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When an Industry Peer Is Accused of Financial Misconduct: Stigma versus Competition Effects on Non-accused Firms

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Abstract

Research on misconduct suggests that accusations against industry peers generate negative consequences for non-accused firms (a ''stigma effect''). Yet, building on research on competitive dynamics, we infer that such accusations can benefit non-accused firms that compete with these peers (a ''competition effect''). To reconcile these opposing perspectives, we posit that the negative stigma effect will increase with greater product market overlap between the non-accused firm and its accused peer, up to a point, beyond which the positive competition effect will counterbalance it. We further conjecture that the competition effect will be relatively more pronounced when the market classification used by investors for assessing the market overlap is more fine-grained. Accordingly, we suggest that more sophisticated investors, who rely on more fine-grained market classifications, increase their shareholdings in non-accused firms to a greater extent than less sophisticated investors as the market overlap between the non-accused firm and the accused peer increases. Using elaborate data on products and investments, we analyze investors' shareholdings and stock market returns of non-accused firms in the U.S. software industry following accusations of financial misconduct by their industry peers, and we find support for our predictions. Our study elucidates the interplay between stigma and competition following misconduct by industry peers.

Keywords: competition, stigma, categories, generalization, corporate wrongdoing, financial misconduct, capital markets, performance

An accusation of financial misconduct, or ''cooking the books,'' can be detrimental not only to the firm accused of misconduct but also to non-accused firms in its industry. While past research has predominantly focused on

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studying the consequences for the accused firm (e.g., Feroz, Park, and Pastena, 1991; Dechow, Sloan, and Sweeney, 1996; Palmrose, Richardson, and Scholz, 2004; Sharkey, 2014), scholars have also documented a stigma effect that generates a negative spillover, whereby other firms in the accused firm's industry suffer negative stock market returns following the accusation (e.g., Xu, Najand, and Ziegenfuss, 2006; Gleason, Jenkins, and Johnson, 2008; Paruchuri and Misangyi, 2015). For example, when WorldCom was accused of financial misconduct in 2002, its stock price fell from $6.97 to $ 0.83, and the accusation also led to negative stock market reactions for non-accused firms in its industry. *The New York Times* reported that ''WorldCom's bad news helped batter stocks of other carriers,'' with the CEO of Infonet complaining that ''the industry is reeling from this black mark'' (Romero, 2002). Such a stigma effect occurs because the accusation against an industry peer triggers perceptions that other firms in the industry may have engaged in similar misconduct (Jonsson, Greve, and Fujiwara-Greve, 2009). Although some studies have shown that non-accused firms that are larger and have stronger governance suffer less from stigma (Paruchuri and Misangyi, 2015; Naumovska and Zajac, 2021), little is known about the heterogeneity of the spillover across non-accused firms in an industry.

Drawing from competitive dynamics research (e.g., Chen and Miller, 2012), we introduce a counterargument, predicting a positive spillover to non-accused firms following an accusation against their industry peer. This research has suggested that a negative event or failed action ascribed to a competitor can improve the competitive positions and performance of competing firms in the same industry (Chen and Miller, 1994). We thus infer that the revelation of financial misconduct by an industry peer may benefit non-accused firms. For example, following the accusation against WorldCom, *The Washington Post* reported that ''major customers were considering switching their telephone and Internet business to other companies,'' with competitors ''fielding scores of phone calls from nervous WorldCom customers'' (Noguchi, 2002). The positive spillover generated by the competition effect counters the literature on corporate misconduct, which has focused on negative spillover due to the stigma effect (e.g., Jonsson, Greve, and Fujiwara-Greve, 2009).

In light of these disparate streams, one rooted in the social psychology literature and the other in competitive dynamics research, what performance consequences can a non-accused firm expect following accusations of misconduct by its industry peer? To resolve this puzzle and reconcile the two opposing perspectives, we propose a composite effect of product market overlap on non-accused firms' performance following accusations against their industry peers. We posit that industry categories represent both cognitive taxonomies through which stakeholders make generalized evaluations and competitive landscapes wherein firms compete (Durand and Paolella, 2013; Vergne and Wry, 2014; Cattani, Porac, and Thomas, 2017). Accordingly, the building blocks for generalized evaluations that prompt the stigma effect and negative spillover also trigger the competition effect and positive spillover. Hence, in the aftermath of an accusation against an industry peer, the accused peer's market overlap with the non-accused firm challenges the legitimacy of the non-accused firm, while also creating opportunities for relative gain.

We proceed by arguing that the stigma effect can be countervailed or even offset by the competition effect for non-accused firms that exhibit high product

market overlap with the accused peer and are thus considered its rivals. Specifically, we predict a U-shaped association between a non-accused firm's product market overlap with the accused peer and its stock market reaction following the accusation. We further propose that the competition effect becomes more pronounced (tilting the shape of the U effect) when using a more fine-grained lens to classify firms' products and assess their market overlap. Consequently, we claim that sophisticated investors, who rely on more refined perceptions of the industry's competitive landscape, are more likely to invest in close rivals of the accused industry peer. We find support for our theory by analyzing accusations of financial misconduct in the U.S. packaged software industry. Using refined product data, we demonstrate the co-existence of the stigma and competition effects, with the extent of product market overlap with the accused peer determining whether a non-accused firm benefits or suffers from the accusations. We also find that more sophisticated investors such as mutual funds and hedge funds better anticipate the competition effect while downplaying the stigma effect, which prompts them to increase their shareholdings in non-accused competitors of the accused peer.

Our study extends research on corporate misconduct that has studied ''stigma by association'' across different industries (Barnett and King, 2008; Jonsson, Greve, and Fujiwara-Greve, 2009; Diestre and Rajagopalan, 2014; Durand and Vergne, 2015; Paruchuri and Misangyi, 2015). We, by contrast, study the valence of intra-industry spillovers and advance this research stream by introducing the competition effect, as well as by showing how both effects vary with the market overlap between a non-accused firm and its accused industry peer. By reconciling opposing views on the implications of financial misconduct, we shed light on the heterogeneity across non-accused firms. Moreover, we identify conditions under which a firm can potentially gain from accusations of financial misconduct by its peers. In so doing, we also extend research that documents more positive spillovers when a behavior can be attributed to specific characteristics of the accused peer and is thus less generalizable to other non-accused firms (Piazza and Jourdan, 2018; Paruchuri, Pollock, and Kumar, 2019; Naumovska and Zajac, 2021). Our study suggests that even when misconduct can be generalized as a result of shared industry characteristics, it can trigger positive spillovers related to the weakened competitive position of the accused peer. Hence, we advance research on industry categories (e.g., Cattani, Porac, and Thomas, 2017; Pontikes, 2018) by demonstrating how categories simultaneously inform the cognitive taxonomies that trigger stigma and represent the competitive landscapes in which firms compete.

Finally, we contribute to competitive dynamics research. We direct attention to actions of industry peers, namely their financial misconduct, which are not part of their repertoire of competitive actions (Ferrier, 2001; Smith, Ferrier, and Ndofor, 2001) yet produce important performance implications for other firms in their industry, besides prompting competitive reactions (e.g., Guo, Yu, and Sengul, 2020). Our study suggests that the consequences of misconduct by an industry peer vary depending on the lens used for assessing market overlap, with a fine-grained lens better capturing the competition effect. In line with this assertion, we demonstrate that more sophisticated investors can leverage their superior industry expertise to discern non-accused firms and invest in close competitors of the accused peer. Hence, we conclude that the valence of the

spillover following financial misconduct by an industry peer is driven by inter-firm heterogeneity as well as by investor heterogeneity.

THEORY AND HYPOTHESES

Financial Misconduct and Stigma by Association

Established research on financial misconduct has shown that when a firm is accused of misrepresenting its financial reports, it suffers regulatory and reputational penalties that decrease its market value (e.g., Karpoff, Lee, and Martin, 2008; Sharkey, 2014). This misconduct also generates negative spillover to non-accused firms in the same industry (e.g., Paruchuri and Misangyi, 2015; Naumovska and Zajac, 2021) because firms in the same industry resemble each other (Porac, Thomas, and Baden-Fuller, 1989; Vergne and Wry, 2014) and have shared reputation by virtue of their industry membership (King, Lenox, and Barnett, 2002; Jonsson, Greve, and Fujiwara-Greve, 2009). Thus, ''when new information is revealed about the characteristics of one firm, it reflects to some degree on all firms within its industry'' (Barnett and King, 2008: 1152), which triggers generalized evaluations of non-accused firms in that industry.

The effect of stigma by association is rooted in the social psychology literature, which has considered stigma as a social attribute that discredits individuals and groups as well as those who are closely connected with them (Goffman, 1963). Imported to organization theory, the notion has been conceptualized as a discrediting label that evokes a perception by a stakeholder group that organizations belonging to the same category, such as an industry, possess a fundamental flaw (Hudson, 2008; Devers et al., 2009). The underlying mechanism of the stigma effect in the context of financial misconduct is that the accusation against an industry peer evokes stakeholders' perceptions that other firms in the industry have engaged in similar misconduct (Paruchuri and Misangyi, 2015).[1] Furthermore, the misconduct by an industry peer challenges the legitimacy and undermines the perceived value of some non-accused firms in that industry (Greve, Palmer, and Pozner, 2010). As a result, investors ''minimize their downside risk, spreading the negative impact of the crisis to other organizations'' (Yu, Sengul, and Lester, 2008: 453).

The established research on stigma by association, however, has not considered how non-accused firms belonging to the same industry vary in the extent of their market overlap with the accused peer and hence in the spillovers they experience. Firms differ with respect to attributes such as their organizational size, geographical location, and product offerings. Still, when stakeholders evaluate the extent to which two firms resemble each other, they tend to rely not on all their attributes, nor on the most diagnostic ones, but on the most cognitively accessible attribute (Sherman, Judd, and Park, 1989). Research on industries as cognitive taxonomies has shown that the most accessible and commonly used attribute for categorizing firms in an industry and assessing their similarity is product offerings (Hodgkinson and Johnson, 1994; Porac and Thomas, 1994; Porac et al., 1995; Durand and Vergne, 2015). The ''psychological mechanism behind this phenomenon is likely to be information availability.

[1] This may be reinforced if the U.S. Securities and Exchange Commission (SEC) targets firms in specific industries (Gadinis, 2012; Alawadhi et al., 2020).

The business world tends to favor product offerings . . . as a way of classifying firms'' (Clark and Montgomery, 1999: 69). Thus, we study the heterogeneity of spillovers based on the overlap in product markets in which the accused peer and non-accused firms both operate.[2]

Accordingly, we posit that a non-accused firm that exhibits greater product market overlap with an accused peer will be perceived as more similar to it and thus more likely than other firms to be assigned to the same industry category as the accused peer. Because investors are likely to rely on firms' product offerings for categorizing them and making generalized evaluations, we expect a stronger negative spillover to that non-accused firm. Moreover, customers, suppliers, and other stakeholders would also generalize their assessments to non-accused firms, prompting them to restrict their business transactions with firms that are more similar to the accused peer in fear that they also engage in misconduct, which carries reputational loss and reallocation of resources and attention. This, in turn, reinforces the negative spillover, because investors react not only to credibility concerns but also to stakeholder attrition. The stigma effect is thus expected to be stronger for non-accused firms that are perceived as having greater market overlap with their accused industry peer. For example, when WorldCom was accused of financial misconduct, the North American Telecom Index fell by more than 10 percent (Romero, 2002). Per this baseline argument, the greater the product market overlap between a non-accused firm and an accused industry peer, the more negative the stock market valuation of that non-accused firm (see Figure 1).

Financial Misconduct and Competitive Interactions

Although the stigma by association argument has dominated the conversation in the misconduct literature, it clashes with another perspective originating in strategy research on competitive dynamics. According to this research, categorization of firms in an industry hints at their likely competitive interactions (Smith et al., 1997). We conjecture that, because of these competitive interactions, some non-accused firms in the accused peer's industry can benefit from a positive spillover because of that peer's weakened competitive position. This countervailing perspective suggests that firms that are more similar to each other are more likely to be fierce competitors and that, among such competitors, one firm's loss is its competitor's gain (Kilduff, Elfenbein, and Staw, 2010). Even though this research has not drawn implications for corporate misconduct, it treats industry categories as competitive landscapes (Porac and Thomas, 1990) in which some industry peers are considered more direct competitors by virtue of the overlap in the markets they serve (Smith et al., 1997). The greater a firm's market overlap with the industry peer, the more likely they are to be perceived as competitors and the more visible, salient, and consequential the peer's actions become for that firm (Ferrier, 2001; Chen, Su, and Tsai, 2007).

[2] This does not imply that stakeholders rely exclusively on product offerings when categorizing firms. Rather, we focus on product offerings because they take precedence in generalization processes and play a role in competitive interactions. We account for similarity across other attributes in our research design.

