Strategic Corporate Responses to External Shocks and Competitive Pressures

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Xiaohui Liu

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ABSTRACT

This thesis comprises three studies in corporate finance. The first study examines the impact of cyberattacks on a target firm's decision to issue seasoned equity offerings (SEOs, hereafter) and the spillover effect on SEO decisions made by non-attacked peer firms in the same industry. Our findings show that target firms and their peer firms undertake fewer and smaller SEOs in post-attack years. Peer firms are likely to become subsequent victims after a cyber incident has occurred in their industry. Specifically, we find that the negative impact of a cyberattack on peer firms' SEOs is more pronounced when the firms exhibit a higher potential risk of future attacks and have greater visibility. This is because of the perception that these firms present a higher transaction risk than their industry peers. Additionally, we find the negative effect of a cyberattack on peer firms' decisions about SEOs to be more pronounced than for those firms with substantial IT expenditure and cash reserves, because these firms have less necessity to issue equity.

The second study examines the role of acquisitions in determining the adoption of relative performance evaluation (RPE, hereafter) based on CEO compensation among non-merging peers of the acquirer. Our findings show that peer firms exhibit an increased propensity to adopt RPE in their CEO compensation. This strategic move aims to counter competitive pressures induced by an acquisition and defends the company's competitive position in the product market. Our result aligns with RPE theory that suggests that incorporating RPE into CEO compensation incentivizes firms to aggressively improve their relative competitive position.

The third study focuses on the spillover effect of major hurricanes by investigating the impact on the decisions of industry peers of hurricane-hit firms to issue management forecasts. Our findings show that industry peers tend to increase the frequency of their management

forecasts after a major hurricane. This increase in forecast frequency is positively related to firm visibility and changes in market share, suggesting that a major hurricane gives peers an incentive to capitalize on the difficulties faced by hurricane-hit firms. This is achieved by attracting investor attention and enhancing market share.

Overall, the thesis contributes to existing studies on intra-industry spillover effects by providing a comprehensive understanding of how firms not directly involved in a specific event strategically respond to reputation loss, competitive pressure, and opportunities in the post-event era. The thesis offers valuable insights for both researchers and practitioners, shedding light on the complex interplay between external events, competitive pressures, and firms' strategic responses in the ever-evolving corporate environment.

Chapter 1: Introduction

1. Overview

Sun Tzu's timeless adage, if you know the enemy and know yourself, you need not fear the result of a hundred battles, rings especially true in today's era when most businesses are highly interdependent. Firms must not only understand their own strengths and weaknesses but also anticipate and adapt to the challenges and opportunities posed by related firms. This study focuses on the strategic responses of peer firms when a firm in their industry is subjected to a cyberattack, a major hurricane disaster, or an acquisition. The study's findings reveal how peer firms navigate these complex battles to secure victory through financing decisions, compensation design, and corporate disclosure strategies.

2. Equity Offering Following Cyberattacks

In recent decades, the amount of data collected, processed, and stored by corporations has grown exponentially, along with the increasing use of digital technologies. Firms spend 36 billion US dollars annually collecting, storing, and analysing large amounts of customer data (Columbus 2014)[1]. Therefore, a cyberattack is becoming one of the biggest threats for firms and their stakeholders in today's era of electronic technology. The second chapter of the thesis explores how a cyberattack influences the equity financing decisions (i.e., SEOs) of attacked firms and how the impact of a cyberattack spills over to influence the equity financing decisions of peer firms in the same industry.

The literature suggests that an attacked firm experiencing a cyberattack can incur substantial financial costs, such as those associated with detection and remediation, loss of

[1] Columbus, L. 2014. The year Big Data adoption goes mainstream in the enterprise. Forbes (January 12). Available at: https://www.forbes.com/sites/louiscolumbus/2014/01/12/2014-the-year-big-data-adoption-goes-mainstream-in-the-enterprise/#1aad46da2055

brand image, customer trust, and market share (e.g., Huang and Wang., 2021; Kamiya et al., 2021). These circumstances present a dichotomy in the strategic decision-making of target firms. On one side, a cyberattack necessitates immediate remedial actions such as substantial investments in IT security and the acquisition of cybersecurity talent (Haapamäki and Sihvonen, 2019; Bana et al., 2022). These demands may drive attacked firms to raise additional capital through equity issuance. Conversely, the reputation loss associated with a cyberattack signals a heightened risk to investors. Notably, a cyberattack depresses the share price of target firms (Kamiya et al., 2021) and increases their cost of equity financing (e.g., Ashraf, and Sunder, 2023; Elmawazini et al., 2023; Jiang et al., 2022; Sheneman, 2021; Baker and Wurgler, 2002). Consequently, target firms may refrain from issuing new shares after experiencing a cyberattack because of the heightened cost. From this perspective, we find that target firms conduct fewer and smaller SEOs after experiencing cyber incidents.

Firms in the same industry often share similar fundamental characteristics. We provide some evidence showing that peer firms are more likely to become the victims of future cyberattacks following a cyberattack in the industry. In the context of a cyberattack's spillover effects on peer firms' SEO decisions, peer firms may require funding to invest in precautionary measures to mitigate potential cyber risks, prompting them to conduct SEOs following a cyberattack. However, Kamiya et al. (2021) illustrate that a cyberattack negatively impacts not only the share price of the attacked firm but also its peer firms. This suggests that peer firms also suffer from increased costs associated with conducting SEOs. As a result, peer firms may be inclined to reduce their SEO activity following a cyberattack. Consistent with this view, we find that peer firms conduct fewer, smaller SEOs after a cyberattack, indicating that peer firms also prioritize avoiding the increased costs of SEOs over fulfilling their financial needs through SEOs. In the cross-sectional analyses of the spillover effect of a cyberattack, we find that peer firms that are more susceptible to future cyberattacks and with greater visibility decrease the likelihood of conducting SEOs to a greater extent. This is because these peers are perceived to have higher equity issue costs because of potentially higher transaction risks. Furthermore, we find that the negative impact of a cyberattack on a peer firm's SEO is more pronounced when it has sufficient IT investments and cash holdings. This is because such firms rely less on equity financing, thereby reducing their need to conduct SEOs following a cyberattack.

This study makes the following contributions: first, we contribute to the SEO literature by examining how specific events, such as cyberattacks, that simultaneously trigger potentially costly SEOs and create short-term cash needs, affect equity issuances. Though explanations for SEOs are well-documented, the impact of such events on SEO decisions is less well known. We fill this gap by demonstrating that a cyberattack acts as a disincentive for SEOs by showing that firms prioritize concerns over costlier SEOs over investment needs in post-attack years. Second, we complement the growing body of work on cyberattack impacts on firms' corrective and precautionary measures. Prior studies focus on post-attack managerial behaviours and quantifying cyberattack consequences. We diverge by studying the impact of cyberattacks on external equity financing. We provide evidence that a cyberattack significantly reduces a firm's likelihood of making SEO decisions in subsequent years. Finally, we contribute to the broad literature on spillover effects of unanticipated events. Recent research has seen a surge in the exploration of the spillover effects of unanticipated events such as earthquakes, hurricanes, and credit shocks (e.g., Carvalho et al., 2021; Lei et al., 2021; Massa and Zhang, 2021). A related study by Kamiya et al. (2021) illustrates that a cyberattack not only has an adverse impact on the stock price of the target firm but also spills over to affect industry peers. Our study extends Kamiya et al.'s (2021) perspective by indicating that adverse information incorporated by peer firms can escalate their cost of equity issuance, thereby leading to higher costs of equity financing.

3. Competitive Pressure and Relative Performance Evaluation: Evidence from Mergers and Acquisitions

Prevailing theory and conventional wisdom suggest that firms initiating acquisitions gain various advantages, including strategic flexibility, acquisition of new technologies, stimulation of innovative outputs, and reduction of labour costs (e.g., Chatterjee, 1986; Sanchez, 1995; Bena and Li, 2013; Lee et al., 2018). Given the potential competitive advantages an acquirer may gain from an acquisition, it is anticipated that peer firms in the same industry will undertake aggressive actions to counteract these advantages. Both anecdotal and empirical evidence suggest that acquisitions indeed exert competitive pressure on peer firms, representing a spillover effect of an acquisition in terms of competitive pressure. Consequently, peer firms are prompted to behave more aggressively after an acquisition, such as engaging in more advertising and pricing campaigns, to defend their competitive positions. However, the mechanisms motivating CEOs of peer firms to navigate these competitive pressures remain relatively unexplored.

The third study addresses this gap by exploring how peer firms use RPE-based compensation in response to competitive pressures, treating an acquisition as a relatively exogenous competitive shock among peer firms. We specifically focus on RPE-based compensation because, compared with traditional absolute performance evaluation, RPE motivates managers to act aggressively and enhance their firms' relative market position by putting firms in direct competition with their peers. Consistently, we observe that peer firms exhibit an increased propensity to adopt RPE in their CEO compensation after an acquisition. We also quantify the intensity of these competitive pressures induced by an acquisition and provide evidence that a peer firm's propensity to adopt RPE-based compensation increases in the scale of acquisitions regarding the total frequency and total deal value within an industry. To add to the understanding of our baseline findings, we conduct several cross-sectional analyses. Hoberg and Phillips (2012) argue that highly competitive firms with similar products face similar cost and demand shocks, thereby leading to a higher level of stock co-movement. The baseline effect is particularly pronounced when the peer firm and the acquirer exhibit a close co-movement before the acquisition announcement, underscoring the importance of the relevance between the acquirer and the peer firm. In line with Oh and Shin's (2020) argument that acquisitions driven by competition-related purposes are likely to have a more direct impact on the product market, we categorize all acquisitions into two groups based on their intent: competition-related purpose and other purposes. The baseline finding is particularly pronounced when the acquisition is driven by a competition-related purpose rather than other purposes, reinforcing the argument that competition pressure increases peer firms' tendency to adopt RPE compensation. Furthermore, we find that, following an acquisition, peer firms using RPE compensation tend to incur more advertising expenditure and have a lower profit margin than those not using RPE compensation. This supports the effectiveness of RPE compensation in stimulating competitive actions among peer firms in response to a sudden surge in competitive pressure.

This study makes the following contributions: it contributes to the literature on the spillover effects of an acquisition. Motivated by Servaes and Tamayo's (2014) finding that the control threat faced by a hostile takeover's target firm has important spillover effects for industry peers, our findings complement Servaes and Tamayo (2014) by illustrating that the competitive advantages gained by an acquirer also exert competitive pressures that spill over to peer firms in the same industry. This induces peer firms to strategically implement RPE-based compensation after an acquisition. This study also contributes to the RPE compensation literature. Given economic theory prefers relative performance-based compensation over absolute performance-based ones, because of its ability to mitigate common risk and improve the competitive position, RPE compensation has witnessed recent increased popularity. Gong et al. (2006) report that, in 2006, only 25 percent of firms incorporated RPE compensation. According to the Institutional Shareholder Service (ISS) Incentive Lab, two-thirds of firms now have RPE compensation (Do et al., 2022). However, some studies criticize the adoption of RPE compensation, arguing that it gives managers opportunities for collusion with peers or deliberate selection of inappropriate reference groups (e.g., Dye, 1984; Gibbons and Murphy, 1990; Aggarwal and Samwick, 1999). Our results largely align with the theoretical competition benefits of RPE. We find that firms increase their use of RPE in the face of competitive pressures, implying that RPE is an efficient mechanism for shareholders to motivate firms to overcome competitive pressures.

4. The Spillover Effects of Exogenous Events on Managerial Disclosure of Earnings Forecasts: Evidence from U.S. Major Hurricanes

In recent decades, approximately 300 natural disasters have struck globally each year, resulting in an annual economic cost of around 100 billion US dollars [2]. Hurricanes, in particular, are a regular event in the U.S., with an average of two hurricanes having struck the U.S. Mainland every year since the 1850s. Hurricanes usually cause widespread destruction, major collateral damage and loss of life. Although prior studies have largely assessed the direct consequences of hurricanes, they have scarcely evaluated the spillover effects of a major hurricane.

This study examines the impact of a major hurricane on management forecast issuance of industry peers located in non-hurricane areas. Research on competitive dynamics suggests an interdependence between rival firms, where the gain (or loss) of one often corresponds to the loss (or gain) of others (e.g., Lang and Stulz 1992; Lien et al., 2021). Lang and Stulz (1992) suggest that a firm-specific negative event (i.e., bankruptcy) can potentially increase the market share of other firms in the industry through a redistribution of wealth from the affected to the

[2] https://ourworldindata.org/natural-disasters#empirical-view

unaffected. The literature shows that natural disasters significantly disrupt affected firms' operations and economic development (e.g., Kong et al., 2021). Industry peers located in non-affected areas can potentially benefit from an improved competitive position following a hurricane. According to the theory of strategy-based voluntary disclosure (Verrecchia, 1983; Dye, 2001), high-performing firms often distinguish themselves by offering a higher level of voluntary disclosure. These voluntary disclosures can enable peer firms to assert and exploit their competitive advantage after a major hurricane. Consistent with this, our baseline results show that industry peers respond to a major hurricane by increasing the issuance of management forecasts. We also find that a peer firm's forecast frequency is positively associated with firm visibility and market share. This suggests that such strategic actions by peer firms following a major hurricane can redirect investor and customer attention towards themselves, potentially leading investors to view peers with less frequent forecasts as less transparent and of lower quality. After documenting the competitive spillover of a major hurricane, we show that the positive effect of a hurricane on industry competitors' management forecasts is more pronounced when the hurricane-hit firm is a market leader. This is because a market leader, when subjected to a major hurricane, can lose a higher proportion of market share than a non-market leader. Industry competitors have stronger incentives to claim that market share. We find that industry peers are more likely to increase management forecasts after a hurricane when they are in more competitive industries and in industries that are particularly sensitive to extreme weather.

This study makes the following contributions. First, it adds to the growing literature on the spillover effects of exogenous events. Unlike a cyberattack, which signals industry-level cyber risks and results in the spreading of reputation loss across the industry, a major hurricane is a regional event. In such circumstances, industry peers can benefit from the difficulties of hurricane-hit firms, and are motivated to attract investors and seize market share from the affected firm by issuing management forecasts. Second, our study contributes to the literature on related firms learning from each other. Existing studies indicates that a firm's disclosures can influence the disclosure decisions of its industry peers (e.g., Seo, 2021). Our study complements these studies by documenting that firms not only make disclosure decisions by learning from the disclosure behaviors of other firms in the same industry but also by considering their competitive position, which can be affected by specific events. The study also sheds light on a new dimension of management forecast motives and contributes to the growing literature on corporate disclosure. Focusing on the competition effect, industry peers are in a more advantageous competitive position in the aftermath of a hurricane. We find that industry peers respond by issuing more management forecasts, revealing that the intent to expand existing competitive advantages plays an important role in motivating corporate disclosure.

5. Thesis structure

The remainder of this thesis is organized as follows. Chapter 2 investigates equity offerings following cyberattacks, Chapter 3 explores how peer firms of acquirers respond to acquisition-induced competitive pressures by adopting relative performance evaluation compensation, and Chapter 4 examines the spillover effects of an exogenous event, U.S. major hurricanes, on managerial disclosure of earnings forecasts of peer firms locating in non-hurricane areas. Chapter 5 concludes the thesis.

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Chapter 2: Equity Offering Following Cyberattacks

ABSTRACT

We examine whether a cyberattack affects a firm's decision to issue equity. We find that attacked firms issue fewer and smaller SEOs after experiencing cyberattack; this adverse impact spills over to their peers in the same industry. These results suggest that, following a cyberattack, both the target and peer firms prioritize avoiding the increased cost of equity issues over fulfilling their financing requirements through equity issuance. In a cross-sectional test, we find that the negative impact of a cyberattack on peer firms' SEO decisions is particularly significant when peer firms have a higher potential risk to future attacks and are highly visible firms. This is attributable to the higher financing costs these peers might face because they are perceived to be riskier to transact with compared with other industry peers. We also find that the negative impact of a cyberattack on peer firms' SEO decisions is more pronounced for peer firms with high IT expenditure and cash reserves, because these firms have less need to issue equity.

JEL classification:

Keywords: seasoned equity offerings (SEOs), cyberattacks, information spillovers, market reactions

1. Introduction

"*We didn't live up to the expectations we have for ourselves to protect our customers. Knowing that we failed to prevent this exposure is one of the hardest parts of this event. We know we need additional expertise to take our cybersecurity efforts to the next level - and we've brought in the help. To say we are disappointed and frustrated that this happened is an understatement."* - Mike Sievert, Chief Executive of T-Mobile US, August 27, 2021.

Recently, the amount of data collected, processed, and stored by corporations has grown exponentially, along with the increasing use of digital technologies. Stored data and information are usually highly sensitive and extremely valuable, attracting more attention from hackers and cybercriminals (Rosati et al., 2020). According to the report by McAfee and the Center for Strategic & International Studies (2020), cybercrimes have significant financial and unseen impacts worldwide, costing the world economy over 1 trillion US dollars (over one percent of global GDP). Over the last three years, the frequency and impact of cyberattacks have been increasing at a 25 percent annual rate in the United States (Simon and Omar, 2020). In a survey, over 50 percent of CEOs believe a cyberattack can threaten their stakeholders' trust in their industry over the next five years (Risk in Review 2017 study, 2017). Overall, cyberattacks are becoming one of the biggest threats for corporations and their stakeholders in today's era of digital technology.

In this study, we examine how a cyberattack affects the target firm's equity financing decisions (i.e., seasoned equity offerings)[3]. Huang and Wang (2021) investigated how data breaches affect the cost of bank loans and find firms that have reported data breaches get less favourable loan terms (e.g., higher loan spreads, more demand for collateral and covenants). Their evidence also suggests the firms that take more remedial action suffer less from unfavourable loan terms. Since data breaches depress the share price of target firms (Kamiya

[3] In the following and for brevity, we use the term "attacked firm", "target firm", and "affected firms" synonymously.

et al., 2021) and increase their cost of equity financing (Ashraf, and Sunder, 2023; Elmawazini et al., 2023; Jiang et al., 2022; Sheneman, 2021; Baker and Wurgler, 2002), attacked firms may refrain from issuing new shares at a higher cost after experiencing a cyberattack. On the other hand, a cyberattack also creates a short-term need for information technology (IT) security investment (Haapamäki and Sihvonen, 2019), investing in cybersecurity talent (Bana et al., 2022), and motivates attacked firms to pursue new capital, potentially equity, given the adverse impact of cyberattacks on bank loans. Therefore, the effect of a cyberattack on the target firm's seasoned equity offering (SEO) decisions is an empirical question.

We investigate the relationship between cyberattacks and target firms' SEO decisions from 2005 to 2017, using a firm's appearance in the Privacy Rights Clearinghouse (i.e., PRC) database to identify whether a firm experienced a cyberattack in a given year. We end the sample period in 2017 to allow post-cyberattack analysis. When attacked firms are unlisted subsidiaries, we consider cyberattacks as having occurred in their parent firm (Kamiya et al., 2021). Our baseline results show that the probability of conducting SEOs is lower for attacked firms than for non-attacked firms. This result is robust when we use the propensity score matching (PSM) approach to alleviate sample selection bias. Moreover, attacked firms raise less SEO proceeds in post-attack periods. The finding that target firms do fewer and smaller SEOs persists for up to three years after the cyberattack.

Kamiya et al. (2021) show that a cyberattack negatively affects the market value of not only the target firm but also its peers, revealing adverse information about industry-wide cybersecurity risk. Industry peers that share similar fundamental characteristics as the target are highly susceptible to future cyberattacks and subject to reputation loss. Consistently, our empirical evidence shows that a firm's probability of experiencing a cyberattack in a given year increases when another firm in the same industry has previously suffered a cyberattack. In terms of SEO, a peer firm's investors may still be willing to buy its shares but at a lower price because the firm may not be as reliable or trustworthy as they thought it was, representing a reputation loss (Karpoff, 2012). Graham and Harvey (2001) and Baker and Wrugler (2002) document that equity market prices are considered one of the most important factors in firms' decision to issue common stock, both in theory and practice. Therefore, peer firms would be reluctant to issue shares following a negative stock price shock induced by a cyberattack (Kamiya et al., 2021) and exacerbated adverse selection issues because of their potential reputation loss in future cyberattacks. Garg (2020) finds that peer firms increase their cash holdings after a cyberattack, suggesting a pre-emptive approach to mitigate potential losses from industry-wide cyber risk. In relation to SEOs in the years following an attack, peer firms may exhibit a propensity to issue new equities as an alternative precaution. Hence, the direction of the impact of a cyberattack on the peer firms' SEO decisions is, therefore, an empirical question. Our results show that peer firms make fewer and smaller SEOs after the target firm experiences a cyberattack, documenting a negative spillover effect of cyberattacks on equity financing among industry peers.

We then perform cross-sectional tests to reinforce the validity of the negative effect of a cyberattack on peer firms' SEO decisions. First, we find that the negative effect of a cyberattack on peer firms' future SEO decisions is more pronounced when peer firms have a higher likelihood of becoming a cyberattack target. Peers with a higher susceptibility to future attacks suffer more reputation losses, incurring higher costs when conducting SEOs. This results in a diminished likelihood of conducting a SEO in the near future. Second, we find that the negative effect of a cyberattack on peer firms' SEO decisions is more pronounced when the peer firms are more visible. This is because more visible firms are more likely to become a cyberattack target (Kamiya et al., 2021) and the public often reacts more strongly and critically to potential reputation losses, refraining to a greater extent these peer firms from conducting SEOs.

The baseline results suggest that, within the context of SEOs, peer firms reduce the likelihood of conducting an SEO because of the increased cost of equity. However, this does not imply that peer firms entirely disregard the financing needs induced by a cyberattack. In an additional cross-sectional test, we find that the negative effect of a cyberattack on peer firms' SEO decisions is more pronounced for those with high IT investment and cash holdings. Firms often respond to a cyberattack by enhancing IT-related investment as a precautionary measure (e.g., Hausken, 2006; Bose and Luo, 2014), indicating the potential financing needs triggered by a cyberattack. Firms with ample IT investment are less concerned with such financing needs and have a stronger incentive to reduce equity issuance following a cyberattack. The Pecking Order Theory (Myers and Majluf, 1984) posits that firms prioritize the use of internal cash over equity financing. Consequently, peer firms with larger cash reserves (i.e., less dependent on equity financing) are better equipped to minimize their use of SEOs to evade costlier options.

We make several contributions to the literature. First, this study contributes to the SEO literature in general. The extensive literature on equity issuance examines the determinants of a firm undertaking an SEO. For example, market timing theory and investment financing theory are popular explanations for firms undertaking SEOs (Loughran and Ritter, 1995; Kim and Weisbach, 2008; DeAngelo et al., 2010). Though theories on equity issuances are extensively documented in the literature, the effects of specific events (e.g., cyberattacks) on equity issuances are less explored, especially when such events increase equity financing costs and simultaneously create short-term financing needs. Our study fills that gap by highlighting the role of cyberattacks in dissuading firms from conducting SEOs.

Second, this study adds to the growing literature on the impact of a cyberattack on firms' corrective and precautionary actions. Kamiya et al. (2021) conducted a comprehensive study to investigate the impact of cyberattacks on target firms. They show that a cyberattack changes the board's assessment of a target firm's risk or risk appetite, so the target firm adjusts risk management policies and compensation policies in the post-attack years. Xu et al. (2019) find that firms manipulate earnings upwards through real earnings management to avoid performance decreases after becoming the target of a cyberattack. Garg (2020) documents that attacked firms increase cash holdings from 23% to 26.87% in the post-attack year. We provide new insights by showing that firms refrain from issuing equity after experiencing cyberattacks and reputation loss. In particular, we find that the probability of (the proceeds raised from) attacked firms conducting SEOs in the next three years post cyber hacks is 53.96% (102.41%) lower than that of non-attacked firms.

