to perpetrators' celebrity is greater for high-status bystanders (bars on right-hand side) than for non-high-status bystanders (bars on left-hand side).

Table 3.2. Results Predicting Investor Reactions to Bystanders

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
constant	0.606	0.602	0.606	0.609	0.592	0.606	0.597	0.611	0.601
	(0.480)	(0.482)	(0.481)	(0.482)	(0.482)	(0.482)	(0.481)	(0.483)	(0.481)
Mega breach	-0.162†	-0.264**	-0.264**	-0.264**	-0.264**	-0.264**	-0.264**	-0.264**	-0.264**
	(0.095)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)
Sensitive information	0.120	0.188†	0.188†	0.188†	0.188†	0.188†	0.188†	0.188†	0.188†
	(0.088)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Hacker attack	-0.000	-0.092	-0.092	-0.092	-0.092	-0.092	-0.092	-0.092	-0.092
	(0.133)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
Breached through contractor	-0.018	0.123	0.123	0.123	0.124	0.123	0.124	0.123	0.123
	(0.185)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)
Breached through subsidiary	0.151	0.034	0.034	0.035	0.034	0.035	0.034	0.035	0.035
	(0.108)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Product similarity	-0.082*	-0.086*	-0.086*	-0.087*	-0.086*	-0.086*	-0.086*	-0.087*	-0.086*
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Vertical relatedness	-0.015	-0.016	-0.016	-0.016	-0.015	-0.016	-0.015	-0.016	-0.014
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)
Analyst co-coverage	-0.122	-0.115	-0.116	-0.121	-0.102	-0.125	-0.104	-0.130	-0.123
	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.098)	(0.099)	(0.098)
Perpetrator size	0.138*	0.083	0.083	0.083	0.083	0.083	0.083	0.083	0.083
	(0.066)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)
Perpetrator ROA	1.814**	2.106**	2.107**	2.108**	2.103**	2.108**	2.103**	2.110**	2.106**
	(0.561)	(0.636)	(0.636)	(0.636)	(0.636)	(0.636)	(0.636)	(0.636)	(0.636)
Perpetrator TSR	-0.355**	-0.134	-0.135	-0.135	-0.134	-0.135	-0.134	-0.135	-0.134
	(0.112)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
Perpetrator age	-0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perpetrator analyst coverage	0.002	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Perpetrator prior breaches	-0.061	-0.248**	-0.248**	-0.248**	-0.248**	-0.247**	-0.248**	-0.247**	-0.247**
	(0.064)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)
S&P 500 perpetrator	-0.299**	-0.392**	-0.391**	-0.391**	-0.392**	-0.391**	-0.392**	-0.391**	-0.391**
	(0.107)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)	(0.123)
Bystander size	-0.031	-0.031	-0.031	-0.031	-0.031	-0.031	-0.031	-0.031	-0.031
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Bystander ROA	-1.620*	-1.618*	-1.618*	-1.616*	-1.622*	-1.615*	-1.622*	-1.613*	-1.615*
	(0.647)	(0.647)	(0.647)	(0.647)	(0.647)	(0.647)	(0.647)	(0.647)	(0.647)
Bystander TSR	-1.113**	-1.113**	-1.113**	-1.112**	-1.113**	-1.112**	-1.113**	-1.112**	-1.112**
	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)
Bystander age	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bystander analyst coverage	0.011*	0.011*	0.011*	0.011*	0.011*	0.011*	0.011*	0.011*	0.011*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Bystander prior breaches	0.013	0.014	0.014	0.014	0.013	0.014	0.013	0.014	0.014
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
High-status bystander	0.029	0.028	0.005	-0.009	0.027	0.029	-0.009	-0.005	-0.020
	(0.105)	(0.105)	(0.112)	(0.105)	(0.105)	(0.105)	(0.111)	(0.106)	(0.110)
Celebrity bystander	0.133	0.133	0.133	0.133	0.298	0.078	0.304	0.084	0.263
	(0.183)	(0.183)	(0.183)	(0.183)	(0.191)	(0.177)	(0.191)	(0.178)	(0.187)
High-status perpetrator		-0.395**	-0.411**	-0.395**	-0.351**	-0.395**	-0.373**	-0.394**	-0.344*
		(0.130)	(0.131)	(0.130)	(0.130)	(0.130)	(0.132)	(0.130)	(0.135)
Celebrity perpetrator		0.353*	0.353*	0.297†	0.351*	0.321*	0.351*	0.274†	0.248
		(0.152)	(0.152)	(0.156)	(0.152)	(0.156)	(0.152)	(0.159)	(0.162)
High-status perpetrator			0.095				0.150		0.080
x High-status bystander			(0.168)				(0.160)		(0.182)
Celebrity perpetrator				0.335†				0.305†	0.256
x High-status bystander				(0.178)				(0.177)	(0.206)
High-status perpetrator					-0.688**		-0.714**		-0.979**
x Celebrity bystander					(0.227)		(0.225)		(0.273)
Celebrity perpetrator						0.495*		0.446†	0.962**
x Celebrity bystander						(0.248)		(0.245)	(0.317)
Perpetrator industry dummies					Included				
R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

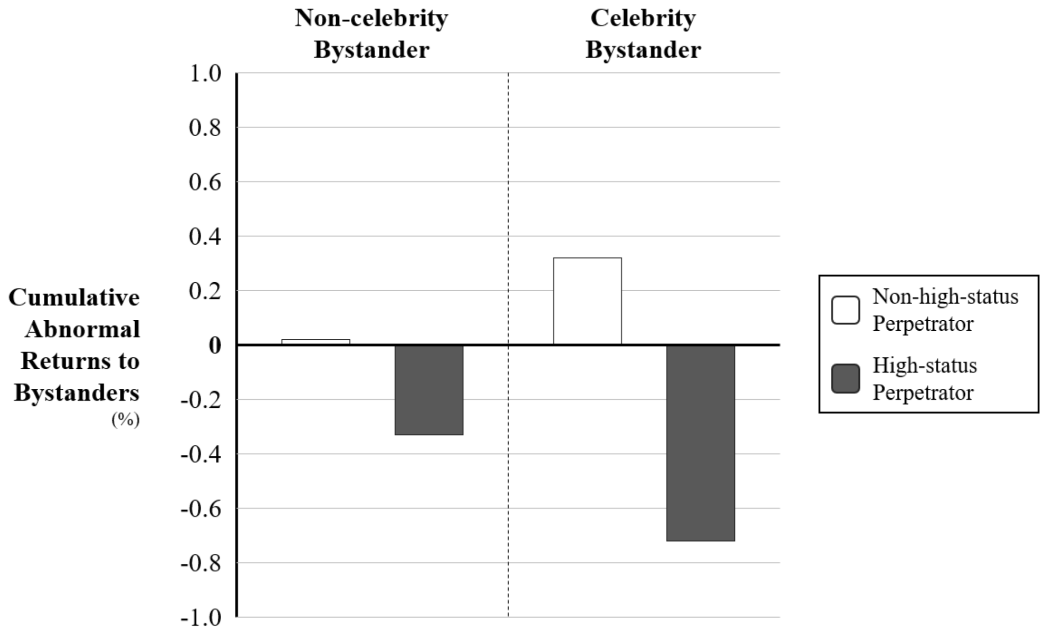
$p^{\dagger} < 0.10$; $p^{*} < 0.05$; $p^{**} < 0.01$; N = 27,069 (441 clusters).

Figure 3.2. Interaction between Perpetrators' Celebrity and Bystanders' Status



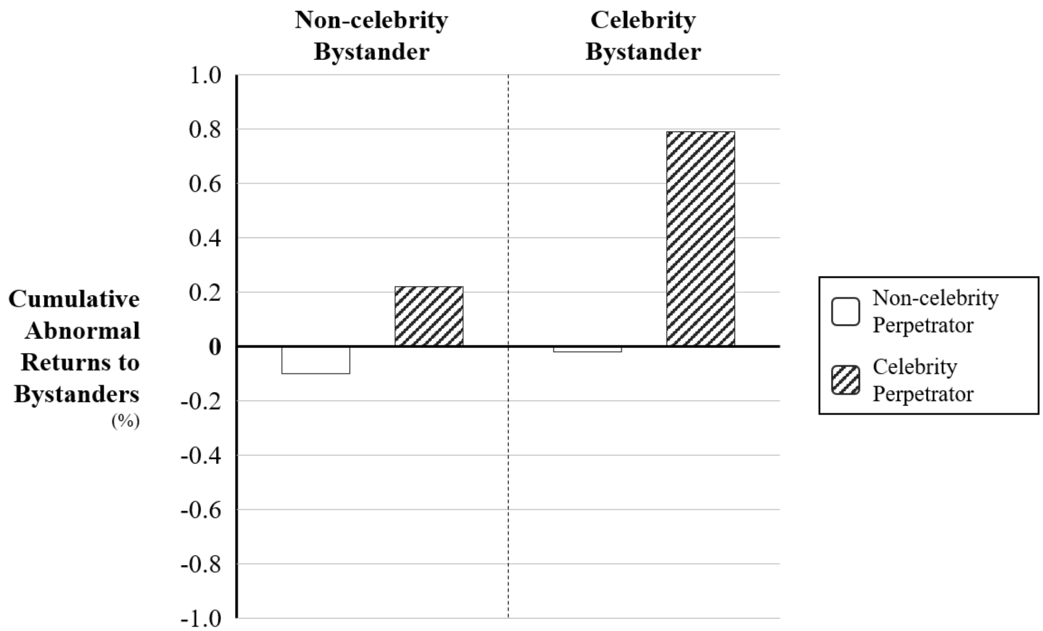
Model 5 tests Hypothesis 5 that bystanders' celebrity weakens or reverses the negative effect of perpetrators' status. However, the interaction between *high-status perpetrator* and *celebrity bystander* is significant in the opposite direction from what I predicted (p = 0.003). That is, bystanders' celebrity amplifies negative spillovers from high-status firms' misconduct. Figure 3.3 illustrates this interaction. The plots show that the difference in CARs to bystanders in the wake of high-status and non-high-status perpetrators' misconduct widens for celebrity bystanders (bars on right-hand side). Thus, Hypothesis 5 is not supported, but in a surprising way, calling for potential explanations.

Figure 3.3. Interaction between Perpetrators' Status and Bystanders' Celebrity



Model 6 also shows a surprising result. Although Hypothesis 6 predicts that bystanders' celebrity weakens or reverses the positive spillovers from celebrity firms' misconduct, the results in Model 6 show that *celebrity bystander* amplifies, rather than attenuates, the positive effect of *celebrity perpetrator* (p = 0.046). Figure 3.4 confirms that the gains for bystanders from celebrity firms' misconduct is greater for celebrity bystanders (bars on right-hand side) than for non-celebrity bystanders (bars on left-hand side). Hence, although Hypothesis 6 failed to receive support, the results suggest that an alternative theoretical mechanism regarding the role of bystanders' celebrity might be at play, particularly when considered in tandem with the finding from Hypothesis 5.

Figure 3.4. Interaction between Perpetrators' Celebrity and Bystanders' Celebrity



Models 7 and 8 examine the significance of the interaction terms when they are grouped together according to the type of perpetrators' social evaluations. Model 7 shows that the interaction between *high-status perpetrator* and *celebrity bystander* maintains its significance (p = 0.002) even when the interaction between *high-status perpetrator* and *high-status bystander* is simultaneously included. Model 8 shows that the interaction terms involving *celebrity perpetrator* all remain significant, although the significance level slightly deteriorates for both *celebrity perpetrator* x *high-status bystander* (p = 0.087) and *celebrity perpetrator* x *celebrity bystander* (p = 0.069). These interaction terms maintain their significance in the saturated model (Model 9) except for the one between *celebrity perpetrator* and *high-status bystander* (p = 0.214).