Research on competitive dynamics indicates that competitive actions or events that weaken an industry peer's competitive position can benefit a competing firm (Chen, 1996). We suggest that similar competitive implications apply for actions that are not part of firms' competitive repertoires, such as accusations of financial misconduct committed by an industry peer. We thus expect a non-accused firm to gain from the misfortune of a peer with which it competes following the accusation. This competition effect is invoked when adversarial information about the weakened competitive position of the peer implies an improved competitive position for the non-accused firm.

The mechanism underlying the competition effect is that revealed misconduct by an industry peer may endanger its competitive position and result in loss of market share to competing firms, which, because of this positive spillover, can enhance their competitive positions. In line with our prediction, prior research has suggested that a firm's misconduct can deter its customers, business partners, and other stakeholders, who may be concerned about a decline in product quality or potential loss of business or reputation given these stakeholders' association with the accused firm (Jensen, 2006; Sullivan, Haunschild, and Page, 2007; Johnson, Xie, and Yi, 2014; Xin, Zhou, and Hu, 2018). For example, Johnson and colleagues (2014: 18) reported that following an accusation of financial misconduct, the accused firm's ''trading relationship with its large customer is more likely to break up'' and ''its revenue attributable to that large customer decreases.'' As well, following a financial misconduct accusation, ''skepticism about a firm's intent or ability to fulfill its commitments leads to a decline in customer demand'' (Chakravarthy, DeHaan, and Rajgopal, 2014: 1334). This expected failure to meet commitments stems from the accused firm's financial distress (Karpoff, Lee, and Martin, 2008) and from customers' and business partners' tendency to discontinue their business with an accused firm (Sutton and Callahan, 1987).

We contend that when a firm is accused of financial misconduct, its customers will switch to other firms in the same market that offer comparable products. In the WorldCom case, an executive at Cable & Wireless USA Inc. reported, ''We've gotten hundreds of calls from WorldCom customers in the last few days and have closed a number of new deals'' (Noguchi and Reddy, 2002). The media reported that WorldCom's accounting scandal ''could spook customers, creating a windfall for WorldCom rivals'' (Hall, 2002a).[3]

Therefore, we claim that investors would anticipate this competition effect and react positively to a non-accused firm's opportunity to capitalize on the market lost by its direct competitor following accusations against that industry peer. The greater the market overlap between the non-accused firm and its peer, the stronger the competition effect that creates positive spillover to firms that can enhance their competitive position vis-à-vis that peer. Hence, our counterargument to stigma by association is that the greater the product market overlap between a non-accused firm and its accused peer, the more positive the firm's stock market valuation (see Figure 1).

[3] When accusations of financial misconduct can lead to bankruptcy (Karpoff, Lee, and Martin, 2008), customers and suppliers are even more likely to discontinue their business with the firm (Sutton and Callahan, 1987), resulting in loss of contracts and sales to competitors. Hence, scholars have shown positive stock market returns for firms whose competitors are on the verge of bankruptcy (Ferris, Jayaraman, and Makhija, 1997; Chi, 2009).

Toward Reconciliation of the Stigma and Competition Effects

When do non-accused firms suffer a negative spillover ascribed to the stigma effect, and when do they enjoy a positive spillover due to the competition effect? Neither perspective implies that the peer's misconduct would benefit the whole industry or undermine its legitimacy. Rather, the stigma effect implies that investors would seek to reduce their investments in firms that they perceive as more likely to have engaged in financial misconduct, whereas the competition effect entails increasing investments in firms that are close rivals of the accused peer. To reconcile these opposing views, we contend that industry categories represent both cognitive taxonomies and competitive landscapes (Porac, Thomas, and Baden-Fuller, 1989; Cattani, Porac, and Thomas, 2017). When making generalizations, stakeholders assign firms to industry categories based on the product markets in which they operate (Durand and Vergne, 2015), while product market overlap also indicates the intensity of competition between these firms (Chen, 1996). Taking both cognitive and competitive stances, we expect the stigma effect to be stronger than the competition effect at lower levels of market overlap between the accused peer and non-accused firms. We also expect the competition effect to become stronger than the stigma effect at higher levels of market overlap.

Specifically, we posit that the greater the market overlap between the accused peer and the non-accused firm, the stronger the expected negative spillover following the misconduct, but that the spillover increases at a diminishing rate. This is because the perceived similarity between two entities is based on judgment (Tversky, 1977; Tversky and Gati, 1982; Medin, Goldstone, and Markman, 1995), so the generalization of unobservable attributes from one entity to the other depends on the two entities reaching some ''threshold level of similarity'' (Medin and Smith, 1984: 117). Accordingly, for investors to judge that a non-accused firm and its accused peer are sufficiently similar for stigma to occur, the investors need to identify only a sufficient level of market overlap between them. Further increases in their market overlap provide little additional information for perceiving them as more similar to each other (Goldstone, 1994). This process follows the satisficing principle (Simon, 1987), whereby investors gather only sufficient information to determine whether the non-accused firm belongs to the category of its industry peer. Gathering further information about the attributes of the firm and its industry peer is cognitively taxing and considered unnecessary for assigning them to the same broad category. Indeed, stigma by association relies on categorization of firms using limited information about their attributes in order to make generalized inference about their unobserved characteristics (Greve, Kim, and Teh, 2016). Therefore, we expect investors to engage in generalizations when a non-accused firm and its accused peer are perceived as sufficiently similar, yet further increases in their market overlap would not substantially enhance their perceived similarity. The negative spillover following the accusation against the industry peer, which is ascribed to the stigma effect, is thus likely to persist (Jonsson, Greve, and Fujiwara-Greve, 2009; Durand and Vergne, 2015) but to increase at a diminishing rate with increasing market overlap with the peer.

In contrast, competitive dynamics research relates the intensity of competition to the market overlap between competitors, acknowledging that fierce

rivalry emerges when firms are perceived as close competitors (Porac and Thomas, 1990; Chen, 1996). However, conventional industry categorization encompasses a broad range of firms without distinguishing competitors from non-competing peers (Clarke, 1989; Porac and Thomas, 1990). We expect an event that endangers the competitive position of an industry peer to create a positive spillover to firms that are most proximate to this peer's market domain. Firms with a sufficiently high market overlap with the accused peer are likely to benefit from that peer's lost market share, with the most proximate firms gaining most.

Firms are affected by the actions of a limited set of proximate competitors within the broader group of firms that operate in their industry (Porac and Thomas, 1994). As a result, we predict that low levels of market overlap between an accused peer and a non-accused firm are likely to have limited consequences for the non-accused firm as far as the competition effect is concerned. But as their market overlap increases, their competitive interactions become more consequential, so that one firm's loss becomes the other's gain (Kilduff, Elfenbein, and Staw, 2010). Indeed, ''one company's scandal is another's opportunity'' (Lohr, 2009) when customers and business partners of the accused peer switch to non-accused firms that offer comparable products or services.[4] We expect switching to be more common when the firm is perceived as a close substitute for the accused peer. Investors are increasingly likely to consider a non-accused firm as a substitute when its product market overlap with the accused peer becomes very high. To that end, they follow the maximizing principle in gathering information and searching for the closest competitors, as opposed to the satisficing principle (Simon, 1987), which is invoked in category judgments. The positive spillover to a non-accused firm following an accusation against its industry peer is thus likely to increase at an increasing rate as their market overlap increases.

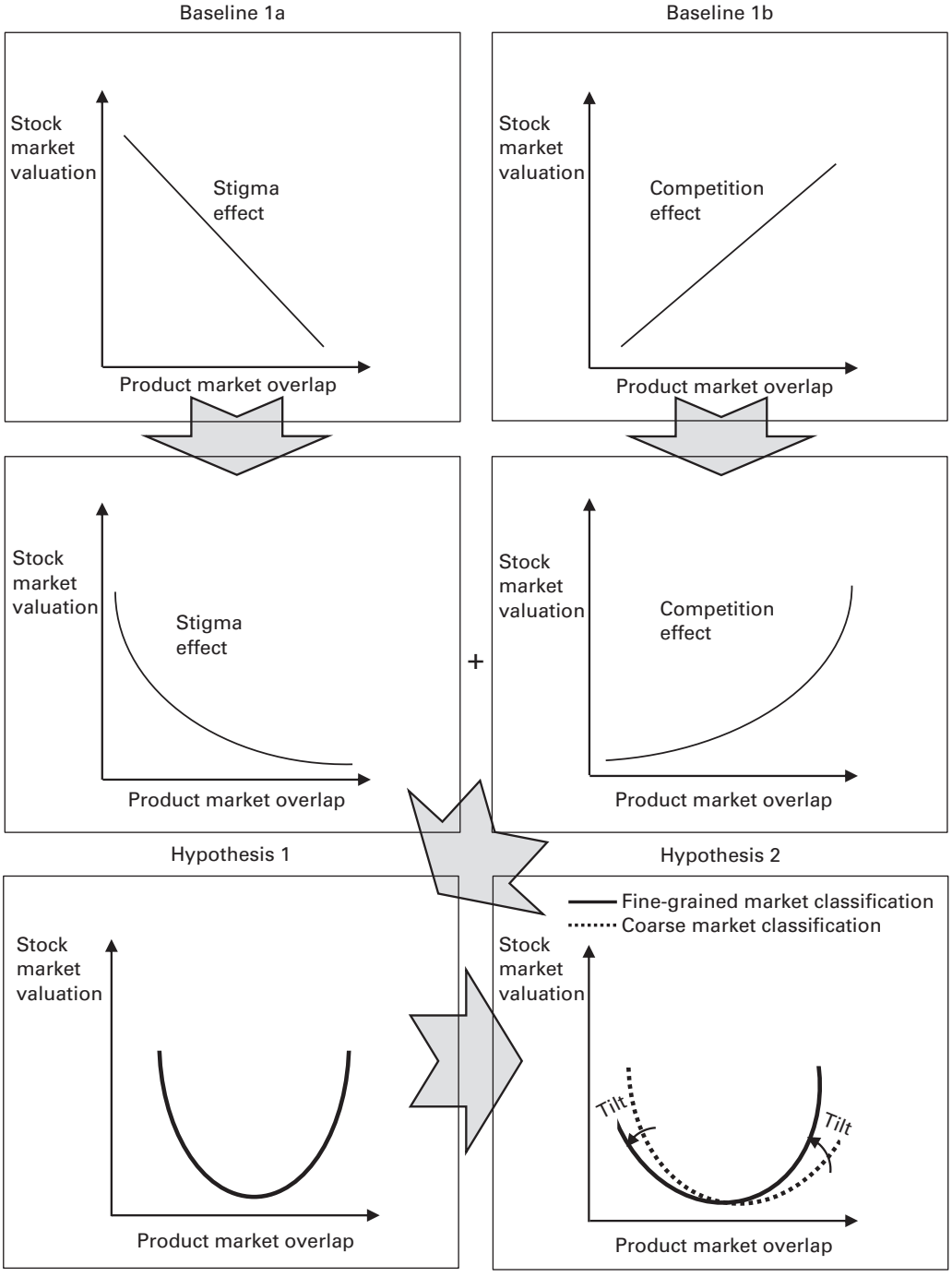
When considering the aggregate market reaction, we thus expect the stigma effect to increase more at lower levels of market overlap between the non-accused firm and its accused peer and then to flatten at higher levels of market overlap as the competition effect becomes increasingly stronger and offsets it (see Figure 1).

> **Hypothesis 1:** The product market overlap between a non-accused firm and an accused industry peer will exhibit a U-shaped effect on the non-accused firm's stock market valuation, with the expected stock market valuation first becoming more negative as the product market overlap increases and then becoming more positive with further increases in product market overlap.

We next tease out the stigma versus competition mechanisms by claiming that the granularity of the market classification used by investors for assessing the non-accused firm and its accused peer affects the categorization of firms and their identification as competitors, which in turn influences the relative dominance of the stigma versus competition effects. We proceed by arguing that the stigma effect becomes stronger than the competition effect when

[4] Lohr (2009) discussed the financial misconduct by Saytam Computer Services, stating that ''the financial fraud at Satyam is rippling through the technology services industry, as customers scramble to line up other suppliers and rivals look to pick up business. . . . The big winners from the fallout are likely to be two American companies, Accenture and IBM.''

Figure 1. Predicted Association of Stock Market Valuation and Product Market Overlap



investors rely on a coarse market classification. In turn, the competition effect becomes stronger relative to the stigma effect when they use a fine-grained market classification, because such a classification can discern which non-accused firms compete directly with the accused peer and thus are likely to gain following the accusation.