Finally, this study contributes to the broad literature on the spillover effects of certain events. Many studies have examined the spillover effects of corporate events on peer firms in different settings. For instance, Erwin and Miller (1998) investigated the spillover effects of open market share repurchase programmes on peer firms in the same industry. Aslan and Kumar (2016) examined the spillover effects of hedge fund activism on industry peers of the target firms. Apart from investigating spillover effects associated with corporate events, there has been a surge in recent studies exploring the spillover effects of unexpected events. For example, Carvalho et al. (2021) investigated how disruptions caused by an earthquake propagate along supply chains. Massa and Zhang (2021) examined the spillover effects of a major hurricane on the debt financing policy of bond issuers that are funded by insurance companies exposed to the shock of the hurricane. Lei et al. (2021) analysed the spillover effect of a credit shock on industry peers' cash holdings. A related study conducted by Kamiya et al. (2021) demonstrates that a cyberattack not only has an adverse impact on the stock price of the target company but also spills over to its industry peers. Our study extends Kamiya et al.'s (2021) study by suggesting that, to avoid the higher costs of equity financing, peer firms decrease the likelihood of conducting SEOs following a cyberattack.

The rest of the chapter is as follows. Section 2 discusses the relevant literature and introduces our hypotheses. Section 3 describes the data. Section 4 reports our analysis of the main propositions and presents some additional analyses. Section 5 concludes the paper.

2. Related Literature and Hypothesis Development

The growing reliance on digital technology, such as social media, cloud computing, and mobile devices, amplifies the risks of and vulnerabilities to cyber threats for companies. Additionally, the frequency of cybersecurity incidents is steadily increasing year after year. Over just a few decades, cyberattacks have emerged as one of the top concerns on the minds of management and boards across firms worldwide (Islam et al., 2018). Cyberattacks possess distinct characteristics compared with other corporate events, given their unpredictability in terms of timing and frequency of occurrence (Ko et al., 2009). Therefore, it is imperative to examine how companies respond to these cyber incidents. A new literature strand is paying attention to the impact of cyberattacks on firm value and corporate policies. For example, Kamiya et al. (2021) document that attacked firms experience significant loss in shareholder wealth following a cyberattack, hence adjust their risk management policies post the cyberattack. Xu et al. (2019) find that target firms manipulate earnings upwards to avoid performance decrease after a cyberattack. Garg (2020) provides evidence that firms significantly increase their cash holdings after experiencing a cyberattack. According to Huang and Wang (2021), target firms take remedial actions to avoid less favourable loan terms after a cyberattack.

We have taken the initiative to study how unexpected cyberattacks affect firms' equity financing decisions. Given that target firms suffer significant tangible and intangible losses[4]

[4] For example, cyberattacks can result in damage and destruction of data, stolen money, lost productivity, theft of intellectual property, theft of personal and financial data, embezzlement, fraud, post-attack disruption to the normal course of business, forensic investigation, restoration and deletion of hacked data and systems, and reputation harm.

from cyberattacks, they have a strong need to invest in cybersecurity to mitigate negative outcomes and/or future cyberattack occurrence following such attacks. For instance, Hausken (2006) finds that firms exposed to cyberattacks increase their investment in security technology. Bose and Luo (2014) document that security-related investments made by organizations can safeguard tangible, intangible, physical, and intellectual assets during a cyberattack. Using firm-level job posting data, Bana et al. (2022) document that target firms significantly increase their hiring for both cybersecurity, public relations and legal workers after suffering a data breach.

The investment needed to enhance cybersecurity could motivate target firms to pursue external financing, potentially equity financing, given that the terms of bank loans deteriorate (Huang and Wang, 2021) and their credit rating decreases (Kamiya et al., 2021) after an attack. This prediction is consistent with the literature that investment financing motivates equity offerings (Kim and Weisbach, 2008) and issuers tend to invest significantly more than their non-issuer counterparts following a seasoned equity offering (Lyandres et al., 2007). Overall, the investment financing view predicts that the increased financing demand for cyber-related investment following cyber incidents is a significant driving force behind equity issuance.

However, there is an opposing view that successful cyberattacks discourage target firms from undertaking equity financing. Based on the findings of Kamiya et al. (2021) that a cyberattack depresses the share price of the target firm and hence results in higher capital raising costs, we posit that a cyberattack can reduce a firm's likelihood of engaging in seasoned equity offerings (SEOs) in the post-attack period. Karpoff (2012) indicates that a firm suffers when stakeholders demand better terms to transact with it following an unexpected event that makes the firm riskier to transact with for stakeholders is called reputation loss. Kamiya et al. (2021) conclude that target firms suffer from significant reputation loss following a cyberattack. A firm's loss from a cyberattack could change shareholders' assessment of its risk exposure and exacerbate the adverse selection of uninformed investors in equity offerings (Myers and Majluf, 1986). Cao et al. (2014) and Pfister et al. (2020) provide empirical evidence showing that that the cost of equity is lower for firms with a higher reputation. Conversely, attacked firms experience a higher cost of equity following a cyberattack because of their significant reputation loss. This agrees with the market timing theory (Loughran and Ritter, 1997), that less favourable stock prices adversely affect firms' propensity to undertake equity offerings (Kim and Weisbach, 2008). The disincentivising view suggests that target firms are less likely to undertake SEOs because of the increased cost of raising equity capital post a cyberattack. In summary, the investment financing view and the disincentivising view have opposing predictions on the impact of a cyberattack on equity issuance.

Our study is also motivated by the growing interest in understanding information spillover in financial markets. The literature has identified information spillover in various corporate event settings, such as liquidity (Allen and Gale, 2000), bankruptcy (Jorion and Zhang, 2007), changes in regulatory policies (Slovin et al., 1992), changes in dividends (Firth, 1996), share repurchases (Erwin and Miller, 1998), and IPOs (Benveniste et al., 2003). These studies delve into how peer firms in the same industry respond to macroeconomic shocks experienced by another firm by strategically adapting and making managerial decisions. However, not many researchers have studied information spillover from cyberattacks (exceptions are Kamiya et al. (2021) and Garg (2020)). As an extension of the impact of a cyberattack on the target firm's equity issuance, we investigate, in the context of SEO, whether the impact of a cyberattack on equity financing spills over to other firms in the same industry.

The literature provides some indicative evidence largely supporting the contagion effect of a cyberattack. Kamiya et al. (2021) find that the adverse information conveyed by a cyberattack is related to a more general industry-wide cyber risk. Two seemingly opposite hypotheses related to the spillover effect of a cyberattack have been advanced. Garg (2020) finds that peer firms increase their cash reserves after a firm in their industry experiences a cyberattack, indicating that peer firms take precautions to avoid the potential loss from an industry-wide cyber-risk. In the context of SEOs in post-attack years, peer firms may also tend toward issuing new equity. This action can facilitate precautionary measures such as investing in IT security and recruiting cybersecurity talent (Haapamäki and Sihvonen, 2019; Bana et al., 2022) and, as a consequence, prevent the potential risk of being the target of a future cyberattack.

Alternatively, considering that unexpected negative events can have repercussions that extend beyond the intended company(ies) (e.g., Arena and Julio, 2011; Lei et al., 2021), we next propose that the impact of a firm's cyberattack on equity financing spills over to other firms in the same industry can also be explained by the increased cost of raising external finance. Since firms in the same industry share similar fundamental characteristics, such as business model, operational process, customer base and investment opportunities, a cyber incident can reveal that other peer firms in the industry are highly susceptible to future cyberattacks and are also subject to so-called reputation loss. Stakeholders of peer firms may require more favourable terms to transact with these firms. For instance, investors may be willing to buy shares but only at a lower price to account for the diminished trustworthiness perceived across the entire industry that has experienced a cyberattack. Consequently, peer firms, even if they are not directly attacked by a cyberattack, diminish their motivation to issue new equity. This conjecture is consistent with Kamiya et al. (2021), who find a successful cyberattack adversely affects the stock price of both the target and peer firms in an industry. This adverse impact can be explained by the fact that some stakeholders in industry peer firms conclude that cyber risk is higher than they previously believed and expect better terms to deal with those firms (Kamiya et al., 2021), leading to increased equity financing cost across the industry after an attack. Graham and Harvey (2001) and Baker and Wrugler (2002) document that equity market prices are considered one of the most important factors in firms' decision to issue common stock, both in theory and practice. In addition, El Ghoul et al. (2011) indicate that the cost of equity is defined as the required rate of return, reflecting the market's perception of the firm's riskiness and thus mirroring investors' expectations about future returns. After a cyberattack, peer firms experience an adjustment in the market's perception of their risk profile, because peer firms are often perceived as having an increased risk of being future victims of attacks. Peer firms' increased risk of being the victim of future attacks can be reflected as an increased cost of issuing external finance, because investors may demand a higher rate of return to compensate for the perceived increase in such risk. Therefore, in aiming to avoid the increased SEO cost, peer firms may tend toward conducting fewer SEOs following a cyberattack. Overall, how a cyberattack influences peer firms' SEO decisions remains an empirical question.

3. Data

3.1 Sample and data

Since 2005, firms have been required to disclose data breaches under the State Security Breach Notification Law. In this study, we follow the approach of Garg (2020) and Kamiya et al. (2021) to collect data on data breaches for public firms from 2005 to 2019 using the PRC database. Our initial sample includes all data breach incidents from the PRC database. Consistent with Kamiya et al. (2021; 2018), we focus only on attacks involving information leakage caused by hacking and/or malware and initiated by external parties. We exclude cyberattacks that target government entities, military organizations, educational institutions, medical and healthcare providers, and non-profit organizations (Kamiya et al., 2018; Garg, 2021). If attacked firms are unlisted subsidiaries of public firms, we consider the cyberattacks to have occurred in their parent firms. After applying these criteria, our final sample consists of 319 cyberattacks that took place between 2005 and 2019, as recorded in the PRC database. Table 1 presents the distribution of these 319 cyberattacks by year and industry (categorized according to the 2-digit standard industrial classification (SIC) code). Our analysis reveals that cyberattacks tend to concentrate in industries that handle a large volume of customers, such as manufacturing (20-39), finance (60-69), wholesale, trade, and retail industry (50-59), and the service industry (70-89).

[Insert Table 1 here]

To undertake post-cyberattack analysis, we limit our cyberattack sample to the period from 2005 to 2017, resulting in a sample of 300 cyberattacks. Our SEO sample encompasses U.S. common stock offerings between 2005 and 2020. To obtain an initial sample of SEOs, we extract data from the SDC Global New Issues database. Following Eckbo et al. (2000), we include SEO issuers that meet the following criteria: (1) their stock is listed on NYSE, NYSE MKT (AMEX, NYSE AMEX), or NASDAQ exchanges; (2) the issuer has at least one year of prior stock return data available from CRSP; and (3) the issuer has no missing values for our baseline regression analysis (as presented in Table 3).

Next, we manually match the company names reported in the PRC database with the firm names listed in Compustat to determine the specific identifier (i.e., GVKEY) for each cyberattack firm. In cases where the listed names do not provide a clear distinction for the identifier, we rely on additional sources such as the company website, Dun & Bradstreet, and Crunchbase, or use latitude and longitude data reported in the PRC database to verify the unique identifier for each attacked firm. Using the linkage among GVKEY, PERMNO, and 6-digit header CUSIP from the CRSP/Compustat Merged database, we link PRC with the Compustat, CRSP, and SDC databases. These procedures yield a final sample of 63,287 firm-year observations for our baseline model, with no missing values. Among these observations, 63,056 belong to the nontarget group that did not experience a cyberattack in a given year, and 231 are in the target group that experienced a cyberattack in a given year.

3.2 Univariate test

In Table 2, Panel A, we examine whether firm characteristics and the probability of issuing equity are significantly different between target firms experiencing a cyberattack in a given year (i.e., Target group) and firms experiencing no cyberattack in a given year (i.e., Nontarget group). $Pr(SEO)_{t+3}$, $Pr(SEO)_{t+2}$, and $Pr(SEO)_{t+1}$ refer to the probability of firms that conduct at least one SEO in the next three years, two years and one year, respectively, after the focal year. The last two columns report the mean and median differences between the two groups based on the standard *t*-tests and Wilcoxon signed-rank tests. We find that the likelihood of undertaking SEOs in the next three years, two years and one year are only 0.9, 0.9 and 0.4 percent for the target group, whereas they are much higher for the nontarget group at 4.9, 4.4 and 3.3 percent, respectively. The mean (median) differences in $Pr(SEO)_{t+3}$, $Pr(SEO)_{t+2}$, and $Pr(SEO)_{t+1}$ are all statistically significant at least at the 5 percent level, suggesting that the likelihood of conducting an SEO in the post-attack period is much lower for target firms than that for nontarget firms hence providing supportive evidence for the disincentivising view stated in Section 2. For other firm characteristics, our findings suggest that firms in the target group exhibit a significantly lower market-to-book ratio and larger firm size than those in the nontarget group.

In Table 2, Panel B, we examine whether the probability of future SEOs differs between peer firms in the industry experiencing a cyberattack (i.e., Peerattack group) and firms in the industry experiencing no cyberattack (i.e., Nonpeerattack group). The results show that $Pr(SEO)_{t+3}$, $Pr(SEO)_{t+2}$, and $Pr(SEO)_{t+1}$ are 5.3, 4.8 and 3.6 percent, respectively, for the Nonpeerattack group; and 4.2, 3.7 and 2.8 percent, respectively, for the Peerattack group. The mean (median) differences in the likehood of future SEOs between the Peerattack group and Nonpeerattack group are all statistically significant at the 1 percent level, providing preliminary support for the hypothesis that peers are less likely to conduct SEOs following a cyberattack. For other firm characteristics, our analysis reveals notable distinctions between the Peerattack group firms and the Nonpeerattack group firms. Peerattack group firms have a significantly lower market to book ratio and are larger than the Nonpeerattack group firms. In the next step, we use multivariate analysis to examine how cyberattacks affect target firms' and peer firms' equity financing decisions.

[Insert Table 2 here]

4. Results

4.1 The effect of a cyberattack on a target firm's SEO decisions

To assess the validity of the disincentivising view in Section 2, we use a probit model described by Equation (1) to estimate the likelihood of issuing equity after a cyberattack. In Equation (1), the dependent variable is an indicator variable, $Pr(SEO)_{t+i}$ (i =1, 2, and 3), which equals one if a firm initiates at least one SEO during a given time period, and zero otherwise. Specifically, $Pr(SEO)_{t+1}$ equals one if a firm initiates at least one SEO within one year after a given year t, and zero otherwise. We further include $Pr(SEO)_{t+2}$ ($Pr(SEO)_{t+3}$) which equals one if a firm initiates at least one SEO within the next two (three) years after a given year t and zero otherwise.

$$\begin{aligned} Pr(SEO)_{t+i} \quad &= \alpha_0 + \alpha_1 Cyberattack_t + \alpha_2 MTB_t + \alpha_3 Prior\ stock\ return_t \\ &+ \alpha_4 Firm\ size_t + \alpha_5 Leverage_t + industry\ and\ year\ FE + \delta \end{aligned} \qquad (1)$$

We investigate whether firms experiencing a cyberattack in year t exhibit a lower probability of engaging in SEO activity in subsequent years than firms that do not encounter any cyberattacks in year t. The variable of interest, *Cyberattack*, is an indicator variable that equals one if a firm becomes the target of a cyberattack in year t, and zero otherwise. The coefficient α_1 on the *Cyberattack* variable captures the relationship between a firm being the victim in a cyberattack and its likelihood of engaging in SEO activity after the attack. Following prior literature (DeAngelo et al., 2010; Altı and Sulaeman, 2012), our baseline model includes:

(1) firm size; (2) leverage[5]; (3) standardized market to book ratio; and (4) prior stock returns (i.e., the market-adjusted stock return over the 12 months ending immediately before year *t*) as the explanatory variables[6]. We also include year and industry fixed effects to control for time-variant trends and time-invariant industry-specific effects that might affect a firm's SEO decisions.

Table 3, Columns (1) to (3) report the results of the baseline probit regression in Equation (1). When the dependent variable is $Pr(SEO)_{t+3}$, the coefficient estimate on *Cyberattack* is -0.540, which is statistically significant at the 5 percent level. The marginal effect of *Cyberattack* is -0.048, suggesting that experiencing a cyberattack reduces a firm's likelihood of initiating SEO activity in the subsequent three years by 4.8 percentage points. When the dependent variables are $Pr(SEO)_{t+2}$ and $Pr(SEO)_{t+1}$, the coefficient estimates for *Cyberattack* are -0.492 and -0.622, respectively, both of which are statistically significant at the 10 percent level. In terms of economic significance, a cyberattack diminishes a firm's probability to undertake SEOs by 4.0 percentage points and 3.9 percentage points in the following two years and in the subsequent year, respectively. These probit regression results support the disincentivising view stated in Section 2, suggesting that firms targeted by cyberattacks are less likely to engage in SEO activity in the years following the attacks than firms unaffected by cyberattacks. The coefficient estimates for the control variables align with previous research. Specifically, the market-to-book ratio and past stock returns have a positive association with the probability of undertaking an SEO (DeAngelo et al., 2010). Additionally,

[5] In untabulated results, we substitute Leverage with alternative control variables *Financial slack and Debt Structure*. Financial slack refers to the ratio of current assets minus current liabilities to total assets; debt structure is debt maturity structure, which is calculated as the ratio of long-term debt to total debt. Our baseline results are robust when using other variables to capture a firm's financial slack and access to the debt market.
[6] In untabulated results, we conduct the robustness tests by incorporating the two dummy variables controlling the firms' propensity in conducting the SEOs. *D_IT* is equal to one if a firm's IT expense in year *t* is higher than the industry median level, and zero otherwise. *D_Cashholding* is equal to one if a firm's cash holding level in year *t* exceed the corresponding industry median levels, and zero otherwise. In general, Our baseline results are robust by the inclusion of cash holding and IT expenditures.

leverage shows a negative association with the SEO probability, although its significance may vary (Harjoto and Garen, 2003; Kim and Purnanandam, 2014).

Next, we examine whether experiencing a cyberattack affects how much the target firm can raise from subsequent SEOs. To estimate these effects, we use Tobit regressions, where we replace *Pr (SEO)*$_{t+i}$ (i =1, 2, and 3) in Equation (1) with *Size (SEO)*$_{t+i}$ (i =1, 2, and 3) in Equation (2). We examine three proxies for the dependent variable, i.e., *Size (SEO)*$_{t+3}$, *Size (SEO)*$_{t+2}$, and *Size (SEO)*$_{t+1}$. *Size (SEO)*$_{t+3}$ is calculated as the sum of a firm's SEO proceeds from year t+1 to t+3 divided by the firm's total assets in year *t*; if the firm has no SEOs in the next three years. Similarly, *Size (SEO)*$_{t+2}$, and *Size (SEO)*$_{t+1}$ are calculated as the sum of a firm's SEO proceeds in two and one year(s) after year t divided by the firm's total assets in year t, respectively. All these measures quantify the relative size of capital raised from subsequent SEOs. However, it's important to note that these variables are left-censored at zero for firms that do not undertake an SEO within three, two, or one year(s) after year *t*. As a result, we are unable to observe the relative size measures of SEOs for firms that do not engage in such activity. To account for the left-censoring of the dependent variables at zero, we use the following Tobit model, as in Harjoto and Garen (2003):

$$\begin{aligned} Size(SEO)_{t+i} \quad &= \alpha_0 + \alpha_1 Cyberattack_t + \alpha_2 MTB_t + \alpha_3 Prior\ stock\ return_t \\ &\quad + \alpha_4 Firm\ size_t + \alpha_5 Leverage_t + industry\ and\ year\ FE + \delta \end{aligned} \tag{2}$$

The estimation results of Equation (2) are presented in Table 3, Columns (4) to (6). In Columns (4) and (5), the coefficient estimates on *Cyberattack* are -1.024 and -0.802, respectively. These coefficients indicate that attacked firms raise fewer proceeds from subsequent SEOs than non-attacked firms, while holding other control variables constant. The coefficient estimate on *Cyberattack* in Column (6) is also negative (-0.403), although statistically insignificant. Taken together, our findings indicate that target firms tend to raise smaller proceeds from SEOs when they undertake them after experiencing a cyberattack than firms that are unaffected by such cyber incidents.

[Insert Table 3 here]

4.2. Propensity score matching method: A comparison of SEO decisions between the attacked and nonattacked firms

Though cyber incidents are generally unexpected, it is important to acknowledge that our findings in Table 3 may still be susceptible to endogeneity issues, such as self-selection bias. This bias arises when there are inherent differences between participants and nonparticipants, even in the absence of the treatment (Caliendo and Kopeinig, 2008). For instance, it is possible that firms with certain characteristics opt to undertake fewer SEOs regardless of experiencing cyberattacks, which could introduce self-selection bias into our sample.

In this subsection, we address this concern using the propensity score matching methodology (PSM). Specifically, we use the 1:1 nearest-neighbour matching, the radius matching and kernel matching approaches to locate the matching control firms. Our objective, through PSM, is to mitigate the potential self-selection bias by identifying a control firm that has not experienced cyberattacks for each attacked firm.

The first set of matching variables we used in this process are fundamental firm characteristics, including firm size, leverage, market-to-book ratio, and previous stock returns. We also require that both the attacked and matched control firms' observations belong to the same 2-digit SIC industry and year. This design helps control for the possibility that any observed differences in SEO decisions between attacked firms and non-attacked firms could be attributed to firm-specific characteristics.

Table 4, Panel A, compares the SEO decisions between the attacked firms (*Treated*) and non-attacked firms (*Controls*) when the PSM matching variables consist of fundamental firm characteristics. Both the pre-matching and post-matching[7] analyses reveal that the average

[7] The treated group refers to firms that have experienced a cyberattack in year t (i.e., attacked firms), and the control group consists of firms that have not experienced any cyberattack in year t (i.e., non-attacked firms). In the pre-matching analysis, we consider the initial sample without matching treated and control groups, where the

treatment effect on the treated (ATT) on the probability of undertaking SEOs in the next three, two and one year(s), i.e., $Pr(SEO)_{t+3}$, $Pr(SEO)_{t+2}$ and $Pr(SEO)_{t+1}$, is significantly negative at the 1 percent level. These findings demonstrate that firms that experience cyberattacks exhibit a reduced likelihood of conducting SEOs even after accounting for potential sample selection bias arising from firm-specific characteristics.

Next, we use another set of variables that have been found in Kamiya et al. (2021) to be associated with the likelihood of firms experiencing a cyberattack, to perform PSM matching. These variables include firm size, firm age, Tobin's q, ROA, sales growth, stock performance, leverage, financial constraint, stock return volatility, institutional block ownership, asset intangibility, year, and 2-digit SIC industry. By using this multidimensional matching strategy, our aim is to identify control firms that are comparable to the attacked firms in terms of their likelihood of experiencing a cyberattack. This approach accounts for the possibility that differences in SEO decisions may stem not only from the occurrence of a cyberattack itself but also from the likelihood of experiencing a cyberattack.