Together, these results imply that perpetrator status and celebrity have profound impacts on stakeholders' processing of bystanders' potential culpability and/or immunity.

Nonetheless, the surprising findings regarding the moderation effects of bystander celebrity call for alternative explanations, which I address in the Discussion section. Furthermore, I explore potential boundary conditions that could account for the non-finding regarding the interaction between perpetrator and bystander status in the post hoc analysis section.

3.3.1. Robustness tests

Because the findings based on the event study method can be sensitive to different event windows used to compute the CARs (Paruchuri & Misangyi, 2015), I ran a series of regressions using CARs based on a shorter window of [t – 1, t + 1] and a longer window of [t – 1, t + 10] as the dependent variables. Tables 3.3 presents the results using the shorter window. Models 11 shows that only *high-status perpetrator* has a significantly negative main effect in the shorter (p = 0.001). In Model 13, *high-status bystander* significantly amplifies the positive effect of *celebrity perpetrator* (p = 0.010) and in Model 14, *celebrity bystander* significantly amplifies the negative effect of *high-status perpetrator* (p = 0.049). However, the interaction between *celebrity perpetrator* and *celebrity bystander* becomes less significant than the original result in Model 15 (p = 0.135), which regains significance in the saturated model (p = 0.032).

Table 3.3. Robustness Test Using a Shorter Event Window

Variables	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16
constant	0.207	0.262	0.261	0.269	0.258	0.264	0.263
	(0.253)	(0.255)	(0.254)	(0.254)	(0.254)	(0.255)	(0.254)
Mega breach	0.018	-0.084	-0.084	-0.084	-0.084	-0.084	-0.084
	(0.067)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
Sensitive information	0.076	-0.037	-0.037	-0.037	-0.037	-0.037	-0.037
	(0.056)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Hacker attack	-0.076	-0.085	-0.085	-0.085	-0.085	-0.085	-0.085
	(0.082)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
Breached through contractor	-0.134	-0.170	-0.170	-0.170	-0.170	-0.170	-0.170
	(0.125)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)
Breached through subsidiary	0.087	0.013	0.013	0.013	0.013	0.013	0.013
	(0.071)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Product similarity	-0.075**	-0.085**	-0.085**	-0.086**	-0.085**	-0.085**	-0.086**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Vertical relatedness	-0.027	-0.033	-0.033	-0.033	-0.032	-0.033	-0.032
	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Analyst co-coverage	0.024	0.042	0.042	0.035	0.046	0.036	0.034
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Perpetrator size	0.064	0.017	0.017	0.017	0.017	0.017	0.017
	(0.042)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Perpetrator ROA	1.216**	1.888**	1.888**	1.890**	1.886**	1.889**	1.889**
	(0.332)	(0.393)	(0.393)	(0.393)	(0.393)	(0.393)	(0.393)
Perpetrator TSR	-0.238**	-0.172†	-0.172†	-0.172†	-0.171†	-0.172†	-0.172†
	(0.084)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)	(0.099)
Perpetrator age	0.000	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perpetrator analyst coverage	-0.004	0.000	0.000	0.000	0.000	0.000	0.000
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Perpetrator prior breaches	0.017	-0.133*	-0.133*	-0.133*	-0.133*	-0.133*	-0.133*
	(0.048)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
S&P 500 perpetrator	-0.192**	-0.173*	-0.173*	-0.172*	-0.173*	-0.173*	-0.172*
	(0.072)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Bystander size	0.007	0.007	0.007	0.007	0.007	0.007	0.007
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Bystander ROA	-0.468	-0.465	-0.465	-0.462	-0.467	-0.463	-0.462
	(0.377)	(0.378)	(0.378)	(0.378)	(0.378)	(0.378)	(0.378)
Bystander TSR	-0.463**	-0.463**	-0.463**	-0.463**	-0.463**	-0.463**	-0.463**
	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
Bystander age	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bystander analyst coverage	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bystander prior breaches	0.001	0.002	0.002	0.002	0.002	0.002	0.002
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
High-status bystander	0.103*	0.103*	0.107†	0.060	0.103*	0.103*	0.084
	(0.052)	(0.052)	(0.057)	(0.056)	(0.052)	(0.052)	(0.058)
Celebrity bystander	0.074	0.073	0.073	0.074	0.128	0.043	0.111
	(0.090)	(0.090)	(0.090)	(0.090)	(0.087)	(0.085)	(0.086)
High-status perpetrator		-0.278**	-0.275**	-0.278**	-0.263**	-0.278**	-0.236**
		(0.085)	(0.086)	(0.085)	(0.086)	(0.085)	(0.087)
Celebrity perpetrator		-0.108	-0.108	-0.170†	-0.108	-0.125	-0.203*
		(0.099)	(0.099)	(0.101)	(0.099)	(0.101)	(0.102)
High-status perpetrator			-0.015				-0.120
x High-status bystander			(0.110)				(0.116)
Celebrity perpetrator				0.381*			0.428**
x High-status bystander				(0.148)			(0.156)
High-status perpetrator					-0.228*		-0.330**
x Celebrity bystander					(0.115)		(0.116)
Celebrity perpetrator						0.272	0.385*
x Celebrity bystander						(0.182)	(0.179)
Perpetrator industry dummies				Included			
R^2	0.01	0.01	0.01	0.01	0.01	0.01	0.01

$p^{\dagger} < 0.10$; $p^{*} < 0.05$; $p^{**} < 0.01$; $N = 27{,}069$ (441 clusters).

Tables 3.4 presents the results using the longer window. Models 18 shows that only *high-status perpetrator* has a significantly negative main effect (p = 0.023). However, only the interaction between *high-status perpetrator* and *celebrity bystander* is significant in Model 21 (p = 0.005); this interaction is also significant in Model 23 (p = 0.001), along with the interaction between *celebrity perpetrator* and *celebrity bystander* (p = 0.011), the fully saturated model. Surprisingly, the interaction between *high-status perpetrator* and *high-status bystander* also becomes significant in the direction predicted in Hypothesis 3, although marginally (p = 0.098), in Model 23. In essence, the results using shorter and longer event windows are generally in line with the original results. However, using shorter windows can prevent the observation of spillover effects to bystanders (Barnett & King, 2008) and using longer windows can risk contamination from irrelevant events on abnormal returns (McWilliams & Siegel, 1997). Thus, I posit that the original findings best reflect the actual spillover processes.

Table 3.4. Robustness Test Using a Longer Event Window

Variables	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23
constant	1.440†	1.470†	1.479†	1.470†	1.457†	1.472†	1.468†
	(0.853)	(0.856)	(0.855)	(0.856)	(0.854)	(0.856)	(0.855)
Mega breach	-0.301*	-0.436**	-0.436**	-0.436**	-0.437**	-0.436**	-0.436**
	(0.142)	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)	(0.137)
Sensitive information	0.118	0.103	0.103	0.103	0.103	0.103	0.103
	(0.119)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)	(0.153)
Hacker attack	0.016	-0.057	-0.057	-0.057	-0.057	-0.057	-0.057
	(0.174)	(0.188)	(0.188)	(0.188)	(0.188)	(0.188)	(0.188)
Breached through contractor	-0.048	0.037	0.037	0.037	0.037	0.037	0.037
	(0.235)	(0.227)	(0.227)	(0.227)	(0.227)	(0.227)	(0.227)
Breached through subsidiary	0.048	-0.082	-0.082	-0.082	-0.082	-0.082	-0.082
	(0.129)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)	(0.147)
Product similarity	-0.191**	-0.199**	-0.199**	-0.199**	-0.199**	-0.199**	-0.198**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.054)	(0.053)	(0.053)
Vertical relatedness	-0.077	-0.082	-0.082	-0.082	-0.080	-0.081	-0.080
	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)
Analyst co-coverage	-0.293*	-0.277*	-0.281*	-0.277*	-0.262*	-0.285*	-0.279*
	(0.127)	(0.127)	(0.127)	(0.128)	(0.128)	(0.127)	(0.127)
Perpetrator size	0.064	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.075)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
Perpetrator ROA	0.494	1.096	1.097	1.096	1.091	1.097	1.093
	(0.817)	(0.942)	(0.942)	(0.942)	(0.942)	(0.942)	(0.942)
Perpetrator TSR	-0.300*	-0.097	-0.097	-0.097	-0.096	-0.097	-0.097
	(0.152)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)	(0.197)
Perpetrator age	0.001	0.002	0.002	0.002	0.002	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Perpetrator analyst coverage	-0.002	0.010	0.010	0.010	0.010	0.010	0.010
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Perpetrator prior breaches	0.003	-0.222*	-0.222*	-0.222*	-0.222*	-0.222*	-0.222*
	(0.079)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
S&P 500 perpetrator	-0.245†	-0.303†	-0.303†	-0.303†	-0.304†	-0.303†	-0.303†
	(0.148)	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)
Bystander size	-0.088	-0.088	-0.088	-0.088	-0.088	-0.088	-0.088
	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)
Bystander ROA	-1.039	-1.036	-1.035	-1.036	-1.041	-1.034	-1.036
	(0.975)	(0.975)	(0.976)	(0.975)	(0.976)	(0.975)	(0.975)
Bystander TSR	-2.267**	-2.267**	-2.267**	-2.267**	-2.267**	-2.267**	-2.267**
	(0.303)	(0.304)	(0.304)	(0.304)	(0.304)	(0.304)	(0.304)
Bystander age	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bystander analyst coverage	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Bystander prior breaches	0.272*	0.273*	0.273*	0.273*	0.272*	0.273*	0.273*
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
High-status bystander	0.210	0.210	0.152	0.210	0.209	0.210	0.144
	(0.180)	(0.180)	(0.189)	(0.179)	(0.180)	(0.180)	(0.186)
Celebrity bystander	0.274	0.273	0.273	0.273	0.470	0.233	0.442
	(0.342)	(0.342)	(0.342)	(0.342)	(0.357)	(0.332)	(0.350)
High-status perpetrator		-0.454*	-0.493*	-0.454*	-0.400*	-0.453*	-0.441*
		(0.198)	(0.201)	(0.198)	(0.200)	(0.198)	(0.206)
Celebrity perpetrator		0.202	0.202	0.202	0.200	0.179	0.177
		(0.210)	(0.210)	(0.215)	(0.210)	(0.212)	(0.219)
High-status perpetrator			0.242				0.383†
x High-status bystander			(0.212)				(0.231)
Celebrity perpetrator				-0.000			-0.236
x High-status bystander				(0.232)			(0.270)
High-status perpetrator					-0.821**		-1.153**
x Celebrity bystander					(0.288)		(0.335)
Celebrity perpetrator						0.369	0.984*
x Celebrity bystander						(0.311)	(0.385)
Perpetrator industry dummies				Included			
R^2	0.03	0.03	0.03	0.03	0.03	0.03	0.03

$p^\dagger < 0.10$; $p^* < 0.05$; $p^{**} < 0.01$; N = 27,069 (441 clusters).