Specifically, when investors rely on a coarse market classification to categorize firms, this increases the likelihood of perceiving two firms as belonging to the same broad industry category, which in turn prompts generalized evaluations (Paruchuri and Misangyi, 2015). Having more firms per category makes generalization and negative spillover to a non-accused firm more likely. When investors use a coarse classification, this also facilitates a perception of homogeneity across dissimilar firms that overstates their similarities and thus prompts generalizations (Smith, Shafir, and Osherson, 1993). Thus, when a peer is accused of financial misconduct, investors' reliance on a coarse classification can increase perceived similarity and lead to the conclusion that a non-accused firm belongs to the same category as the accused peer, which prompts the stigma effect.

At the same time, a coarse market classification is insufficient for investors to determine whether a non-accused firm and its accused industry peer can be considered competitors. To discern competitors, investors need more detailed information about their product offerings (Porac and Thomas, 1990). Even if the actual market overlap between a non-accused firm and its accused peer is high, investors need to rely on a fine-grained market classification to identify the firm as a close competitor that may gain from the market loss of its accused peer. As a result, the more fine-grained the market classification used by investors for assessing the market overlap between the non-accused firm and its accused peer, the more dominant the competition effect becomes relative to the stigma effect.

Therefore, when investors rely on a coarse market classification, the stigma effect is expected to become stronger with increases in market overlap, while the competition effect becomes weaker and may not be detectible. Consequently, when investors use a coarse market classification, we expect the stigma effect to be more salient, with the corresponding decline in the firm's market value not counterweighted by the increase in value ascribed to the competition effect. In contrast, when investors rely on a more fine-grained market classification for perceiving the competitive landscape, we expect the competition effect to become more pronounced relative to the stigma effect for non-accused firms whose market overlap with the accused peer is higher relative to other firms. The resulting prediction is illustrated in Figure 1. We conclude:

> **Hypothesis 2:** The more fine-grained the product market classification used by investors for assessing the product market overlap, the stronger the increase in the stock market valuation of the non-accused firm at higher levels of product market overlap relative to the decline in its stock market valuation at lower levels of product market overlap.

Thus far, we have considered the aggregate stock market reactions experienced by non-accused firms and argued that the stigma effect is reinforced when investors rely on a coarse market classification that is conducive for making generalized evaluations. In turn, when investors use a fine-grained

classification, they can detect the competition effect that counterbalances the stigma effect. Nevertheless, there are persistent differences in the classification systems used by different investors, which cannot be observed at the aggregate level of the stock market yet are important to explain. We next relate the granularity of the classification system to an investor's level of sophistication and explain the corresponding heterogeneity in investment behavior.

We contend that given their different levels of analytical skills and industry expertise, investors vary with respect to the granularity of the market classification they use for discerning firms. We build on research on categorization, which suggests that non-experts tend to categorize entities at a coarse level (Rosch et al., 1976), while experts categorize them at a more refined level (Tanaka and Taylor, 1991; Johnson and Mervis, 1997). In this process, experts leverage extensive domain knowledge and expertise, as in the case of stock market analysts with industry-specific expertise who rely on their product knowledge to evaluate firms' stocks (Zuckerman, 1999). This enables experts to make finer-grained distinctions and perceive subcategories (Boulongne, Cudennec, and Durand, 2019). Accordingly, compared with less sophisticated investors, more sophisticated investors rely on a more fine-grained market classification to effectively map the competitive landscape and thus identify close competitors that may gain following the accusation against their industry peer.

For example, the accusation against WorldCom ''weighed on the entire telecommunications industry'' and even harmed firms in related sectors, such as Lucent Technologies and Nortel Networks (Romero, 2002), because most investors formed broad impressions of firms and overgeneralized to other firms in the industry. Less sophisticated investors who use a relatively coarse lens to assess firms were not fully informed about the nuanced ways in which the non-accused firm and the accused peer's products resemble each other. In turn, more sophisticated investors who leverage a fine-grained market classification of firms in the telecommunications industry identified AT&T as a fierce rival of WorldCom in the early 2000s. Indeed, AT&T gained from the accusation against WorldCom, which lost 10 percent of its revenues in only two months. AT&T's CFO acknowledged that ''AT&T's sales were benefiting from WorldCom's financial woes and accounting scandals'' (Powell, 2002). This competition effect was anticipated by sophisticated investors, who could apply a fine-grained market classification to distinguish the few close competitors from other non-accused firms. For instance, Marc Crossman, a leading telecommunications securities analyst, ''estimated that WorldCom could lose as much as $700 million in quarterly revenues as corporate and government clients defect to rival carriers and new customers hesitate to forge ties with WorldCom'' and that AT&T could capture ''70 percent of the incremental business . . . [and] pick up $500 million of revenue'' (Hall, 2002b). Hence, experts, such as sophisticated investors, who have a more refined perspective of product markets and competitive landscapes can better identify non-accused firms that would gain from their market overlap with the accused peer and thus can better anticipate the competition effect.

Specifically, more sophisticated investors with industry expertise and relevant knowledge of product functionality can perceive more refined competitive landscapes in the industry. This enables them to determine whether the products of a non-accused firm substitute for those of its accused peer. More sophisticated investors are also less likely than less sophisticated investors to

assume that a non-accused firm would engage in misconduct once its industry peer was accused of misconduct and to trade on the basis of this stigma effect. The fine-grained market classification used by more sophisticated investors places a smaller number of non-accused firms in the same category as the accused peer, reducing unwarranted generalized evaluations. As a result, more sophisticated investors—who rely on a more fine-grained market classification and hence are less sensitive to stigma by association while acknowledging gain in market share to the peer's competitors—are more likely to increase their investments in non-accused firms following the accusation against their industry peer. In turn, less sophisticated investors, who rely on a less refined market classification, are less likely to increase their investments in non-accused firms given these investors' sensitivity to stigma by association and their inability to discern close competitors.

Moreover, because the competition effect intensifies with the market overlap with the accused peer, more sophisticated investors, who rely on a fine-grained market classification, are likely to further increase their investments in the non-accused firm as its market overlap with the accused peer increases. Stated differently, because more sophisticated investors can better discern close competitors and minimize generalized evaluations, the competition effect is expected to become more pronounced relative to the stigma effect in their investment decisions as the market overlap with the accused peer increases. Therefore:

> **Hypothesis 3:** More sophisticated investors tend to increase their shareholdings in non-accused firms to a greater extent than less sophisticated investors, and this tendency becomes stronger as these firms' product market overlap with the accused industry peer increases.

DATA AND METHODS

Research Setting and Sample

We tested our hypotheses with data on 242 publicly traded U.S. firms operating in the prepackaged software industry—standard industry classification (SIC) 7372—during the years 1991–2001. Sampled firms were active in 2001 and had at least five records in the Compustat database. We studied the prepackaged software industry in the 1990s because it features a high number of publicly traded firms accused of financial misconduct (Karpoff, Lee, and Martin, 2008). This industry also features a wide range of products and frequent product introductions (Campbell-Kelly, 2003), allowing us to study product market overlap. U.S. firms capture a major share of the global market (Mowery and Nelson, 1999) and go public at a relatively early stage, so our data were not subject to age or size biases (Lavie, 2007). This allowed us to effectively study the stigma and competition effects.

To identify accused peers, we used a database on financial misconduct in the U.S., listing firms that were subjected to enforcement actions for financial misrepresentation (''cooking the books'') by the SEC (Karpoff, Lee, and Martin, 2008; Karpoff et al., 2017). The data covered all known instances of financial misconduct in the U.S. that violated provisions of the 1934 Securities Exchange Act. This allowed us to ensure that our findings were not sensitive to omission of relevant cases or to differences in the type of misconduct. All the

events were comparable because they referred to violations of clearly stated provisions.[5] Compared with alternative data sources (the Government Accountability Office, Audit Analytics, Stanford Securities Class Action Clearinghouse, and SEC Accounting and Auditing Enforcement Releases), our database more effectively excludes errors or non-fraudulent activities such as minor accounting irregularities; it is also more accurate in identifying the first date at which the financial misconduct was revealed to the public (Karpoff et al., 2017). Identifying the earliest event date is essential for making valid causal inferences in stock market event studies (MacKinlay, 1997) because this date represents the point in time when stakeholders such as investors first learned about the misconduct and realized that the performance of the accused firm was not as positive as had been previously reported. As a result, investors revised their expectations about the future performance of the accused peer. The identified events of revealed financial misconduct bore substantial consequences for the accused firms, including but not limited to monetary and legal penalties, reputational penalties, and delisting from the stock exchange.[6]

During the study's period, we observed a total of 16 events of software firms that were subject to enforcement actions by the SEC for financial misrepresentation.[7] The first recorded accusation event in the study period took place on July 10, 1991, with the last event reported on December 14, 2001. On average, the accused firms had been misrepresenting their financial accounts for 28 months, while the enforcement period between the initial revelation of misconduct and the conclusion of all legal proceedings was 54 months. None of the events resulted in bankruptcy within the 48 months after the enforcement period ended, and all of the accused firms were subject to legal monetary penalties. This suggests that the events were consequential and that there was limited heterogeneity across events. For each accusation event, we defined ''non-accused firms'' as all sampled firms in the prepackaged software industry that were public at the event's date, except the accused firm.

[5] The misconduct accusations were all initiated by the SEC for violation of one or more of three 13(b) provisions of the Securities and Exchange Act of 1934 as amended by the Foreign Corrupt Practices Act of 1977, which requires firms to keep and maintain books and records that accurately reflect all transactions, requires firms to devise and maintain a system of internal accounting controls, and establishes that no person shall knowingly circumvent or knowingly fail to implement a system of internal accounting controls or knowingly falsify any book record or account.

[6] Karpoff et al. (2017) discussed the qualities of this database for studying financial misconduct and its consequences for the accused firms. They revealed that a firm's stock price drops dramatically when the firm is accused of financial misconduct. The drop in market value is typically more than 7.5 times the monetary penalties imposed by the regulatory system (Karpoff, Lee, and Martin, 2008). This drop is explained by the revelation that the accused firm's actual performance is weaker than previously assumed, with investors anticipating the monetary penalties, loss of sales, and increasing contracting and financing costs.

[7] Accusation events for financial misconduct are rare (Karpoff, Lee, and Martin, 2008), and the 16 events that we identified represent all the accusations involving our sample of firms in the software industry during the study's timeframe. Given the rarity of such events, research on corporate misconduct and spillovers relies on small samples (e.g., Jonsson, Greve, and Fujiwara-Greve, 2009; Durand and Vergne, 2015; Paruchuri, Pollock, and Kumar, 2019). It was unnecessary to consider follow-up events (informal inquiry, formal investigation, initial regulatory proceeding, regulatory events such as a Wells notice, concluding regulatory proceeding, and class-action lawsuits) subsequent to the accusation events, because the stock market can foresee much of the progression of the investigation and its implications. Indeed, extending our analysis to the corresponding 58 follow-up events yielded only marginally significant cumulative abnormal returns to the non-accused firms.

Financial data on the accused peer and non-accused firms, including their assets, sales, net income, research and development (R&D) expenses, cash, long-term debt, market value, and headquarters location, were extracted annually from the Compustat database. Secondary SIC data were gathered annually from the Compustat Segments database, while firm age was measured based on the date of incorporation indicated in firms' SEC filings reported in the EDGAR database. Data on stock prices and common stock outstanding were gathered on a daily basis from the CRSP database, while the abnormal stock market returns were calculated using Eventus. Abnormal stock market return data were available for 238 firms, with five additional firms dropped because of missing data relating to control variables, such as R&D expenses and financial solvency, resulting in an effective sample of 233 firms.[8]

Data on firms' shareholders were derived from the Thomson Reuters 13F SEC filings (e.g., Griffin and Xu, 2009; Agarwal et al., 2015). This dataset covers the quarter-end holdings of U.S. stocks by institutional investors, including banks, insurance firms, hedge funds, mutual funds, investment advisors, and others (e.g., pension funds and endowments), which managed at least $100 million and held more than $200,000 or 10,000 shares in the non-accused firm. In total, we observed 151,062 changes in holdings among 2,246 institutional investors, of which 642 (28.58 percent) were hedge funds and mutual funds. The mutual funds category was identified based on the investors' classification in the Thomson Reuters database, while hedge funds were identified based on the listing provided by Griffin and Xu (2009) and further elaborated with a manual online search for the identity of the institutional investors in our database.[9]

Data on the firms' software products were gathered from press items published in the LexisNexis and Thomson's Dialog New Product Announcements databases since 1985. We supplemented these databases with information on products listed in firms' 10-K forms (SEC filings) searched via the EDGAR database and in the Gale Business & Company Resource Center database. The press items were manually screened for product information and then coded by expert coders who relied on detailed coding guidelines. Each product was coded by two trained coders who analyzed its functionality. Interrater reliability was 84.570 percent, with coding differences resolved by careful deliberation until agreement was reached. In total, during 1991–2001, the 233 firms introduced 13,165 products, which were categorized using a product classification system developed with the help of industry experts. The system consists of three nested levels: four product classes (personal applications, system infrastructure, vertical applications, and business applications), 54 product segments, and 464 product

[8] On average, an accused firm was 12.375 years old at the time of accusation, with sales of $1,233.880 million and 12.701 percent of its assets invested in R&D; its return on assets (ROA) was –7.052 percent, its ratio of market-to-book value (MTBV) was 13.472, and the ratio of cash to debt was 4.971. A non-accused firm was 14.154 years old, with sales of $322.894 million and 17.772 percent of its assets spent on R&D; its ROA was –15.403 percent, its ratio of MTBV was 8.587, and its ratio of cash to debt was 6.388.