Table 4, Panel B reports the results of PSM matching based on the factors that predict the occurrence of cyber incidents. Both the pre-matching and post-matching analyses consistently reveal a significantly lower likelihood of engaging in the SEO activity for the treated group than the control group. For example, when examining $Pr(SEO)_{t+3}$, the average probability of conducting SEOs during the three years following year t for the treated group is 0.005, whereas it is 0.037 for the control group after 1:1 nearest-neighbour matching. The average treatment effect on the treated (ATT) is calculated to be -0.033, which is statistically significant at the 5 percent level. These results corroborate the findings from the baseline model analysis, further supporting that a cyberattack discourages target firms from taking SEOs in

control group comprises all non-attacked firms in the Compustat database. In the post-matching analysis, we narrow down the sample through matching procedures. Specifically, the post-matching control group consists of non-attacked firms whose propensity score values are as similar as possible to those of the attacked firms.

subsequent years. The results remain robust when control firms are restricted to those with either similar firm-level characteristics or a similar likelihood of experiencing a cyberattack.

[Insert Table 4 here]

4.3 The spillover effects of a cyberattack: The effect of a cyberattack on peer firms' SEO decisions

In this section, we turn our attention to the spillover effects of a cyberattack by investigating how a cyberattack affects peer firms' SEO decisions. First, we do preliminary tests to verify that a cyberattack reveals industry-wide cyber risks. We examine whether a firm's probability of experiencing a cyberattack in a given year (t) increases when another firm in the same industry has previously encountered a cyberattack. Specifically, we regress $Cyberattack_t$ on $Peerattack_{t-i}$ using the following model:

$$\begin{aligned} Cyberattack_t = \quad & \delta_0 + \delta_1 Peerattack_{t-i} + \delta_2 Firmsize_{t-1} + \delta_3 Firmage_{t-1} \\ & + \delta_4 Tobinsq_{t-2} + \delta_5 ROA_{t-1} + \delta_6 Salesgrowth_{t-1} \\ & + \delta_7 InstOwnership_{t-1} + \delta_8 SP500_{t-1} + \delta_9 Assetintangibility_{t-1} \\ & + \delta_{10} Financial\ constraint_{t-1} + Industry\ and\ year\ FE + \varepsilon \qquad (3) \end{aligned}$$

The dependent variable, *Cyberattack*, is an indicator variable equal to one if a firm experiences a cyberattack in the year *t*, and zero otherwise. The interested variable, $Peerattack_{t-i}$ (i =1, 2, and 3), determines whether there any other firms in a firm's industry encountered a cyberattack in previous years (i.e., we use $Peerattack_{t-i}$ to measure whether a firm is an industry peer of a previous cyberattack target). Specifically, $Peerattack_{t-1}$, $Peerattack_{t-2}$, and $Peerattack_{t-3}$ are assigned a value of one if at least one other firm in the same 2-digit SIC industry as the firm that has been cyberattacked in the previous one year, two year, and three years, respectively, otherwise, they are assigned a value of zero. Following Kamiya et al. (2021), we also include firm size, firm age, Tobin's *q*, ROA, sales growth, institutional ownership, S&P 500 membership, asset intangibility, financial constraint, and year and industry fixed effects, as explanatory variables in the model[8]. The results of Equation (3) are presented in Table 5.

[8] Consistent with Kamiya et al. (2020), all the explanatory variables are measured one year before year t except for Tobin's q, which is measured two years before year t since it is highly correlated with past stock performance.

The coefficient estimates for *Peerattack*$_{t-1}$, *Peerattack*$_{t-2}$, and *Peerattack*$_{t-3}$ are all positive and significant at the 1 percent level. Overall, the results suggest that a cyberattack significantly increases peer firms' likelihood of falling victim to future cyberattacks. The coefficient estimates for control variables are also generally consistent with Kamiya et al. (2021). For example, the results show that a firm with higher past visibility (e.g., larger firm size, S&P 500 membership) and higher past valuation (e.g., higher ROA, higher Tobin's q) are more susceptible to experiencing a cyberattack in year *t*. Our results are consistent with the contagion effect theory of a cyberattack: a cyberattack reveals negative information about cyber threats that are common across all firms in the industry. Our analysis suggests that the social costs borne by peer firms are manifest through increased vulnerability to future cyber threats. Given the social costs imposed on peer firms by a cyberattack, contagion appears to go beyond merely being an informational effect (Lang and Stulz, 1992). The findings also imply that there is a general increasing trend in the frequency of cyberattacks over time, and cyberattacks are more likely to cluster in particular industries, consistent with our findings in Table 1.

[Insert Table 5 here]

We now proceed to investigate whether the impact of cyberattacks on equity financing goes beyond the target firm and spills over to peer firms that operate in the same industry as the target firm[9]. To analyse this effect, we estimate the following probit model (Equation (4)), with *Pr(SEO)*$_{t+i}$ (i =1, 2, and 3) serving as the dependent variable. *Pr(SEO)*$_{t+3}$, *Pr(SEO)*$_{t+2}$ and *Pr(SEO)*$_{t+1}$ are indicator variables that equal one if a firm conducts at least an SEO within three, two, or one year(s) after year t, and zero otherwise.

$$\begin{aligned} Pr(SEO)_{t+i} \quad &= \alpha_0 + \alpha_1 Peerattack_t + \alpha_2 Attackitself_t + \alpha_3 MTB_t \\ &+\alpha_4 Prior\ stock\ return_t + \alpha_5 Firm\ size_t + \alpha_6 Leverage_t \\ &+industry\ and\ year\ fixed\ effect + \varepsilon \end{aligned} \tag{4}$$

[9] In Appendix B, we conduct univariate analyses of the Cumulative Abnormal Returns (CARs) for both the targeted firms and their peers, centred around the date of the cyberattack. The CARs of both groups are significantly negative around this time, offering preliminary evidence supporting the notion of a cyberattack's potential for contagion.

In Equation (4), we introduce an independent variable, *Peerattack,* to capture whether a firm can be identified as a peer firm of a cyberattack target in the same industry. *Peerattack* equals one if a firm does not experience a cyberattack itself but another firm in the same industry encounters a cyberattack in year *t*, and zero otherwise. In addition to the control variables used in the baseline model in Table 3 (i.e., firm size, leverage, market to book, prior stock return, and year and industry fixed effects), we include a variable named *Attack_itself* to account for a firm's own cyberattack experience in year *t*. *Attacked_itself* equals one if a firm, though not a peer of a cyberattack target, itself experiences a cyberattack in year t and zero otherwise.

The results estimating Equation (4) are presented in Table 6, Columns (1) to (3). In Column (1), the coefficient estimate of *Peerattack*, -0.201, is statistically significant at the 1 percent level, showing that firms are less likely to engage in SEO activity in the next three years after one of their industry peers became the victim of a cyberattack. Similarly, in Columns (2) and (3), the coefficient estimates of *Peerattack*, -0.206 and -0.202, are significant at the 1 percent level when the dependent variables are $Pr(SEO)_{t+2}$ and $Pr(SEO)_{t+1}$. Additionally, if a firm is a peer of a cyberattack target, there is a decline in the likelihood of this firm undertaking SEO activity in the subsequent three, two, and one-year periods by 1.8, 1.7, and 1.3 percentage points respectively, compared with firms in industries untouched by cyberattacks. The coefficient estimates on *Attack_itself* are negative and significant, consistent with the findings in Table 3 that firms experiencing cyberattacks are less likely to undertake SEOs in the post-attack years. Overall, the probit regression results provide strong evidence supporting the spillover effect of cyberattacks on SEO decisions among peer firms. Specifically, the results demonstrate that a cyberattack discourages peer firms from engaging in SEOs in the years following the attack[10].

Furthermore, we investigate whether peer firms tend to raise less capital from SEOs following a cyberattack in the industry. To explore this aspect, we substitute *Pr (SEO)*$_{t+i}$ (i =1, 2, and 3) in Equation (4) with *Size (SEO)*$_{t+i}$ (i =1, 2, and 3) in the following Tobit model, denoted as Equation (5):

$$\begin{aligned} Size(SEO)_{t+i} \quad &= \alpha_0 + \alpha_1 Peerattack_t + \alpha_2 Attackitself_t + \alpha_3 MTB_t \\ &+\alpha_4 Prior\ stock\ return_t + \alpha_5 Firm\ size_t + \alpha_6 Leverage_t \\ &+industry\ and\ year\ fixed\ effect + \varepsilon \qquad (5) \end{aligned}$$

The results of Equation (5) are presented in Table 6, Columns (4) to (6). The coefficient estimates on *Peerattack* are all negative and statistically significant at the 1 percent level, revealing that peer firms of a cyberattack target tend to generate lower proceeds from SEOs in the post-cyberattack period than firms operating in industries unaffected by cyberattacks. For instance, in Column (4), the results indicate that the total expected proceeds raised by peers of the cyberattack target during the three years after the focal year t, on average, are approximately 31.3% lower than the proceeds raised by firms operating in industries with no cyber incidents in year *t*, holding other factors constant.

[Insert Table 6 here]

4.4 Cross-sectional analyses

In our study, we find that peer firms, to avoid the increased cost of issuing equities, reduce their SEO probability in the aftermath of a cyberattack. Our empirical evidence reveals that these peer firms indeed face an increased likelihood of being the subsequent victims of a cyberattack. This implies that the negative information incorporated by these peer firms may reflect as an increased probability of becoming victim of a cyberattack in the near future. In

[10] In Appendix F, we use other methods to define peer firms as part of our robustness checks. The results remain consistent when using the majority of these other definitions for peer firms.

this section, considering the fact that not all peers within the same industry are equally impacted by the spillover effect of a cyberattack, we provide a more in-depth of assessment of which peer firms are more subject to the increased financing costs induced by a cyberattack, refraining them from conducting SEOs to a greater extent. We expect that peers with a greater probability of being targeted in future cyberattacks are less inclined to pursue SEOs subsequent to the initial cyber incident. This is because those peers most vulnerable to future cyberattacks might experience a more severe reputation loss and, consequently, incur higher costs when conducting SEOs. We verify this hypothesis through additional cross-sectional analyses.

We use two measures to proxy for the vulnerability of peer firms to future cyberattacks. First, we introduce an indicator variable, *D_Highprobability*, which equals one if a firm's predicted likelihood of experiencing a cyberattack in year *t* exceeds the industry median level, and zero otherwise. To predict the probability of being targeted by a cyberattack for each firm-year observation, we conduct a Probit regression analysis using the cyberattack indicator (i.e., Dependent variable= $Cyberattack_t$) and the set of explanatory variables in Kamiya et al. (2021) (i.e., $Firm\ size_{t-1}$, $Firm\ age_{t-1}$, $Tobin's\ q_{t-2}$, ROA_{t-1}, $Sales\ growth_{t-1}$, $Institutional\ ownership_{t-1}$, $S\&P500\ indicator_{t-1}$, $Asset\ intangibility_{t-1}$, and $Financial\ constraint\ indicator_{t-1}$), plus year and industry fixed effects. We then add the interaction term $Peerattack_t \times D\_Highprobability$ and the indicator variable *D_Highprobability* into the analysis in Equation (4)[11]. The results are reported in Table 7, Columns (1) to (3). When examining $Pr(SEO)_{t+3}$ as the dependent variable, the coefficient estimate on the interaction term $Peerattack_t \times D\_Highprobability$ is negative and statistically significant at the 5% level. The results remain robust when the dependent variables are $Pr(SEO)_{t+2}$ and $Pr(SEO)_{t+1}$. This suggests that peer firms are highly susceptible to future

[11] We also add the interaction term *Peerattackt×D_Highprobability* and the indicator variable *D_Highprobability* into the analysis in Equation (5). The results are reported in Appendix E.

cyberattacks and experience a more pronounced reduction in their likelihood of engaging in SEOs during the years following an attack.

Secondly, we investigate whether the negative impact of a cyberattack on peer firms' probability of engaging in SEOs is amplified for firms with higher visibility. Previous research by Kamiya et al. (2021) suggests that firms with greater visibility are more likely to be targeted by cyberattacks. This is because hackers tend to focus on firms where the benefits of hacking outweigh the costs, specifically those that possess more valuable and accessible information, such as visible firms. We argue that highly visible firms often receive more public attention and scrutiny than lesser-known ones. When such firms are affected by a cyberattack, either directly or indirectly, the investors react more strongly and critically, leading to higher costs of conducting SEOs. To examine this relationship, we introduce an indicator variable, *D_Highvisibility*, which equals one if a firm's total assets and institutional ownership both surpass the corresponding industry median levels in year t, and zero otherwise. The results are presented in Table 7, Columns (4) to (6). When the dependent variable is $Pr(SEO)_{t+3}$, the coefficient on the interaction term $Peerattack_t \times D\_Highvisibility$ is negative and significant at the 1 percent level. The results remains robust when we use $Pr(SEO)_{t+2}$ and $Pr(SEO)_{t+1}$ as the dependent variable. Consistently, these findings suggest that peer firms with greater visibility experience a more pronounced decrease in their likelihood of pursuing SEOs in the years following a cyberattack.

[Insert Table 7 here]

4.5 Additional Cross-sectional analyses

In Section 2, we highlighted the dilemma faced by peer firms: weighing the increased cost of raising capital, which discourages them from conducting SEOs, against the increased financing demand, which motivates them to do so. Section 4 shows that peer firms generally reduce their SEO probability after a cyberattack, indicating that the deterrent effect of increased costs of issuing equity has a more substantial influence on SEO decisions. In this section, we provide a more in-depth assessment of the situations under which peer firms have stronger incentives to decrease SEO probability. Specifically, we examine whether our results are influenced by cross-sectional variations in a peer firm's IT expenditure and cash holdings.

Our first set of tests investigates whether a cyberattack has a more significant negative impact on the SEO probability of peer firms with substantial IT investments. We begin our discussion with information technology. IT investment includes investment in networks and platform security, file and data security, and response to security breach/attack. Because of the lack of physical substance but the likelihood of producing future benefits, IT investment is classified as computerized information intangible investments (Corrado et al., 2005). Compared with firms with deficient IT investment, those with sufficient proactive IT investment need less IT-related finance following a cyberattack, therefore having fewer incentives to conduct SEOs. Following the literature (e.g., Mitra and Chaya, 1996; McKinsey, 2002;), we construct a measure of IT investment using SG&A expenditure. We define a dummy variable *D_IT*, which equals one if the firm's SG&A expenses in year *t* are above the industry median SG&A and interact it with $Peerattack_t$. Table 8, Columns (1) and (2) show negative coefficient estimates on the interaction between *D_IT* and $Peerattack_t$ that are significant at the 1 and 5 percent level, respectively. The coefficient on the interaction term in Column (3) lacks significance. In general, our finding implies that peer firms with greater IT expenditure experience a more pronounced decrease in SEO probability following a cyberattack, since they have less of a financing need, and are better positioned to avoid costly SEOs rather than addressing financing needs triggered by a cyberattack.

Our next set of tests examines whether the negative impact of a cyberattack on SEO probability is stronger for peer firms with a greater cash position. Peer firms must balance multiple considerations following a cyberattack. On the one hand, they face increased financing costs because of reputation loss following the cyberattack. Additionally, they need to consider funding measures for effective cyber risk management. The Pecking Order Theory, as proposed by Myers and Majluf (1984), posits that firms prefer a particular hierarchy for capital financing - they lean towards internal financing before turning to the capital market. Thus, we anticipate that firms with high cash reserves are less likely to seek external capital following a cyberattack. To examine this, we introduce an interaction between $Peerattack_t$ and a dummy variable, *D_Cashholding*, which equals one if the firm's cash reserves in the year t exceed the industry median and zero otherwise. The results are presented in Table 8, Columns (4) to (6). All coefficients are significantly negative at the 1 percent level. Our findings reinforce the view that peer firms with larger cash holdings tend to reduce the likelihood of conducting SEOs to a greater extent following a cyberattack.

[Insert Table 8 here]

6. Conclusion

Our study provides evidence that a cyberattack significantly influences a firm's decision to issue equity in subsequent years. Specifically, firms that experience a cyberattack undertake fewer and smaller SEOs and this effect persists for up to three years after the attack. As highlighted by Kamiya et al. (2021), the adverse information disclosed by a cyberattack not only affects the targeted firm but also spills over to its industry peers because of the shared fundamental characteristics among firms in the same industry. In line with this information revealing effect, we find that peer firms become more vulnerable to future cyberattacks following a cyber incident in the industry. In the context of equity issuance, our findings illustrate that peer firms engage in fewer, smaller SEOs subsequent to a cyberattack.

In addition, acknowledging that not all peers are equally affected by a cyberattack, we find the disincentive effect on equity issuance among peers more pronounced for those more vulnerable to future cyberattacks and possessing higher visibility; these firms suffer more substantial reputation damage. We argue there is a dilemma faced by peer firms: balancing the increased cost of capital raising against the increased financing need. The disincentive effect of a cyberattack on equity issuance is more pronounced among peers with substantial IT investments and cash holdings because of their diminished need for equity financing.

Overall, our study underscores the lasting impact of cyberattacks on firms' financial decisions, revealing the influence an attack has on both the attacked firm and its industry peers. The adverse consequences of a cyberattack extend beyond immediate financial losses and affect the equity issuance strategies of firms and the risk profiles of their peers.

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Appendix A

This appendix provides definitions of the variables we use in our study.

Variable	Definition
Asset intangibility	(1-total property, plant, and equipment)/total assets
Attackeditself	An indicator that equals one if a firm is a target of a cyberattack, and zero otherwise
CAR_attack	The cumulative abnormal return for the attacked firms during (-1, 1) event windows surrounding the cyberattack date
CAR_peer	The cumulative abnormal return for peer firms around the target's first cyberattack announcement date during the event window (-1, 1)
$Cyberattack_t$	An indicator variable equal to one if a firm experiences a cyberattack in year *t*, and zero otherwise
D_Highprobabiliy	An indicator equal to one if a firm's predicted probability of being cyberattacked in year *t* is higher than the industry median level, and zero otherwise.
D_Highvisibility	An indicator equal to one if a firm's total assets and institutional ownership both exceed the corresponding industry median levels, and zero otherwise.
Financially constraint	An indicator equal to one if a firm's WW index is in the top tercile of the sample in a given year, and zero otherwise
Firm age	Natural logarithm of max (years in CRSP, years in Compustat)
Firm size	Natural logarithm of total assets
Institutional block ownership	Proportion of shares held by 5% or greater block holders
Leverage	Ratio of total liabilities to total assets
Market to book	The standardized market to book value of equity
$Pr(SEO)_{t+1}$	An indicator variable equal to one if a firm initiates an SEO in year *t+1*, and zero otherwise
$Pr(SEO)_{t+2}$	An indicator variable equal to one if a firm initiates at least one SEO from year *t+1* to year *t+2*, and zero otherwise
$Pr(SEO)_{t+3}$	An indicator variable equal to one if a firm initiates at least one SEO within year *t+1* to year *t+3*, and zero otherwise
Prior stock return	The market-adjusted stock return over the 12 months ending immediately before year *t*.
$Peerattack_{t-1}$	An indicator equal to one if a firm has at least one other peer in the same 2-digit SIC industry experience at least one cyberattack in year *t-1*, and zero otherwise
$Peerattack_{t-2}$	An indicator equal to one if a firm has at least one other peer in the same 2-digit SIC industry experience at least one cyberattack from year *t-2* to year *t-1*, and zero otherwise
$Peerattack_{t-3}$	An indicator equal to one if a firm has at least one other peer in the same 2-digit SIC industry experience at least one cyberattack from year *t-3* to year *t-1*, and zero otherwise
ROA	Net income/total assets
sales growth	Sales in the focal year/sales in the prior year
$Size(SEO)_{t+1}$	The sum of SEO proceeds in the next year over the total assets in the focal year, and left-censored at zero for firms that do not conduct an SEO in year *t+1*.
$Size(SEO)_{t+2}$	The sum of SEO proceeds from year *t+1* to year *t+2* over the total assets in the focal year, and left-censored at zero for firms that do not conduct an SEO from year *t+1* to year *t+2*.
$Size(SEO)_{t+3}$	The sum of SEO proceeds from year *t+1* to year *t+3* over the total assets in year *t*, and left-censored at zero for firms that do not conduct an SEO within three years after the focal year.

SP500	An indicator equal to one if a firm is included in the list of Standard & Poor 500 companies in a given year, and zero otherwise.
Stock performance	Buy-and-hold return for the year net of CRSP value-weighted index return
Stock return volatility	Standard deviation of a firm's monthly stock returns during a fiscal year
Tobin's q	(Total assets- common/ordinary equity+ market value of equity)/ total assets

Appendix B

Univariate tests of cumulative abnormal returns (CARs) for attacked firms and peer firms around cyberattack announcement dates

This table reports the mean and median values of CARs over the window (-1, 1). Statistics are reported in percentages. The sample includes 257 firm-year observations that experienced cyberattacks, and 18,270 firm-year observations as industry peers (i.e., same 2-digit SIC code) from 2005 to 2017. CARs are obtained by subtracting the value-weighted CRSP market return from the raw return of the issuing firms (Kim and Purnanandam, 2014). *p-values* for means are based on standard t-tests; z- statistics for medians are based on Wilcoxon signed-rank tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

CAR (-1, 1) (%)	Mean	Median
CAR_attack (N=257)	-0.335**	-0.150*
	(0.039)	(-1.37)
CAR_Peer (N=18270)	-0.098***	-0.048***
	(0.000)	(-4.69)

Appendix B provides preliminary evidence that a cyberattack reveals adverse information that is contagious in an industry. Our key event window of interest is day -1 to day +1 around the cyberattack announcement date. This appendix reports cumulative abnormal returns (CARs) over the window (-1, +1) for the attacked firms (with 257 firm-year observations) and peer firms (with 18,270 firm-year observations). Following prior studies (e.g., Loughran and Ritter, 1997; Kim and Purnanandam, 2014; Malmendier et al., 2016), CARs are obtained by subtracting the value-weighted CRSP market returns from the raw returns of the issuing firms.

For the attacked firms, the mean (median) CAR (-1, +1) is -0.335% (-0.150%), which is consistent with anecdotal and empirical evidence suggesting that cyberattacks are negative shocks to market returns (Goel and Shawky 2009; Johnson et al., 2017; Kamiya et al. 2021). For the peer group, the mean (median) CAR (-1, +1) is -0.098% (-0.048%), providing some evidence that detrimental effects of a cyberattack are not idiosyncratic to attacked firms (Kamiya et al., 2021), peer firms may also suffer from the negative market reaction. In brief, the univariate results show that a cyberattack can drive comovements in market reactions between attacked firms and their peers. The results also show that the market reactions are more negative for attacked firms, which are more directly affected by cyberattacks, than for peers that are indirectly affected by cyberattacks.