Because my observations concern dyads of perpetrators and bystanders, there exists a potential estimation problem caused by the recurrent appearance of the same perpetrators where unobserved attributes affect outcomes for bystanders and result in underestimation of standard errors (Cameron, Gelbach, & Miller, 2011). Thus, I estimated robust standard errors that are simultaneously clustered on both perpetrators and bystanders, using the Stata command *clus_nway* developed by Kleinbaum and colleagues (2013). Table 3.5 presents the results. In Model 25, the negative main effect of *high-status perpetrator* (p = 0.001) and the positive main effect of *celebrity perpetrator* (p = 0.004) remains strongly significant. However, the significance of the interaction between *celebrity perpetrator* and *high-status bystander* slightly deteriorates in Model 27 (p = 0.196), and the interaction between *high-status perpetrator* and *high-status bystander* remains nonsignificant in Model 26. The interaction between *high-status perpetrator* and *celebrity bystander* is significant in both Models 28 (p = 0.007) and 30 (p = 0.004). The interaction between *celebrity perpetrator* and *celebrity bystander* becomes nonsignificant in Model 29 and gains significance in Model 30 (p = 0.060). The results using the multiway clustering of standard errors demonstrate similar patterns with my original findings except for slightly deteriorated significance of some interactions. However, Angrist and Pischke (2009) advised exercising extra caution when using a small number of clusters. Because my observations concern only 56 perpetrators, the results should be interpreted with caution.

Table 3.5. Robustness Test Using Multiway Clustering of Standard Errors

Variables	Model 24	Model 25	Model 26	Model 27	Model 28	Model 29	Model 30
constant	0.606	0.602	0.606	0.609	0.592	0.606	0.601
	(0.533)	(0.536)	(0.535)	(0.535)	(0.534)	(0.536)	(0.535)
Mega breach	-0.162	-0.264**	-0.264**	-0.264**	-0.264**	-0.264*	-0.264*
	(0.101)	(0.096)	(0.096)	(0.098)	(0.096)	(0.101)	(0.100)
Sensitive information	0.120	0.188†	0.188†	0.188†	0.188†	0.188†	0.188†
	(0.082)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
Hacker attack	-0.000	-0.092	-0.092	-0.092	-0.092	-0.092	-0.092
	(0.124)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)	(0.136)
Breached through contractor	-0.018	0.123	0.123	0.123	0.124	0.123	0.123
	(0.168)	(0.156)	(0.156)	(0.157)	(0.156)	(0.157)	(0.159)
Breached through subsidiary	0.151	0.034	0.034	0.035	0.034	0.035	0.035
	(0.129)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Product similarity	-0.082	-0.086	-0.086	-0.087	-0.086	-0.086	-0.086
	(0.070)	(0.074)	(0.074)	(0.073)	(0.074)	(0.073)	(0.072)
Vertical relatedness	-0.015	-0.016	-0.016	-0.016	-0.015	-0.016	-0.014
	(0.123)	(0.127)	(0.127)	(0.126)	(0.127)	(0.126)	(0.126)
Analyst co-coverage	-0.122	-0.115	-0.116	-0.121	-0.102	-0.125	-0.123
	(0.146)	(0.146)	(0.146)	(0.147)	(0.146)	(0.146)	(0.148)
Perpetrator size	0.138*	0.083	0.083	0.083	0.083	0.083	0.083
	(0.061)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.055)
Perpetrator ROA	1.814**	2.106**	2.107**	2.108**	2.103**	2.108**	2.106**
	(0.592)	(0.483)	(0.483)	(0.482)	(0.483)	(0.487)	(0.485)
Perpetrator TSR	-0.355**	-0.134	-0.135	-0.135	-0.134	-0.135	-0.134
	(0.130)	(0.115)	(0.115)	(0.116)	(0.115)	(0.116)	(0.116)
Perpetrator age	-0.000	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perpetrator analyst coverage	0.002	0.015	0.015	0.015	0.015	0.015	0.015
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Perpetrator prior breaches	-0.061	-0.248**	-0.248**	-0.248**	-0.248**	-0.247**	-0.247**
	(0.071)	(0.083)	(0.083)	(0.082)	(0.082)	(0.083)	(0.083)
S&P 500 perpetrator	-0.299*	-0.392**	-0.391**	-0.391**	-0.392**	-0.391**	-0.391**
	(0.123)	(0.135)	(0.135)	(0.135)	(0.136)	(0.135)	(0.136)
Bystander size	-0.031	-0.031	-0.031	-0.031	-0.031	-0.031	-0.031
	(0.060)	(0.061)	(0.060)	(0.060)	(0.061)	(0.060)	(0.060)
Bystander ROA	-1.620*	-1.618*	-1.618*	-1.616*	-1.622*	-1.615*	-1.615*
	(0.677)	(0.677)	(0.677)	(0.677)	(0.677)	(0.677)	(0.677)
Bystander TSR	-1.113**	-1.113**	-1.113**	-1.112**	-1.113**	-1.112**	-1.112**
	(0.244)	(0.244)	(0.244)	(0.245)	(0.244)	(0.243)	(0.244)
Bystander age	-0.002*	-0.002*	-0.002*	-0.002*	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bystander analyst coverage	0.011	0.011	0.011	0.011	0.011	0.011	0.011
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Bystander prior breaches	0.013	0.014	0.014	0.014	0.013	0.014	0.014
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
High-status bystander	0.029	0.028	0.005	-0.009	0.027	0.029	-0.020
	(0.120)	(0.121)	(0.136)	(0.122)	(0.121)	(0.120)	(0.132)
Celebrity bystander	0.133	0.133	0.133	0.133	0.298	0.078	0.263
	(0.224)	(0.225)	(0.225)	(0.225)	(0.250)	(0.216)	(0.238)
High-status perpetrator		-0.395**	-0.411**	-0.395**	-0.351**	-0.395**	-0.344**
		(0.108)	(0.113)	(0.108)	(0.108)	(0.110)	(0.120)
Celebrity perpetrator		0.353**	0.353**	0.297*	0.351**	0.321*	0.248†
		(0.117)	(0.117)	(0.128)	(0.117)	(0.123)	(0.132)
High-status perpetrator			0.095				0.080
x High-status bystander			(0.185)				(0.217)
Celebrity perpetrator				0.335			0.256
x High-status bystander				(0.256)			(0.323)
High-status perpetrator					-0.688**		-0.979**
x Celebrity bystander					(0.244)		(0.330)
Celebrity perpetrator						0.495	0.962†
x Celebrity bystander						(0.548)	(0.500)
Perpetrator industry dummies				Included			
R^2	0.02	0.02	0.02	0.02	0.02	0.02	0.02

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; N = 27,069 (56 perpetrator clusters; 441 bystander clusters).

Finally, to explore potential sources of endogeneity, I conducted an ITCV analysis examining the influence of potential omitted variables, as introduced in Chapter 2 (Busenbark et al., 2017; Frank, 2000; Harrison et al., 2018; Hubbard et al., 2017). This analysis is intended to capture the effects of, for instance, unobserved associations between perpetrators and bystanders that affect investors' perceptions or unobserved characteristics of breach incidents that affect the valence and magnitude of spillovers. I used the fully saturated model (i.e., Model 9 in Table 3.2) for the analysis. The results indicate that 23.12 percent (6,258 cases) of the estimate would have to be due to bias to invalidate the effect of *high-status perpetrator* in the results, which is close to the number of observations categorized as involving high-status perpetrators (24.17 percent; 6,543 cases). Similarly, to invalidate the effects of *celebrity perpetrator*, *high-status bystander*, and *celebrity bystander,* 21.85 percent, 90.89 percent, and 28.21 percent of the observations would have to be due to bias, respectively.

Furthermore, for endogeneity to exist, minimum correlations would need to be exceeded between a hypothetical omitted variable and both the dependent variable (*CAR*) and a focal variable, in this case, *high-status perpetrator* (0.06), *celebrity perpetrator* (0.05), *high-status bystander* (0.10), and *celebrity bystander* (0.06). None of the variables in my study except for *bystander TSR* (r = 0.10) are this highly correlated with *CAR*. This aligns with results of previous event study research, as no correlations with *CAR* have exceeded 0.05 (Barnett & King, 2008; Bowers & Prato, 2018; Martin et al., 2017; Paruchuri & Misangyi, 2015). Overall, the evidence suggests that the likelihood of a high correlation between an omitted variable and the dependent variable of this study is extremely low. Thus, endogeneity is not likely to be an issue in this study.

3.3.2. Post hoc analysis

Although results for almost all of my interaction hypotheses are significant, albeit some in the opposite direction from my predictions, the interaction between perpetrator and bystander status is nonsignificant. Thus, I suspect that there could be a boundary condition to my theorizing that stakeholders group firms based on status. That is, there could be a possibility that stakeholders' inferences of associations between perpetrators and bystanders based on their status are augmented by additional dimensions of organizational similarities.

As highlighted above, prior studies on both positive and negative spillovers have revealed significant effects of product similarities in determining spillover boundaries (Paruchuri et al., 2019; Paruchuri & Misangyi, 2015; Piazza & Jourdan, 2018). Indeed, horizontal market categories play a crucial role, along with vertical status distinctions, in defining firms' market identities (Jensen, Kim, & Kim, 2011). Thus, although stakeholders may view high-status perpetrators and bystanders as being vaguely associated, such suspicions can be further sharpened by applying additional information about interfirm similarity, because categorical delineations based on specific attributes imbue actors' status positions with a sense of collective identities (Han & Pollock, 2020). Thus, in the wake of a high-status firm's misconduct, culpability tends to be generalized more to bystanders with similar products, because the underlying reason for the high-status firm's failure may be more pertinent to those bystanders. Among firms with similar products, high-status bystanders may be perceived as more blameworthy because they are exemplars of a particular market category, just like the perpetrator.

To explore this possibility, I examined the three-way interaction between *high-*

status perpetrator, *high-status bystander*, and *product similarity* (a control variable in the original analysis) to test whether the interaction between perpetrator and bystander status becomes significant as a function of high product similarity. Table 3.6 presents the results. Model 31 is the main effects model (like Model 2 in Table 3.2), and Model 32 includes the interaction between *high-status perpetrator* and *high-status bystander* which is not significant (like Model 3 of Table 3.2). Model 33 shows that the negative spillover from a high-status perpetrator is significantly stronger for bystanders with high product similarity (p = 0.000). However, Model 34 shows that the interaction between *high-status bystander* and *product similarity* is not significant. Model 35 includes both interaction terms involving *high-status perpetrator* and *high-status bystander,* where the interaction between *high-status perpetrator* and *product similarity* is still significant (p = 0.000). Model 36 tests the three-way interaction among *high-status perpetrator*, *high-status bystander,* and *product similarity* which is significant (p = 0.074).