[9] We cannot observe the trading of retail investors and small institutional investors when we use available sources such as the 13F SEC filings. As a result, our database covers a very small fraction of investors (who hold on average only 0.449% of the outstanding shares of non-accused firms), while excluding some of the least sophisticated investors. This research design is conservative because their inclusion would have magnified the increase in shareholdings in non-accused firms of sophisticated investors relative to less sophisticated investors.

functions.[10] To measure market overlap, we relied on firms' complete product portfolios, assuming a product life expectancy of three years (e.g., Frank, 1997: 96) unless noted otherwise in press items. For example, for an event taking place on July 10, 1991, we accounted for all the products introduced since July 10, 1988. Our measure is more suitable for testing our theory compared with alternative classification systems introduced by Hoberg and Phillips (2010, 2016) and Pontikes and Barnett (2015).[11]

To account for alternative channels of stigma and competition, we also studied board interlocks and alliances. We collected data on board members serving on the boards of the accused peer and non-accused firms in the year of accusation from BoardEx, Institutional Shareholder Services (ISS), and firms' annual reports accessible via EDGAR. The number of board interlocks was low, with a total of 10 interlocks between accused peers and non-accused firms, corresponding to an average of 0.004 interlocks per dyad. Alliance data were gathered from the SDC Platinum, Factiva, and EDGAR databases and from corporate websites, tracking all alliances formed by the non-accused firms and accused peers in the three years preceding each accusation. In 13 of the 16 accusations, an accused peer had at least one joint alliance with a non-accused firm, with an average of 0.063 joint alliances per dyad.

We relied on two distinctive datasets to test our hypotheses. To test Hypotheses 1 and 2, our unit of analysis is the non-accused firm and an event of a misconduct accusation against its industry peer. Data on the non-accused firms and their accused peers were pooled to the non-accused firm–accusation event level, resulting in 2,759 records with stock market reactions. To test Hypothesis 3, we analyzed investors' decisions to change their shareholdings in a non-accused firm following the accusation against its industry peer, using the investor and the non-accused firm as the unit of analysis. This resulted in 151,062 observations corresponding to changes in the holdings of institutional investors.

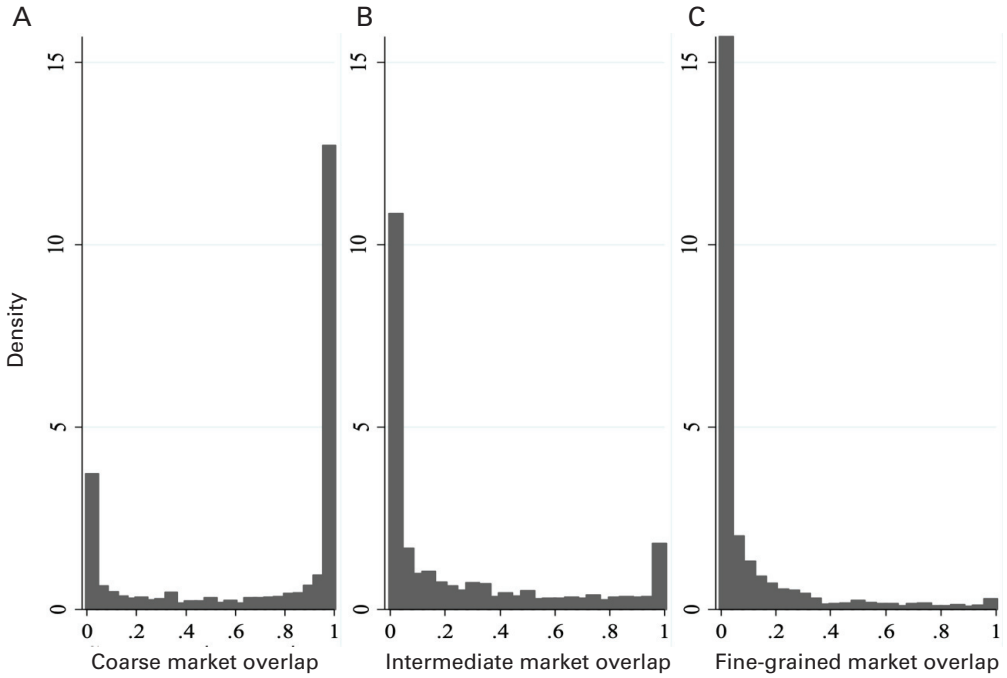
Independent Variables and Moderators

Our independent variable per Hypotheses 1 and 2 is the *market overlap* between the accused industry peer and the non-accused firm, measured at three different levels of granularity based on the software product classification

[10] The product classification system was developed in consultation with the Software & Information Industry Association (SIIA). Prevalent systems (provided by SIIA, IDC Research, NPD Group, and CorpTech) offered partial coverage and thus were integrated, supplemented, and elaborated to provide more complete and coherent coverage. The classification system was finalized following feedback from a review board of 12 renowned software industry experts and pretested. The system (see the illustration in the supplemental material, http://journals.sagepub.com/doi/suppl/10.1177/00018392211020662) was also used by prior research (e.g., Zahavi and Lavie, 2013; Stettner and Lavie, 2014).

[11] Hoberg and Phillips (2010, 2016) relied on automated content analysis of firms' business descriptions in 10-K forms, whereas we relied on multiple sources (including 10-K forms) and expert coders to analyze more extensive information. They isolated only one category corresponding to SIC 737, so their measure is too coarse to capture the competition effect. In turn, our product classification system identified 464 product functions in three nested levels under SIC 7372. Similarly, Pontikes and Barnett (2015) relied on firms' self-claimed membership in market categories, while our theory focused on the perceptions of external stakeholders. They also did not offer a hierarchy of product categories. Moreover, we relied on an independent classification system developed with the help of industry experts and updated our measure daily, which is essential for our event study.

Figure 2. Distributions of Market Overlap at Three Levels of Granularity



system. The coarse level consisted of four product classes, with the ratio of market overlap measured as the number of product classes to which both firms introduced software products in the three years preceding the event date, divided by the number of product classes in which the non-accused firm operated during that period (*coarse market overlap*). We also computed a measure for market overlap between the non-accused firm and the accused peer at the intermediate level of the classification system, which consisted of 54 product segments (*intermediate market overlap*), and at the more fine-grained level, which consisted of 464 product functions (*fine-grained market overlap*). The values of each measure range from 0 to 1, with higher values indicating greater overlap.

Figure 2 depicts the distributions of the market overlap variables at the three levels. When moving from the coarse to the fine-grained classification, the distributions shift from being right-skewed to left-skewed. For example, the coarse market overlap for Group 1 Software (non-accused firm) and McAfee (accused peer) is 0.889, the intermediate overlap is 0.472, and the fine-grained overlap is 0.028. The distribution of market overlap at the coarse level (Figure 2A) has a mean value of 0.690, with only 35.556 percent of the accused peer–non-accused firm dyads having an overlap lower than the mean. At the intermediate level (Figure 2B), the mean value of market overlap is 0.259, with 64.967 percent of the values below the mean. At the fine-grained level (Figure 2C), the distribution has a mean value of 0.109, and 74.773 percent of the observations have a value lower than the mean. The market overlap between the peer and the firm declines with more refined market classification.

Our independent variable per Hypothesis 3 is *investor sophistication*. To measure it we relied on literature that has established that hedge funds (Brunnermeier and Nagel, 2004; Stein, 2009; Chen, Kelly, and Wu, 2018) and mutual funds (Grinblatt and Titman, 1993; Chen, Jegadeesh, and Wermers, 2000; Wermers, 2000; Berk and van Binsbergen, 2015) are the most sophisticated institutional investors that earn higher returns than the rest of the market, including other institutional investors (e.g., banks and insurance firms). Their superior performance has been attributed to their human capital and expertise: ''Among different types of institutions, hedge funds and mutual funds (as opposed to pension funds and endowments or banks and insurance companies) attract the top talent as their portfolio managers'' (Choi et al., 2017: 195). Such top talent comes with ''money management skill'' (Berk and van Binsbergen, 2015: 2), ''superior stock selection skills'' (Chen, Jegadeesh, and Wermers, 2000: 367), and ''expertise about industry trends and competitive situations of the main players'' (Brav et al., 2018: 255). Hedge funds have ''fundamental technical research staff organized by industry or sector'' with ''deep industry expertise'' (Mirabile, 2015: 118) and ''structures that feature investment professionals with industry specializations'' (Zoia and Finkel, 2008: 60). Similarly, when evaluating a particular firm, mutual funds consider ''its industry and competing firms . . . by talking to company management, industry experts, suppliers, customers, or government officials; by conducting proprietary surveys; or by tracking and synthesizing industry data'' (Fidelity Investments, 2020: 1).

To shed further light on the superior industry expertise of hedge funds and mutual funds, we conducted two semi-structured interviews with an investment research analyst and a portfolio manager who consult for hedge funds, mutual funds, and investment advisory firms. The interviewees indicated that less sophisticated institutional investors, such as banks and insurance companies, do not typically employ analysts with industry expertise. In contrast, analysts in mutual funds and hedge funds specialize in particular industry sectors and analyze detailed industry and corporate information to support investment decisions, offering a fine-grained perspective on a firm's industry and its specific competitors. The portfolio manager gave the example of Amazon, noting that their analyst would know that ''a big part of the revenues of Amazon comes from cloud computing'' and not ''home delivery.'' Their analyst ''will read more about the product, and . . . he will find the competitors and who has the largest market share for the product.'' This interviewee concluded that their analyst ''understands the product market better than an investment consultant in a bank,'' who is unlikely to analyze the cloud computing market when considering an investment in Amazon. We asked the other interviewee, who worked as a research analyst advising various institutional investors, ''who do you think is the most sophisticated type?'' The research analyst decisively replied that ''hedge funds are the most sophisticated. . . . I would also say mutual funds are the more sophisticated ones . . . you can discuss with them in terms of fundamentals, in terms of technical aspects. . . . Insurance companies and banks, they are just looking at the safe instruments, and they have many constraints.'' The interviewee noted that banks and insurance companies do not have in-house analysts with ''sector expertise'' and ''deep knowledge . . . to analyze these instruments. Maybe they have one analyst, and it's like very broad and is not specialized in any sector. And they are mostly buying safe, high

quality names. So, they don't even need, let's say, a specialized analyst for any sector.'' Instead, he said, the in-house analysts at mutual funds and hedge funds ''have knowledge about the product of the company and about competitors, because they have to compare these companies.'' Thus our independent variable, *investor sophistication*, received a value of 1 for hedge funds and mutual funds and a value of 0 for banks, insurance firms, investment advisors, and other institutional investors.[12]

Our moderator per Hypothesis 3 is market overlap. Because our data are limited to institutional investors, in this analysis we considered only the fine-grained and intermediate market classifications, which are correspondingly associated with more and less sophisticated institutional investors. We created a measure of contingent market overlap (a spline function) using the fine-grained level for more sophisticated institutional investors and the market overlap at the intermediate level for less sophisticated institutional investors.

Dependent Variables

To test Hypotheses 1 and 2, we employed the event study method, examining the abnormal stock market returns of non-accused firms around the date the information about the misconduct was first made public. This enabled us to measure the spillover from the accusation event by tracking stock market reactions to the non-accused firms at the time of the event. This reaction reflects an ex ante expectation about possible reputation loss and the perceived risk that the non-accused firm will be accused of similar misconduct, as well as the perceived change in its competitive position vis-à-vis the accused peer. Prior research has used the event study method to account for negative spillover based on investors' expectations (e.g., Paruchuri and Misangyi, 2015). The same method has also been used for capturing positive spillover stemming from the announcement that an industry peer is facing bankruptcy (Lang and Stulz, 1992). More generally, event studies of stock market reactions can anticipate firms' future performance (e.g., Fama, 1998; Kale, Dyer, and Singh, 2002; Eberhart, Maxwell, and Siddique, 2004).