Appendix C

Univariate analysis of the cyberattack's spillover effect on market timing

This table reports the mean and median values of different proxies for market timing. The proxies are (1) market to book ratio; (2) the market-adjusted return over one year ending immediately before the year in question (i.e., prior stock return); and (3) the market-adjusted returns over the one-year interval starting with the closing price of the year in question (i.e., future stock returns). The sample includes 6,237 SEO issuers from 2008 to 2018. We divide the sample into *Peerattack* group (N=3,125) and *Nonpeerattack* group (N=3,112) according to whether one issuer has an industry peer experiencing a cyberattack over the last three years. *p-values* for differences in means (medians) between non-peer-attack- and peer-attack- firms are based on standard t-tests (Wilcoxon signed-rank tests). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	A: Nonpeerattack group (N=3,125)		B: Peerattack group (N=3,112)		Test of difference (A=B)	
	Mean	Median	Mean	Median	Mean	Median
Market to book	3.644	2.663	3.065	2.399	0.027**	0.000***
Prior stock returns	0.059	0.003	0.038	-0.012	0.071*	0.009***
Future stock returns	-0.069	-0.119	-0.040	-0.047	0.007***	0.000***

We propose a potential candidate explanation for the decreased SEO probability of peer firms. Market timing captures the investment opportunities in a given year and has become the most prominent theoretical explanation for SEOs (Loughran and Ritter, 1995; 1997). We expect that the decreased SEO probability of peer firms also, to some extent, is reflected in the unfavourable market-timing in the post-attack period.

We restrict our sample to SEO issuers that meet specific requirements (see table legend), and divide SEO issuers into two groups based on whether the issuer is a peer firm of a prior cyberattack target. We assign an issuer to *Nonpeerattack* group if all industry peers of this issuer experiencing no cyberattack within three years before year *t*. We assign an issuer to *Peerattack* group if at least one industry peer of this issuer experiencing a cyberattack within three years before year *t*. Then we perform a univariate test on the differences in market-timing measures between the two subsamples. Following prior literature (Loughran and Ritter, 1995, 1997; Baker and Wurgler, 2002; DeAngelo et al., 2010), we use three measures for market-timing: *Market to book*, *Prior stock returns* (e.g., a higher market to book and a higher prior stock return indicates a more favourable market timing), and *Future stock returns* (a higher future stock return indicates a less favourable market timing). Appendix D reports the results of the univariate analyses. The last two columns, report the differences between the *Peerattack* group and the *Nonpeerattack* group and their p-values based on standard t-tests (means) and Wilcoxon signed-rank tests (medians). For instance, the results show that the mean (median) *Market to book* in year t is 3.644 (2.663) for the *Nonpeerattack* group whereas the mean (median) *Market to book* in year *t* is 3.065 (2.399) for the *Peerattack* group. The mean (median) difference is significant at 5% (1%), indicating that an issuer faces relatively less favourable market timing if it is a peer firm of a prior cyberattack target. In other words, less favourable market timing can be another explanation of why peer firms decrease SEO probabilities following the cyberattack. The results are robust to the alternative measures of market timing: *Prior stock return* and *Future stock returns*.

APPENDIX D.

Cross-sectional analyses of the spillover effect: the impact of a cyberattack on peers' SEO size

This table presents the cross-sectional variation in the effect of a cyber incident in the industry on the peer firms' SEO size. We estimate the Tobit model where the dependent variable, $Size(SEO)_{t+i}$ (i =1, 2, and 3), is the total proceeds raised from SEOs in the post-cyberattack year(s) over a firm's total assets. Specifically, $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are calculated as the sum of SEO proceeds three, two, and one year(s) after year *t* over the firm's total assets in year *t*, respectively. $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are left-censored at zero for firms that do not conduct an SEO in these years. $Peerattack_t$ is coded one if there is another firm in the same 2-digit SIC industry as the focal firm being cyberattacked in year *t*, and zero otherwise. From Columns (1) to (3), the moderating variable, *D_Highprobabiliy*, equals one if a firm's predicted probability of being cyberattacked in year *t* is higher than the industry median level, and zero otherwise. We obtain the predicted probability of being cyberattacked as follows: First, we regress the cyberattack likelihood (i.e., Dependent variable= $Cyberattack_t$) on the set of explanatory variables in Kamiya et al (2021) (i.e., *Firm size*, *Firm age*, *Tobin's q*, *ROA*, *Sales growth*, *Institutional ownership*, *S&P500 (indicator)*, *Asset intangibility*, and *Financial constraint (indicator)*), along with year and industry fixed effects. Next, we obtain a predicted cyberattack probability for each firm-year (Kamiya et al., 2021). From Columns (4) to (6), the moderating variable, *D_highvisibility*, equals one if a firm's total assets and institutional ownership both exceed the corresponding industry median levels, and zero otherwise. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Size\ (SEO)_{t+3}$	$Size\ (SEO)_{t+2}$	$Size\ (SEO)_{t+1}$	$Size\ (SEO)_{t+3}$	$Size\ (SEO)_{t+2}$	$Size\ (SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
$Peerattack_t$	-0.187***	-0.136**	-0.128**	-0.203***	-0.165***	-0.131***
	(-2.76)	(-2.31)	(-2.47)	(-4.19)	(-3.92)	(-4.51)
$Peerattack_t$ * D_Highprobability	**-0.142***	**-0.141***	**-0.098**			
	(-1.65)	**(-1.89)**	**(-1.51)**			
D_Highprobability	-0.338***	-0.295***	-0.205***			
	(-4.65)	(-4.65)	(-3.71)			
$Peerattack_t$ * D_Highvisiblity				**-0.144****	**-0.129****	**-0.035**
				(-2.36)	**(-2.43)**	**(-0.97)**
D_Highvisibility				0.768***	0.645***	0.352***
				(17.69)	(16.99)	(13.74)
Attackitself	-7.588	-6.787	-5.545	-1.072**	-0.845**	-0.433*
	(-0.01)	(-0.01)	(-0.00)	(-2.12)	(-1.99)	(-1.66)
Market to book	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(3.59)	(3.21)	(3.45)	(3.10)	(2.69)	(3.21)
Prior stock return	0.167***	0.128***	0.086***	0.120***	0.090***	0.050***
	(6.03)	(5.25)	(4.09)	(5.78)	(4.93)	(4.01)

Firm size	-0.068***	-0.053***	-0.037***	-0.217***	-0.182***	-0.103***
	(-5.17)	(-4.63)	(-3.73)	(-22.83)	(-21.94)	(-18.38)
Leverage	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.84)	(0.93)	(0.23)	(-0.38)	(-0.34)	(-0.49)
Intercept	-3.420***	-2.912***	-2.446***	-3.529***	-2.932***	-1.817***
	(-23.08)	(-22.55)	(-20.74)	(-7.97)	(-7.89)	(-7.99)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	51,631	51,631	51,631	63,287	63,287	63,287
Pseudo R^2	0.044	0.047	0.049	0.063	0.066	0.072

APPENDIX E.

Additional cross-sectional analyses of the spillover effect: The impact of a cyberattack on peers' SEO size

This table presents an additional set of cross-sectional variation in the effect of a cyber incident in the industry on the peer firms' SEO size. We estimate the Tobit model where the dependent variable, $Size(SEO)_{t+i}$ (i =1, 2, and 3), is the total proceeds raised from SEOs in the post-cyberattack year(s) over the firm's total assets. Specifically, $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are calculated as the sum of SEO proceeds within three, two, and one year(s) after year *t* over the firm's total assets in year *t*, respectively. $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are left-censored at zero for firms that do not conduct an SEO in these years. $Peerattack_t$ is coded one if there is another firm in the same 2-digit SIC industry as the focal firm being cyberattacked in year *t*, and zero otherwise. $Peerattack_t$ is coded one if there is another firm in the same 2-digit SIC industry as the focal firm being cyberattacked in year *t*, and zero otherwise. From Columns (1) to (3), the conditional variable, *D_IT*, equals one if a firm's IT expense in year *t* is higher than the industry median level, and zero otherwise. From Columns (4) to (6), the conditional variable, *D_Cashholding*, equals one if a firm's cash holding level in year *t* exceed the corresponding industry median levels, and zero otherwise. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Size\ (SEO)_{t+3}$	$Size\ (SEO)_{t+2}$	$Size\ (SEO)_{t+1}$	$Size\ (SEO)_{t+3}$	$Size\ (SEO)_{t+2}$	$Size\ (SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
$Peerattack_t$	-0.211***	-0.183***	-0.133***	-0.065	-0.047	-0.033
	(-3.54)	(-3.49)	(-3.55)	(-0.89)	(-0.74)	(-0.76)
$Peerattack_t$ * D_IT	**-0.070**	**-0.065**	**-0.022**			
	(-0.94)	**(-1.00)**	**(-0.47)**			
D_IT	0.187***	0.161***	0.098***			
	(3.58)	(3.53)	(3.01)			
$Peerattack_t$ * D_Cashholding				**-0.361*** **	**-0.319*** **	**-0.200*** **
				(-4.12)	**(-4.19)**	**(-3.80)**
D_Cashholding				0.356***	0.305***	0.170***
				(6.86)	(6.74)	(5.47)
Attackitself	-0.888*	-0.706	-0.360	-6.872	-6.416	-3.907
	(-1.69)	(-1.58)	(-1.27)	(-0.03)	(-0.01)	(-0.01)
Market to book	-0.000	-0.000	-0.000	0.000***	0.000**	0.000***
	(-0.74)	(-0.68)	(-0.54)	(2.65)	(2.28)	(2.83)
Prior stock return	0.134***	0.103***	0.055***	0.152***	0.115***	0.063***
	(5.31)	(4.59)	(3.37)	(5.91)	(5.07)	(4.03)
Firm size	-0.138***	-0.116***	-0.069***	-0.153***	-0.127***	-0.073***

	(-12.48)	(-11.95)	(-10.05)	(-15.46)	(-14.84)	(-12.42)
Leverage	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.17)	(0.18)	(-0.03)	(-0.28)	(-0.25)	(-0.45)
Intercept	-4.092***	-3.446***	-2.237***	-4.370***	-3.626***	-2.292***
	(-6.82)	(-6.80)	(-7.03)	(-7.78)	(-7.72)	(-7.87)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	52,116	52,116	52,116	51,164	51,164	51,164
Pseudo R^2	0.045	0.048	0.055	0.060	0.065	0.071

APPENDIX F.

Robustness check: Alternative measures of peer firms

This table presents the results of robustness tests by re-estimating Equation (3) with other measures of the peer firms of a cyberattack target. The dependent variable is $Pr(SEO)_{t+i}$ (i =1, 2, and 3) an indicator variable that equals one if a firm undertakes at least one SEO within three/ two/ one year(s) after year t, and zero otherwise. Throughout this study, $Peerattack_t$, captures whether the firm can be identified as a 2-digit SIC industry peer of a cyberattack target. From Columns (1) to (3), we define the peers as firms operating in the same 3-digit SIC industry. From Columns (4) to (6), we define peers are the attacked firm's character-matched firms. Each attacked firm has three character-matched peers, and the set of matching variables comprise size, ROA, MTB, and leverage within same industry and year. From Columns (7) to (9), peers are firms operating in the same 4- Digit GICS industry. From Columns (10) to (12), peers are firms operating in the same 6- Digit GICS industry. N denotes the number of observations, Z-statistics shown in parentheses are based in standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	3-Digit SIC Peer			Character-Matched Peer			4- Digit GICS Peer			6- Digit GICS Peer		
Peerattack	**-0.005**	**-0.008**	**0.014**	**-0.169*** **	**-0.187*** **	**-0.201*** **	**-0.185*** **	**-0.184*** **	**-0.169*** **	**-0.181*** **	**-0.183*** **	**-0.173*** **
	(-0.19)	**(-0.32)**	**(0.51)**	**(-5.68)**	**(-6.03)**	**(-5.89)**	**(-8.73)**	**(-8.37)**	**(-6.97)**	**(-7.61)**	**(-7.42)**	**(-6.36)**
Attackitself	-0.539**	-0.494*	-0.616*	-0.599**	-0.562**	-0.740**	-0.664***	-0.616**	-0.731**	-0.612**	-0.565**	-0.691**
	(-2.10)	(-1.92)	(-1.86)	(-2.23)	(-2.10)	(-2.08)	(-2.59)	(-2.40)	(-2.22)	(-2.38)	(-2.20)	(-2.08)
Market to book	0.000***	0.000**	0.000***	-0.000	-0.000	-0.000	0.000**	0.000**	0.000**	0.000**	0.000**	0.000***
	(2.60)	(2.08)	(2.64)	(-0.74)	(-0.69)	(-0.64)	(2.51)	(1.98)	(2.55)	(2.56)	(2.05)	(2.61)
Prior stock return	0.079***	0.073***	0.067***	0.113***	0.114***	0.113***	0.077***	0.070***	0.065***	0.079***	0.072***	0.066***
	(6.14)	(5.39)	(4.56)	(6.07)	(5.96)	(5.62)	(5.96)	(5.22)	(4.39)	(6.09)	(5.33)	(4.47)
Firm size	-0.058***	-0.057***	-0.049***	-0.033***	-0.030***	-0.022***	-0.059***	-0.058***	-0.051***	-0.056***	-0.055***	-0.048***
	(-13.65)	(-13.00)	(-10.28)	(-5.11)	(-4.45)	(-3.02)	(-13.90)	(-13.25)	(-10.51)	(-13.32)	(-12.68)	(-10.01)
Leverage	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.37)	(-0.32)	(-0.41)	(-0.03)	(-0.03)	(0.03)	(-0.36)	(-0.30)	(-0.39)	(-0.37)	(-0.31)	(-0.40)
Intercept	-2.357***	-2.343***	-2.399***	-2.423***	-2.420***	-2.546***	-2.383***	-2.368***	-2.426***	-2.367***	-2.353***	-2.412***
	(-8.31)	(-8.25)	(-8.42)	(-8.37)	(-8.35)	(-8.64)	(-8.30)	(-8.25)	(-8.42)	(-8.28)	(-8.23)	(-8.40)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Number of observations	63,287	63,287	63,287	40,912	40,912	40,912	63,272	63,272	63,272	63,272	63,272	63,272
Pseudo R^2	0.044	0.044	0.043	0.060	0.059	0.062	0.047	0.047	0.046	0.046	0.046	0.045

Tables

Table 1
Distribution of cyberattacks by industry and year
The table presents the distribution of 319 cyberattacks against 263 firms covered in Compustat from 2005 to 2019 by year and industry (the 2-digit SIC codes are classified using the Standard Industrial Classification in Centurion Lists & Information Services.

Year of breach	Mineral and construction	Manufacturing	Transport and communications	Electric, gas, and sanitary service	Wholesale, trade, and retail trade	Finance	Service industry	Not classified establishments	Total
	(2-digit SIC =10-17)	(2-digit SIC =20-39)	(2-digit SIC =40-48)	(2-digit SIC =49)	(2-digit SIC =50-59)	(2-digit SIC =60-69)	(2-digit SIC =70-89)	(2-digit SIC =99)	
2005	0	1	0	0	1	0	1	0	3
2006	0	0	1	0	4	2	0	0	7
2007	1	1	0	0	2	9	3	0	16
2008	0	0	0	0	3	4	2	0	9
2009	0	0	1	0	1	3	4	0	9
2010	0	1	0	0	4	3	1	1	10
2011	0	7	1	0	2	3	7	0	20
2012	1	6	5	0	3	4	9	0	28
2013	0	7	4	1	2	7	12	0	33
2014	1	10	4	0	12	9	16	1	53
2015	0	4	3	0	5	3	5	1	21
2016	0	7	5	0	7	8	18	0	45
2017	1	12	3	0	10	6	14	0	46
2018	0	5	1	0	0	3	5	0	14
2019	0	0	0	0	0	3	2	0	5
Total	4	61	28	1	56	67	99	3	319

Table 2
Summary statistics
This table reports summary statistics for the variables used in our baseline models from 2005-2017. Panel A shows the summary statistics for a sample of 231 firm-year observations that experience a cyberattack in the focal year (*Target group*) and 63,056 firm-year observations that experience no cyberattack in the focal year (*Nontarget group*). Panel B shows the summary statistics for a sample of 22,801 firm-year observations whose peer firms experience at least one cyberattack in the focal year (*Peerattack group*) and 40,486 firm-year observations whose peers experience no cyberattack in the focal year (*Nonpeerattack group*). *p*-values for differences in means (medians) between two groups are based on the Standard *t*-tests (Wilcoxon signed-rank tests). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of variables used in the table.

Panel A: attacked group versus nonattacked group

	A: Target group (N=231)		B: Nontarget group (N=63,056)		Test of difference (A=B)	
Variable	Mean	Median	Mean	Median	Mean	Median
$Pr(SEO)_{t+3}$	0.009	0.000	0.049	0.000	0.000***	0.005***
$Pr(SEO)_{t+2}$	0.009	0.000	0.044	0.000	0.000***	0.009***
$Pr(SEO)_{t+1}$	0.004	0.000	0.033	0.000	0.000***	0.015**
Market to book	1.257	0.000	19.005	0.821	0.000***	0.000***
Prior stock return	0.027	0.011	0.018	-0.035	0.656	0.016**
Firm size	9.148	9.037	6.562	6.589	0.000***	0.000***
Leverage	1.408	0.513	1.703	0.393	0.859	0.020**

Panel B: attacked peer group versus nonattacked peer group

	A: Peerattack group (N=22,801)		B: Nonpeerattack group (N=40,486)		Test of difference (A=B)	
Variable	Mean	Median	Mean	Median	Mean	Median
$Pr(SEO)_{t+3}$	0.042	0.000	0.053	0.000	0.000***	0.000***
$Pr(SEO)_{t+2}$	0.037	0.000	0.048	0.000	0.000***	0.000***
$Pr(SEO)_{t+1}$	0.028	0.000	0.036	0.000	0.000***	0.000***
Market to book	11.765	0.720	22.982	0.860	0.002***	0.000***
Prior stock return	0.018	-0.027	0.018	-0.039	0.949	0.000***
Firm size	6.655	6.653	6.525	6.562	0.000***	0.000***
Leverage	0.580	0.374	2.334	0.405	0.206	0.051*

Table 3
The impact of a cyberattack on the seasoned equity offering (SEO) decision
This table presents Probit and Tobit estimates of the following model:

$$Pr(SEO)_{t+i} \text{ or } Size(SEO)_{t+i} = \alpha_0 + \alpha_1 Cyberattack_t + \alpha_2 Market\ to\ Book_t + \alpha_3 Prior\ stock\ return_t + \alpha_4 Firm\ size_t + \alpha_5 Leverage_t + Year\ and\ industry\ FE + \delta$$

From Columns (1) to (3), we estimate the Probit model where the dependent variable is $Pr(SEO)_{t+i}$ (i =1, 2, and 3). In column (1), the dependent variable, $Pr(SEO)_{t+3}$, is an indicator variable that equals one if a firm undertakes at least one SEO within three years after a given year *t*, and zero otherwise; In column (2), the dependent variable, $Pr(SEO)_{t+2}$, is an indicator variable that equals one if a firm undertakes at least one SEO within two years after a given year *t*, and zero otherwise; In column (3), the dependent variable, $Pr(SEO)_{t+1}$, is an indicator variable that equals one if a firm undertakes at least one SEO within one year after a given year *t*, and zero otherwise. From Columns (4) to (6), we estimate the Tobit model where the dependent variable, $Size(SEO)_{t+i}$ (i =1, 2, and 3), is the total proceeds raised from SEOs in the post-cyberattack year(s) over the firm's total assets. Specifically, $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are calculated as the sum of SEO proceeds within three, two, and one year(s) after year *t* over the firm's total assets in year *t*, respectively. $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are left-censored at zero for firms that do not conduct an SEO in these years. *Cyberattack* is an indicator variable that equals one if a firm experienced a cyberattack in a given year *t*, and zero otherwise. The explanatory variables are firm size, leverage, standardized market to book ratio, and prior stock return (i.e., the market-adjusted stock return over the 12 months ending immediately before year *t*, following DeAngelo et al. (2010) and Altı and Sulaeman (2012)). The sample includes all firm-year observations with available data in Compustat and CRSP from 2005-2017. All regressions include year and industry fixed effects. Industries are classified using the 2-digit SIC codes. *z*-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Size\ (SEO)_{t+3}$	$Size\ (SEO)_{t+2}$	$Size\ (SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Cyberattack	**-0.540****	**-0.492***	**-0.622***	**-1.024****	**-0.802***	**-0.403**
	(-2.10)	**(-1.92)**	**(-1.87)**	**(-1.97)**	**(-1.84)**	**(-1.51)**
Market to book	0.000***	0.000**	0.000***	0.000***	0.000***	0.000***
	(2.60)	(2.08)	(2.64)	(3.18)	(2.77)	(3.31)
Prior stock return	0.079***	0.073***	0.066***	0.133***	0.102***	0.056***
	(6.13)	(5.39)	(4.51)	(6.51)	(5.72)	(4.67)
Firm size	-0.057***	-0.056***	-0.049***	-0.113***	-0.095***	-0.054***
	(-13.57)	(-12.94)	(-10.24)	(-16.15)	(-15.61)	(-13.12)
Leverage	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000

	(-0.38)	(-0.32)	(-0.41)	(-0.36)	(-0.32)	(-0.52)
Intercept	-2.355***	-2.339***	-2.397***	-3.514***	-2.913***	-1.803***
	(-8.30)	(-8.25)	(-8.41)	(-7.80)	(-7.73)	(-7.87)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	63,287	63,287	63,287	63,287	63,287	63,287
Pseudo R^2	0.043	0.043	0.043	0.042	0.046	0.051

Table 4
A comparison of SEO decisions between the attacked- and non-attacked firms
This table reports the differences in SEO decisions, ATT (average treatment effect on the treated), based on a sample in which cyberattacked firms are matched with non-attacked firms in Compustat using the propensity score matching algorithms. To address sample selection bias, we propensity score match each attacked firm in our sample (i.e., treated group) with a non-attacked control firm in Compustat (i.e., control group), using the 1:1 nearest neighbour, radius, and kernel approaches. Pre-matching refers to the sample without matching the treated group with the control group, and post-matching refers to groups after propensity score matching. In panel A, the matching variables are firm-level characteristics from the baseline model, including firm size, leverage, standardized M/B ratio, prior stock return, year and 2-digit SIC industry. In panel B, the matching variables are the determinants of firms being cyberattacked in Kamiya et al (2021), including firm size, firm age, Tobin's q, ROA, sales growth, stock performance, leverage, financially constraint, stock return volatility, institutional block ownership, asset intangibility, year and 2-digit SIC industry. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Panel A. Propensity score matching: using firm fundamental characters as matching variables

Variable	Sample	Treated	Controls	Difference (ATTs)	Standard Error	**t-statistics**
1:1 NN matching						
Pr(SEO)$_{t+3}$	pre-matching	0.009	0.049	-0.041	0.014	**-2.85**
	post-matching	0.009	0.052	-0.043	0.017	**-2.59**
Pr(SEO)$_{t+2}$	pre-matching	0.009	0.044	-0.035	0.014	**-2.62**
	post-matching	0.009	0.048	-0.039	0.016	**-2.42**
Pr(SEO)$_{t+1}$	pre-matching	0.004	0.032	-0.028	0.012	**-2.40**
	post-matching	0.004	0.035	-0.030	0.014	**-2.24**
Radius matching						
Pr(SEO)$_{t+3}$	pre-matching	0.009	0.049	-0.041	0.014	**-2.85**
	post-matching	0.009	0.033	-0.024	0.007	**-3.25**
Pr(SEO)$_{t+2}$	pre-matching	0.009	0.044	-0.035	0.014	**-2.62**
	post-matching	0.009	0.030	-0.021	0.007	**-2.86**
Pr(SEO)$_{t+1}$	pre-matching	0.004	0.032	-0.028	0.012	**-2.40**
	post-matching	0.005	0.023	-0.019	0.005	**-3.44**
Kernel matching						
Pr(SEO)$_{t+3}$	pre-matching	0.009	0.049	-0.041	0.014	**-2.85**
	post-matching	0.009	0.043	-0.034	0.007	**-5.12**