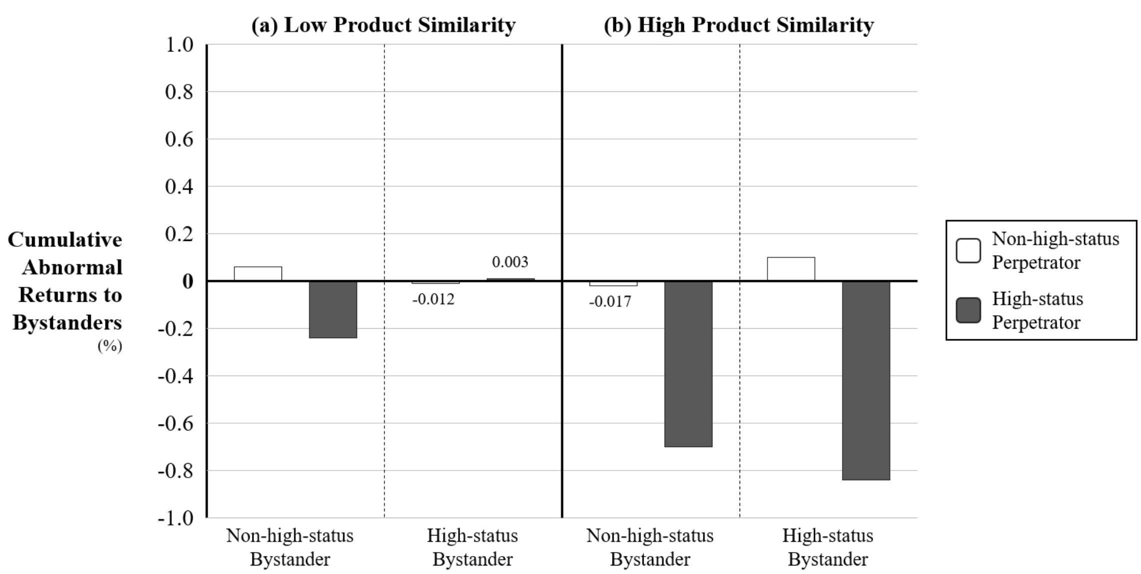
Table 3.6. Post Hoc Analysis Exploring Product Similarity as a Boundary Condition

Variables	Model 31	Model 32	Model 33	Model 34	Model 35	Model 36
constant	0.602	0.606	0.565	0.610	0.569	0.580
	(0.482)	(0.481)	(0.481)	(0.484)	(0.484)	(0.484)
Mega breach	-0.264**	-0.264**	-0.276**	-0.264**	-0.276**	-0.276**
	(0.091)	(0.091)	(0.090)	(0.091)	(0.091)	(0.090)
Sensitive information	0.188†	0.188†	0.191†	0.188†	0.191†	0.192†
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)
Hacker attack	-0.092	-0.092	-0.086	-0.092	-0.087	-0.091
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
Breached through contractor	0.123	0.123	0.125	0.123	0.124	0.128
	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)	(0.187)
Breached through subsidiary	0.034	0.034	0.055	0.035	0.055	0.052
	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)
Analyst co-coverage	-0.115	-0.116	-0.089	-0.119	-0.020	-0.088
	(0.098)	(0.098)	(0.098)	(0.099)	(0.098)	(0.099)
Vertical relatedness	-0.016	-0.016	-0.020	-0.016	-0.092	-0.019
	(0.098)	(0.098)	(0.098)	(0.098)	(0.099)	(0.098)
Perpetrator size	0.083	0.083	0.089	0.083	0.090	0.090
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)
Perpetrator ROA	2.106**	2.107**	2.052**	2.108**	2.053**	2.077**
	(0.636)	(0.636)	(0.636)	(0.636)	(0.637)	(0.637)
Perpetrator TSR	-0.134	-0.135	-0.129	-0.135	-0.129	-0.126
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
Perpetrator age	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perpetrator analyst coverage	0.015	0.015	0.016†	0.015	0.016†	0.016†
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Perpetrator prior breaches	-0.248**	-0.248**	-0.232**	-0.248**	-0.232**	-0.236**
	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)
S&P 500 perpetrator	-0.392**	-0.391**	-0.410**	-0.391**	-0.410**	-0.411**
	(0.123)	(0.123)	(0.123)	(0.123)	(0.124)	(0.124)
Bystander size	-0.031	-0.031	-0.031	-0.031	-0.032	-0.032
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Bystander ROA	-1.618*	-1.618*	-1.618*	-1.614*	-1.613*	-1.621*
	(0.647)	(0.647)	(0.648)	(0.647)	(0.647)	(0.647)
Bystander TSR	-1.113**	-1.113**	-1.111**	-1.112**	-1.110**	-1.110**
	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)
Bystander age	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bystander analyst coverage	0.011*	0.011*	0.011*	0.011*	0.012*	0.012*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Bystander prior breaches	0.014	0.014	0.020	0.013	0.020	0.020
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Celebrity bystander	0.133	0.133	0.132	0.134	0.133	0.134
	(0.183)	(0.183)	(0.184)	(0.184)	(0.184)	(0.185)
Celebrity perpetrator	0.353*	0.353*	0.351*	0.352*	0.350*	0.354*
	(0.152)	(0.152)	(0.151)	(0.152)	(0.151)	(0.151)
High-status bystander	0.028	0.005	-0.004	-0.017	-0.027	-0.075
	(0.105)	(0.112)	(0.112)	(0.119)	(0.120)	(0.124)
High-status perpetrator	-0.395**	-0.411**	-0.266*	-0.411**	-0.266*	-0.298*
	(0.130)	(0.131)	(0.132)	(0.131)	(0.132)	(0.132)
Product similarity	-0.086*	-0.086*	-0.025	-0.092*	-0.032	-0.046
	(0.036)	(0.036)	(0.040)	(0.039)	(0.041)	(0.042)
High-status perpetrator x High-status bystander		0.095	0.124	0.098	0.127	0.313
		(0.168)	(0.165)	(0.165)	(0.162)	(0.191)
High-status perpetrator x Product similarity			-0.284**		-0.284**	-0.221**
			(0.074)		(0.074)	(0.081)
High-status bystander x Product similarity				0.034	0.035	0.109
				(0.102)	(0.103)	(0.117)
High-status perpetrator x High-status bystander x Product similarity						-0.327†
						(0.182)
Perpetrator industry dummies				Included		
R^2	0.02	0.02	0.02	0.02		0.02

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; N = 27,069 (441 clusters).

Figure 3.5 illustrates the three-way interaction. Plot (a) represents the interaction between *high-status perpetrator* and *high-status bystander* at low product similarity (10th percentile) and plot (b) represents the interaction at high product similarity (90th percentile). When product similarity is low and bystanders are not high status, misconduct by high-status perpetrators results in -0.30 percent decrease in CARs to bystanders. However, when product similarity is low and bystanders are high status, the effect of perpetrators' status is minimal, indicating that neither positive nor negative spillovers occur.

Figure 3.5. Three-Way Interaction among Perpetrators' and Bystanders' Status and Product Similarity



When product similarity is high and bystanders are not high status, misconduct by high-status perpetrators leads to approximately a -0.68 percent decrease in CARs to bystanders. This decrease is further amplified to -0.94 percent when bystanders are also high status. In other words, the amplification of negative spillovers from high-status perpetrators due to bystanders also being high-status is observed only at high levels of product similarity between the perpetrators and bystanders. Thus, the results of this post hoc analysis suggest that product similarity serves as an important boundary condition for the status-based generalization of culpability, as I theorized above. I discuss the implications of these results next.

3.4. Discussion

In this study, I have revisited the widely-accepted notion that organizational misconduct often results in undeserved losses for innocent firms (Barnett & King, 2008; Goffman, 1963; Jonsson et al., 2009; Paruchuri & Misangyi, 2015), and have explored the relatively newer idea that misconduct can benefit bystanders (Paruchuri et al., 2019; Piazza & Jourdan, 2018). Whereas scholars who have studied spillovers from misconduct have tended to pick sides between positive and the negative spillovers, I have argued and found that both may be at play, building on the distinctive foundations of status and celebrity. Specifically, investors devalue bystanders in response to the disclosure of misconduct by high-status perpetrators, which are exemplars among firms within the same hierarchy. However, celebrity isolates culpability for misconduct to the perpetrators themselves due to their atypicality, and results in positive spillovers to bystanders.

The results regarding the moderation effect of bystanders' status and celebrity include some surprising findings. Perpetrator status does not interact significantly with bystander status, although my post hoc analysis reveals that high-status bystanders suffer more from high-status perpetrators' misconduct when product similarity is high. This finding confirms the notion that audiences often use both horizontal identity categories and vertical status distinctions when evaluating actors (Han & Pollock, 2020; Jensen et al., 2011; Wang & Jensen, 2019). Thus, although belonging to the same high-status class may not be sufficient to invite negative spillovers, such status similarity can be particularly onerous when augmented by high product similarity, which provides a clear boundary to which stakeholders' status-based inferences should be applied. Bystander status, however, amplifies positive spillovers from celebrity perpetrators, as hypothesized. Thus, when a highly visible yet atypical firm engages in misconduct, stakeholders tend to appreciate high status bystanders who are perceived as more trustworthy in conventional ways (D'Aveni, 1990; Jonsson et al., 2009).

The most surprising findings are those regarding the effects of bystander celebrity. First, bystander celebrity amplifies, rather than attenuates or reverses the negative effect of perpetrator status. That is, although I expected stakeholders to appreciate unconventional, yet highly evaluated celebrity firms because these firms are viewed as different from those tarnished by a high-status firm's misconduct, celebrity invites additional penalties. This may be due to the impact of high-status deviations increasing stakeholders' distaste for any acts of nonconformity (Adut, 2005; Piazza & Jourdan, 2018; Pollock et al., 2016), making celebrity bystanders' atypicality unsettling, rather than attractive for stakeholders.

Notably, bystander celebrity also amplifies, rather than attenuates or reverses positive spillovers from celebrity perpetrators. That is, even though a celebrity firm's misconduct increases stakeholders' appreciation of more norm-abiding firms, celebrity bystanders could benefit the most from positive spillovers. The implications are twofold. First, the individuating effect of perpetrator celebrity is even stronger than I theorized, such that although a celebrity firm’s misconduct leads stakeholders to appreciate firms that conform to societal norms, the attribution is directed towards the atypicality of the firm itself and does not bring all nonconforming firms under suspicion. This stands in stark contrast to misconduct by high-status firms, which brings all other firms under suspicion. Second, stakeholders perceive different celebrity firms as substantially different from each other, such that stakeholders do not categorize celebrity perpetrators and bystanders under a common, vague umbrella of atypical firms, and even favor celebrity bystanders for standing out from more conventional bystanders, despite their atypicality. Together, these findings suggest that status and celebrity are fundamentally different lenses through which stakeholders infer associations between perpetrators and bystanders and determine the valence of spillovers.

3.4.1. Research implications

The primary contribution of this study is that it helps reveal why a firm’s misconduct sometimes results in positive spillovers and sometimes results in negative spillovers to innocent bystander firms (Barnett & King, 2008; Paruchuri & Misangyi, 2015; Paruchuri et al., 2019; Piazza & Jourdan, 2018). To the best of my knowledge, no previous studies have simultaneously examined positive and negative spillovers. Yet this study addresses an even bigger problem in the literature, in that both types of spillovers have been theorized as stemming from similarities between perpetrators and bystanders (Barnett & King, 2008; Jonsson et al., 2009; Paruchuri & Misangyi, 2015; Paruchuri et al., 2019; Piazza & Jourdan, 2018; Zavyalova et al., 2012). Moreover, in studies on negative spillovers, scholars have argued that stakeholders tend to ignore distinctions between firms and instead apply crude categorizations and generalizations (Jonsson et al., 2009). Yet in studies on positive spillovers, scholars have argued that stakeholders must view bystanders as both distinct from perpetrators and similar in some respects if such firms are to benefit from misconduct (Paruchuri et al., 2019; Piazza & Jourdan, 2018).

Moving away from this overreliance on attribute-based similarities, I have theorized and found that social evaluations previously accorded to a perpetrator can prime stakeholders to view culpability as generalizable to others or isolated to the perpetrator. This finding provides an important foundation for future research on misconduct spillovers because: (a) significant uncertainty about the causes and consequences of misconduct may not allow stakeholders to narrow down a perpetrator's culpability to a specific organizational attribute when determining the range of spillovers; and (b) not all types of misconduct have causes and consequences germane to a specific market category. Specifically, it is often the case that the actual responsibilities and causes of misconduct become revealed over time, despite stakeholders being compelled to immediately resolve the suddenly imposed uncertainty by intuitively processing the information at hand (Lange & Washburn, 2012; Wiesenfeld et al., 2008). Alternatively, some instances of misconduct such as data breaches or financial fraud trigger a generalized concern about all corporate entities, rather than instigating category-specific attributions such as instances of misconduct involving product accidents or failures.