To estimate our dependent variable—the stock market reactions resulting from an accusation against an industry peer—we calculated a three-day *cumulative abnormal return* (CAR) starting the day prior to the announcement (e.g., Zhang and Wiersema, 2009; Flammer, 2013; Hawn, Chatterji, and Mitchell, 2018). Restricting the event window to three days [–1, +1] allowed for a valid causal inference between the event and investors' reactions while excluding confounding events that may have driven stock prices (MacKinlay, 1997; McWilliams and Siegel, 1997). The day preceding the event was included

[12] To further validate our measure of investor sophistication, we analyzed the quarterly buy/sell transactions of institutional investors (e.g., Daniel et al., 1997; Sevcenko and Ethiraj, 2018). We assessed their ''characteristic selectivity'' (Daniel et al., 1997), i.e., their ability to select stocks that outperform the market by benchmarking their portfolios' returns to those of passive portfolios based on market value, book-to-market ratio, and momentum. We obtained the returns of 20,431 portfolios encompassing 7,572,837 shareholdings in various industries in the year prior to the accusation events. We found that the portfolios of hedge funds and mutual funds generated positive excess returns of 4.501 percent on average, which was significantly higher than that of less sophisticated institutional investors (3.356 percent, $p < 0.000$). Thus, hedge funds and mutual funds indeed exhibit superior performance relative to other institutional investors.

because of possible information leakage, while the day after the event was included because some announcements occurred after trading closed for the day (Palmrose, Richardson, and Scholz, 2004; Arthaud-Day et al., 2006). The three-day CAR_{ij} is the sum over the three days of the daily abnormal return (AR_{it}) of a non-accused firm *i* surrounding the accusation event of industry peer *j*. The daily abnormal return represents the difference between the firm's actual return and its expected return on that day. We calculated the daily abnormal return using the market model formula: $AR_{it} = R_{it} - (\alpha_i - \beta R_{mt})$, where R_{it} is the return for firm *i* on day *t*, and R_{mt} is the return of the CRSP value-weighted index. The market model parameters—the systematic risk (β) and the rate of return for firm *i* when R_{mt} is equal to 0 (α)—were estimated using a 255-day window ending 46 days prior to an accusation event.

Per Hypothesis 3, our dependent variable is *shareholding change in non-accused firm*. It was calculated by subtracting the percentage of shares of an investor in the non-accused firm in the quarter prior to the accusation from the percentage of shares held in the quarter following the accusation event. The respective percentages were calculated by dividing the number of shares held by the investor by the number of outstanding shares in the corresponding quarters.

Control Variables

We included a battery of control variables that could influence the CAR of the non-accused firm and the change in shareholdings of institutional investors in the non-accused firm, including characteristics of the non-accused firm and its accused industry peer, as well as measures capturing various aspects of similarity and association between the two firms.

When testing Hypotheses 1 and 2, we controlled for the three-day CAR of the accused peer around the accusation event (*accused peer CAR*), which captures the perceived severity of the financial misconduct and thus may be associated with the stigma and competition effects. We also controlled for the time elapsed in days since the previous event associated with an accusation of financial misconduct against another industry peer (*time since previous accusation*), because when forming expectations, investors may associate the frequency of accusations in the industry with a moral panic or with the SEC's tendency to target other firms in the same industry sector, which can heighten spillover effects.

Next, we controlled for the organizational characteristics of the non-accused firm and its accused peer. With the exception of their financials, all measures were lagged by one year to avoid potential confounding effects stemming from information about the accusation that could affect the financial results of the firms (Paruchuri and Misangyi, 2015). Specifically, we controlled for: the firms' industry segments with the number of four-digit SICs in which they operated (*non-accused firm segments*, *accused peer segments*), because diversity of industry segments can affect judgments of category membership and thus shape the spillover (Durand and Vergne, 2015); the firms' size, measured as the logarithm of sales (*non-accused firm sales*, *accused peer sales*); the firms' age (*non-accused firm age*, *accused peer age*), which can affect investors' familiarity with the firms (Paruchuri and Misangyi, 2015); firm performance, measured as return on assets (ROA) (Kang, 2008) (*non-accused firm ROA*,

accused peer ROA), which relates to competitive pressure (Makarevich, 2018) and the firm's viability (Shepherd, 1999); market to book value (MTBV), measured as the ratio of market value of equity to assets (*non-accused firm MTBV*, *accused peer MTBV*); R&D intensity, measured as R&D expenditure adjusted by assets (*non-accused firm R&D*, *accused peer R&D*); and financial solvency, measured as the log-transformed ratio of cash to debt (*non-accused firm solvency*, *accused peer solvency*) (Gleason, Jenkins, and Johnson, 2008).

In addition, we accounted for various aspects of similarity and difference between the non-accused firm and its accused peer in order to demonstrate that product market overlap matters beyond established measures of similarity (e.g., Paruchuri and Misangyi, 2015) and because firms that resemble each other along various dimensions have alternative channels for negative or positive spillover. First, we accounted for overlap in industry segments between the non-accused firm and the accused peer (including secondary SICs) based on the ratio of shared four-digit SIC segments to the total number of SIC segments in which both firms operated in the year of accusation (*segments overlap*). Next, we accounted for alternative channels for spillover by calculating differences between the non-accused firm and the accused peer with respect to sales, ROA, MTBV, R&D intensity, and financial solvency in the year preceding the event. We measured these control variables by taking the absolute difference in the values for the accused peer and the non-accused firm. The smaller the difference, the more similar the two (*sales difference*, *age difference*, *ROA difference*, *MTBV difference*, *R&D difference*, and *solvency difference*). We also included indicators for whether the accused peer and the non-accused firm were listed on the *same stock exchange* and headquartered in the *same state*, given that geographic proximity and co-listing can facilitate stigma and competition (Froot and Dabora, 1999; Borah and Tellis, 2016). Another possibility is that by investing in a firm that is a close competitor of the accused peer, investors do not respond to the competition effect but rather attempt to rebalance their investment portfolio with an untarnished substitute. To account for such substitution of the firm's stock from a financial portfolio management standpoint, we accounted for the pairwise correlation of returns of the accused peer and non-accused firm in the 12 months preceding the accusation event (*stock prices co-movement*) (Barberis, Shleifer, and Wurgler, 2005; Farago and Hjalmarsson, 2019).

Finally, we controlled for the direct network ties between the accused industry peer and non-accused firm, given the possible spillovers via interfirm relations. In particular, stakeholders may suspect that partners of an accused industry peer have engaged in misconduct in cooperation with that peer—or that they would be negatively affected by the penalties imposed on that peer following the accusation (Kang, 2008; Pontikes, Negro, and Rao, 2010). Moreover, direct ties between firms shape their performance (Lavie, 2007; Sytch and Tatarynowicz, 2014), suggesting co-dependence between the accused peer and non-accused firm and potential performance implications for the non-accused firm. We considered three types of ties: *director interlocks*, *joint alliances*, and *shared alliance partners*. To measure director interlocks, we counted the number of directors serving on the boards of both the non-accused firm and its accused peer (Mizruchi, 1996) in the year of accusation. To measure joint alliances, we counted the number of alliances formed between the accused peer and the non-accused firm within the past three years up to one

day prior to the accusation event. To measure shared alliance partners, we counted the number of third-party firms that formed alliances with both the non-accused firm and the accused peer during that same period (Lavie, 2007). Remaining interfirm and temporal unobserved heterogeneity was accounted for by using the market model in the calculation of CAR.

When testing Hypothesis 3, we incorporated all the controls used for testing Hypotheses 1 and 2. We added controls for the investors' *shareholding change in the accused peer* by subtracting the percentage of shares an investor held in the quarter before the accusation event from the percentage of shares that the investor held in the quarter following the accusation event; both terms were scaled by the outstanding shares in the respective quarters. This variable accounts for potential asset substitution between the accused peer and the non-accused firm. Finally, we controlled for the investor's *shareholding in the non-accused firm* and *shareholding in the accused peer*, both measured in the quarter prior to the accusation event. The magnitude of the initial holding can affect investors' change in holdings following the accusation event. In particular, greater shareholding in the non-accused firm (accused peer) prior to the accusation may lead investors to increase their subsequent holdings to a lower (greater) extent following the accusation in light of their portfolio diversification strategies (Duchin and Levy, 2009).

Model Specification

To test Hypotheses 1 and 2, we ran OLS regressions using the CAR of the non-accused firm as the dependent variable. This allowed us to test the cross-sectional predictions based on the market overlap between the accused peer and non-accused firms while controlling for their characteristics. To examine the extent to which the CAR reflects stigma or competition effects, we estimated the model $CAR_{ij} = \alpha_{ij} + \beta_1 X_{ij} + \beta_2 X_{ij}^2 + \beta_3 Z_{ij} + \varepsilon_{ij}$, where CAR_{ij} is the cumulative abnormal return for the non-accused firm i in the three days surrounding the accusation event of peer j, X_{ij} is the market overlap between i and j at that time, Z_{ij} is the vector of control variables, and ε_{ij} is the error term. Standard errors were heteroskedasticity-robust and clustered on the non-accused firm (Paruchuri and Misangyi, 2015; Joe and Oh, 2018). When testing Hypothesis 1, we relied on market overlap at the intermediate level (Zahavi and Lavie, 2013; Stettner and Lavie, 2014) and examined whether the linear term of *intermediate market overlap* is negative while its quadratic term is positive. When testing Hypothesis 2, we compared the *coarse market overlap* to the *fine-grained market overlap*. At each level, we ran a Stata utest procedure for the standardized beta coefficient of market overlap, which compares the slopes at the minimum and maximum levels of market overlap (Lind and Mehlum, 2010). Hypothesis 2 gains support if the difference between the declining slope at minimum market overlap and the increasing slope at maximum market overlap decreases when shifting from the coarse to the fine-grained market classification.

Per Hypothesis 3, we expect a positive effect of investor sophistication on the change in the investor's shareholding in the non-accused firm. We also expect market overlap based on the fine-grained market classification to positively moderate this effect for more sophisticated investors. We ran OLS regressions estimating the model *shareholding change in non-accused firm*$_{ijk} = \alpha_{ijk} + \beta_1 S_{Mk} + \beta_2 S_{Mk} \times X_{Fij} + \beta_3 (1 - S_{Mk}) \times X_{Iij} + \beta_3 Z_{ijk} + \varepsilon_{ijk}$, where

shareholding change in non-accused firm$_{ijk}$ is the dependent variable capturing the change in shareholding of investor *k* in non-accused firm *i* in the quarters surrounding the accusation event of industry peer *j*, X_{Fij} is the market overlap at the fine-grained level between *i* and *j* at that time, X_{Iij} is the corresponding market overlap at the intermediate level, S_{Mk} is a dummy variable indicating whether the investor is more sophisticated, Z_{ijk} is the vector of control variables, and ε_{ijk} is the error term. Standard errors were heteroskedasticity-robust and clustered on the non-accused firm.

RESULTS

Table A1 in the Online Appendix (http://journals.sagepub.com/doi/suppl/10.1177/00018392211020662) details the means, standard deviations, and correlations of the variables that served for testing Hypotheses 1 and 2. The average CAR was –1.981 percent ($p = 0.000$) for the non-accused firms and –30.844 percent ($p = 0.001$) for the accused peers. On average, non-accused firms lost $78.006 million and accused peers lost $447.433 million in market value. Although the negative CAR for the non-accused firm is much smaller than that of its accused peer, this loss suggests that, on average, the stigma effect is stronger than the competition effect. Our descriptive statistics also reveal that the intermediate market overlap was negatively correlated with the CAR of the non-accused firm ($r = –0.047$) but positively correlated with the CAR of the accused industry peer ($r = 0.106$).

Table 1 reports our regression results for Hypotheses 1 and 2. The maximum VIF index reached 3.92, below the threshold level of 10 (Kleinbaum, Kupper, and Muller, 1998). Model 1 is the baseline model with controls. The non-accused firm's CAR increases when the firm and the accused peer are listed in the same state ($\beta = 1.488$, $p = 0.036$) and with their difference in R&D expenses ($\beta = 4.789$, $p = 0.041$) but falls when they ally with the same partners ($\beta = –0.219$, $p = 0.012$) and with increasing co-movement of their historical stock prices ($\beta = –1.726$, $p = 0.004$).[13] On average, a one-standard-deviation increase in differences in their R&D expenses led to a $21.419 million gain in market value for the non-accused firm, while a one-standard-deviation increase in their number of shared partners led to a $22.944 million loss. In turn, headquarters in the same state led to a $56.434 million gain in value to the non-accused firm. Additionally, the accused peer's CAR has a negative effect on the firm's CAR ($\beta = –0.037$, $p = 0.000$). The non-accused firm's CAR is positively related to the time elapsed since a previous misconduct accusation against another industry peer ($\beta = 0.009$, $p = 0.025$) and the accused peer's

[13] Our findings hold despite this co-movement effect, which suggests that they cannot be attributed to rebalancing of the investment portfolio. In auxiliary analysis we also find no evidence of a curvilinear effect of this control variable, probably because we already account for various aspects of similarity between the firm and its accused peer. Furthermore, in the analysis of investors' shareholdings (see Table 2), we find no negative association between an increase in stock ownership in the non-accused firm and increase in stock ownership in the accused peer, while controlling for the investor's stock ownerships in the accused peer and in the non-accused firm in the quarter prior to the accusation. This suggests that the portfolio diversification strategies of institutional investors are not merely based on substituting the holdings of accused peers with non-accused firms. Overall, we can rule out portfolio rebalancing as an alternative explanation for our reported findings.