$Pr(SEO)_{t+2}$	pre-matching	0.009	0.044	-0.035	0.014	**-2.62**
	post-matching	0.009	0.038	-0.030	0.007	**-4.46**
$Pr(SEO)_{t+1}$	pre-matching	0.004	0.032	-0.028	0.012	**-2.40**
	post-matching	0.004	0.028	-0.024	0.005	**-4.93**

Panel B. Propensity score matching: using cyberattack factors as matching variables

Variable	Sample	Treated	Controls	Difference (ATTs)	Standard Error	**t-statistics**
<u>1:1 NN matching</u>						
$Pr(SEO)_{t+3}$	pre-matching	0.005	0.040	-0.035	0.013	**-2.64**
	post-matching	0.005	0.037	-0.033	0.016	**-2.00**
$Pr(SEO)_{t+2}$	pre-matching	0.005	0.036	-0.031	0.013	**-2.44**
	post-matching	0.005	0.037	-0.033	0.016	**-2.00**
$Pr(SEO)_{t+1}$	pre-matching	0.000	0.026	-0.026	0.011	**-2.38**
	post-matching	0.000	0.028	-0.028	0.014	**-2.06**
<u>Radius matching</u>						
$Pr(SEO)_{t+3}$	pre-matching	0.005	0.040	-0.035	0.013	**-2.64**
	post-matching	0.005	0.025	-0.020	0.007	**-2.89**
$Pr(SEO)_{t+2}$	pre-matching	0.005	0.036	-0.031	0.013	**-2.44**
	post-matching	0.005	0.022	-0.017	0.007	**-2.65**
$Pr(SEO)_{t+1}$	pre-matching	0.000	0.026	-0.026	0.011	**-2.38**
	post-matching	0.000	0.018	-0.018	0.004	**-4.88**
<u>Kernel matching</u>						
$Pr(SEO)_{t+3}$	pre-matching	0.005	0.040	-0.035	0.013	**-2.64**
	post-matching	0.005	0.034	-0.029	0.005	**-5.29**
$Pr(SEO)_{t+2}$	pre-matching	0.005	0.036	-0.031	0.013	**-2.44**
	post-matching	0.005	0.030	-0.025	0.005	**-4.71**
$Pr(SEO)_{t+1}$	pre-matching	0.000	0.026	-0.026	0.011	**-2.38**
	post-matching	0.000	0.022	-0.022	0.002	**-10.62**

Table 5

Probit analysis of the impact of peer' previous cyberattack records on a firm's likelihood of being cyberattacked in a given year

This table examines whether firms are more likely to experience a cyber incident if it has an industry peer targeted in a recent cyberattack. Columns (1) to (3) present the estimates of the Probit model in which the dependent variable, $Cyberattack_t$, is an indicator variable that equals one if a firm experienced a cyberattack in year t, and zero otherwise. $Peerattack_{t-i}$ (i =1, 2, and 3) measures whether the focal firm has a peer having been cyberattacked in previous years. $Peerattack_{t-1}$ is an indicator variable that equals one if at least another firm in the same 2-digit SIC industry as the focal firm has been cyberattacked in the previous year, and zero otherwise. $Peerattack_{t-2}$ is an indicator variable that equals one if at least another firm in the same 2-digit SIC industry as the focal firm has been cyberattacked in the previous two years, and zero otherwise. $Peerattack_{t-3}$ is an indicator variable that equals one if at least another firm in the same 2-digit SIC industry as the focal firm has been cyberattacked in the previous three years, and zero otherwise. All control variables are one-year lagged except for Tobin's q, which is two-year lagged. We use the Wald tests to compare the equality of two coefficients in a single regression model and report *p*-values for the one-tailed test. z-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=		$Cyberattack_t$	
Independent variable	(1)	(2)	(3)
$Peerattack_{t-1}$	**0.773*** **		
	(4.42)		
$Peerattack_{t-2}$		**0.744*** **	
		(4.13)	
$Peerattack_{t-3}$			**0.736*** **
			(3.99)
Firm size	0.351***	0.357***	0.352***
	(7.93)	(8.03)	(7.97)
Firm age	-0.498***	-0.473***	-0.473***
	(-6.89)	(-6.71)	(-6.70)
Tobin's q	0.011	0.007	0.008
	(1.04)	(0.60)	(0.72)
ROA	2.565***	2.934***	2.590***
	(2.86)	(3.34)	(2.97)
Sales growth	-1.823***	-1.706***	-1.743***

	(-4.73)	(-4.61)	(-4.64)
Institutional ownership	-0.931***	-0.936***	-0.931***
	(-3.66)	(-3.74)	(-3.74)
S&P500 (indicator)	1.713***	1.676***	1.654***
	(6.96)	(7.01)	(6.97)
Asset intangibility	-3.144***	-3.129***	-3.106***
	(-10.92)	(-10.99)	(-11.08)
Financial constraint (indicator)	1.680*	1.985**	1.818*
	(1.65)	(2.03)	(1.84)
Intercept	-3.436***	-6.717***	-6.689***
	(-13.04)	(-12.81)	(-12.83)
Year fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Number of observations	56,278	56,278	56,278
Pseudo R^2	0.875	0.874	0.873

Table 6

The spillover effect: the impact of a cyberattack on the peer firm's seasoned equity offering (SEO) decisions

This table presents estimates from the following model:

$$Pr(SEO)_{t+i} \text{ or } Size(SEO)_{t+i} = \alpha_0 + \alpha_1 Rivalattack_t + \alpha_2 Attackitself_t + \alpha_3 Market\ to\ book_t + \alpha_4 Prior\ stock\ return_t + \alpha_5 Firm\ size_t + \alpha_6 Leverage_t + Year\ and\ industry\ FE + \delta$$

From Columns (1) to (3), we estimate the Probit model where the dependent variable is $Pr(SEO)_{t+i}$ (i =1, 2, and 3). In column (1), the dependent variable, $Pr(SEO)_{t+3}$, is an indicator variable that equals one if a firm undertakes at least one SEO within three years after a given year *t*, and zero otherwise; In column (2), the dependent variable, $Pr(SEO)_{t+2}$, is an indicator variable that equals one if a firm undertakes at least one SEO within two years after a given year *t*, and zero otherwise; In column (3), the dependent variable, $Pr(SEO)_{t+1}$, is an indicator variable that equals one if a firm undertakes at least one SEO within one year after a given year *t*, and zero otherwise. From Columns (4) to (6), we estimate the Tobit model where the dependent variable, $Size(SEO)_{t+i}$ (i =1, 2, and 3), is the total proceeds raised from SEOs in the post-cyberattack year(s) over the firm's total assets. Specifically, $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are calculated as the sum of SEO proceeds within three, two, and one year(s) after year *t* over the firm's total assets in year *t*, respectively. $Size(SEO)_{t+3}$, $Size(SEO)_{t+2}$, and $Size(SEO)_{t+1}$ are left-censored at zero for firms that did not conduct an SEO in these years. The variable of interest, $Peerattack_t$, captures whether the focal firm has an industry peer being targeted in a cyberattack. $Peerattack_t$ is coded one if there is another firm in the same 2-digit SIC industry as the focal firm being cyberattacked in year *t*, and zero otherwise. An additional indicator variable, *Attack_itself*, is included. It equals one if the focal firm itself is cyberattacked, and zero otherwise. The explanatory variables are firm size, leverage, standardized market to book ratio, and prior stock returns (i.e., the market-adjusted stock return over the 12 months ending immediately before year *t*, following DeAngelo et al. (2010) and Altı and Sulaeman (2012). The sample includes all firm-year observations with available data in Compustat and CRSP from 2005-2017. All regressions include year and industry fixed effects. Industries are classified using 2-digit SIC codes. *z*-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Size(SEO)_{t+3}$	$Size(SEO)_{t+2}$	$Size(SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Peerattack	**-0.201*** **	**-0.206*** **	**-0.202*** **	**-0.313*** **	**-0.261*** **	**-0.163*** **
	(-9.30)	**(-9.15)**	**(-8.13)**	**(-8.87)**	**(-8.47)**	**(-7.75)**
Attackitself	-0.654**	-0.609**	-0.733**	-1.190**	-0.941**	-0.490*
	(-2.55)	(-2.37)	(-2.22)	(-2.31)	(-2.18)	(-1.85)
Market to book	0.000**	0.000*	0.000**	0.000***	0.000***	0.000***
	(2.47)	(1.95)	(2.51)	(3.02)	(2.63)	(3.16)
Prior stock return	0.079***	0.072***	0.066***	0.131***	0.101***	0.055***
	(6.08)	(5.33)	(4.44)	(6.43)	(5.63)	(4.57)

Firm size	-0.057***	-0.056***	-0.049***	-0.112***	-0.094***	-0.053***
	(-13.44)	(-12.82)	(-10.13)	(-16.03)	(-15.51)	(-13.02)
Leverage	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.37)	(-0.31)	(-0.40)	(-0.35)	(-0.31)	(-0.50)
Intercept	-2.427***	-2.413***	-2.470***	-3.617***	-3.000***	-1.858***
	(-8.50)	(-8.44)	(-8.61)	(-7.99)	(-7.91)	(-8.06)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	63,287	63,287	63,287	63,287	63,287	63,287
Pseudo R^2	0.046	0.047	0.046	0.046	0.049	0.055

Table 7
Cross-sectional analyses of the spillover effect: The impact of a cyberattack on the peer's SEO decisions
This table presents the cross-sectional variation in the effect of a cyber incident in the industry on the focal firm's SEO decision. In columns (1) and (4), the dependent variable, $Pr(SEO)_{t+3}$, is an indicator variable that equals one if a firm undertakes at least one SEO within three years after a given year *t*, and zero otherwise; In columns (2) and (5), the dependent variable, $Pr(SEO)_{t+2}$, is an indicator variable that equals one if a firm undertakes at least one SEO within two years after a given year *t*, and zero otherwise; In columns (3) and (6), the dependent variable, $Pr(SEO)_{t+1}$, is an indicator variable that equals one if a firm undertakes at least one SEO within one year after a given year *t*, and zero otherwise. $Peerattack_t$ equals one if there is another firm in the same 2-digit SIC industry as the focal firm being cyberattacked in year *t*, and zero otherwise. From Columns (1) to (3), the moderating variable, *D_Highprobabiliy*, equals one if a firm's predicted probability of being cyberattacked in year *t* is higher than the industry median level, and zero otherwise. We obtain the predicted probability of being cyberattacked as follows: we regress the cyberattack likelihood (i.e., Dependent variable= $Cyberattack_t$) on the set of explanatory variables in Kamiya et al (2021) (i.e., *Firm size*, *Firm age*, *Tobin's q*, *ROA*, *Sales growth*, *Institutional ownership*, *S&P500 (indicator)*, *Asset intangibility*, and *Financial constraint (indicator)*), along with year and industry fixed effects. Next, we obtain a predicted cyberattack probability for each firm-year (Kamiya et al., 2021). From Columns (4) to (6), the moderating variable, *D_highvisibility*, equals one if a firm's total assets and institutional ownership both exceed the corresponding industry median levels, and zero otherwise. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
$Peerattack_t$	-0.070**	-0.059	-0.064	-0.125***	-0.130***	-0.151***
	(-2.01)	(-1.62)	(-1.58)	(-4.30)	(-4.32)	(-4.53)
$Peerattack_t$ * D_Highprobability	**-0.107****	**-0.128*****	**-0.122****			
	(-2.41)	**(-2.78)**	**(-2.37)**			
D_Highprobability	-0.183***	-0.187***	-0.172***			
	(-4.84)	(-4.77)	(-3.90)			
$Peerattack_t$ * D_Highvisiblity				**-0.120*****	**-0.118*****	**-0.074***
				(-3.20)	**(-3.04)**	**(-1.73)**
D_Highvisibility				0.359***	0.358***	0.304***
				(14.25)	(13.72)	(10.59)
Attackitself	-0.833**	-0.796**	0.000	-0.616**	-0.570**	-0.711**
	(-2.40)	(-2.29)	(.)	(-2.40)	(-2.22)	(-2.12)

Market to book	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***
	(7.24)	(7.03)	(6.32)	(5.45)	(5.30)	(4.70)
Prior stock return	0.131***	0.124***	0.105***	0.112***	0.106***	0.094***
	(5.97)	(5.39)	(4.08)	(5.79)	(5.30)	(4.24)
Firm size	-0.028***	-0.024***	-0.019**	-0.103***	-0.102***	-0.089***
	(-4.09)	(-3.29)	(-2.42)	(-18.77)	(-17.99)	(-14.29)
Leverage	0.013***	0.014***	0.012***	0.017***	0.018***	0.017***
	(3.19)	(3.30)	(2.68)	(4.93)	(4.98)	(4.25)
Intercept	-1.852***	-1.917***	-2.138***	-2.416***	-2.401***	-2.454***
	(-27.67)	(-27.67)	(-26.72)	(-8.58)	(-8.52)	(-8.65)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	51,631	51,631	51,419	63,287	63,287	63,287
Pseudo R^2	0.051	0.052	0.052	0.058	0.059	0.056

Table 8

Additional cross-sectional analyses of the spillover effect: The impact of a cyberattack on the peer's SEO decisions

This table presents the cross-sectional variation in the effect of a cyber incident in the industry on the focal firm's SEO decision. In columns (1) and (4), the dependent variable, $Pr(SEO)_{t+3}$, is an indicator variable that equals one if a firm undertakes at least one SEO within three years after a given year *t*, and zero otherwise; In columns (2) and (5), the dependent variable, $Pr(SEO)_{t+2}$, is an indicator variable that equals one if a firm undertakes at least one SEO within two years after a given year *t*, and zero otherwise; In columns (3) and (6), the dependent variable, $Pr(SEO)_{t+1}$, is an indicator variable that equals one if a firm undertakes at least one SEO within one year after a given year *t*, and zero otherwise. $Peerattack_t$ equals one if there is another firm in the same 2-digit SIC industry as the focal firm being cyberattacked in year *t*, and zero otherwise. From Columns (1) to (3), the conditional variable, *D_IT*, equals one if a firm's IT expense in year *t* is higher than the industry median level, and zero otherwise. From Columns (4) to (6), the conditional variable, *D_Cashholding*, equals one if a firm's cash holding level in year *t* exceed the corresponding industry median levels, and zero otherwise. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A provides a detailed description of the construction of the variables.

Dependent variable=	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$	$Pr(SEO)_{t+3}$	$Pr(SEO)_{t+2}$	$Pr(SEO)_{t+1}$
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
$Peerattack_t$	-0.070*	-0.084**	-0.102**	-0.013	-0.012	-0.009
	(-1.95)	(-2.23)	(-2.41)	(-0.36)	(-0.30)	(-0.21)
$Peerattack_t$ * D_IT	**-0.116*** **	**-0.108** **	**-0.083**			
	(-2.59)	**(-2.32)**	**(-1.60)**			
D_IT	0.129***	0.126***	0.109***			
	(4.04)	(3.80)	(2.95)			
$Peerattack_t$ * D_Cashholding				**-0.179*** **	**-0.198*** **	**-0.201*** **
				(-3.96)	**(-4.23)**	**(-3.88)**
D_Cashholding				0.146***	0.156***	0.135***
				(5.41)	(5.59)	(4.34)
Attackitself	-0.445*	-0.408	-0.531	-0.729**	-0.689**	0.000
	(-1.69)	(-1.55)	(-1.61)	(-2.08)	(-1.97)	(.)
Market to book	-0.000	-0.000	-0.000	0.000**	0.000*	0.000**
	(-0.90)	(-0.80)	(-0.68)	(2.26)	(1.76)	(2.34)
Prior stock return	0.082***	0.076***	0.064***	0.077***	0.069***	0.061***
	(5.30)	(4.72)	(3.53)	(5.58)	(4.73)	(3.83)

Firm size	-0.069***	-0.067***	-0.057***	-0.075***	-0.074***	-0.066***
	(-10.45)	(-9.78)	(-7.56)	(-15.00)	(-14.15)	(-11.49)
Leverage	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.10)	(0.09)	(-0.09)	(-0.32)	(-0.27)	(-0.41)
Intercept	-2.733***	-2.738***	-2.833***	-2.415***	-2.409***	-2.473***
	(-7.29)	(-7.28)	(-7.48)	(-8.12)	(-8.09)	(-8.26)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	52,116	52,116	52,116	51,164	51,164	50,974
Pseudo R^2	0.049	0.050	0.051	0.063	0.064	0.061

Chapter 3: Competitive Pressure and Relative Performance Evaluation: Evidence from Mergers and Acquisitions

ABSTRACT

We examine the spillover effects of an acquisition on the industry peer firms of the acquirer. We treat an acquisition as a shock that increases competitive pressure in the product market. Our findings reveal that, with the intent to defend their competitive position in the product market, peer firms exhibit an increased propensity to adopt relative performance evaluation (RPE, hereafter) in their CEO compensation as a strategic response to an acquisition. This effect is more pronounced when the peer firm exhibits a close co-movement with the acquirer before the acquisition announcement and when the acquisition is driven by competitive motives. The effect is also varies with peer firms' characteristics; we find a stronger effect when peer firms are market followers, operating in competitive industries, producing products that are hard to replicate, and have efficient boards. In addition, we provide evidence showing that peer firms that adjust RPE compensation exhibit a higher level of aggressiveness than peer firms that do not adjust RPE. Collectively, our findings are consistent with the theory that incorporating RPE into CEO compensation design incentivizes firms to aggressively improve their relative competitive position.

JEL classification:

Keywords: M&A, Relative performance evaluation (RPE), Product market competition, Spillover effect

1. Introduction

RPE incentive contracts have recently become popular. Gong et al. (2011) find that, in 2006, only 25 percent of firms explicitly employed RPE in setting executive compensation. According to the Institutional Shareholder Service (ISS) Incentive Lab, however, two-thirds of firms now incorporate RPE in their executive compensation (Do et al., 2022). Firms implementing RPE-based compensation may use different metrics, including a peer's accounting performance (e.g., sales, profits) and stock performance (e.g., stock returns) (Gong et al., 2011; Du and Shen, 2018). A typical RPE compensation package has two important features. First, a firm compensates its managers based on whether the firm outperforms a predetermined benchmark of peer firms. Managers usually receive no RPE-based award if they fail to achieve the benchmark. Secondly, managers place great importance on their firm's ability to come out on top of the competition. Features of an RPE contract induce tournament-like incentives (Do et al., 2022). In this study, we argue that firms respond to competition pressures by adopting RPE compensation.

We focus on a specific form of the competitive pressure: the strength of other firms in the same industry. We use an acquirer firm's M&A (acquisition, hereafter) activity as a relatively exogenous competitive pressure from the non-merging industry peer firms' perspective and explore how peer firms use RPE in response to acquisition-induced competitive pressures. Berger et al. (2004) suggest that an acquisition is significant in changing the structure and conditions of market competition, because it creates a competitive advantage for the acquirer. The competitive advantages gained by an acquirer include, but are not limited to, reducing transaction costs, engaging in relationship-specific investments between suppliers and customers in vertical takeovers (Shenoy, 2012), improving production efficiency and buying power in horizontal takeovers (Hoberg and Phillips, 2010; Bhattacharyya and Nain, 2011), obtaining new technologies and patents (Bena and Li, 2014), reorganizing their human capital (Lee et al., 2018), having the ability to use specialized resources (Chatterjee, 1986; Peteraf, 1993), and achieving additional strategic flexibility (Sanchez, 1995). Peer firms in the same industry are often threatened by the strengthened acquirer's position (e.g., Bradley et al., 1988; Mitchell and Mulherin, 1996; Maksimovic and Phillips, 2001; Jovanovic and Rousseau, 2002). We provide a plausible reason to believe that non-merging peer firms are more likely to adopt RPE compensation in response to an acquisition. *The competitive pressure theory* assumes that the improved competitive position of the acquirer forces its peers to become more competitive. The literature shows that, after an acquisition, peer firms are engaged in competitive behaviors such as price cuts, advertising campaigns, introducing new products and product improvements (Geroski, 1995; Uhlenbruck et al., 2017).

Although non-merging peers would be better off to take defensive actions to preserve their competitive positions following acquisitions, the driving mechanisms behind such actions remain uncertain. Jensen and Meckling (1976) recognize that managers face an agency problem and do not automatically seek to maximize firm value. Thus, providing managers with adequate incentives is important. The compensation literature illustrates the benefits of using RPE, especially in an increased competitive environment. Gibbons and Murphy (1990) suggest that RPE puts a firm in direct competition with its peers; firms are encouraged to engage in competitive actions to gain an advantage over peers. Aggarwal and Samwick (1999) demonstrate that managers act more aggressively competitive when they work under a relative performance plan than when they work under an absolute performance plan. Do et al. (2022) suggest that the tournament incentives induced by RPE compensation are because of the substantial spread in rewards between winners and losers. Consequently, we test the hypothesis that an RPE-contract is a mechanism used by shareholders to motivate managers in peer firms to take action to overcome the competitive threat induced by the acquirer.

There are plausible reasons to believe that non-merging peer firms may not use RPE in response to an acquisition. First, based on *the lazy manager theory*, firms might lack motivation on realizing that the compensation rewards are very difficult to achieve in severe market competition. For example, Schmidt's (1997) model of lazy managers shows a reduction in profitability as competition reduces the incentives for managers to exert greater effort. Despite previous studies often rejecting the lazy manager theory in favour of the competition pressures theory (e.g., Giroud and Mueller, 2010; Aghion et al., 2013), Oh and Shin (2020) posit an exception where shareholders strategically allow weak governance in response to a competitive threat. They argue that intense competition makes it challenging for managers to achieve performance rewards, leading managers to be unmotivated and devote less effort to promoting firm level activities. In such circumstances, shareholders incentivize managers by allowing them to enjoy private benefits under a weak governance structure. Markman et al. (2009) suggests that an acquisition can intensify overall product market rivalry. In such an environment, RPE-based compensation might be less effective because of *the lazy manager theory*; severe market competition induced by acquisitions makes it too difficult for non-merging peers to outperform relative benchmarks (i.e., difficult to achieve an RPE-based compensation). As a result, peer firms may opt to maintain traditional absolute performance evaluations rather than adopting RPE compensation to prevent their managers from being lazy and unmotivated. Secondly, the hypothesis premises that RPE gives managers incentives to act aggressively. However, being aggressive can be costly to a firm. Direct competition can potentially incentivize managers to engage in collusion, committing them to refrain from competitive aggression, particularly when an overlapping relationship exists in the RPE compensation package.

Our main analysis examines the effects of acquisitions on changes in non-merging industry peers' use of RPE. Our regression sample consists of 18409 firm-year observations from 2006 to 2020. The starting point of our sample period is 2006 because proxy disclosure on the details of RPE contracts in the U.S. became mandatory then. In the baseline section, we define a peer firm as all other firms in the same 2-digit SIC industry as the acquirer. We find that peers are more likely to adopt RPE after an acquisition. The results are consistent with the view that RPE incentives make firms more aggressive in dealing with increased competitive pressure. We also investigate the extent to which a peer firm's exposure to competitive pressures correlates with its propensity to adopt RPE. To quantify the intensity of these competitive pressures, we use the frequency and aggregate transaction values of acquisitions in the industry. Our findings reveal that the likelihood of a peer firm adopting RPE increases by the scale of acquisitions.