By bringing in the role of social evaluations as interpretive frames held by stakeholders (Hubbard et al., 2018; Pollock et al., 2019), research on misconduct spillovers need not identify context-specific attributes that serve as the basis for spillovers, nor confine the range of the spillovers to a specific group of firms. More importantly, the problematic theorization of attribute-based similarities incurring both positive and negative spillovers can be avoided. With social evaluations serving as an eminent heuristic device for stakeholders under uncertainty (Bundy & Pfarrer, 2015; Hoffman & Ocasio, 2001), prior studies have revealed that firms with social approval assets become targeted and scrutinized to a greater extent, particularly in the face of misconduct (Adut, 2005; Graffin et al., 2013). What has been far less considered is that, apart from drawing attention, different social approval assets can lead to different implications in the wake of misconduct, because the assets' sociocognitive content influences stakeholders' perceptions (Pollock et al., 2019). This is an important oversight in the misconduct literature. Stakeholders' understandings of and responses to misconduct could differ depending on what was expected of the perpetrators and the surrounding others.

Whereas the interpretive frames argument has only been tested in contexts involving positive and negative earnings surprises (Pfarrer et al., 2010) and underpricing, an equivocal cue that can be viewed both positively and negatively (Hubbard et al., 2018), it is particularly relevant in the context of misconduct, where stakeholders actively seek to understand the extent to which other firms are to be blamed and which can be trusted. With virtually all social evaluations being relative in nature (Pollock et al., 2016; Sauder et al., 2012), the social comparisons involved in the conferrals of different social approval assets matter significantly in the generalization or isolation of culpability, because the nature of the comparisons delineates the relationships between the perpetrator and other firms: some are valued because they are *similar* and yet superior to other firms, whereas others are valued because they are *unique*. Aside from the comparisons based on organizational attributes, stakeholders may use the heuristics provided by social approval assets and their sociocognitive content to compare and contrast perpetrators and bystanders rather than cherry-picking specific organizational attributes to draw such comparisons and selectively punish some and reward others.

3.4.2. Practical implications

Negative spillovers from others' misconduct can be particularly devastating for firms because the criteria stakeholders use to generalize culpability to bystanders are unclear, despite the significantly adverse outcomes found in various contexts. Likewise, benefiting from others' misconduct may not be easy without knowing how similar and/or different a firm should be relative to the perpetrators. My findings nonetheless provide some useful insights into the matter. When a misconduct incident involving a high-status firm is disclosed, bystander firms should communicate why and how they differ from the perpetrator to minimize the undeserved losses. Nonetheless, appearing too different from the majority of firms can intensify losses, as stakeholders are likely to be increasingly wary of atypical or abnormal behaviors. On the contrary, bystander firms could potentially benefit more from a celebrity firm's misconduct by reifying their compliance with central norms and practices among peers. To maximize unexpected gains, however, firms could demonstrate that they differ not only from the perpetrator, but also from other firms.

On the perpetrators' side, albeit a truism, high-status and celebrity firms should exercise extra caution to prevent misconduct, as the aftermath can be consequential. A high-status firm's misconduct can result in the devaluation of the entire corporate community and the costs may be tremendous due to a loss of legitimacy stemming from feelings of antipathy and distrust toward corporations (Jonsson et al., 2009). Although a celebrity firm's misconduct might not have such an expansive impact, it could still decrease the firm's competitive advantage by allowing others to benefit from positive spillovers. Considering that a firm's celebrity is based on weaker criteria and thus is more ephemeral than other types of social evaluations (Rindova et al., 2006), allowing other firms to benefit from misconduct could create bigger hurdles to overcome later when stakeholders no longer view the firm's atypicality as attractive (Pollock et al., 2016).

3.4.3. Limitations and future research directions

Like all research, this study has limitations and opens several avenues for future research. First, for the purpose of contrasting stakeholders' different levels of emphasis on (non)conformity, I specifically chose to explore the effects of status and celebrity (Hubbard et al., 2018; Pollock et al., 2019). One omitted social approval asset is reputation (Pollock et al., 2019). Reputation shares some features with both status and celebrity due to its emphasis on conformity and individuating nature. That is, because reputation is based on evidence of stable and superior capabilities (Pfarrer et al., 2010; Pollock et al., 2015), stakeholders evaluate reputation according to shared standards and nonconformity is rarely valued. However, reputational differences rarely evolve into an enduring pattern of social hierarchy and instead result in individuating perceptions (Lange et al., 2011; Pollock et al., 2015). Thus, a high-reputation firm's misconduct may not necessarily alter stakeholders' perceptions of lower-reputation firms. Instead, because reputation is much more closely associated with actual organizational attributes than with status (Pollock et al., 2015) and celebrity (Zavyalova et al., 2017), stakeholders might have greater precision in determining which firms are penalized or rewarded following a high-reputation firm's misconduct. Studying whether the mechanisms and outcomes differ for reputation-based evaluations should provide useful insights.

Also, consistent with the notion that unexpected exposure to uncertainty evokes intuitive and instantaneous stakeholder responses (Bundy & Pfarrer, 2015; Lange & Washburn, 2012) and thus leads to spillovers (Paruchuri & Misangyi, 2015; Paruchuri et al., 2019), this study captures the immediate stock market reactions to bystanders upon the revelation of misconduct. Thus, a promising avenue would be to examine whether positive and negative spillovers are corrected over time or have sustained impacts on bystanders' evaluations and performances (Paruchuri et al., 2019; Piazza & Jourdan, 2018). Moreover, given that more information regarding the causes and consequences of misconduct is likely to become available later, studying whether perpetrators' and bystanders' social approval assets and associated interpretive frames also shape the processing of these types of information and create or suppress further spillovers should provide valuable insights.

My theorization builds on a specific type of misconduct: data breaches. Whereas extending my framework to other types of misconduct can be useful for establishing generalizability, testing my predictions on more industry- or category-specific misconduct can be useful for exploring how attribute-based categories complement or replace the effects of the interpretive frames provided by social evaluations. Specifically, my post hoc analysis suggests that the effects of status and celebrity can be amplified by product similarity between bystanders and perpetrators. When a misconduct incident is more pertinent to a specific market category, such amplification by product similarity can be more prominent. Alternately, due to the high relevance of category boundaries as the criterion for spillovers, social evaluations may have much less significance for stakeholders. Lastly, examining whether my findings hold for other types of stakeholders known to incur spillovers such as the media (Zavyalova et al., 2012) or consumers (Paruchuri et al., 2019), or exploring how the conclusions drawn by different types of stakeholders influence the ultimate valence of spillovers can be promising.

3.4.4. Conclusion

In the wake of misconduct, stakeholders engage in a complex sensemaking process whereby they extend their punitive reactions to some bystanders and reward others. This study provides insights into the conditions that allow negative or positive spillovers to prevail and determine which bystanders are likely to be the recipients of the spillovers by focusing on the social evaluations previously accorded to perpetrators and bystanders. Going beyond prior findings on the devastating outcomes of highly-regarded firms' misconduct, I have shown that impacts are not only far-reaching, but also can have different valences depending on which social approval asset underlies stakeholders' high regard. Misconduct by firms that are highly regarded because they have demonstrated excellence in conventional ways imparts a sense of systematic failure, whereas misconduct by firms that have distinguished themselves by challenging the status quo is deemed an individual aberration, inadvertently benefiting other firms. Furthermore, these trajectories matter for bystander firms, as stakeholders (fail to) generalize culpability based on firms' social evaluations, regardless of actual organizational (dis)similarities.

Chapter 4

DISCUSSION AND CONCLUSION

4.1. Broad Overview of Findings

This dissertation consists of two empirical studies. In each study, I examined different processes involved in stakeholders' sensemaking of misconduct. Collectively, I sought to address an overarching question: How do firms' social evaluations such as status, reputation, and celebrity guide stakeholders' processing of misconduct and shape their judgments? In both studies, I focused on the role of social evaluations as the interpretive frames through which stakeholders selectively attend to certain information cues to which they impart specific meanings based on their preexisting intersubjective expectations (Hubbard et al., 2018; Pfarrer et al., 2010; Pollock et al., 2019).

In Chapter 2, I explored how reputation and celebrity shape the scandalization of a firm's misconduct in different ways. I hypothesized that both high reputation and celebrity increase the likelihood of a firm's misconduct receiving media coverage, because misconduct fits both the rational and emotional frames held by stakeholders when evaluating high-reputation and celebrity firms. I further hypothesized that reputation amplifies the positive effects of misconduct severity and recency of similar misconduct in the past on the likelihood of publicity, because the rational lens held by stakeholders calls for greater attention to detailed information about the misconduct. In contrast, I hypothesized that celebrity attenuates the effects of the severity and recency dimensions because the emotional lens leads stakeholders to seek emotionally surprising information cues rather than details. Although the results do not support all hypotheses, they broadly support my expectations that reputation and celebrity have different effects on how members of the media—and more broadly, the public—process misconduct-related information and ultimately determine the extent to which a firm's misconduct becomes publicized.

In Chapter 3, I investigated the effects of status and celebrity as antecedents of negative and positive spillovers to innocent bystanders upon disclosure of a firm's misconduct. I hypothesized that misconduct by high-status firms results in negative spillovers to bystanders, because stakeholders perceive misconduct by such exemplar firms as epitomizing problems that are endemic to the entire system. In contrast, I hypothesized that misconduct by celebrity firms results in positive spillovers to bystanders, because celebrity firms by definition are considered atypical, and thus acts of misconduct are perceived as individual aberrations. I further hypothesized that matching social evaluations amplify the negative and positive spillovers associated with status and celebrity, respectively, by highlighting the commonalities between perpetrators and bystanders, whereas mismatched social evaluations mitigate or even reverse the valence of the spillovers by highlighting dissimilarities. Although the results do not support all of my hypotheses, my findings collectively suggest that status and celebrity have opposing effects on how stakeholders compare firms, and create spillovers with opposite valences.

4.2. Future Research Directions

In this dissertation, I have focused on the role of social evaluations as interpretive frames through which stakeholders view different firms' misconduct. Thus, the basic assumption is that differences in the sociocogntive content underlying different types of social evaluations drive stakeholders' information processing and behavioral responses after misconduct is revealed. Although the two empirical studies in this dissertation provide evidence of the unequal outcomes from misconduct associated with different types of social evaluations, deeper understandings can be achieved by dissecting the psychological mechanisms underlying stakeholders' post-misconduct sensemaking. Employing experimental (e.g., Hahl & Zuckerman, 2014) or policy-capturing methods (e.g., Connelly, Ketchen, Gangloff, & Shook, 2016) to examine the detailed cognitive processes associated with stakeholders' use of social evaluations as they perceive and react to the firms' misconduct can contribute to the literatures on organizational misconduct and social evaluations by solidifying the microfoundations of my theory.