Table 1. Regression of Non-accused Firm's CAR on Market Overlap at Three Levels of Granularity (N = 2,759)

Non-accused Firm's CAR	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intermediate market overlap		–1.300^{+}	–6.458$^{••}$				
		(0.666)	(2.272)				
Intermediate market overlap^2			5.836$^{•}$				
			(2.326)				
Coarse market overlap				–1.509$^{••}$	–3.491		
				(0.554)	(2.501)		
Coarse market overlap^2					1.884		
					(2.380)		
Fine-grained market overlap						–1.033	–6.485$^{•}$
						(1.059)	(2.794)
Fine-grained market overlap^2							7.163$^{•}$
							(3.302)
Segments overlap	–0.161	–0.085	0.095	–0.062	–0.046	–0.122	0.018
	(0.854)	(0.860)	(0.870)	(0.860)	(0.861)	(0.859)	(0.872)
Sales difference	0.017	0.023	0.041	0.067	0.077	0.018	0.019
	(0.140)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)	(0.139)
Age difference	–0.007	–0.004	–0.007	–0.007	–0.010	–0.005	–0.008
	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.033)	(0.034)
ROA difference	0.362	0.319	0.194	0.369	0.338	0.350	0.303
	(1.034)	(1.041)	(1.037)	(1.040)	(1.035)	(1.039)	(1.040)
MTBV difference	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
R&D difference	4.789$^{•}$	5.138$^{•}$	5.190$^{•}$	4.835$^{•}$	4.760$^{•}$	4.868$^{•}$	4.945$^{•}$
	(2.334)	(2.341)	(2.328)	(2.333)	(2.330)	(2.332)	(2.317)
Solvency difference	0.033	0.031	0.033	0.032	0.031	0.032	0.033
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
Same stock exchange	0.464	0.437	0.422	0.356	0.361	0.449	0.448
	(0.407)	(0.407)	(0.407)	(0.411)	(0.411)	(0.410)	(0.409)
Same state	1.488$^{•}$	1.468$^{•}$	1.508$^{•}$	1.616$^{•}$	1.612$^{•}$	1.491$^{•}$	1.473$^{•}$
	(0.706)	(0.707)	(0.706)	(0.700)	(0.700)	(0.706)	(0.706)
Stock price co-movement	–1.726$^{••}$	–1.584$^{••}$	–1.443$^{•}$	–1.431$^{•}$	–1.453$^{•}$	–1.673$^{••}$	–1.548$^{•}$
	(0.596)	(0.604)	(0.615)	(0.616)	(0.617)	(0.600)	(0.604)
Director interlocks	0.307	0.277	0.227	0.195	0.150	0.351	0.391
	(1.996)	(1.934)	(1.898)	(1.950)	(1.947)	(1.976)	(1.957)
Joint alliances	0.041	0.110	–0.001	0.015	0.019	0.103	0.065
	(0.541)	(0.544)	(0.536)	(0.538)	(0.540)	(0.553)	(0.552)
Shared alliance partners	–0.219$^{•}$	–0.191$^{•}$	–0.183$^{•}$	–0.189$^{•}$	–0.188$^{•}$	–0.204$^{•}$	–0.201$^{•}$
	(0.087)	(0.086)	(0.086)	(0.087)	(0.087)	(0.086)	(0.084)
Accused peer CAR	–0.037$^{•••}$	–0.036$^{•••}$	–0.037$^{•••}$	–0.035$^{•••}$	–0.035$^{•••}$	–0.037$^{•••}$	–0.037$^{•••}$
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Time since previous accusation	0.009$^{•}$	0.008$^{•}$	0.007^{+}	0.007^{+}	0.007^{+}	0.009$^{•}$	0.008$^{•}$
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Accused peer segments	–0.215	–0.227	–0.222	–0.206	–0.211	–0.227	–0.218
	(0.463)	(0.463)	(0.465)	(0.462)	(0.462)	(0.463)	(0.464)
Accused peer sales	–0.149	–0.085	–0.125	–0.141	–0.151	–0.114	–0.105
	(0.116)	(0.121)	(0.121)	(0.117)	(0.117)	(0.121)	(0.122)
Accused peer age	0.415$^{•••}$	0.423$^{•••}$	0.420$^{•••}$	0.417$^{•••}$	0.417$^{•••}$	0.420$^{•••}$	0.422$^{•••}$
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Accused peer ROA	2.772^{+}	2.949^{+}	3.182$^{•}$	3.340$^{•}$	3.391$^{•}$	2.793^{+}	2.906^{+}
	(1.526)	(1.529)	(1.538)	(1.543)	(1.541)	(1.525)	(1.532)
Accused peer MTBV	–0.076$^{•••}$	–0.074$^{•••}$	–0.073$^{•••}$	–0.068$^{•••}$	–0.069$^{•••}$	–0.076$^{•••}$	–0.075$^{•••}$
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
Accused peer R&D	–2.632	–1.808	–0.859	–1.043	–0.757	–2.439	–1.777
	(3.412)	(3.477)	(3.546)	(3.490)	(3.468)	(3.419)	(3.476)

(continued)

Table 1. (continued)

Non-accused Firm's CAR	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Accused peer solvency	–0.029	–0.023	–0.019	–0.024	–0.020	–0.026	–0.024
	(0.042)	(0.043)	(0.043)	(0.043)	(0.044)	(0.042)	(0.043)
Non-accused firm segments	–0.230	–0.230	–0.262	–0.220	–0.231	–0.230	–0.239
	(0.245)	(0.244)	(0.243)	(0.247)	(0.248)	(0.245)	(0.243)
Non-accused firm sales	0.444••	0.426••	0.453••	0.449••	0.446••	0.440••	0.445••
	(0.146)	(0.146)	(0.144)	(0.147)	(0.146)	(0.146)	(0.145)
Non-accused firm age	0.024	0.022	0.023	0.021	0.022	0.023	0.024
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Non-accused firm ROA	0.958	0.964	0.873	1.063	1.036	0.948	0.949
	(0.994)	(0.999)	(0.989)	(0.995)	(0.994)	(0.999)	(0.996)
Non-accused firm MTBV	–0.012+	–0.013+	–0.012+	–0.013+	–0.013+	–0.012+	–0.012+
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Non-accused firm R&D	1.698	1.508	1.477	1.818	1.898	1.733	1.668
	(2.129)	(2.129)	(2.110)	(2.149)	(2.137)	(2.131)	(2.123)
Non-accused firm solvency	–0.198••	–0.188••	–0.200••	–0.204••	–0.208••	–0.191••	–0.194••
	(0.068)	(0.067)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
Intercept	–6.650•••	–6.914•••	–6.616•••	–6.069•••	–5.832•••	–6.878•••	–6.932•••
	(1.693)	(1.714)	(1.712)	(1.717)	(1.713)	(1.722)	(1.731)
R^2	0.070	0.071	0.073	0.072	0.072	0.070	0.071
F-statistic	8.048	7.939	8.091	8.358	8.087	7.874	7.983

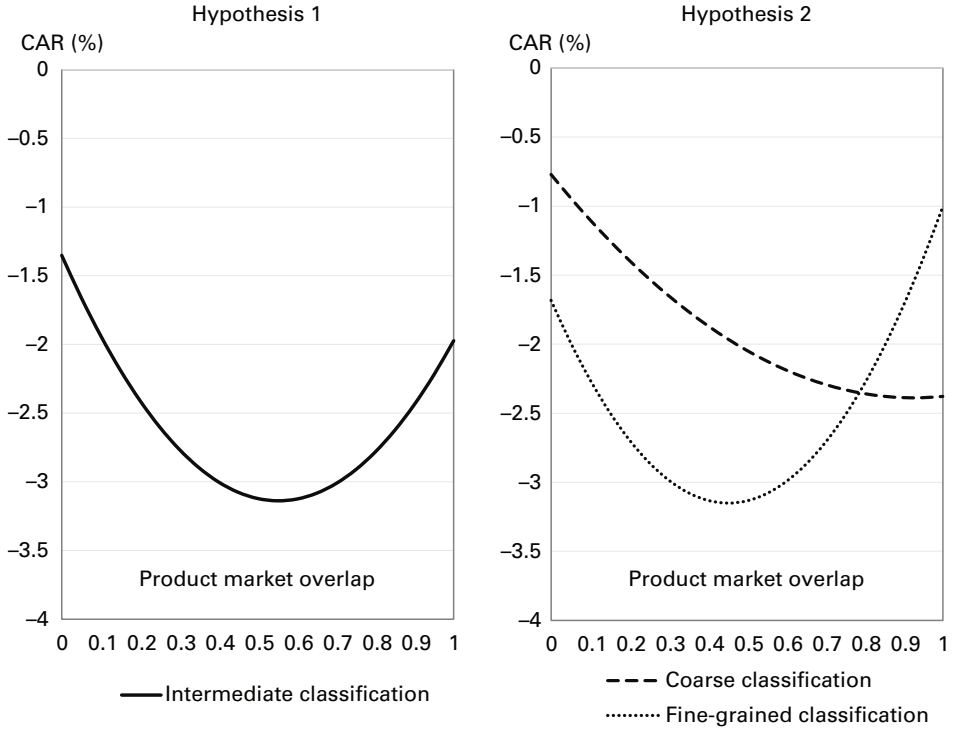
+ $p < 0.10$; • $p < 0.05$; •• $p < 0.01$; ••• $p < 0.001$.

* Standard errors in parentheses are clustered on non-accused firms.

age ($\beta = 0.415$, $p = 0.000$) but negatively associated with the peer's MTBV ($\beta = –0.076$, $p = 0.000$). It is positively related to the firm's sales ($\beta = 0.444$, $p = 0.003$) but negatively related to its solvency ($\beta = –0.198$, $p = 0.004$).

Model 2 introduces the linear effect of market overlap at the intermediate market classification. As this model reveals, the coefficient for the market overlap is negative ($\beta = –1.300$, $p = 0.052$), lending more support to stigma than to competition. Model 3 serves for testing Hypothesis 1 after including the quadratic effect of market overlap at the intermediate market classification. Hypothesis 1 suggested that the market overlap between a non-accused firm and its accused industry peer would exhibit a U-shaped effect on the non-accused firm's CAR. As reported in model 3, the linear term of market overlap is negative ($\beta = –6.458$, $p = 0.005$) and its quadratic term is positive ($\beta = 5.836$, $p = 0.013$), granting support to this hypothesis. The inflection point occurs at a market overlap of 0.553 (within range), where the CAR reaches a minimum of –3.138 percent; see Figure 3. We corroborated the presence of the U-shaped pattern using the utest procedure in Stata (Lind and Mehlum, 2010), which shows that both slopes are different from 0 (negative slope = –6.458, $p = 0.002$; positive slope = 5.215, $p = 0.022$). Accordingly, a one-standard-deviation increase in market overlap from 0.259 (the mean) to 0.592 led to a 0.498 percentage point decrease in the non-accused firm's CAR, or $18.885 million loss in market value, whereas a two-standard-deviation increase in market overlap to 0.926 led to a 0.802 percentage point increase in CAR, or a gain of $30.424 million in market value for the non-accused firm.

Figure 3. Observed Association between CAR and Product Market Overlap



Finally, models 4 and 5 report the effects of market overlap using the coarse market classification, while models 6 and 7 report its effects using the fine-grained classification. We tested Hypothesis 2 by comparing these models. Hypothesis 2 predicted that the more fine-grained the classification, the weaker the stigma effect and the stronger the competition effect would become as the market overlap increases. This implies that the increase in CAR beyond the inflection point would become stronger, relative to the decline in CAR below that inflection point, as the market classification shifts from coarse to fine-grained.

In model 4, the market overlap relies on a coarse market classification, and its effect on the non-accused firm's CAR is negative (β = –1.509, p = 0.007). When its quadratic term is added in model 5, neither the linear term nor the quadratic term is significant, suggesting that the competition effect cannot be observed at that level of granularity. A utest rejects the presence of a U-shaped pattern, suggesting that model 4 should be used for testing Hypothesis 2. In model 6, we tested the linear effect of market overlap at the fine-grained market classification and found it insignificant (β = –1.033, p = 0.331). In model 7, when its quadratic term is added, both the linear (β = –6.485, p = 0.021) and the quadratic (β = 7.163, p = 0.031) terms are significant, suggesting a U-shaped effect of market overlap on the non-accused firm's CAR. The inflection point falls within range (market overlap = 0.453), where the CAR reaches a minimum of –3.150 percent. We verified the presence of the U-shape with a utest (negative slope = –6.485, p = 0.011; positive slope = 7.840, p = 0.031).