Having established the main result, which shows that peer firms adopt RPE as a response to acquisition-induced competitive pressure, we perform several analyses to provide direct evidence of how an acquisition can affect peer firms' RPE use. Barberis et al. (2005) suggest that any co-movement in stock returns must be because of co-movement in firm fundamentals. Hoberg and Phillips (2012) argue that highly competitive firms with similar products face similar cost and demand shocks, leading to a higher level of stock co-movement. Consequently, we hypothesize that peer firms are more concerned about the strengthened position gained by an acquirer when the peer firm exhibits a tight co-movement with the acquirer before the acquisition. Our objective is to examine whether the spillover effect of an acquisition on peer firms' RPE use is driven by the high stock return co-movements between the peer firm and the acquirer. In line with our expectations, we find that a peer firm exhibits an increased propensity to use RPE in response to an acquisition when the pre-acquisition stock returns between the acquirer and the peer firm are highly correlated. To provide additional evidence on the *Competitive pressure theory*, we classify acquisitions into two groups based on the deal purpose mentioned in the acquisition announcement: competition-related purpose vs other purpose. The results indicate that the spillover effect of an acquisition on peer firms' RPE is pronounced only for the acquisitions with a competition-related purpose. Conversely, when acquisitions are driven by other purposes, the impact on peer firms' RPE use is not significant, indicating that such acquisitions do not exert the same level of competitive pressure on industry peers.

We perform further cross-sectional tests to shed light on the mechanisms behind the baseline results. First, peer firms are likely to encounter different levels of competitive pressure induced by acquisitions. The extent to which a peer firm is threatened by the strengthened competitive position of the acquirer largely depends on the peer firm's market position. Firms with a smaller market share are typically subjected to greater competition (Nickell et al., 1992; Nickell, 1996) and, thus, are more susceptible to competitive threats induced by acquisitions. Consistently, we find that the impact of acquisitions on a peer firm's RPE use is more pronounced when the peer firm functions as a market follower. Secondly, RPE literature shows that firms operating in competitive industries are more prone to using RPE compensation than those operating in concentrated industries (e.g., Aggarwal and Samwick, 1999; Gong et al., 2011). One reason for this is the higher degree of common risks in competitive industries that renders the adoption of RPE more beneficial to such firms (DeFond and Park, 1999). In addition, the competitive pressures induced by acquisitions might be offset by an increased likelihood of monopolistic collusion in concentrated industries because of the limited number of competitors (Eckbo, 1983). We find that peer firms are more likely to adopt RPE after acquisitions, particularly when operating in a competitive industry. Thirdly, we consider which peer firms are less sensitive to the strengthened acquirer's competitive situation. Hwang et al. (2002) suggest that a firm can use a differentiation strategy to achieve a competitive advantage. A differentiation strategy often emphasizes responsiveness to customer requests in the form of design for product uniqueness and product innovation. Hoberg and Phillips (2014) argue that firms with unique, differentiated products are very difficult to duplicate by competitors, which, in turn, makes them less susceptible to market competition. We expect that peer firms producing more unique products will be less impacted by acquisitions and, consequently, less likely to adjust RPE in response to acquisitions. Our results support the argument by showing that the positive impact of acquisitions on peer firms' RPE use is mitigated when peer firms produce unique products.

In our final cross-sectional analysis, we focus on board efficiency. After an acquisition, peer firms may suffer a loss in market share because of the acquirer's enhanced competitive position (e.g., Colougherty and Duso, 2011; Uhlenbruck et al., 2017), leading peer firms' shareholders to become concerned about such potential losses of competitive position in the market. A more efficient board is likely to represent shareholder interests more effectively, facilitating the adoption of RPE compensation to address these concerns over potential losses in market position. We find that peer firms are more likely to adopt RPE compensation after an acquisition when the board efficiency is high.

Finally, we examine the consequences of adjusting RPE compensation following an acquisition. By restricting the baseline sample to acquirers' peer firms, we analyse the differences in aggressive actions between peer firms that adjust to RPE and those that do not. Our analysis focuses on two specific measures: advertising expense and operating margin. Relying on different methods to define peer firms, we find that, in general, peer firms that adjust RPE compensation exhibit a higher level of advertising expense and a lower operating margin than peer firms that do not adjust to RPE. These findings provide empirical support for the premise that adjusting to RPE compensation leads to more aggressive behaviour among peer firms following an acquisition, suggesting that RPE serves as a mechanism that motivates firms to actively compete and strive in the face of increased competitive pressures.

Our study contributes to the literature on acquisition spillover effects of CEO compensation design. The literature (e.g., Coakley and Iliopoulou, 2006; Girma et al., 2006) illustrates that acquirers award CEOs significantly higher bonuses and salaries following acquisitions; our evidence suggests that there are important spillover effects that also influence compensation package design in non-merging peer firms. Servaes and Tamayo (2014) find that peer firms change investment and financing policies when another firm in the industry is the target of a hostile acquisition attempt, suggesting that the control threat faced by the target firm generates important spillover effects for non-target peers in the industry. Our evidence complements Servaes and Tamayo's (2014) findings by showing that the competitive advantage gained by an acquirer result in competitive pressures for peer firms in the same industry. This prompts peer firms to strategically adopt RPE-based compensation in the aftermath of an acquisition, highlighting a spillover effect from the acquirer side.

Our study also contributes to the literature on the use of RPE contracts. Economic theory predicts that an incentive plan based on relative performance is superior to an incentive plan based on individual performance, because relative performance captures exogenous shocks, insulating an agent from common risk. Besides this risk-sharing benefit, RPE tournament theory proposes potential competition benefits of RPE (e.g., Nalebuff and Stiglitz, 1983; Hannan et al., 2008; Do et al., 2022). Despite its theoretical appeal, RPE involves potential costs. Early studies suggest that RPE contracts create adverse incentives for agents such as sabotaging peer performance, colluding with peers, and/or choosing inappropriate reference groups (e.g., Dye, 1984; Gibbons and Murphy, 1990; Aggarwal and Samwick, 1999). The theory and evidence cited above provide potential explanations for a lack of consistent empirical evidence supporting the use of RPE in executive compensation. We complement the literature by directly examining firms' decisions on RPE compensation associated with changes in market competition. Our findings are largely consistent with the view that competition benefits by using RPE and provides evidence that firms increase the use of RPE in response to increasing competitive pressures in an industry.

The remainder of this chapter is organized as follows. We review related literature and develop our hypotheses in Section 2. Section 3 contains the research design and data collection procedure. Section 4 describes the results. Section 5 provides several additional tests, and Section 6 concludes the chapter.

2. Literature Review and Hypothesis Development

2.1 Acquisition-induced competitive pressures

In this section, we develop hypotheses regarding the product market spillovers of acquisitions. Specifically, we aim to establish a theoretical framework to explain why acquisitions are perceived as competitive threats to peer firms. Additionally, we discuss how peer firms respond to the competitive threats induced by acquisitions. Acquisition activity is a means of corporate restructuring. Research on corporate strategy has traditionally conceptualized acquisitions based on a narrow cost-benefit analysis- related to market power, synergies, diversification, access to new technologies or capabilities and tax considerations. Akdoğu (2009) argues that acquisition activity awards the acquirer a competitive advantage and, thereby, makes acquisitions costly for the non-merging peers of the acquirer.

Our study considers an acquisition as a competitive threat that is relatively exogenous from an individual peer firm's perspective. On completing an acquisition, the acquirer may realize an improvement in its competitive position (Hitt et al., 2001). For example, acquirers gain strategic flexibility through the acquisition of various resources such as new distribution and marketing channels, product lines, and manufacturing processes (Chatterjee, 1986; Sanchez, 1995), obtain new technologies, and incentivize more innovative outputs (Bena and Li, 2013), reduce labour costs by laying off low quality and/or duplicate employees (Lee et al., 2018). These potential benefits may signal that the acquirer has enhanced its ability to compete

(Chen et al., 2007), leading non-merging firms in the same industry to view the acquisition as a competitive threat (e.g., Bradley et al, 1988). Indeed, Clougherty and Duso (2011) find that nearly 50 percent of peer firms of acquirers lose market share because of acquisitions. Concerned with the competitive disadvantage relative to acquirers, non-merging peer firms are forced to respond to acquisitions with aggressive actions to defend their position in the product market (Insead and Chatain, 2008). Both anecdotal and empirical evidence highlight aggressive competitive responses carried out by peer firms after acquisitions. For example, Rayovac and Energizer engaged in pricing strategies and special promotion campaigns after Gillette, one of their biggest competitors, acquired Duracell in 1996 (Business Week Online 2000 [12]). Following acquisitions, peer firms respond by engaging in R&D investment, advertising campaigns, taking action related to pricing and marketing, introducing new products and improving existing products, and increasing capacity (e.g., Keil and Laamanen, 2011; King and Schriber, 2016; Uhlenbruck et al., 2017; Gomes-Casseres, 2018). This is consistent with the notion that an acquisition can push up the general level of competition in the industry (Akdoğu, 2009) and can increase competitive pressures and provoke aggressive responses for non-merging peers.

2.2 A tournament-like incentive under RPE

RPE compensation has been extensively discussed over past decades. The earlier RPE literature argues that RPE serves as a means of distinguishing between managers' contribution to firm performance and the effect of common shocks. Firm performance is subject to common market and industry shocks, therefore agency theory suggests that relative performance should be considered when evaluating managers' talent and effort (e.g., Holmstrom 1979; 1982). Accordingly, when determining managerial compensation, many boards adopt RPE as a benchmark to control for common shocks (e.g., Lazear and Rosen 1981; Holmstrom 1982;

[12] Available at: wwwbusinessweekcom/stories/2000-10-15/can-gillette-regain-its-voltage

Nalebuff and Stiglitz 1983; Holmstrom and Milgrom 1987; Du and Shen, 2018). We focus on the competition benefits of RPE proposed by tournament incentives. Under RPE-based compensation, executive compensation levels are evaluated by comparing the performance of a reference group of firms in terms of accounting or stock performance metrics (Gong et al., 2011; Du and Shen, 2018). This evaluation may incorporate various components of compensation, including base salary, annual and long-term incentive plan targets, other potential equity awards and total compensation.

A typical RPE compensation package has two features. First, relative rather than absolute performance matters. In the context of RPE compensation, the CEO usually receives no award if their firm fails to pass a predetermined percentage of reference peers. Once the firm reaches the performance threshold, the CEO's award increases with the ranking of the firm relative to reference peers[13]. Second, for the CEO, it is important that the firm emerges as the top performer in the competitive landscape (Do et al., 2022). The two features mirror the definition of a tournament. The literature reports the impact of intra-firm tournament incentives on firm performance and behaviours. Kale et al. (2009) find tournament incentives, as measured by the pay differential between the CEO and vice presidents, relate positively to firm performance. Kini and Williams (2012) measure the tournament incentives as the pay gap between the CEO and the next layer of senior managers and find stronger tournament incentives result in greater risk-taking. RPE compensation serves more of the inter-firm tournament incentives, because RPE compensation puts firms in direct competition/tournament with their peers. Firms often engaged in aggressive actions to gain advantages over competitors

[13] For example, as stated in the PG&E Corporation's 2006 proxy statement, the firm adopted a RPE-based compensation, with a group of peer firms' stock return serving as the relative performance metric. The payout structure was as follows: No payout if PG&E's stock return fell below the 25th percentile of peer firms; a 25 percent payout if PG&E's stock return was at the 25th percentile; a 100 percent payout if PG&E's stock return reached the 75th percentile; a 200 percent payout if PG&E's stock return ranked first among the peer firms. If PG&E's stock return is between the 25th percentile and 75th percentile, or above the 75th percentile, award payouts will be determined by straight-line interpolation.

and improve their relative position. Hannan et al. (2008) find that firms compensated under RPE perform better than firms compensated under traditional individual incentives. Do et al. (2022) find that RPE firms exhibit higher financial leverage, increased R&D investment, and greater within-GAAP earnings manipulations than non-RPE firms. Feichter et al. (2022) find a positive relationship between RPE compensation and competitive aggressiveness, in terms of greater advertising expenditure and smaller operating margins. In summary, the RPE literature suggests that RPE-induced tournament incentives are effective in motivating executives in terms of firm performance, risk-taking, and competitive behaviour.

In this study, we investigate whether peer firms are more likely to adopt RPE in response to a sudden increase in competitive pressure induced by an acquisition. We postulate that when acquirers gain a competitive advantage through acquisitions, peer firms are more inclined to adopt RPE as a means to encourage CEOs to engage in aggressive competitive actions aimed at defending their position in the market. Except for the competitive benefits, prior literature highlights the complex nature of RPE because of the potential costs associated with using RPE. Dikolli et al. (2018) find firms choose to not implement RPE if expected peer performance is sufficiently high. Gibbon and Murphy (1990) suggest that firms may not adopt RPE because of the difficulty in identifying appropriate peers. Some studies argue that RPE can introduce a significant incentive-distorting side effect, costly sabotage. For example, managers could take action to inflate their relative performance even at a high cost to their firm's value (e.g., Lazear, 1989; Gibbons and Murphy, 1990; Chowdhury and Gurtler, 2015; Bloomfield et al., 2021). Accordingly, we test the following hypothesis:

H1: *Peer firms are more inclined to adopt RPE in response to an acquisition that leads to competitive pressure in the industry.*

3. Data and Methodology

3.1 Sample and methodology

We compile the acquisition data from the Securities Data Corp (SDC) Platinum on all acquisition activities for U.S. public firms from 2006 to 2020[14]. Following previous M&A literature (e.g., Servaes and Tamayo, 2014; Oh and Shin, 2020), we apply the following requirements to our sample acquisitions: (1) exclude transactions for which the acquirer's goal is to purchase less than 50% of the shares of the target; (2) exclude transactions if the acquirer already owns over 50% of the shares before announcement date; (3) exclude transactions with deal value less than $10 million (in year 2000 US dollars) because we want to use transactions that are influential enough to affect market competition; and (4) exclude transactions for financial firms (SIC=6000-6900) because these firms' acquisition activities are regulated. We collect the data on relative performance evaluation (RPE) from Institutional Shareholder Services Incentive Lab (ISS Incentive Lab, hereafter), and we find that about 30 percent of our sample firms explicitly use RPE in setting executive compensation. This is consistent with Gong et al. (2011) who find about 25 percent of their sample firms are RPE users, and Do et al. (2022) who indicate that the use of RPE grants in executive compensation has increased steadily over time. We obtain the necessary accounting and board information from Compustat and BoardEx, respectively. After data-matching, we eliminate an observation if any of the required regression variables are missing. Our final sample consists of 18409 firm-year observations.

Our main analysis examines the effects of an acquisition on the changes in peer firms' RPE use by estimating the following probit model:

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[14] In 2006, the Securities and Exchange Commission (SEC) issued Release No. 33-8732A, which requires "both a general discussion and analysis of compensation and specific material information regarding tabular items where necessary to an understanding of the tabular disclosure" in a new section titled Compensation Discussion and Analysis (CD&A) (SEC 2006, 18). The new disclosure rules were initially proposed in January 2006 and are effective for fiscal years ending on or after December 2006. Prior to 2006, proxy disclosure on the details of RPE contracts in the U.S. had been voluntary, but became mandatory since 2006.

$$\Delta RPE_{i,t} = \beta_0 + \beta_1 \times PEER\_ACQ_{i,t-1} + \gamma' \times X_{i,t-1} + \alpha_j + \alpha_t + \varepsilon_{i,t} \quad (1)$$

The dependent variable ΔRPE_t is an indicator variable capturing a firm's tendency to adopt an RPE contract. ΔRPE_t is equal to one if the firm use RPE in their executive compensation in year *t* but does not use RPE in year *t-1*, and zero otherwise. The interested explanatory variable $PEER\_ACQ_{i,\,t-1}$, captures whether a firm is a peer firm of an acquirer, is an indicator variable that equals one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise. If a firm itself is an acquirer, we do not include it in the sample pool because our focus is on firms that are not directly involved in acquisitions (i.e., non-merging firms). $X_{i,t-1}$ represents a set of control variables that are known to be related to a firm's decision on RPE use. We follow Albuquerque (2009) and Gong et al. (2011) in choosing control variables: common risks (*Commonrisk*), availability of similar peers (*Sizerkadj*), industry competition (*Industryconcentrate*), growth opportunities (*MTB*), size (*Size*), industry-adjusted firm operating performance (*Roaindadj*), and the proportion of outside directors on the board (*Board Independence*); α_j and α_t are industry- and year-fixed effects, respectively.

3.2 Descriptive statistics

Table 1, Panel A, presents the descriptive statistics for the primary variables. The average $PEER\_AQC_{t-1}$ is 0.600, suggesting that approximately 60 percent of the observations can be classified as peer firms of an acquirer, given that the acquisition occurs in *t-1*. The average ΔRPE_t is only 0.039, suggesting that most firms barely change their tendency to use RPE. We note that, in general, the mean and median values of other variables are similar to those reported in prior research. For example, the mean (median) values of firm size, industry adjusted return, and board independence are 8.630 (8.560), 0.048 (0.026), and 0.751 (0.875), respectively, which are similar to those found in prior studies (e.g., Gong et al., 2011). Panel B provides correlations among the main variables. ΔRPE_t is positively correlated with

$PEER\_AQC_{t-1}$ (corr.=0.029), suggesting that a peer firm's use of RPE is weakly correlated with acquisitions. The correlation matrix also reveals that ΔRPE_t is positively associated with the availability of similar peers (*Sizerkadj*), firm size, and board independence. Some studies (e.g., Aggarwal and Samwick, 1999; Gong et al., 2011) consider board size as a determinant of RPE compensation. However, in untabulated results, we observe a strong correlation between *Boardsize* and *Boardindepend* (corr.=0.85). Thus, we include only *Boardindepend* in our baseline regression. The results remain consistent throughout when board size is included instead of board independence.

[Insert Table 1 here]

4. Results

4.1 Main analyses: How do acquisitions affect industry peers' RPE use?

Table 2 presents the results of the regression for the effect of an acquisition on peer firms' change in RPE compensation using Equation (1). In Column (1), we include only the key explanatory variable as well as year and industry fixed effects. The coefficient on $PEER\_ACQ_{t-1}$ is positive and significant at the 5 percent level (coef.=+0.085, z-stat=2.24). In Column (2), we add all control variables. The coefficient on $PEER\_AQC_{t-1}$ is positive and significant at the 1 percent level (coef.=+0.134, z-stat =3.28). Consistent with Hypothesis 1, peer firms are more likely to adopt RPE compensation after an acquisition in the industry. Our findings suggest that when acquirers obtain a competitive advantage through an acquisition, the competitive edge gained by the acquirer spills over to non-merging peer firms. These peer firms, threatened by the acquirer's enhanced competitive position, tend to adopt RPE as a strategy to motivate CEOs to protect their competitive position in the product market. This is agrees with prior RPE literature, illustrating that tying CEO compensation to relative performance puts the firm in direct competition with its peers. Indeed, in the context of head-to-head competition, firms fight for market share, and competitors often directly and aggressively challenge each other in an effort to improve relative performance (e.g., Gibbons and Murphy, 1990; Ferrier, 2001). Aggarwal and Samwick (1999) suggest that the intuition of RPE contracts is that they commit the managers to behaving aggressively in the product market to deter competitors.

[Insert Table 2 here]

We further explore the extent to which a peer firm faces competition pressure by quantifying the acquisition's effect. Uhlenbruck et al. (2017) illustrate that large acquisitions are more notable to industry peers. This is because large-scale acquisitions could signal a significant strategic move by the acquirers (e.g., acquiring key technology or resources, entering a new market). Peer firms often closely monitor such acquisitions because they may signal a greater change in the competitive landscape. The frequency of acquisitions at industry level can also serve as an appropriate measure of competitive pressure. As more firms gain competitive advantage through an increase in acquisitions, competition intensifies among the remaining peer firms who jostle for market share. Following Oh and Shin (2020), we use the industry-level total acquisition value and acquisition frequency to measure the level of competitive pressure faced by peer firms. Our variable of interest is $PEER\_TDV_{t-1}$ (Total deal value) and $PEER\_TDF_{t-1}$ (Total deal frequency). $PEER\_TDV_{t-1}$ is defined as the log value of the total deal value of acquisitions announced by other firms in the 2-digit SIC industry. It is equal to zero if no acquisition is announced in an industry. $PEER\_TDV_{t-1}$ is defined as the log value of the total number of acquisitions undertaken by other firms in the 2-digit SIC industry, and is equal to zero if no acquisition is announced in an industry. The results are presented in Table 3. In Column (1), we see that the coefficient of $PEER\_TDV_{t-1}$ is positive and significant at the 1% level (coef.=+0.039, z-stat=5.93). In Column (2), the coefficient of $PEER\_TDF_{t-1}$ is also positive and significant at the 1% level (coef.=+0.069, z-stat=5.96). These results suggest that the likelihood of a peer firm adopting RPE increases with the scale of acquisitions in an industry.

[Insert Table 3 here]

4.2 Robustness check: Alternative measures of peer firms

In the baseline analysis, we define peer firms as non-merging firms that operate in the same 2-digit SIC industry as the acquirer. Although the SIC industry classification is one of the most convenient and frequently-used classifications in published studies, some studies from the industrial organization literature highlight several shortcomings of the SIC classification. First, although the SIC categories were established by the Federal US Census Bureau, responsibility for assigning the primary industry code to a specific firm falls to the data vendor; this assignment is not always made on a consistent basis across data vendors (Bhojraj et al., 2003). Secondly, Clarke (1989) examined whether firms in the same SIC category exhibit more similar characteristics in terms of sales and profit rate, and concludes that SIC codes are not successful at identifying firms with similar characteristics. In this section, we perform a robustness test to determine whether our main results remain consistent when we use other methods for defining peer firms. We construct an independent variable $PEER\_AQC_{t-1}$ based on other methods while keeping all control variables unchanged, and re-estimate Equation (1). The results are presented in Table 4. In Column (1), we define peers as firms that operate in the same 3-digit SIC industry as the acquirer. $PEER\_AQC_{t-1}$ equals 1 if at least one acquisition activity is announced by another firm in the same 3-digit SIC industry in *t-1*, and zero otherwise. In Column (2), we use a 1:3 nearest-neighbour matching approach to identify an acquirer's firm-character-matched peers. We match each acquirer to the three most similar peers in the same industry (two-digit SIC) and year. The set of matching variables are fundamental firm characteristics: size, ROA, MTB, and leverage. The independent variable $PEER\_ACQ_{t-1}$ equals one if a firm is the character-matched peer of an acquirer in *t-1*, and 0 otherwise.

Bhojraj et al. (2003) argue that the GICS classification provides a better technique for identifying industry peers, considering the increased availability of GICS information at a relatively low cost and its wide acceptance by finance practitioners. Therefore, we use the 4- and 6-digit GICS classifications to allow for the possibility that the different classification systems may potentially have an impact on the empirical results. In Column (3) (Column (4)), $PEER\_AQC_{t-1}$ is equal to 1 if at least one acquisition activity is announced by another firm in the same 4- digit (6-digit) GICS industry in *t-1*, and zero otherwise. All the coefficients on $PEER\_ACQ_{t-1}$ are still positive and significant at the 1 percent level, consistent with the main results presented in Table 4.

[Insert Table 4 here]

4.3 Endogeneity issues

In this study, we treat an acquisition as an exogenous shock that increases competitive pressure among industry peers. However, one might contest this premise, suggesting that members within the same industry often have access to similar information and share certain expectations about industry trends, events, and changes. This implies that peer firms could anticipate an acquisition in their industry, therefore, an acquisition may not occur as an exogenous shock to peer firms. The positive correlation between an acquisition and industry peer firms' adoption of RPE compensation could be attributable to an omitted industry common factor. In this section, we take reasonable steps to address endogeneity concerns.