Because the purpose of this dissertation was to examine how stakeholders deal with the uncertainty created by misconduct, I focused on the periods immediately following the disclosure of misconduct in both studies—two weeks in Chapter 2 and five days in Chapter 3—when intuitive and instantaneous information processing based on social evaluations prevails (Bundy & Pfarrer, 2015). However, some scandals persist and even grow over a longer period of time, continuously producing spillovers that affect bystander firms (Dewan & Jensen, 2019). Thus, employing a more dynamic research design to further investigate the evolving role of social evaluations in shaping stakeholders' reception and processing of constantly updated information cues can yield valuable insights. In particular, as information about actual root causes becomes available over time (Bundy & Pfarrer, 2015), social evaluations may interfere with stakeholders' perceptions of culpability, even in the presence of objective evidence (McDonnell & King, 2018). In a similar vein, multiple types of stakeholders (e.g., the media, investors, consumers) can co-create scandals (Dewan & Jensen, 2019) and materialize spillovers from misconduct (Paruchuri & Misangyi, 2015; Paruchuri et al., 2019; Zavyalova et al., 2012). Although I chose the most representative stakeholders for each study—the media in Chapter 2 and investors in Chapter 3—it may be useful to examine how multiple types of stakeholders' inferences based on social evaluations converge or diverge, as one type of stakeholder can rely on other types of stakeholders to form their own judgments (Fini et al., 2018; Pollock et al., 2008).

In this dissertation, I have focused on a particular type of misconduct: data breaches. Although data breaches are among the most critical issues affecting businesses today (Accenture, 2019; Peterson, 2020), extending the focus to different types of misconduct and examining the interactive relationships between misconduct type and social evaluations should be fruitful. For instance, misconduct can be categorized based different levels of perceived culpability (Wei et al., 2017) or the specificity of victims (Marcus & Goodman, 1991). Moreover, as I suggested in Chapter 3, some types of misconduct may be pertinent only to specific market categories, whereas others can be perceived as more endemic to all corporate entities. These differences inherent to different types of misconduct could affect the media's decision to scandalize a misconduct case or the range and/or valence of spillovers to bystanders. Accordingly, the role of social evaluations as interpretive frames could change. For instance, due to a stronger emphasis on morality in the conferral of organizational status relative to reputation and celebrity (Pollock et al., 2019), acts of misconduct (e.g., fraud) for which high-status firms are undeniably responsible may be more salient to the public. Similarly, misconduct of an illegal nature can be of particular importance for stakeholders who are evaluating high-reputation firms due to the costs associated with litigation (Greve et al., 2010) than for stakeholders who are evaluating celebrity firms, which are expected to have some involvement in gray areas (Pollock et al., 2016).

Lastly, although I have primarily examined how stakeholders process misconduct, firms' crisis management practices are becoming increasingly crucial and common (Bundy et al., 2017; Wang, Reger, & Pfarrer, 2019). Intimately related to the predefined expectations of firms, social evaluations could determine the effectiveness of specific types of firm responses to misconduct in mitigating stakeholder punishments (Bundy & Pfarrer, 2015). Moreover, with social evaluations dictating actors' behavioral tendencies (Lovelace et al., 2018; Pfarrer et al. 2010; Phillips & Zuckerman, 2001), firms may be inclined to choose specific crisis management practices according to the types of social evaluations they are accorded. Exploring the role of social evaluations in the cycle of stakeholders' and firms' actions and reactions during the post-misconduct period may yield findings with important theoretical and practical implications.

4.3. Conclusion

In this dissertation, I have aimed to answer two important questions that remain unresolved in the organizational misconduct literature by adopting the social evaluations perspective: Why are some instances of misconduct readily publicized and scandalized while others go largely unnoticed? Why do some innocent bystanders suffer from undeserved penalties in the wake of others' misconduct while other bystanders enjoy unexpected gains? The findings across both studies in this dissertation highlight the importance of social evaluations in stakeholders' sensemaking of misconduct. Social evaluations, as heuristic devices used in situations involving significant uncertainty (e.g., organizational misconduct), could account for stakeholders' counterintuitive, unpredictable conclusions about misconduct incidents by amplifying and attenuating the importance of certain cues, and sometimes even imbuing different meanings to the same cues. Galatians 6:7 states, "for whatsoever a man soweth, that shall he also reap;" likewise, a firm's trajectory and stakeholders' expectations determine the outcomes experienced by both the firm and bystanders upon the revelation of misconduct. In conclusion, this dissertation makes important contributions to the literatures on organizational misconduct and social evaluations, and more broadly to strategy scholarship and organization theory by exploring the influence of firms' social evaluations on various aspects of stakeholders' responses to corporate misconduct.

Bibliography

Accenture. 2019. ***Ninth annual cost of cybercrime study: Unlocking the value of improved cybersecurity protection***. Available online at https://www.accenture.com/_acnmedia/PDF-96/Accenture-2019-Cost-of-Cybercrime-Study-Final.pdf#zoom=50. Accessed on February 6, 2020.

Adut, A. 2005. A theory of scandal: Victorians, homosexuality, and the fall of Oscar Wilde. ***American Journal of Sociology***, 111: 213-248.

Agrawal, N., & Maheswaran, D. 2005. Motivated reasoning in outcome-bias effects. ***Journal of Consumer Research***, 31: 798-805.

Alexander, C.R. 2008. On the nature of the reputational penalty for corporate crime: Evidence. ***Journal of Law and Economics***, 42: 489-526.

Ali, U., & Hirshleifer, D. 2020. Shared analyst coverage: Unifying momentum spillover effects. ***Journal of Financial Economics***, 136: 649-675.

Allison, P.D. 2012a. ***Logistic regression using SAS: Theory and application*** (2nd Ed.). Cary, NC: SAS Institute Inc.

Allison, P.D. 2012b. Do we really need zero-inflated models? (blog post) ***Statistical Horizons***, August 7, https://statisticalhorizons.com/zero-inflated-models.

Anderson, N. 1981. ***Foundations of information integration theory***. New York: Academic Press.

Andriole, S. 2019. The Capital One data breach is no exception & Why we can expect many, many more. ***Forbes***, July 30. Available online at https://www.forbes.com/sites/steveandriole/2019/07/30/the-capital-one-data-breach-is-no-exception-why-we-can-expect-many-many-more/#6cfabe1efc48. Accessed on February 6, 2020.

Angrist, J.D., & Pischke, J-S. 2009. ***Mostly harmless econometrics: An empiricist's companion. Princeton***, NJ: Princeton University Press.

Angst, C.M., Block, E.S., D'Arcy, J., & Kelley, K. 2017. When do IT security investments matter? Accounting for the influence of institutional factors in the context of healthcare data breaches. ***MIS Quarterly***, 41: 893-916.

Arikan, I., Arikan, A.M., & Shenkar, O. 2019. Nation-dyadic history and cross-border corporate deals: Role of conflict, trade, generational distance, and professional education. ***Strategic Management Journal***, 41: 422-466.

Barnett, M.L. 2014. Why stakeholders ignore firm misconduct: A cognitive view. ***Journal of Management***, 40: 676-702.

Barnett, M.L., & King, A.A. 2008. Good fences make good neighbors: A longitudinal analysis of an industry self-regulatory institution. ***Academy of Management Journal***, 51: 1150-1170.

Bednar, M.K. 2012. Watchdog or lapdog? A behavioral view of the media as a corporate governance mechanism. ***Academy of Management Journal***, 55: 131-150.

Bednar, M.K., Love, E.G., & Kraatz, M. 2015. Paying the price? The impact of controversial governance practices on managerial reputation. ***Academy of Management Journal***, 58: 1740-1760.

Belsley, D.A., Kuh, E., & Welsch, R.E. 2005. ***Regression diagnostics: Identifying influential data and sources of collinearity***. New York: John Wiley & Sons.

Boivie, S., Graffin, S.D., & Gentry, R.J. 2016. Understanding the direction, magnitude, and joint effects of reputation when multiple actors' reputations collide. ***Academy of Management Journal***, 59: 188-206.

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

Bothner, M.S., Smith, E.B., & White, H.C. 2010. A model of robust positions in social networks. ***American Journal of Sociology***, 116: 943-992.

Bowers, A., & Prato, M. 2018. The structural origins of unearned status: How arbitrary changes in categories affect status position and market impact. ***Administrative Science Quarterly***, 63: 668-699.

Bundy, J., & Pfarrer, M.D. 2015. A burden of responsibility: The role of social approval at the onset of a crisis. ***Academy of Management Review***, 40: 345-369.

Bundy, J., Pfarrer, M.D., Short, C.E., & Coombs, W.T. 2017. Crises and crisis management: Integration, interpretation, and research development. ***Journal of Management***, 43: 1661-1692.

Burgoon, J.K. 1993. Interpersonal expectations, expectancy violations, and emotional communication. ***Journal of Language and Social Psychology***, 12: 30-48.

Busenbark, J.R., Lange, D., & Certo, S.T. 2017. Foreshadowing as impression management: Illuminating the path for security analysts. ***Strategic Management Journal***, 38: 2486-2507.

Cameron, A.C., Gelbach, J.B., & Miller, D.L. 2011. Robust inference with multi-way clustering. ***Journal of Business and Economic Statistics***, 29: 238-249.

Campbell, K., Gordon, L.A., Loeb, M.P., & Zhou, L. 2003. The economic cost of publicly announced information security breaches: empirical evidence from the stock market. ***Journal of Computer Security***, 11: 431-448.

Carter, W. 2019. Companies get off too easy with data breaches. Bigger fines are a good place to start. ***CNN Business***, July 21. Available online at https://www.cnn.com/2019/07/31/perspectives/capital-one-data-breach. Accessed on February 6, 2020.

Cattani, G., Porac, J.F., & Thomas, H. 2017. Categories and competition. ***Strategic***

Management Journal, 38: 64-92.

Chandler, D., Polidoro, F., & Yang, W. 2019. When is it good to be bad? Contrasting effects of multiple reputations for bad behavior on media coverage of serious organizational errors. ***Academy of Management Journal***, forthcoming.

Chen, H., Noronha, G., & Singal, V. 2004. The price response to S&P 500 index additions and deletions: Evidence of asymmetry and a new explanation. ***Journal of Finance***, 59: 1901-1930.

Choi, H., & Varian, H. 2012. Predicting the present with Google Trends. ***Economic Record***, 88: 2-9

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

Connelly, B.L., Certo, S.T., Ireland, R.D., & Reutzel, C.R. 2011. Signaling theory: A review and assessment. ***Journal of Management***, 37: 39-67.

Connelly, B.L., Ketchen, D.J., Gangloff, K.A., & Shook, C.L. 2016. Investor perceptions of CEO successor selection in the wake of integrity and competence failures: A policy capturing study. ***Strategic Management Journal***, 37: 2135-2151.

Cornelissen, J.P., & Werner, M.D. 2014. Putting framing in perspective: A review of framing and frame analysis across the management and organizational literature. ***Academy of Management Annals***, 8: 181–235.

Culnan, M.J., & Armstrong, P.K. 1999. Information privacy concerns, procedural fairness, and impersonal trust: An empirical investigation. ***Organization Science***, 10: 104-115.

D'Aveni, R.A. 1990. Top managerial prestige and organizational bankruptcy. ***Organization Science***, 1: 121-142.

Deephouse, D.L. 1999. To be different, or to be the same? It's a question (and theory) of strategic balance. ***Strategic Management Journal***, 20: 147-166.

Denrell, J. 2005. Why most people disapprove of me: Experience sampling in impression formation. ***Psychological Review***, 112: 951-978.

Desai, V.M. 2011. Mass media and massive failures: Determining organizational efforts to defend field legitimacy following crises. ***Academy of Management Journal***, 54: 263-278.

Dewan, Y., & Jensen, M. 2019. Catching the big fish: The role of scandals in making status a liability. ***Academy of Management Journal***, forthcoming.