Next, we calculated the difference between the absolute values of the slopes at maximum and minimum market overlap, corresponding to regression models reporting standardized coefficients, and then compared model 4 (coarse classification) to model 7 (fine-grained classification). For the coarse market classification, the utest reports no positive slope at maximum market overlap, so the absolute value of the negative slope at minimum market overlap equals –|(–0.137)| = –0.137. For the fine-grained market classification, the difference between the absolute values of the positive slope at maximum market overlap and the negative slope at minimum market overlap (as reported by the utest procedure) equals |(0.164)| –|(–0.136)| = 0.028. Hypothesis 2 gains support based on these results, because the slope corresponding to the competition effect becomes steeper relative to that of the stigma effect when the market overlap measure shifts from coarse to fine-grained classification.

Figure 3 plots the effects of market overlap for the coarse and fine-grained classifications while holding other variables at their mean values. It shows how the increase in a non-accused firm's CAR at high levels of market overlap (dominant competition effect) becomes steeper relative to the decline in CAR at low levels of market overlap (dominant stigma effect) as the classification shifts from coarse to fine-grained. At the fine-grained classification, despite high market fragmentation (76.368 competitors per firm on average), we observe the strongest competition effect, which offsets the stigma effect for close competitors with market overlap larger than 0.905. This corresponds to 5.666 close competitors per accused peer, which is the typical number of major competitors identified by managers (Clark and Montgomery, 1999). See robustness tests in the Online Appendix.

Table A2 in the Online Appendix details the means, standard deviations, and correlations of the variables that served for testing Hypothesis 3. To test this hypothesis, we examined the changes in quarterly shareholdings of institutional investors in non-accused firms following the accusation event. Table 2 reports our regression results. Model 1 reveals that investors that had greater shareholdings in the non-accused firm increase their shareholdings to a lesser extent following the accusation (β = –0.119, p = 0.000), and those that had greater shareholdings in the accused peer increase their shareholdings in the non-accused firm to a greater extent (β = 0.035, p = 0.003). Additionally, shareholdings in the non-accused firm decline with the ROA difference between the firms (β = –0.027, p = 0.030) but increase with their number of interlocked directors (β = 0.031, p = 0.035). Increases in shareholdings in the non-accused firm are also related to the accused peer's ROA (β = –0.037, p = 0.026) and to the non-accused firm's age (β = 0.001, p = 0.053). Model 2 reports consistent findings under the assumption that institutional investors rely on a fine-grained market classification rather than intermediate market classification, exhibiting a positive effect of market overlap on increase in shareholdings (β = 0.030, p = 0.013).[14]

[14] The effect of market overlap is positive rather than U-shaped as predicted by Hypothesis 1 because the sample for testing Hypothesis 3 includes only large institutional investors while excluding most of the investors, in particular, the least sophisticated retail investors and small institutional investors. Per our theory, the omitted investors, on aggregate, are likely to exhibit a trading behavior that is consistent with our predicted U-shape, so their exclusion does not allow us to observe how the shareholding in a non-accused firm declines with market overlap.

Table 2. Regression on Change in Investor Shareholding in Non-accused Firms (N = 151,062)

Shareholding Change in Non-accused Firm	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Investor sophistication			0.035••	0.035••	0.030••	0.024•	0.031••		
			(0.011)	(0.011)	(0.010)	(0.011)	(0.011)		
Investor sophistication × Contingent market overlap					0.047•				
					(0.018)				
Contingent market overlap					0.000				
					(0.010)				
Investor sophistication × Intermediate market overlap						0.043••			
						(0.015)			
Investor sophistication × Fine-grained market overlap							0.035•		
							(0.017)		
Mutual funds & hedge funds								–	–
Banks								–0.027•	–0.016
								(0.012)	(0.011)
Insurance firms								–0.024+	–0.015
								(0.012)	(0.013)
Independent advisors								–0.041•••	–0.027••
								(0.009)	(0.009)
Other investors								–0.047••	–0.037+
								(0.017)	(0.022)
Bank × Intermediate market overlap									–0.039
									(0.024)
Insurance × Intermediate market overlap									–0.033•
									(0.015)
Independent advisor × Intermediate market overlap									–0.051•••
									(0.015)
Other investors × Intermediate market overlap									–0.034
									(0.025)
Intermediate market overlap	0.019+		0.018+			0.003		0.018+	0.046••
	(0.011)		(0.011)			(0.011)		(0.011)	(0.016)
Fine-grained market overlap		0.030•		0.029•			0.017		
		(0.013)		(0.013)			(0.012)		
Segments overlap	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Sales difference	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002	–0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age difference	–0.001+	–0.001+	–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)	(0.000)	(0.000)
ROA difference	–0.027•	–0.026•	–0.026•	–0.025•	–0.025•	–0.026•	–0.025•	–0.026•	–0.026•
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
MTBV difference	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D difference	–0.007	–0.006	–0.009	–0.007	–0.004	–0.008	–0.007	–0.007	–0.006
	(0.040)	(0.039)	(0.040)	(0.039)	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)
Solvency difference	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)	(0.001)
Same stock exchange	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Same state	–0.004	–0.005	–0.005	–0.005	–0.006	–0.005	–0.005	–0.005	–0.005
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Stock price co-movement	–0.002	–0.002	–0.002	–0.002	–0.001	–0.002	–0.002	–0.002	–0.002
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Director interlocks	0.031•	0.030•	0.030•	0.029•	0.029•	0.030•	0.029•	0.030•	0.029•
	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)
Joint alliances	0.003	0.002	0.003	0.002	0.002	0.003	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Shared alliance partners	–0.001	–0.001	–0.001	–0.001	–0.000	–0.001	–0.001	–0.001	–0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Shareholding change in accused peer	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Shareholding in accused peer prior to event	0.035••	0.035••	0.034••	0.034••	0.034••	0.035••	0.034••	0.034••	0.034••
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Time since previous accusation	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accused peer segments	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Accused peer sales	0.002	0.001	0.002	0.001	0.002	0.002	0.001	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

(continued)

Table 2. (continued)

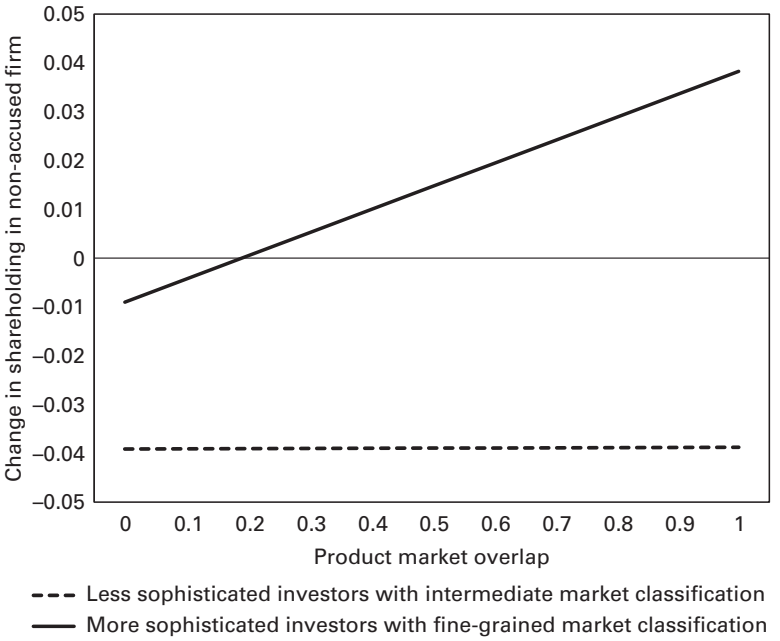
Shareholding Change in Non-accused Firm	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Accused peer age	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accused peer ROA	–0.037•	–0.036•	–0.037•	–0.035•	–0.034•	–0.036•	–0.035•	–0.037•	–0.036•
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)
Accused peer MTBV	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accused peer R&D	0.051	0.054	0.050	0.052	0.057	0.051	0.053	0.049	0.051
	(0.037)	(0.040)	(0.037)	(0.040)	(0.038)	(0.037)	(0.040)	(0.037)	(0.037)
Accused peer solvency	–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)	(0.001)
Shareholding in non-accused firm prior to event	–0.119•••	–0.119•••	–0.120•••	–0.120•••	–0.120•••	–0.120•••	–0.120•••	–0.120•••	–0.120•••
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Non-accused firm segments	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Non-accused firm sales	–0.005	–0.005	–0.005	–0.005	–0.005	–0.005	–0.005	–0.004	–0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Non-accused firm 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)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-accused firm ROA	0.006	0.008	0.006	0.008	0.008	0.006	0.008	0.006	0.006
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)
Non-accused firm MTBV	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-accused firm R&D	–0.014	–0.020	–0.012	–0.018	–0.018	–0.012	–0.018	–0.015	–0.015
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)
Non-accused firm solvency	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intercept	0.037	0.042	0.024	0.029	0.028	0.028	0.030	0.058	0.051
	(0.037)	(0.038)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.042)	(0.041)
R^2	0.066	0.066	0.067	0.067	0.067	0.067	0.067	0.067	0.067
F-statistic	8.083	8.240	8.104	8.235	8.130	7.888	7.994	10.385	12.415

+ $p < 0.10$; • $p < 0.05$; •• $p < 0.01$; ••• $p < 0.001$.

* Standard errors in parentheses are clustered on non-accused firms.

Models 3 and 4 introduce the investor sophistication variable, suggesting that more sophisticated investors tend to increase their shareholdings in the non-accused firm following the accusation more than less sophisticated investors ($\beta = 0.035$, $p = 0.001$). This is consistent with Hypothesis 3 that predicted that more sophisticated investors are better able to identify opportunities to invest in non-accused firms that compete with accused peers and minimize unwarranted generalized evaluations, resulting in a more dominant competition effect. This result holds regardless of whether investors rely on the intermediate (model 3) or fine-grained (model 4) market classification for assessing market overlap, as well as in model 5 in which we introduce the moderating effect of market overlap. In this model, we moderate the effect of investor sophistication with a measure of contingent market overlap, using fine-grained market overlap for more sophisticated investors and intermediate market overlap for less sophisticated investors. In line with Hypothesis 3, we find that more sophisticated investors increase their shareholdings in non-accused firms compared with less sophisticated investors ($\beta = 0.030$, $p = 0.006$), with further increases in such shareholdings as the fine-grained market overlap between the accused peer and non-accused firm increases ($\beta = 0.047$, $p = 0.011$). In turn, the corresponding moderation effect of intermediate market overlap for less sophisticated investors is insignificant. Figure 4 depicts this

Figure 4. Shareholdings in Non-accused Firms by Market Overlap and Investor Sophistication



moderating effect, revealing how more sophisticated investors increase their shareholdings in the non-accused firms more than less sophisticated investors do and that this difference widens with increases in market overlap. For a one-standard-deviation increase in market overlap, on average, more sophisticated investors increased their shareholding in non-accused firms by $11.678 million, while less sophisticated investors did not significantly increase their shareholding.

Next, in models 6 and 7 we correspondingly assumed that all institutional investors rely on either intermediate or fine-grained market classification when assessing firms' market overlap. Both models reveal a positive main effect of investors' sophistication ($\beta = 0.024$, $p = 0.011$; $\beta = 0.031$, $p = 0.011$) and a positive interaction effect of investor sophistication with market overlap ($\beta = 0.043$, $p = 0.004$; $\beta = 0.035$, $p = 0.038$). Finally, in models 8 and 9 we replaced our investor sophistication variable with a series of dummy variables relating to different types of investors, including banks, insurance firms, investment advisors, and others (e.g., pension funds and endowments). As evidenced in the corresponding results, all of these investor types were less likely to increase their investments in non-accused firms compared with hedge funds and mutual funds, and these differences increased with intermediate market overlap that corresponds to less sophisticated investors, in line with Hypothesis 3. This analysis demonstrates the distinctive sophistication of mutual funds and hedge funds compared with all other types of institutional investors. We conducted several robustness tests, such as portfolio analyses in which we examined whether more sophisticated investors outperform less

sophisticated investors when investing in the non-accused firms (see the Online Appendix).

DISCUSSION

"Stigma by Association" versus "Gain by Misfortune"

An industry peer's financial misconduct can generate either positive or negative spillovers to non-accused firms. Understanding these spillovers calls attention to the underlying mechanisms. Our theory discerns two mechanisms: the stigma effect, which generates negative spillover, and the competition effect, which yields positive spillover.