We introduce the *compensation peer* of an acquirer as firms that satisfy the following two criteria: (1) the acquirer firm's performance is used as a performance reference in the compensation peer firm's compensation; and (2) the compensation peer firm operates in a different industry (2-digit SIC) from the acquirer. The definition of a compensation peer is motivated by Albuquerque et al. (2013) and Choi et al. (2022), who suggest that a firm and its compensation peers are likely to share similar product market characteristics, chief executive officer (CEO) talent/skill/characteristics, and compensation schemes. A recent Equilar Inc. report highlights that direct competition is a crucial dimension in the compensation peer selection process. Consequently, compensation peers can be considered potential labour market competitors for an acquirer. Unlike the selection of industry peers for an acquirer, we mandate that compensation peers must originate from different industries (from an acquirer), thereby excluding the potential influence of industry-level factors in anticipating an acquisition. We expect to see that compensation peers are more likely to adopt RPE following an acquisition, implying that the increased tendency in RPE adoption is attributed to competitive pressures rather than an unobserved industry common factor.

The detailed data on compensation peer companies used in this study are from ISS Incentive Lab from 2006-2020. The ISS Incentive Lab provides information from firms' DEF 14A forms (also known as a definitive proxy statement), which is also the section in which peer firms that are used for benchmarking executive compensation are listed. Given that most compensation peers are in the same industry as an acquirer, this results in a significant drop in sample size. Our regression sample contains 5,428 observations that have reported at least one cross-industry compensation peer.

We re-estimate the baseline regression by replacing $PEER\_ACQ_{t-1}$ with $COMPPEER\_ACQ_{t-1}$. $COMPPEER\_ACQ_{t-1}$ is an indicator variable equal to one if a firm is a cross-industry compensation peer of an acquirer who initiated an acquisition in *t-1*, and zero otherwise. The dependent variable ΔRPE_t equals one if the firm uses RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. The results are presented in Table 5. The coefficient on $COMPPEER\_ACQ_{t-1}$ is still positive and significant at the 5 percent level (coef. =+0.140, z-stat=2.21). This indicates that compensation peers are more likely to use RPE in response to competitive pressure, even if they belong to a different industry. Our evidence mitigates the concern that the baseline result is driven by latent industry common factors.

[Insert Table 5 here]

4.4 Cross-sectional analyses

4.4.1 The effect of pre-acquisition stock co-movement

We further conduct cross-sectional analyses to provide further insights into the reported results. Here, we attempt to link peer firms' RPE use to stock return co-movements between the peers and acquirers before the acquisition announcement date. We introduce the concept of stock return co-movement, which is the extent to which a stock returns to an industry peer firm (*Peer_Ret*) and is explained by the stock return of an acquirer (*Acquirer_Ret*) within a one-year period before the acquisition date. A common feature of stock return co-movements literature is that firms that are highly competitive with each other move more tightly together given that competing firms with similar products face similar cost and demand shocks (e.g., Hoberg and Phillips, 2012). Our objective is to examine whether the spillover effect of an acquisition on peer firms' RPE use is driven by the high stock return co-movements between the peer firm and the acquirer. To achieve this objective, we perform a two-stage test. First, following a methodology similar to Morck et al. (2000) and Drake et al. (2017), we regress each peer firm's stock return on an acquirer's stock return controlling for market returns. We use the coefficient on *Acquirer_Ret* as a measure of return co-movements of the peer firm and an acquirer. The estimation equation is:

$$Peer\_Ret_{i,t} = \beta_0 + \beta_1 \times Acquirer\_Ret_t + \beta_2 \times Mkt\_Ret_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where: the dependent variable *Peer_Ret* is the daily return for a peer firm during one year before the acquisition announcement date and the independent variable *Acquirer_Ret* is the daily return for the acquirer during the same period. We include *Mkt_Ret*, the value-weighted market return as the control. We estimate Equation (3) for each peer firm and fiscal period, requiring at least 200 daily observations. β_1 captures the magnitude of stock return co-movement between the peer firm and the acquirer. If more than one acquisition is announced in the same industry in a year, we take the mean value of multiple β_1 as the co-movement measure.

In the next step, we categorize peer firms into two groups based on the extent to which they co-vary with the acquirers (e.g., β_1). We require only the co-varied pairs by excluding all negative β_1. A firm is classified into the '*highcom*' group if β_1 is positive and above the industry median co-movement level, and into the '*lowcom*' group if β_1 is positive and below the industry median co-movement level. We re-estimate the baseline regression by replacing *PEER_ACQ* with *PEER_ACQ_highcom* and *PEER_ACQ_lowcom*. *PEER_AQC_highcom* is an indicator variable that equals one if the firm is a peer of an acquirer and belongs to the *highcom* group, and zero otherwise. *PEER_AQC_lowcom* is an indicator variable that equals one if the firm is a peer of an acquirer and belongs to the *lowcom* group, and zero otherwise. The results are reported in Table 6, Panel A. In Column (1), we include only firm size as the control variable. The coefficient of *PEER_AQC_highcom* is significantly positive at a 5% level (coef.=+0.093, z-stat=1.80), whereas the coefficient of *PEER_AQC_lowcom* is insignificant. The results for estimating the full regression are reported in Column (2). The coefficient of *PEER_AQC_highcom* is significantly positive at the 5% level (coef.=+0.116, z-stat=2.13), wheres the coefficient of *PEER_AQC_lowcom* is insignificant. The coefficient of *PEER_AQC_highcom* is larger than the coefficient of *PEER_AQC_lowcom,* and the difference is significant at the 5% level (p-value=0.037 and 0.033) in both columns, suggesting that peer firms react to an acquisition-induced competitive threat when the peer firm's stock return exhibits a strong co-movement with the acquirer's stock return before the acquisition announcement. Hoberg and Phillips (2012) suggest that when two competing firms share more common fundamentals, including supply and demand shocks, there will be more co-movements in their stock returns. Our findings also imply that not all industry peers react equally to an acquisition. Specifically, those peers whose products are more easily replicated by the acquirer are highly motivated to take action (e.g., increase the use of RPE compensation) to protect their market position, than peer firms whose products are less similar to the acquirer.

4.4.2 The effect of deal purpose

There is a wide variety of reasons that drive a firm to acquire another, with the primary objective being to achieve synergy by integrating two or more business units, thereby creating a combined entity with a heightened competitive advantage (Porter, 1985). In this section, we provide further evidence supporting the competition effect by focusing on acquisitions more likely to directly impact product market competition. We collect information on deal purpose mentioned in acquisition announcements available on the SDC Platinum (see Deal Purpose Code[15]), and classify acquisitions into two groups based on their intent: competition-related and other purposes (Oh and Shin, 2020). We expect that the spillover effect of acquisitions on peer firms' RPE is pronounced when the acquisitions are directly related to product market competition. We define $PEER\_AQC_{t-1}\_competitionpurpose$ as an indicator variable equal to one if a firm is an industry peer of an acquirer and over half of the acquisitions are competition-related purpose acquisitions in the industry, and zero otherwise. We define $PEER\_AQC_{t-1}\_otherpurpose$ as an indicator variable equal to one if the firm is an industry peer of an acquirer and over half of the acquisitions are other purpose acquisitions in the industry, and zero otherwise. The results are presented in Table 6, Panel B. In Column (1), we include only firm size as the control variable. The coefficient of *PEER_AQC_competitionpurpose* is significantly positive at the 1% level (coef.=+0.214, z-stat=3.30), whereas the coefficient of *PEER_AQC_otherpurpose* is insignificant. The results for estimating the full regression are reported in Column (2). The coefficient of *PEER_AQC_competitionpurpose* is significantly

[15] Following Oh and Shin (2020), competition-related purposes consist of the following codes: CMP, COR, EPG, EPM, ESM, GEN, PRD, STR, and SYN. Meanwhile, other purposes consist of the following codes: CSH, DBT, EXP, ISV, OTH, PEB, and RST.

positive at the 1% level (coef.=+0.196, z-stat=2.94), whereas the coefficient on *PEER_AQC_otherpurpose* is insignificant. The coefficient on *PEER_AQC_competitionpurpose* is larger than the coefficient on *PEER_AQC_otherpurpose*, and the difference is significant at the 10% level (p-value=0.082) In Column (2). Competition-related purpose acquisitions directly help acquirers achieve a competitive advantage that eventually can incentivize product market competition to a greater extent. The results further support the argument that competition threats increase the use of RPE compensation by industry peers.

[Insert Table 6 here]

4.4.3 Other cross-sectional tests: firm characteristics

We perform additional cross-sectional tests to shed light on the mechanisms behind the baseline results. So far, competition arising from an acquisition is measured at the industry level and all non-merging peer firms in the same industry are assumed to face the same level of competition. However, peer firms are likely to face different levels of competition depending on their market position. As suggested by Nickell et al. (1992) and Nickell (1996), firms with a greater market share typically confront less competition because of their increased market monopoly power. This monopoly power permits these firms to maintain higher prices and enjoy larger profit margins. Consequently, they are often less subjected to pressures to innovate or enhance their products and services, because competitors find it challenging to steal their customers. Therefore, we further divide peer firms into subgroups based on their market share. The argument is that, compared with industry leaders (with greater market power), industry followers (with lesser market power) face more competitive induced pressures from an acquisition. We expect the positive association between an acquisition and peer firms' RPE use to be more pronounced for industry followers. In Table 7, Column (1), firms with a market share in the industry's top quartile are identified as industry leaders and the rest are recognized as industry followers. We define an indicator variable *D_Marketfollower* equal to 1 if a firm is an industry follower and 0 otherwise. The main variable of interest is the interaction term $PEER\_ACQ_{t-1} \times D\_Marketfollower$, which indicates how a peer firm changes its preference in using RPE after an acquisition depending on whether the firm is an industry follower. Consistent with the argument, the coefficient on the interaction term is positive and significant at the 5 percent level (coef. =+0.287, t-stat =2.45), indicating that when peer firms are industry followers, they are more likely to adopt RPE after an acquisition because industry followers face more competitive pressure than industry leaders.

Second, we examine the effect of an acquisition on peer firms' RPE use conditional on industry competition. We expect to observe that the positive association between an acquisition and peer firms' RPE use is more pronounced in competitive industries. The idea is that, in concentrated industries, competitive pressures might be offset by an increased likelihood of monopolistic collusion because of the fewer competitors (Eckbo, 1983). Thus, the competitive pressure induced by an acquisition is stronger in competitive industries than in concentrated industries. In addition, DeFond and Park (1999) argue that a competitive environment is characterized by a higher degree of common risk and, hence, brings greater benefits to firms that use RPE. The literature provides consistent evidence that RPE is used more in competitive industries (e.g., Aggarwal and Samwick, 1999; Gong et al., 2011). Therefore, the positive association between an acquisition and peer firms' RPE use will be more pronounced in competitive industries because: (1) firms in competitive industries have more incentives to compete with each other; and/or (2) the potential benefits of using RPE are higher for firms in competitive industries. In Table 7, Column (2), we use the Herfindahl-Hirschman index (HHI) to proxy for industry competition. An HHI value of less (more) than 2500 represents a competitive (less-competitive) industry. We define an indicator variable equal to one if a firm is in a competitive industry, and zero otherwise. The coefficient estimate on the interaction term $PEER\_ACQ_{t-1} \times D\_Competitive_t$ is positive and weakly significant at the 10 percent level (coef.= +0.389, t-stat= +1.71). Consistent with our expectation, peer firms are more likely to implement RPE following an acquisition in a competitive industry because, after an acquisition, peer firms in competitive industries typically face higher competitive pressure than peers in concentrated industries.

Third, Hoberg and Phillips (2014) argue that firms that are harder to replicate are likely to have more unique and differentiated products, and likely face less direct product market competition and a less severe competitive threat. Therefore, those firms are less affected by an acquisition announced by another firm in their industry. We expect peer firms that are harder to replicate to be less active in RPE use in response to competition concerns following an acquisition. By analysing firms' 10-K fillings, Hoberg and Phillips (2014) use product description word overlaps, and assign closely related competitors (HP-competitor) to each firm based on similarity scores. With fewer (more) HP-competitors, a firm's products are harder (easier) to replicate. We define an indicator variable *D_Uniqueness* to capture how hard a firm can be replicated. *D_Uniqueness* equals 1 if a firm has fewer HP-competitors than its industry median level (i.e., hard to replicate), and zero if a firm has more HP-competitors than the industry median level (i.e., easy to replicate). The results are reported in Table 7, Column (3). The coefficient estimate for the interaction term $PEER\_ACQ_{t-1} \times D\_Uniqueness_t$ is negative and significant at the 1 percent level (coef. =-0.318, t-stat=-1.94), suggesting that the impact of an acquisition on a peer firm's RPE usage is mitigated when the peer firm is harder to replicate.

[Insert Table 7 here]

4.4.4 Other cross-sectional tests: Board characteristics

Next, we examine whether peer firms' adoption of RPE compensation in response to an acquisition is contingent on the peer firms' board efficiency given a board is in charge of setting the compensation contract. The RPE literature commonly argues that RPE compensation provides a firm with incentives to act more competitively but, in our setting, less is known about the mechanism that assists a firm to adapt to competitive pressure. On completing an acquisition, the acquirer's enhanced competitive advantage signal an improved ability to compete (Chen et al., 2017), causing shareholders in peer firms to become concerned about potential losses in market share. Colougherty and Duso (2011) find that over half of peer firms indeed suffer a loss in market value following an acquisition. There is a common statement that more efficient directors can better discipline managers to run firms more efficiently and better align the interests of shareholders and managers. We expect that peer firms respond to an acquisition by adopting RPE to a greater extent when they have highly-efficient boards. This is because a more efficient board can be considered a better representation of shareholder delegation, which may facilitate the implementation of RPE compensation to address shareholders' concern over the potential loss of market position. Following the literature, we use different board characteristics to measure a board's efficiency. Specifically, we use the proportion of outside directors, director qualifications, and years to retirement as measures of a board's efficiency. Following Adams and Ferreira (2007) who state that "Because inside directors' careers are dependent on the CEO, they have incentives to cooperate with the CEO. As a result, outsiders are generally considered to be more effective monitors than insiders." A higher proportion of outside directors suggests higher board efficiency. Adams et al. (2018) highlight the importance of director qualifications and the collective skillset of the entire board. The wider the qualifications held by board members, the better the board efficiency. Cheng et al. (2016) posit that the effectiveness of a firm's key subordinate executives increases with their decision horizon, as proxied by the number of years to retirement. Similarly, we use the board's average years to retirement as a measure of board efficiency, with more years to retirement indicating a more efficient board. The results are presented in Table 8. In Column (1), *D_BoardEfficiency* equals 1 when the proportion of outside directors on a board exceeds the industry median level, and 0 otherwise. In Column (2), *D_BoardEfficiency* equals 1 when the directors' number of qualifications is above the industry median level, and 0 otherwise. In Column (3), *D_BoardEfficiency* equals 1 when the average years to retirement for board members falls below the sample median level (indicating that board members, on average, have a long decision horizon), and 0 otherwise (indicating that board members, on average, have short decision horizon). In general, the coefficient estimates of the interaction term $PEER\_ACQ_{t-1} \times D\_BoardEfficiency$ are positive and significant, suggesting that peer firms are more likely to respond to an acquisition by adopting RPE compensation when the peer firms have a more efficient board.

[Insert Table 8 here]

4.5 The effect of using RPE compensation

Implementing a compensation structure based on relative performance metrics places firms in direct competition with their peers. Consequently, managers in firms using RPE are incentivized to gain an advantage over their peers and enhance their firm's relative position. This can be achieved by engaging in competitive actions (Feichter, 2022). In this section, we complete the loop by answering the question: After an acquisition, do peer firms that adjust to RPE indeed behave more aggressively than peer firms that do not adjust to RPE? We focus on accounting-based input (i.e., advertising expenditure) and output (i.e., operating margins) as measures of competitive aggressiveness. Higher expenditure on advertising indicates a more aggressive posture whereas a lower expenditure indicates a more conservative posture (Fombrun and Ginsberg, 1990). Increased costs in undertaking competitive aggressiveness (e.g., temporary price discounts or trade promotions) will result in squeezed operating margins (Mouzas, 2006). In general, greater advertising expenditure and smaller operating margins imply greater competitive aggressiveness (e.g., Fombrun and Ginsberg, 1990; Vilcassim et al., 1999; Feichter, 2022).

We examine the association between the use of RPE compensation and firms' competitive aggressiveness by estimating the following OLS equation:

$$Aggressiveness_{i,t} = \beta_0 + \beta_1 \times \Delta RPE_{i,t} + \gamma' \times X_{i,t-1} + \alpha_j + \alpha_t + \varepsilon_{i,t} \quad (3)$$

where: the dependent variable $Aggressiveness_t$ is a measure of firm competitive aggressiveness. As discussed above, we use two measures of competitive aggressiveness. $ADEXP_t$ is defined as a firm's advertising expenditure scaled by total assets. $OperatingMargin_t$ is defined as a firm's sales revenue minus the cost of goods sold and selling, general, and administrative expenditure, scaled by sales (Feichter, 2022). Given our interest in the post-acquisition aggressiveness of peer firms, we restrict the regression sample to the industry peer firms of an acquirer for acquisitions that occurred in *t-1*. The interested variable ΔRPE_t equals one if a peer firm uses RPE in its executive compensation in year *t* and does not use RPE in year *t-1*, and zero otherwise. *X* is a vector of control variables, including firm size, market-to-book ratio, leverage, past sales growth, past returns, and competition environment (e.g., Covin and Covin, 1990; Ferrier, 2001; Feichter, 2022); and α_j and α_t are industry- and year-fixed effects.

Table 9 reports the results. In Panel A, the dependent variable is $\Delta ADEXP_t$. In Column (1), consistent with the baseline regression, we define peer firms as firms operating in the same 2-digit SIC industry as the acquirer. The coefficient estimate of ΔRPE_t is 0.064, which is statistically significant at the 10% level, suggesting that peer firms adjusting to RPE compensation incur higher advertising expense than peer firms not adjusting to RPE compensation. As Columns (2) to (5) illustrate, our results remain robust when defining peers different ways (see 4.3 Robustness check for a detailed discussion). In Panel B, the dependent variable is $\Delta OperatingMargin_t$. In Column (1), the coefficient estimate of ΔRPE_t is -0.012, whichis statistically significant at the 10% level, indicating that peer firms adjusting RPE compensation experience lower operating margins than those not making an adjustment. Our results are robust when using different ways to define peers (Columns 2 to 5). However, an exception can be seen in Column (3), when using firm-characteristic matched peers; the coefficient estimate of ΔRPE_t is negative as expected but statistically insignificant. The results align with the RPE literature, showing the effectiveness of RPE contracts in motivating competitive action (e.g., Aggarwal and Samwick, 1999). Specifically, peer firms using RPE contracts tend to incur higher advertising expense and accept lower operating margins. These strategies are deployed as defensive measures to protect their competitive position in the market after an acquisition.

[Insert Table 9 here]

5. Additional Tests

5.1 Competition pressure in alternative compensation components

To investigate whether acquisition-induced competitive pressure can be applied to a broad spectrum of compensation, we examine whether acquisitions influence the level and composition of the peer firms' CEO compensation. Both psychological and economic theories of behaviour provide similar predictions regarding the relationship between CEO compensation and firm behaviour. Expectancy models of motivation suggest that CEOs will engage in competitive actions if they believe those actions will result in outcomes they value (e.g., Offstein and Gnyawali, 2005)[16]. Specifically, CEOs will engage in competitive action with the hope of enhancing their competitive position so that they can increase their personal gain (i.e., compensation). Accordingly, we expect that, in response to acquisition-induced competition pressure, peer firms will increase compensation to motivate CEOs to become more aggressive. Table 10 presents the results. We first examine acquisitions and changes to peers' total compensation level. In Column (1), the coefficient of $PEER\_ACQ_{t-1}$ is significantly positive at the 1% level (coef.=+0.024, t-stat=2.72), suggesting that industry peers increase

[16] In other words, CEOs may initiate competitive actions with the intent of improving firm performance and, consequently, increasing their personal gain such as compensation. Hence, holding all else constant, enhancing the attractiveness of secondary outcomes, like compensation, will result in an increase in motivation, which should be visible through an increase in effort and behaviour (Vroom, 1964).

total CEO compensation following an acquisition. We next examine whether the acquisition influences the composition of peers' CEO compensation package by dividing the CEO compensation into cash-pay composition (i.e., the sum of salaries and bonus) and equity-pay composition (i.e., the sum of option value, stock value, and LTIP value). Typically, cash compensation tends to be awarded on an annual basis, whereas equity compensation aims to reward consistent, continuing progress for an extended time horizon (Gomez-Mejia and Balkin, 1992). Dai et al. (2020) suggest that, compared with long-term stocks/options, bonuses and salaries are effective short-term incentive methods. Given that acquirers could gain market value from acquisitions, industry peer firms may lose market value. Therefore, peer firms' CEOs are better motivated if they are awarded more cash rather than equity compensation. Consistently, in Column 2, we find that the coefficient on $PEER\_ACQ_{t-1}$ remains significantly positive at the 1% level (coef.=+0.017, t-stat=3.17), but insignificant in Column (3) (coef.=+0.009, t-stat=0.78). The results suggest that, after an acquisition, the increase in peer firms' compensation is an increase in cash compensation rather than equity compensation.

[Insert Table 10 here]

5.2 The collusion hypothesis

Ferrier (2001) states that: "As they navigate the competitive landscape, firms often directly and aggressively challenge competitors in an effort to improve relative performance." Aggarwal and Samwick (1999) find that CEOs working under a relative performance plan act more competitively aggressively than CEOs working under an absolute performance plan. Nevertheless, it's notable that RPE compensation may not always effectively motivate a firm's competitive actions. In this section, to further validate our proposition that the use of RPE contracts following an acquisition is aimed at stimulating firms' competitive actions, we investigate the following arguments.

Consider a scenario where Firm A, under an RPE plan, uses Firm B's performance for relative evaluation. An overlapping relationship emerges when Firm B also uses Firm A's performance for its own relative evaluation (Feichter et al., 2022). The collusion hypothesis (e.g., Dye 1984; Aggarwal and Samwick, 1999) argues that, in the presence of overlapping relationships, it is typically the case that agents (e.g., Firm A and Firm B) would be better off if none of them acts aggressively (e.g., a commitment to collusion) than when all engage in aggressive competition. In addition, collusion creates the commitment necessary to escape from the prisoner's dilemma problem in which all firms act aggressively to improve their relative position- firms could collectively agree on product market strategies when they collude, thereby mitigating the negative consequences of overly aggressive competition.

To verify whether the collusion hypothesis plays out in practice in the presence of an overlapping relationship in RPE compensation, we re-estimate the baseline model by replacing the dependent variable ΔRPE_t with $\Delta OverlapRPE_t$. $\Delta OverlapRPE_t$ is an indicator variable equal to one if the firm's RPE compensation involves overlapping relationships[17] in year t and does not have overlapping relationships in RPE in year t-1, and zero otherwise. The result is presented in Table 11, Column (1). The coefficient estimate of $PEER\_ACQ_{t-1}$ is insignificant, leading us to argue that, following an acquisition, peer firms do not adjust the use of RPE compensation including an overlapping relationship. This can be attributed to the high likelihood of collusion, which creates fewer incentives for aggressive behaviour.