Durand, R., & Paolella, L. 2013. Category stretching: Reorienting research on categories in strategy, entrepreneurship, and organization theory. ***Journal of Management Studies***, 50: 1100-1123.

Fama, E.F., & French, K.R. 1992. The cross-section of expected stock returns. ***Journal of***

Finance, 47: 427–465.

Fama, E.F., & French, K.R. 1993. Common risk factors in the returns on stocks and bonds. ***Journal of Financial Economics***, 33: 3–56.

Fini, R., Jourdan, J., & Perkmann, M. 2018. Social valuation across multiple audiences: The interplay of ability and identity judgments. ***Academy of Management Journal***, 61: 2230-2264.

Frank, K.A. 2000. Impact of a confounding variable on a regression coefficient. ***Sociological Methods & Research***, 29: 147-194.

Frésard, L., Hoberg, G., & Phillips, G.M. 2019. Innovation activities and integration through vertical acquisitions. ***Review of Financial Studies***, forthcoming.

Fung, B. 2014. The bright side to the Target hack? It's getting Congress moving. ***Washington Post***, January 10. Available online at https://www.washingtonpost.com/news/the-switch/wp/2014/01/10/the-bright-side-to-the-target-hack-its-getting-congress-moving/. Accessed January 24, 2020.

Fung, B. 2018. Facebook logs 90 million people out of their accounts after security breach. The ***Washington Post***, September 28. Available online at https://www.washingtonpost.com/technology/2018/09/28/facebook-says-million-accounts-affected-by-hackers/?utm_term=.a3423c1df0cf. Accessed on February 5, 2019.

Furnham, A. 1986. The robustness of the recency effect: Studies using legal evidence. ***Journal of General Psychology***, 113: 351-357.

Goffman, E. 1063. ***Stigma: Notes on the management of spoiled identity***. New York: Simon & Schuster.

Goldberg, R. 2018. Most Americans continue to have privacy and security concerns, NTIA survey finds. ***National Telecommunications and Information Administration, U.S. Department of Commerce***, August 20. Available online at https://www.ntia.doc.gov/blog/2018/most-americans-continue-have-privacy-and-security-concerns-ntia-survey-finds. Accessed January 24, 2020.

Gomulya, D., Jin, K., Lee, P.M., & Pollock, T.G. 2019. Crossed wires: Endorsement signals and the effects of IPO firm delistings on venture capitalists' reputations. ***Academy of Management Journal***, 62: 641-666.

Gould, R.V. 2002. The origins of status hierarchies: A formal theory and empirical test. ***American Journal of Sociology***, 107: 1143-1178.

Graffin, S.D., Bundy, J., Porac, J.F., Wade, J.B., & Quinn, D.P. 2013. Falls from grace and the hazards of high status: The 2009 British MP expense scandal and its impact on parliamentary elites. ***Administrative Science Quarterly***, 58: 313-345.

Greve, H.R., Palmer, D., & Pozner, J-E. 2010. Organizations gone wild: The causes, processes, and consequences of organizational misconduct. ***Academy of Management Annals***, 4: 53-107.

Gwebu, K.L., Wang, J., & Wang, L. 2018. The role of corporate reputation and crisis response strategies in data breach management. ***Journal of Management Information Systems***, 35: 683-714.

Hahl, O., & Zuckerman, E.W. 2014. The denigration of heroes? How the status attainment process shapes attributions of considerateness and authenticity. ***American Journal of Sociology***, 120: 504-554.

Haleblian, J.J., Pfarrer, M.D., & Kiley, J.T. 2017. High-reputation firms and their differential acquisition behaviors. ***Strategic Management Journal***, 38: 2237-2254.

Han, J-H., & Pollock, T.G. 2020. The two towers (or somewhere in between): The behavioral consequences of positional inconsistency across status hierarchies. ***Academy of Management Journal***, forthcoming.

Harrison, J.S., Boivie, S., Sharp, N.Y., & Gentry, R.J. 2018. Saving face: How exit in response to negative press and star analyst downgrades reflects reputation maintenance by directors. ***Academy of Management Journal***, 61: 1131-1157.

Haunschild, P.R., & Miner, A.S. 1997. Modes of interorganizational imitation: The effects of outcome salience and uncertainty. ***Administrative Science Quarterly***, 42: 472-500.

Hayward, M.L.A., Rindova, V.P., & Pollock, T.G. 2004. Believing one's own press: The cause and consequences of CEO celebrity. ***Strategic Management Journal***, 25: 637-653.

Helms, W.S., & Patterson, K.D.W. 2014. Eliciting acceptance for "illicit" organizations: The positive implications of stigma for MMA organizations. ***Academy of Management Journal***, 57: 1453-1484.

Higgins, E.T., Bargh, J.A., & Lombardi, W. 1985. Nature of priming effects on categorization. ***Journal of Experimental Psychology***, 1985.

Hoberg, G., & Phillips, G. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. ***Review of Financial Studies***, 23: 3773-3811.

Hoberg, G., & Phillips, G. 2016. Text-based network industries and endogenous product differentiation. ***Journal of Political Economy***, 124: 1423-1465.

Hoffman, A.J., & Ocasio, W. 2001. Not all events are attended equally: Toward a middle-range theory of industry attention to external events. ***Organization Science***, 12: 414-434.

Holmes, A. 2019. Hackers have become so sophisticated that nearly 4 billion records have been stolen from people in the last decade alone. Here are the 10 biggest data breaches of the 2010s. ***Business Insider***, November 13. Available online at https://www.businessinsider.com/biggest-hacks-2010s-facebook-equifax-adobe-marriott-2019-10. Accessed on February 6, 2020.

Howell, D.C. 1992. ***Statistical methods for psychology***. Boston, MA: Cengage Learning.

Huang, X., Rui, Y., Shen, J., & Tian, G.Y. 2017. U.S. class action lawsuits targeting foreign firms: The country spillover effect. ***Journal of Corporate Finance***, 45: 378-400.

Hubbard, T.D., Christensen, D.M., & Graffin, S.D. 2017. Higher highs and lower lows: The role of corporate social responsibility in CEO dismissal. ***Strategic Management Journal***, 38: 2255-2265.

Hubbard, T.D., Pollock, T.G., Pfarrer, M.D., & Rindova, V.P. 2018. Safe bets or hot hands? How status and celebrity influence strategic alliance formations by newly public firms. ***Academy of Management Journal***, 61: 1976-1999.

Isaac, M., & Frenkel, S. 2018. Facebook security breach exposes accounts of 50 million users. ***New York Times***, September 28. Available online at https://www.nytimes.com/2018/09/28/technology/facebook-hack-data-breach.html. Accessed on February 5, 2019.

Jarrell, G., & Peltzman, S. 1985. The impact of product recalls on the wealth of sellers. ***Journal of Political Economy***, 93: 512-536.

Jensen, M. 2006. Should we stay or should we go? Accountability, status anxiety, and client defections. ***Administrative Science Quarterly***, 51: 97-128.

Jensen, M., Kim, B.K., & Kim, H. 2011. The importance of status in markets: A market identity perspective. In J.L. Pearce (Eds.), ***Status, organization and management***: 87-117. Cambridge, UK: Cambridge University Press.

Jensen, M., & Roy, A. 2008. Staging exchange partner choices: When do status and reputation matter? ***Academy of Management Journal***, 51: 495-516.

Jonsson, S., Greve, H.R., & Fujiwara-Greve, T. 2009. Undeserved loss: The spread of legitimacy loss to innocent organizations in response to reported corporate deviance. ***Administrative Science Quarterly***, 54: 195-228.

Josefy, M., Kuban, S., Ireland, R.D., & Hitt, M.A. 2015. All things great and small: Organizational size, boundaries of the firm, and a changing environment. ***Academy of Management Annals***, 9: 715-802.

Kim, K., Gopal, A., & Hoberg, G. 2016. Does product market competition drive CVC investment? Evidence from the U.S. IT industry. ***Information Systems Research***, 27: 259-281.

Kim, K-H., & Tsai, W. 2012. Social comparison among competing firms. ***Strategic Management Journal***, 33: 115-136.

Kleinbaum, A.M., Stuart, T.E., & Tushman, M.L. 2013. Discretion within constraint: Homophily and structure in a formal organization. ***Organization Science***, 24: 1316-1336.

Kölbel, J.F., Busch, T., & Jancso, L.M. 2017. How media coverage of corporate social irresponsibility increases financial risk. ***Strategic Management Journal***, 38: 2266-2284.

Krishnan, R., & Kozhikode, R.K. 2015. Status and corporate illegality: Illegal loan recovery practices of commercial banks in India. ***Academy of Management Journal***, 58: 1287-1312.

Lange, D., Lee, P.M., & Dai, Y. 2011. Organizational reputation: A review. ***Journal of Management***, 37: 153-184.

Lange, D., & Washburn, N.T. 2012. Understanding attributions of corporate social responsibility. ***Academy of Management Review***, 37: 300-326.

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

Lounsbury, M. 2001. Institutional sources of practice variation: Staffing college and university recycling programs. ***Administrative Science Quarterly***, 46: 29-56.

Love, E.G., & Kraatz, M.S. 2009. Character, conformity, or the bottom line: How and why downsizing affected corporate reputation. ***Academy of Management Journal***, 52: 314-335.

Love, E.G., & Kraatz, M.S. 2017. Failed stakeholder exchanges and corporate reputation: The case of earnings misses. ***Academy of Management Journal***, 60: 880-903.

Lovelace, J.B., Bundy, J., Hambrick, D.C., & Pollock, T.G. 2018. The shackles of CEO celebrity: Sociocognitive and behavioral role constraints on "star" leaders. ***Academy of Management Review***, 43: 419-444.

Lungeanu, R., Paruchuri, S., & Tsai, W. 2018. Stepping across for social approval: Ties to independent foundations' boards after financial restatement. ***Strategic Management Journal***, 39: 1163-1187.

Luoma, J., Ruutu, S., King, A.W., & Tikkanen, H. 2017. Time delays, competitive interdependence, and firm performance. ***Strategic Management Journal***, 38: 506-525.

Lutke, J. 2018. Chegg data breach affects 40 million customers. ***Security Today***, September 28. Available online at https://securitytoday.com/articles/2018/09/28/chegg-data-breach-affects-40-million-customers.aspx. Accessed on February 5, 2019.

Magee, J.C., & Galinsky, A.D. 2008. Social hierarchy: The self-reinforcing nature of power and status. ***Academy of Management Annals***, 2: 351-398.

Malhotra, A., & Malhotra, C.K. 2011. Evaluating customer information breaches as service failures: An event study approach. ***Journal of Service Research***, 14: 44-59.

Marcus, A.A., & Goodman, R.S. 1991. Victims and shareholders: The dilemmas of presenting corporate policy during a crisis. ***Academy of Management Journal***, 34: 281-305.

Margolis, J.D., & Walsh, J.P. 2003. Misery loves companies: Rethinking social initiatives by business. ***Administrative Science Quarterly***, 48: 268-305.

Martin, K.D., Borah, A., & Palmatier, R.W. 2017. Data privacy: Effects on customer and firm performance. ***Journal of Marketing***, 81: 36-58.

McCombs, M., & Shaw, D. 1972. The agenda-setting function of mass media. ***Public Opinion Quarterly***, 36: 176-187.

McDonnell, M-H., & King, B.G. 2018. Order in the court: How firm status and reputation shape the outcomes of employment discrimination suits. ***American Sociological Review***, 83: 61-87.

McWilliams, A., & Siegel, D. 1997. Event studies in management research: Theoretical and empirical issues. ***Academy of Management Journal***, 40: 626-657.