Prior research has mostly underscored the stigma effect, paying almost no attention to the competition effect (Jonsson, Greve, and Fujiwara-Greve, 2009; Diestre and Rajagopalan, 2014; Durand and Vergne, 2015; Paruchuri and Misangyi, 2015; Naumovska and Zajac, 2021).[15] Our study is the first to simultaneously consider the stigma and competition effects ascribed to financial misconduct within an industry, and thus it sheds new light on the relative prevalence of these conflicting effects and the resulting net spillover that they generate to non-accused firms. By considering the market overlap between the non-accused firm and its accused peer, we reconcile the two opposing views on the nature of the spillover and explain heterogeneity across non-accused firms, some of which are more susceptible to "stigma by association" while others enjoy more "gain by misfortune." We provide theory and a method for analyzing the duality of generalization and competition judgments, which are simultaneously embodied in the spillovers to non-accused firms.

On average, investors negatively assess non-accused firms in the accused peer's industry (Paruchuri and Misangyi, 2015), suggesting that the stigma effect dominates the competition effect. Yet we find that the net effect of stigma versus competition varies depending on the market overlap between each non-accused firm and its accused peer. The negative spillover increases with product market overlap, but beyond a certain level it gives way to positive spillover attributed to the intensifying competition effect. Accordingly, we explain how financial misconduct leads to undeserved loss for some non-accused firms but at the same time creates benefits for others that are close rivals of the accused peer. In other words, the competition effect offsets the stigma effect for a select group of the accused peer's closest competitors. For those non-accused firms, the negative spillover resulting from "stigma by association" is offset by the "gain by misfortune." We also show that among more

[15] Two recent studies suggest a positive spillover to category members in contexts other than financial misconduct. Paruchuri, Pollock, and Kumar (2019) reported a reputation spillover for Mexican restaurants in the aftermath of Chipotle's E. coli outbreak in Seattle, arguing that this positive spillover was related to specific practices that differentiated the accused peer from other firms in its industry. Such a failure in practices differs from the integrity failure associated with financial misconduct, which has been shown to produce negative spillover. We contend that financial misconduct can also trigger positive spillover that is ascribed to the weakened competitive position of the accused peer. In another study, Piazza and Jourdan (2018) showed how the publicity for scandals in the Catholic Church increased membership in non-Catholic denominations. Although they revealed a positive spillover, they focused on the country level without considering how spillovers varied with the rivalry between non-accused churches and their accused peer. Both studies suggest a need for a differentiating factor to shield the firm from stigma, but our study reveals that the competition effect can offset the stigma effect irrespective of such a mitigant.

sophisticated investors the competition effect is more pronounced than the stigma effect.

We respond to the recent call to study how heterogeneity in classification systems and audiences shapes evaluation processes (Durand and Boulongne, 2017; Boulongne, Cudennec, and Durand, 2019). We do so by demonstrating that the granularity of the classification system and investors' sophistication influence the evaluation of non-accused firms, which drives the interplay of the stigma and competition effects. While we focus on prototype-based categorization—the grouping of entities based on shared attributes—scholars may also consider goal- and causal-based categorization (Durand and Paolella, 2013). If audiences engage in distinct categorization processes, investors may consider not only similarity but also goals and causal explanations when making generalized evaluations (Arjaliès and Durand, 2019). For example, categorization rooted in causal explanations may make some non-accused firms stronger recipients of stigma by association while some accused firms become stronger transmitters of such stigma (Naumovska and Zajac, 2021).

Additionally, our study addresses the concern that classification systems that are frequently used for categorizing firms, such as the North American Industry Classification System (NAICS) and SIC, are relatively coarse (e.g., Porac, Thomas, and Baden-Fuller, 1989). We do so by showing how the granularity of the market classification influences the observed spillovers to non-accused firms. We reveal that the composite U-shaped effect of stigma and competition tilts depending on the granularity of the classification used for assessing the market overlap between firms. Using a more fine-grained classification uncovers a more dominant competition effect that counterbalances the stigma effect.

Competitive Reactions to a Peer's Unethical Behavior

Our study also informs research on competitive dynamics. While scholars have traditionally focused on competitive actions such as price cuts and quality improvements that intentionally aim to enhance a firm's position vis-à-vis a particular competitor (e.g., Ferrier, 2001; Kilduff, Elfenbein, and Staw, 2010), we show that actions outside of that competitive repertoire, such as accusations of financial misconduct, can also influence a firm's relative position vis-à-vis its competitor as a result of stakeholder attrition and loss of market share. Hence, we suggest that firms should anticipate and respond not only to the competitive actions of their industry peers but also to their unethical behavior, which can affect performance much like competitive actions can. This insight advances recent research that shows how critical corporate events that affect a firm's rivals but are not aimed at specific competitors can still trigger competitive reactions (Guo, Yu, and Sengul, 2020). We find that the nature of these reactions depends on the similarity between firms and the granularity of the market classification used for assessing that similarity.

Studying reactions to the accusations against industry peers is beyond the scope of our study, yet we found no reference to the misconduct of accused peers in press releases issued by non-accused firms. This is probably because such actions are not publicly disclosed. Nevertheless, given that some non-accused firms are more susceptible to the stigma effect while others are more sensitive to the competition effect, their reactions can generate various consequences. Particularly intriguing is the notion that reactions to an industry

peer's misconduct entail tradeoffs. While some actions may buffer a firm from stigma (e.g., disassociating or underscoring differences from that peer), they can simultaneously undermine the firm's competitive position relative to that peer if the non-accused firm would be considered a viable substitute. Correspondingly, actions that enhance a firm's competitive position relative to an accused peer (e.g., underscoring a willingness to accommodate the peer's customers and respect its commitments toward them) may unintentionally reinforce stigma by association and result in performance decline.

Future research may study non-accused firms' reactions to the accusation against their industry peer. Such research may also examine whether the accused peers and social control agents attempt to implicate non-accused firms (Hannigan et al., 2020), although we observed no speculation in the media concerning possible misconduct by non-accused firms. We also did not observe significant implications for enforcement actions that follow the initial accusation, but future research may consider how indictments, convictions (or acquittals), and punishments that follow the accusation can shape the stigma versus competition effects.

Moreover, our findings reveal implications of the granularity of the market classification used for comparing firms. Somewhat counterintuitively, close competitors of an accused peer should underscore the similarity of their products at a fine-grained level of market classification, so that the positive spillover ascribed to the competition effect can offset the negative spillover ascribed to the stigma effect. In contrast, firms that do not compete directly with the accused peer would be advised to emphasize the dissimilarity of their products at a coarse level of market classification, as this may weaken the stigma effect.

Investors' Sophistication and Their Use of Classification Systems

Our study advances research on industry categories, according to which industries represent both cognitive taxonomies and competitive landscapes (Porac, Thomas, and Baden-Fuller, 1989). This research assumes that industries serve as an effective means for categorizing firms and thus generate spillovers because stakeholders are familiar with this classification system and because the structural characteristics that delineate firms into industries are assumed to be objective. While industry categories are relevant, we shift focus to the categories that form within an industry around subsets of firms whose markets overlap (Vergne and Wry, 2014). By shifting focus to a more refined classification system, we enhance understanding of the cognitive processes that guide generalized evaluations and competitive interactions.

The granularity of the classification system used by investors is discretionary and depends on their industry knowledge of and proficiency with the firm's products. In line with the notion of competitor acumen (Tsai, Su, and Chen, 2011), our study shows the importance of having more accurate perceptions of competitors' characteristics and behaviors. Furthermore, we qualify that discerning competitors requires a fine-grained lens, while perceiving firms' propensity to engage in misconduct following an accusation against a peer tends to rely on a coarse lens. Hence, we contribute by showing that the stigma effect is easily observed by investors using a coarse market classification, while the competition effect requires a ''magnifying glass'' available to sophisticated investors.

Indeed, sophisticated investors such as mutual funds and hedge funds are better able to discern investment opportunities in non-accused firms that compete directly with the accused peer, while being less responsive to stigma by association that yields unwarranted generalizations. In our analysis, we assumed that mutual funds and hedge funds rely on a fine-grained market classification, whereas other types of institutional investors rely on an intermediate market classification. We reveal that, compared with less sophisticated institutional investors, the most sophisticated investors increase their shareholding in a non-accused firm to a greater extent as its market overlap with the accused peer increases. Because this analysis excludes most of the least sophisticated investors that rely on a coarse market classification, it effectively captures the competition effect.

However, when accounting for all the investors, including the unsophisticated ones, we observe a U-shaped association between these firms' stock market reaction and their product market overlap with the accused peer. This is because when investors are on average less sophisticated, the competition effect becomes less pronounced compared with the stigma effect as the market overlap with the accused peer increases. With the democratization of stock market trading and the rise of trading platforms such as Reddit, one may expect to observe a more pronounced stigma effect, leading to a more negative association with market overlap in the aftermath of financial misconduct by industry peers. Future research may use surveys and other means (e.g., Jenkinson and Jones, 2009; Csaszar and Laureiro-Martinez, 2018) to more accurately measure the cognitive maps or mental representations of individual investors who assess firms' market overlap.

We believe that prior research on corporate misconduct has mostly demonstrated the stigma effect, without evidence of the competition effect, because it relied on coarse classification systems for categorizing firms. We encourage future research to consider the granularity of the classification system and its implications. For example, scholars may consider how firms imitate their industry peers as a function of their market overlap and how such imitation dynamics vary with the granularity of the classification system used to measure market overlap (Naumovska, Gaba, and Greve, 2021). Similarly, scholars may identify different reference groups based on alternative classification systems when seeking to understand how firms select their reference groups (Posen et al., 2018), which in turn influence their social aspirations and strategic behavior.

Additional Research Opportunities

Besides demonstrating how a product market overlap constitutes a basis for assessing the stigma and competition effects, we also account for alternative forms of association between the accused peer and the non-accused firm that can shape the spillover. Firms are characterized by "infinite dimensionality" (Cattani, Porac, and Thomas, 2017: 67), which can serve for categorization and assessing their similarity. But not every dimension of similarity invokes the competition effect. We studied product market overlap, which elicits both stigma and competition, yet other dimensions such as similarity in the firms' organization may support generalization without any competitive gains. Scholars may seek to identify other types of association that invoke both stigma and competition effects.

By alluding to the granularity of information investors use for assessing market overlap and making generalized evaluations, we direct attention to interpretative processes. Informational intermediaries can also shape investors' opinions about an accused industry peer and the penalties extended to other non-accused firms (Jonsson, Greve, and Fujiwara-Greve, 2009; Durand and Vergne, 2015). Media coverage of misconduct not only facilitates attention and spillover but may also affect the relative strength of the stigma and competition effects. Future research may examine how the media's framing of the misconduct shapes these effects.

Besides the availability of information and the granularity of the classification, future research may examine other factors that influence the categorization process, such as investors' cognitive abilities and past experience, which can influence their reactions to the misconduct. Scholars may also separate investors' reactions to credibility loss (a first-order concern) from their reactions to stakeholder attrition (a second-order concern). Another extension would involve studying the temporal dynamics of the stigma and competition effects, which can vary over time. Possibly, the competition effect takes more time to manifest and lasts longer than the stigma effect, which may weaken over time.

Our focus on U.S. publicly traded firms in the packaged software industry during the 1990s may limit generalizability, so future research may corroborate our findings in other industries, countries, and periods, considering settings with various intensities of competition. Future research may also consider alternative proxies for market overlap based on resource similarity, geography, or perceived rivalry (Chen, 1996; Diestre and Rajagopalan, 2014), as well as different types of misconduct. We expect stigma and competition effects to coexist for different types of misconduct, as long as they undermine the legitimacy and performance of the accused peer while creating challenges or opportunities for some other firms in the industry. In studying this, scholars should also rely on sufficiently fine-grained measures to capture the competition effect.

To date, research has mostly demonstrated how corporate misconduct penalizes the accused firm, such as in the case of false advertising (Peltzman, 1981), product recalls (Jarrell and Peltzman, 1985), and environmental violations (Karpoff, Lott, and Wehrly, 2005). Further work is needed to study the implications of positive events that can generate spillovers (Fosfuri and Giarratana, 2009), as it is possible that events such as a peer's announcement of increasing dividends invoke the duality of generalization and competition evaluations for other firms in its industry (Firth, 1996).

Our study reveals how the granularity of the lenses used by stakeholders who assess the market overlap between a non-accused firm and its accused peer explains the relative dominance of the stigma versus competition effects and hence the immediate ramifications of the peer's misconduct. Future research may examine the long-term ramifications as uncertainty dissolves and attention shifts to other corporate events. We expect the stigma effect to fade as uncertainty concerning the behavior of the non-accused firm is resolved. In turn, we expect the competition effect to reinforce changes in the competitive positions of the non-accused firm and its accused peer. Given the substantial economic consequences of corporate misconduct, the interplay between ''stigma by association'' and ''gain by misfortune'' offers a fertile ground for future research that should spur interest from both scholars and managers.

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Supplemental Material

Supplemental material for this article can be found in the Online Appendix at http://journals.sagepub.com/doi/suppl/10.1177/00018392211020662.

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