Mishina, Y., Block, E.S., & Mannor, M.J. 2012. The path dependence of organizational reputation: How social judgment influences assessments of capability and character. ***Strategic Management Journal***, 33: 459-477.

Mishina, Y., & Devers, C.E. 2012. On being bad: Why stigma is not the same as bad reputation. In M.L. Barnett & T.G. Pollock (Eds.), ***Oxford handbook of corporate reputation***: 201-220. Oxford, UK: Oxford University Press.

Mishina, Y., Dykes, B.J., Block, E.S., & Pollock, T.G. 2010. Why "good" firms do bad things: The effects of high aspirations, high expectations, and prominence on the incidence of corporate illegality. ***Academy of Management Journal***, 53: 701-722.

O'Flaherty, K. 2018. This is why people no longer trust Google and Facebook with their data. ***Forbes***, October 10. Available online at https://www.forbes.com/sites/kateoflahertyuk/2018/10/10/this-is-why-people-no-longer-trust-google-and-facebook-with-their-data/#54b80bd94b09. Accessed on February 6, 2020.

Pahnke, E.C., McDonald, R., Wang, D., & Hallen, B. 2015. Exposed: Venture capital, competitor ties, and entrepreneurial innovation. ***Academy of Management Journal***, 58: 1334-1360.

Park, B., & Rogan, M. 2019. Capability reputation, character reputation, and exchange partners' reactions to adverse events. ***Academy of Management Journal***, 62: 553-578.

Paruchuri, S., Han, J-H., & Prakash, P. 2020. Salient expectations? Incongruence across capability and integrity signals and investor reactions to organizational misconduct. ***Academy of Management Journal***, forthcoming.

Paruchuri, S., & Misangyi, V.F. 2015. Investor perceptions of financial misconduct: The heterogeneous contamination of bystander firms. ***Academy of Management Journal***, 58: 169-194.

Paruchuri, S., Pollock, T.G., & Kumar, N. 2019. On the tip of the brain: Understanding when negative reputational events can have positive reputation spillovers, and for how long. ***Strategic Management Journal***, 40: 1965-1983.

Pennebaker, J.W., Boyd, R.L., Jordan, K., & Blackburn, K. 2015. ***The development and psychometric properties of LIWC2015***. Austin, TX: University of Texas at Austin.

Petersen, C. 2020. Nine cybersecurity metrics every CEO should track. ***Forbes***, January 9. Available online at https://www.forbes.com/sites/forbestechcouncil/2020/01/09/nine-cybersecurity-metrics-every-ceo-should-track/#4523abc7723a. Accessed on February 6, 2020.

Petrenko, O.V., Aime, F., Recendes, T., & Chandler, J.A. 2019. The case for humble expectations: CEO humility and market performance. ***Strategic Management Journal***, 40: 1938-1964.

Pfarrer, M.D., Decelles, K.A., Smith, K.G., & Taylor, M.S. 2008. After the fall: Reintegrating the corrupt organization. ***Academy of Management Review***, 33: 730-749.

Pfarrer, M.D., Pollock, T.G., & Rindova, V.P. 2010. A tale of two assets: The effects of firm reputation and celebrity on earnings surprises and investors' reactions. ***Academy of Management Journal***, 53: 1131-1152.

Phillips, D.J., Turco, C.J., & Zuckerman, E.W. 2013. Betrayal as market barrier: Identity-based limits to diversification among high-status corporate law firms. ***American Journal of Sociology***, 118: 1023-1054.

Phillips, D.J., & Zuckerman, E.W. 2001. Middle-status conformity: Theoretical restatement and empirical demonstration in two markets. ***American Journal of Sociology***, 107: 379-429.

Piazza, A., & Castellucci, F. 2014. Status in organization and management theory. ***Journal of Management***, 40: 287-315.

Piazza, A., & Jourdan, J. 2018. When the dust settles: The consequences of scandals for organizational competition. ***Academy of Management Journal***, 61: 165-190.

Pollock, T.G., & Gulati, R. 2007. Standing out from the crowd: The visibility-enhancing effects of IPO-related signals on alliance formation by entrepreneurial firms. ***Strategic Organization***, 5: 339-372.

Pollock, T.G., Lashley, K., Rindova, V.P., & Han, J-H. 2019. Which of these things are not like the others? Comparing the rational, emotional and moral aspects of reputation, status, celebrity, and stigma. ***Academy of Management Annals***, 13: 444-478.

Pollock, T.G., Lee, P.M., Jin, K., & Lashley, K. 2015. (Un)tangled: Exploring the asymmetric coevolution of new venture capital firms' reputation and status. ***Administrative Science Quarterly***, 60: 482-517.

Pollock, T.G., Mishina, Y., & Seo, Y. 2016. Falling stars: Celebrity, infamy, and the fall from (and return to) grace. In D. Palmer, K. Smith-Crowe, & R. Greenwood (Eds.), ***Organizational wrongdoing: Key perspectives and new directions***: 235-269. Cambridge, UK: Cambridge University Press.

Pollock, T.G., & Rindova, V.P. 2003. Media legitimation effects in the market for initial public offerings. ***Academy of Management Journal***, 46: 631-642.

Pollock, T.G., Rindova, V.P., & Maggitti, P.G. 2008. Market watch: Information and availability cascades among the media and investors in the U.S. IPO market. ***Academy of Management Journal***, 51: 335-358.

Pontikes, E., Negro, G., & Rao, H. 2010. Stained red: A study of stigma by association to blacklisted artists during the "Red Scare" in Hollywood, 1945 to 1960. ***American Sociological Review***, 75: 456-478.

Prato, M., Kypraios, E., Ertug, G., & Lee, Y.G. 2019. Middle-status conformity revisited: The interplay between achieved and ascribed status. ***Academy of Management Journal***, 62: 1003-1027.

Rao, H., Monin, P., & Durand, R. 2005. Border crossing: Bricolage and the erosion of categorical boundaries in French gastronomy. ***American Sociological Review***, 70: 968-991.

Rhee, M., & Haunschild, P.R. 2006. The liability of good reputation: A study of product recalls in the U.S. automobile industry. ***Organization Science***, 17: 101-117.

Rindova, V.P., Pollock, T.G., & Hayward, M.L.A. 2006. Celebrity firms: The social construction of market popularity. ***Academy of Management Review***, 31: 50-71.

Roehm, M.L., & Tybout, A.M. 2006. When will a brand scandal spill over, and how should competitors respond? ***Journal of Marketing Research***, 43: 366-373.

Sauder, M., Lynn, F., & Podolny, J.M. 2012. Status: Insights from organizational sociology. ***Annual Review of Sociology***, 38: 267-283.

Savor, P., & Wilson, M. 2016. Earnings announcements and systematic risk. ***Journal of Finance***, 71: 83-138.

Schechner, S. 2018. Facebook faces potential $1.63 billion fine in Europe over data breach. ***Wall Street Journal***, September 30. Available online at https://www.wsj.com/articles/facebook-faces-potential-1-63-billion-fine-in-europe-over-data-breach-1538330906. Accessed on February 5, 2019.

Semadeni, M., & Anderson, B.S. 2010. The follower's dilemma: Innovation and imitation in the professional services industry. ***Academy of Management Journal***, 53: 1175-1193.

Shi, W., Zhang, Y., & Hoskisson, R.E. 2017. Ripple effects of CEO awards: Investigating the acquisition activities of superstar CEOs' competitors. ***Strategic Management Journal***, 38: 2080-2102.

Shiu, Y-M., & Yang, S-L. 2017. Does engagement in corporate social responsibility provide strategic insurance-like effects? ***Strategic Management Journal***, 38: 455-470.

Shoemaker, P.J., & Reese, S.D. 1996. ***Mediating the message***. White Plains, NY: Longman.

Singer, J.B. 2007. Contested autonomy: Professional and popular claims on journalistic norms. ***Journalism Studies***, 8: 79-95.

Straub, D.W. 1990. Effective IS security: An empirical study. ***Information Systems Research***, 1: 255-276,

Sullivan, B.N., Haunschild, P., & Page, K. 2007. Organizations non gratae? The impact of unethical corporate acts on interorganizational networks. ***Organization Science***, 18: 55-70.

Tracey, P., & Phillips, N. 2016. Managing the consequences of organizational stigmatization: Identity work in a social enterprise. ***Academy of Management Journal***, 59: 740-765.

Tversky, A., & Kahneman, D. 1974. Judgment under uncertainty: Heuristics and biases. ***Science***, 185: 1124-1131.

Vergne, J-P., Wernicke, G., & Brenner, S. 2018. Signal incongruence and its consequences: A study of media disapproval and CEO overcompensation. ***Organization Science***, 29: 796-817.

Vosen, S., & Schmidt, T. 2011. Forecasting private consumption: Survey-based indicators vs. Google Trends. ***Journal of Forecasting***, 30: 565-578.

Wang, P., & Jensen, M. 2019. A bridge too far: Divestiture as a strategic reaction to status inconsistency. ***Management Science***, 65: 859-878.

Wang, X., Reger, R.K., & Pfarrer, M. 2019. Faster, hotter, and more linked in: Managing social disapproval in the social media era. ***Academy of Management Review***, forthcoming.

Washington, M., & Zajac, E.J. 2005. Status evolution and competition: Theory and evidence. ***Academy of Management Journal***, 48: 282-296.

Wei, J., Ouyang, Z., & Chen, H. 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: 2103-2120.

Westphal, J.D., & Deephouse, D.L. 2011. Avoiding bad press: Interpersonal influence in relations between CEOs and journalists and the consequences for press reporting about firms and their leadership. ***Organization Science***, 22: 817-1120.

Wiersema, M.F., & Zhang, Y. 2013. Executive turnover in the stock option backdating wave: The impact of social context. ***Strategic Management Journal***, 34: 590-609.

Wiesenfeld, B.M., Wurthmann, K.A., & Hambrick, D.C. 2008. The stigmatization and devaluation of elites associated with corporate failures: A process model. ***Academy of Management Review***, 33: 231-251.

Zavyalova, A., Pfarrer, M.D., & Reger, R.K. 2017. Celebrity and infamy? The consequences of media narratives about organizational identity. ***Academy of Management Review***, 42: 461-480.

Zavyalova, A., Pfarrer, M.D., Reger, R.K., & Hubbard, T.D. 2016. Reputation as a benefit and a burden? How stakeholders' organizational identification affects the role of reputation following a negative event. ***Academy of Management Journal***, 59: 253-276.

Zavyalova, A., Pfarrer, M.D., Reger, R.K., & Shapiro, D.L. 2012. Managing the message: The effects of firm actions and industry spillovers on media coverage following wrongdoing. ***Academy of Management Journal***, 55: 1079-1101.

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RESEARCH INTERESTS

Social evaluations and social approval assets; media behavior; signaling theory

Organizational misconduct, wrongdoing, and scandal, and related stakeholder responses

PUBLISHED RESEARCH

Paruchuri, S., Han, J-H., & Prakash, P. Salient expectations? Incongruence across capability and integrity signals and investor reactions to organizational misconduct. ***Academy of Management Journal***, in-press.

Han, J-H., & Pollock, T.G. The two towers (or somewhere in between): The behavioral consequences of positional inconsistency across status hierarchies. ***Academy of Management Journal***, in-press.

Pollock, T.G., Lashley, K., Rindova, V.P., & Han, J-H. 2019. Which of these things are not like the others? Comparing the rational, emotional and moral aspects of reputation, status, celebrity and stigma. ***Academy of Management Annals***, 13(2): 444-478.