Next, we analyse the governance-related aspect to investigate whether collusion concerns can be addressed in well-governed firms. Given that an acquisition tends to diminish the market share of peer firms (Clougherty and Duso, 2011), shareholders of the peer firms naturally expect them to behave more aggressively to defend their competitive position.

[17] For example, consider Firm A's RPE compensation includes three reference firms: Firms B, C, and D. If any of these reference firms use Firm A's performance for their relative evaluation, we term it as Firm A's RPE compensation involves the overlapping relationship.

However, by committing not to engage in aggressive behaviour through collusion, peer firms using RPE that involves overlapping relationships are less likely to act in line with shareholder interests post-acquisition. Good corporate governance can mitigate agency problems, leading managers to pursue shareholders' interests rather than their own goals (Shleifer and Vishny, 1997). Therefore, we propose that good corporate governance can counteract collusion, thereby enabling firms to adopt aggressive action even under RPE compensation involving overlapping relationships. We expect to find that peer firms increase the use of RPE compensation involving overlapping relationships in response to acquisitions when there is a high level of corporate governance. In Column (1), we follow Bebchuk et al. (2009) and use the E-index to measure corporate governance. A lower E-index suggests better corporate governance. As such, the indicator variable, *Goodgovdummy*, equals one if the E-index of a firm is smaller than the industry median, and zero otherwise. The coefficient on $PEER\_AQC_{t-1} \times$ *Goodgovdummy* is positive and weakly significant at the 10% level (coef.=+0.232, z-stat=1.72). Nevertheless, to ensure that our inferences are not unique to one specific measure of corporate governance, we use other governance measures. In Column (3), we follow Murphy (1999) and Bebchuk and Fried (2003)[18] and use the equity-based compensation ratio to measure good corporate governance. *Goodgovdummy* equals one if the equity compensation ratio exceeds the industry median, and zero otherwise. The coefficient on $PEER\_ACQ_{t-1} \times$ *Goodgovdummy* is positive at the 1% level (coef.=+0.365, z-stat=1.92). In Column (4), we follow Yermack (1996) and Core et al. (1999) and use the proportion of outside directors on a firm's board as a measure of good governance. *Goodgovdummy* equals one if a firm's outside director percentage exceeds the industry median, and zero otherwise. The coefficient on $PEER\_ACQ_{t-1} \times$ *Goodgovdummy* is significantly positive (coef.=+0.317, z-stat=2.44). Overall, our findings suggest that firms

[18] Murphy (1999) suggests that more use of equity-based compensation is a way to better align CEO interests with shareholder interests and improve corporate governance. Bebchuk and Fried (2003) argue that equity-based compensation can align CEO interests with shareholder interests and reduce agency costs, and has significant implications for corporate governance.

generally do not change RPE in response to the competitive threat induced by acquisitions because of the likelihood of collusion if RPE compensation involves the overlapping relationships. However, well-governed peer firms are likely to use RPE compensation involving overlapping relations in response to acquisitions-induced competitive pressure, because corporate governance has a function to reduce such collusion. Our baseline and additional results reveal that RPE typically serves as an effective mechanism to motivate competitive action. This section complements previous sections by showing that peer firms tend to avoid using RPE when it involves overlapping relationships to evade the potential for collusion. However, we also show that the risk of such collusion can be significantly mitigated by strong corporate governance practices.

[Insert Table 11 here]

6. Conclusion

Merger and acquisition activity is significant in changing the structure and competitive conditions of the market. Given the potential competitive strengths that an acquirer can gain from an acquisition, non-merging peer firms in the same industry can be expected to engage in aggressive competitive actions that limit the anticipated advantages. Both anecdotal and empirical evidence show that acquisitions indeed create competitive pressures for peer firms and cause them to respond by engaging in various strategic decisions such as aggressive advertising and pricing. However, we know little about the underlying mechanisms that motivate peer firms' CEOs to overcome such competitive pressures. The aim of this study was to address this fundamental problem by investigating how an acquisition affects peer firms' RPE compensation. We treat an acquisition as a relatively exogenous pressure from the standpoint of peer firms and show that peer firms exhibit an increased propensity to adopt RPE in their CEO compensation package in response to an acquisition. Our baseline findings highlight a spillover effect of acquisitions. This finding is consistent with previous RPE literature in suggesting that RPE places a firm in direct competition with its peers, thereby motivating more aggressive behaviour.

We further investigate variations in the baseline finding. We find that the effect is particularly pronounced when the peer firm and the acquirer exhibit close co-movement before the acquisition announcement, underscoring the importance of the acquirer to the peer firm. The baseline finding is particularly pronounced when the acquisition is driven by a competition-related purpose rather than another purpose, reinforcing the argument that competition threats increase RPE adoption among peer firms. To achieve a better understanding of the positive effect of an acquisition on peer firms' RPE, we explore how the effect varies with firm-level and board-level characteristics of peer firms. We find a stronger effect in cases where peer firms are market followers and operate in a competitive industry, and a mitigated effect when peer firms' products are more challenging to replicate. We also find the effect is stronger when peer firms are governed by efficient boards, suggesting that the boards are more han capable of ensuring firms' behaviour aligns with shareholders' interests.

Our study marks one of the first attempts to analyse the impact of an acquisitions on the adoption of RPE by industry peers of an acquirer and makes two significant contributions. First, we provide a fuller perspective on the spillover effect of an acquisition. Servaes and Tamayo (2014) investigated how peer firms respond when another firm in the industry is a target of a hostile takeover attempt, suggesting that the control threat induced by a hostile takeover has important spillover effects for peer firms. Our study extends their findings by demonstrating that, from the perspective of an acquirer, the competitive advantages gained also have significant spillover implications for peers in the same industry. Second, we contribute to the RPE literature by producing evidence on the use of RPE as a mechanism to incentivize firm aggression. Theoretically, an RPE compensation package introduces tournament-like competition, i.e., firms using RPE engage in competitive actions to gain an advantage over peers and improve their relative position (e.g., Do et al., 2022; Holmstrom, 1982). However, RPE is not widely used in practice (e.g., Gong et al., 2011). Some theory suggests that RPE is seldom used because RPE may create counterproductive incentives for managers such as, sabotage peer performance, collude with peers, and choose inappropriate reference firms. Our study supports the theory of RPE's competitive effect, demonstrating that firms are more likely to adopt RPE in response to increased competitive threats.

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Appendix A

Variable	Definition
$\Delta ADEXP_t$	The advertising expenditure in *t* minus that in year *t-1*, scaled by current total assets.
$\Delta Ln\ (Cash\ Comp)_t$	The logarithm of cash compensation (i.e., the sum of bonuses and salary) in current year minus the logarithm of cash compensation in last year.
$\Delta Ln\ (Equity\ Comp)_t$	The logarithm of equity compensation (i.e., the sum of option value, stock value, and long-term incentive payout value) in current year minus the logarithm of equity compensation in last year.
$\Delta Ln\ (Total\ Comp)_t$	The logarithm of total compensation in current year minus the logarithm of total compensation in last year.
$\Delta OperatingMargin_t$	The operating margin in *t* minus that in year *t-1*, scaled by current total assets.
$\Delta OverlapRPE_t$	An indicator variable equal to one if the firm used overlap RPE in their executive compensation in year *t* and did not use overlap RPE in year *t-1*, and zero otherwise.
$\Delta PROD_t$	The sum of COGS and change in inventory in *t* minus that in year *t-1*.
ΔRPE_t	An indicator variable equal to one if the firm used RPE in their executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise.
Age	Age of executive
Boardindepend	Percentage of independent directors serving on the board
Boardsize	Number of directors serving on the board
Capex	Ratio of capital expenditure to total assets
Cash	Ratio of cash items to total assets
Commonrisk	Common risk is measured based on the proportion of the variance of firm-level stock returns that can be explained by industry returns, defined as R^2 from regressing firms' stock returns on value-weighted industry return over the prior 36 months.
$COMPPEER\_ACQ_{t-1}$	An indicator variable equal to one if a firm is a compensation peer of an acquirer, and zero otherwise. Compensation peers of an acquirer are those comparable firms selected by ISS incentive lab in *t*, but not in the same 2-digit SIC industry with the acquirer.
D_BoardEfficiency	An indicator variable equal to one when the proportion of outside directors/number of qualifications/ years to retirement on a board exceeds the industry median level, and zero otherwise.
D_Competitiveindustry	An indicator variable equal to one if firm *i* is in an industry with HHI value less than 2500 and zero if the firm is in an industry with HHI value more than 2500.
D_Marketfollower	An indicator variable equal to one if firm *i* is a market follower in its industry in t-1, and zero otherwise.
D_Uniqueness	An indicator variable equal to one if firm *i* has fewer HP-competitors than its industry median level, and zero if the firm has more.
Goodgovdummy	When using the institutional ownership/equity compensation ratio/percentage of independent board members to measure governance, *Goodgovdummy* equals one if the firm's governance measure is above the industry median level in year *t*, and zero otherwise. When using the E-index to measure governance, *Goodgovdummy* equals one if the firm's governance measure is below the industry median level in year *t*, and zero otherwise.
HHI	The Herfindahl-Hirschman Index of sales in each two digit-SIC industry.
Indconcentrate	Industry concentration is measured by Herfindahl-Hirschman Index of sales within each two digit-SIC industry.

Leverage	Leverage is measured by sum of current liabilities and long-term debt divided by total assets.
MTB	Market to book ratio is measured by market value of equity divided by book value of equity.
Ownership	Ratio of shares owned by CEO, excluding options owned, to shares outstanding.
Pastreturn	Past return is measured by last year's annual return.
$PEER\_ACQ_{t-1}$	An indicator variable equal to one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise.
$PEER\_ACQ_{t-1}\_highcom$	An indicator variable equal to one if the firm is a peer firm of an acquirer and belongs to the '*highcom*' group, and zero otherwise.
$PEER\_ACQ_{t-1}\_lowcom$	An indicator variable equal to one if the firm is a peer firm of an acquirer and belongs to the '*lowcom*' group, and zero otherwise.
$PEER\_AQC_{t-1}\_competitionpurpose$	An indicator variable equal to one if the firm is a peer firm and the majority of acquisitions are market competition-purpose acquisitions in *t-1* within the industry and zero otherwise.
$PEER\_AQC_{t-1}\_otherpurpose$	An indicator variable equal to one if the firm is a peer firm and the majority of acquisitions are other-purpose acquisitions in *t-1* in the industry and zero otherwise.
$PEER\_TDF_{t-1}$	The logarithm value of the total number of acquisitions announced by other firms in an industry in year *t-1*, zero if no announced acquisitions in *t-1*.
$PEER\_TDV_{t-1}$	The logarithm value of the sum of deal values of acquisitions announced by other firms in an industry in year *t-1*, zero if no announced acquisitions in *t-1*.
ROA	Return on assets is measured as the net income before extraordinary items divided by total assets.
Roaindadj	Industry-adjusted ROA is measured by the return on assets minus the 2-digit SIC industry median return on assets.
RPE	An indicator variable equal to one if the firm used RPE in their executive compensation in year *t*, and zero otherwise.
Salesgrowth	Sales growth is measured by the difference between a firm's current sales and last year's sales divided by last year's sales.
Size	Firm size is measured by the logarithm of total assets.
Sizerkadj	The availability of similar peers is measured by the logarithm of absolute differences in market value of equity between the firm and the median of the decile to which the firm belongs.
Volatility	The standard deviation of the firm's monthly stock return over the previous three-year period.

Tables

Table 1
Descriptive Statistics and Pearson Correlation Matrix
Panel A presents descriptive statistics for the variables used in baseline regression. Panel B provides the Pearson correlation matrix. Detailed variable definitions are available in Appendix A. In Panel B, statistical significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.
Panel A Descriptive statistics

Variable	N	Mean	Std.	Median	Min.	Max.
ΔRPE_t	18,409	0.039	0.193	0.000	0.000	1.000
$PEER\_ACQ_{t-1}$	18,409	0.600	0.490	1.000	0.000	1.000
Commonrisk	18,409	0.009	0.027	0.000	0.000	0.211
Sizerkadj	18,409	6.866	2.198	6.857	1.076	11.970
Indconcentrate	18,409	0.061	0.064	0.039	0.011	0.579
MTB	18,409	3.713	7.232	2.388	-24.296	48.348
Size	18,409	8.630	1.598	8.560	4.498	13.086
Roaindadj	18,409	0.048	0.127	0.026	-0.400	0.483
Boardindepend	18,409	0.751	0.284	0.875	0.000	0.944

Panel B Person correlation matrix

	ΔRPE_t	$PEER\_ACQ_{t-1}$	*Commonrisk*	*Sizerkadj*	*Indconcentrate*	*MTB*	*Size*	*Roaindadj*	*Boardindepend*
ΔRPE_t	1.000								
$PEER\_ACQ_{t-1}$	0.029*	1.000							
Commonrisk	-0.001	-0.004	1.000						
Sizerkadj	0.032*	-0.087*	-0.008	1.000					
Indconcentrate	-0.006	-0.032*	0.082*	-0.036*	1.0000				
MTB	-0.014	-0.018*	-0.017*	0.123*	-0.014	1.000			
Size	0.078*	-0.042*	-0.012	0.613*	0.000	-0.109*	1.000		
Roaindadj	-0.007	-0.072*	0.048*	0.312*	-0.095*	0.111*	0.043*	1.000	
Boardindepend	0.009	-0.067*	0.028*	0.053*	-0.014	-0.001	0.016*	0.030*	1.000

Table 2

Baseline Results: The Effect of Acquisitions on Peer Firms' Relative Performance Evaluation

This table shows how peer firms respond to acquisitions by adopting the relative performance evaluation (RPE) compensation. ΔRPE_t equals one if the firm used RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. In Panel A, the explanatory variable of interest $PEER\_ACQ_{t-1}$ captures whether a firm is an industry peer of an acquirer, which is an indicator variable equal to one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise. Our regression sample consists of 18409 firm-year observations from 2006 to 2020. All regressions include industry and year fixed effects. Industry effects are based on 2-digit SIC codes. N denotes the number of observations, Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A defines all variables.

	Dependent variable= ΔRPE_t	
Independent variable	(1)	(2)
$PEER\_ACQ_{t-1}$	**0.085****	**0.134*****
	(2.24)	**(3.28)**
Commonrisk		-0.402
		(-0.64)
Sizerkadj		-0.014
		(-1.22)
Industryconcentrate		0.312
		(0.35)
MTB		-0.000
		(-0.19)
Size		0.120***
		(6.84)
Roaindadj		0.156
		(0.89)
Boardindepend		0.086
		(1.29)
Intercept	-2.064***	-3.308***
	(-9.54)	(-10.10)
Industry fixed effects	Yes	Yes
Year fixed effect	Yes	Yes
Number of observations	21,079	18,409
Pseudo R^2	0.044	0.055

Table 3
The Effects of Acquisition Size on Peer Firms' RPE Use
This table shows the effects of the size of acquisitions on peer firms' RPE use. The dependent variable ΔRPE_t equals one if the firm used RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. The size of acquisitions is measured by *PEER_TDV* and *PEER_TDF*. *PEER_TDV* is defined as the sum of deal values of acquisitions announced by other firms in an industry in year *t-1*; *PEER_TDF* is defined as the total number of acquisitions announced by other firms in an industry in year *t-1*. We use a log transformation of both measures. If the firm is in an industry with no acquisition announced in *t-1* (i.e., when $PEER\_AQC_{t-1}$=0), both *PEER_TDV* and *PEER_TDF* equal zero. Our regression sample consists of 18409 firm-year observations from 2006 to 2020. All regressions include industry and year fixed effects. Industry effects are based on 2-digit SIC codes. N denotes the number of observations, T-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A defines all variables.

	Dependent variable= ΔRPE_t	
Independent variable	(1)	(2)
$PEER\_TDV_{t-1}$	**0.039*** **	
	(5.93)	
$PEER\_TDF_{t-1}$		**0.069*** **
		(5.96)
Commonrisk	-0.264	-0.305
	(-0.37)	(-0.43)
Sizerkadj	-0.020*	-0.020
	(-1.65)	(-1.61)
Industryconcentrate	0.638	0.622
	(0.69)	(0.67)
MTB	0.001	0.001
	(0.23)	(0.21)
Size	0.123***	0.123***
	(6.69)	(6.66)
Roaindadj	0.151	0.156
	(0.70)	(0.72)
Boardindepend	0.104	0.105
	(1.56)	(1.57)
Intercept	-3.555***	-3.509***
	(-10.56)	(-10.46)
Industry fixed effects	Yes	Yes
Year fixed effect	Yes	Yes
Number of observations	18,409	18409
Pseudo R^2	0.060	0.060

Table 4
Robustness Check: Alternative Measures of Peer Firms
This table presents the results of robustness tests by re-estimating Equation (1) with alternative measures of peer firms. ΔRPE_t equals one if the firm used RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. Throughout the study, $PEER\_ACQ_{t-1}$ captures whether a firm is an industry peer of an acquirer. It is an indicator variable equal to one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise. In Column (1), we define the peers as firms operating in the same 3-digit SIC industry. In Column (2), we define peers as the acquirer's character-matched firms. Each acquirer has three character-matched peers and the set of matching variables including size, ROA, MTB, and leverage within same industry and year. In Column (3), peers are firms operating in the same 4- Digit GICS industry. In Column (4), peers are firms operating in the same 6- Digit GICS industry. N denotes the number of observations, Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A defines all variables.

	Dependent variable= ΔRPE_t			
Independent variable	(1) 3-Digit SIC Peer	(2) Character-Matched Peer	(3) 4- Digit GICS Peer	(4) 6- Digit GICS Peer
$\boldsymbol{PEER\_ACQ_{t-1}}$	**0.127*** **	**0.226*** **	**0.136*** **	**0.145*** **
	(3.11)	**(3.52)**	**(3.43)**	**(3.69)**
Commonrisk	-0.409	-1.493	-0.682	-0.689
	(-0.66)	(-1.26)	(-1.03)	(-1.04)
Sizerkadj	-0.015	0.007	-0.014	-0.015
	(-1.30)	(0.37)	(-1.18)	(-1.25)
Industryconcentrate	0.324	0.001	-0.182	-0.167
	(0.36)	(0.00)	(-0.18)	(-0.17)
MTB	-0.000	-0.013**	-0.000	-0.000
	(-0.20)	(-2.40)	(-0.21)	(-0.21)
Size	0.121***	0.089***	0.120***	0.122***
	(6.90)	(3.09)	(6.57)	(6.65)
Roaindadj	0.154	0.187	0.141	0.140
	(0.89)	(0.60)	(0.80)	(0.80)
Boardindepend	0.081	0.066	0.142*	0.141*
	(1.22)	(0.63)	(1.79)	(1.77)
Intercept	-3.314***	-3.351***	-3.277***	-3.285***
	(-10.10)	(-6.48)	(-9.62)	(-9.65)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	18,409	9,106	17,571	17,571
Pseudo R^2	0.055	0.072	0.059	0.060

Table 5
Endogeneity Issue
This table shows how compensation peers respond to acquisitions by using RPE. ΔRPE_t equals one if the firm used RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. The interested explanatory variable $COMPPEER\_ACQ_{\ t-1}$ is an indicator variable equal to one if a firm is a compensation peer of an acquirer, and zero otherwise. The compensation peer of an acquirer must satisfy the following two criteria: (1) the compensation peer uses an acquirer firm's performance as a performance evaluation, and (2) the compensation peer and the acquirer are in different 2-digit SIC industries. ΔRPE_t equals one if the firm used RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. Our regression sample consists of 5428 firm-year observations from 2006 to 2020. N denotes the number of observations, Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

	Dependent variable= $\boldsymbol{\Delta RPE_t}$
Independent variable	
$\boldsymbol{COMPPEER\_ACQ_{t-1}}$	**0.140****
	(2.21)
Commonrisk	-0.308
	(-0.26)
Sizerkadj	-0.036*
	(-1.67)
Industryconcentrate	0.965
	(0.61)
MTB	0.008*
	(1.66)
Size	0.131***
	(3.61)
Roaindadj	-1.004**
	(-2.41)
Boardindepend	0.160
	(1.14)
Intercept	-2.489***
	(-4.80)
Industry fixed effects	Yes
Year fixed effect	Yes
Number of observations	5,428
Pseudo R^2	0.051

Table 6
Cross-Sectional Analyses
This table report the cross-sectional analysis of the baseline results. ΔRPE_t equals one if the firm used RPE in its executive compensation in year *t* and did not use RPE in year *t-1*, and zero otherwise. $PEER\_ACQ_{i,\ t-1}$ is an indicator variable equal to one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise. Panel A presents the cross-sectional analysis of how stock return co-movements influence our baseline result. We regress a peer firm's stock return on an acquirer's stock return and the market stock return benchmark during the one-year period before the acquisition announcement date. We use the coefficient β_1 on acquirer's return as a measure of pre-acquisition co-movements of the peer and the acquirer. A peer firm is classified as in the '*highcom*' group if it co-moves closely with the acquirer (β_1 is positive and above the overall median level), and in the '*lowcom*' group if it co-moves slightly with the acquirer (β_1 is positive and below the overall median level). $PEER\_AQC_{t-1}\_highcom$ is an indicator variable equal to one if the firm is a peer firm of an acquirer and belongs to the '*highcom*' group, and zero otherwise. $PEER\_AQC_{t-1}\_lowcom$ is an indicator variable equal to one if the firm is a peer firm of an acquirer and belongs to '*lowcom*' group, and zero otherwise. Panel B presents the cross-sectional analysis of how acquisitions' purpose influences the baseline result. SDC Platinum provides variables for M&A purpose code and purpose code description, which we use to divide the acquisitions into two groups according to their intent: competition-related purposes vs other-purposes. Competition-related purposes encompass the following codes: CMP, COR, EPG, EPM, ESM, GEN, PRD, STR, and SYN. Meanwhile, other purposes consist of the following codes: CSH, DBT, EXP, ISV, OTH, PEB, and RST. $PEER\_AQC_{t-1}\_competitionpurpose$ is an indicator variable equal to one if the firm is a peer firm and majority of the acquisitions are competition-related acquisitions in *t-1* in the industry, and zero otherwise. $PEER\_AQC_{t-1}\_otherpurpose$ is an indicator variable equal to one if the firm is a peer firm and majority of acquisitions are other-purpose acquisitions in *t-1* in the industry and zero otherwise. Wald tests are used to test differences between the two coefficients. All regressions include industry and year fixed effects. N denotes the number of observations, Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

Panel A Pre-acquisition stock return co-movements

	Dependent variable= ΔRPE_t	
Independent variable	(1)	(2)
$PEER\_ACQ_{t-1}\_highcom$	**0.093***	**0.116****
	(1.80)	**(2.13)**
$PEER\_ACQ_{t-1}\_lowcom$	**-0.085**	**-0.076**
	(-0.82)	**(-0.70)**
Commonrisk		-0.577
		(-0.57)
Sizerkadj		-0.002
		(-0.11)
Industryconcentrate		-0.392
		(-0.30)
MTB		-0.005
		(-1.25)
Size	0.069***	0.078***
	(4.32)	(2.79)
Roaindadj		-0.049
		(-0.18)
Boardindepend		0.000
		(0.01)
Intercept	-2.367***	-2.336***
	(-9.77)	(-8.06)

p-value for coefficient inequality between *PEER_ACQ$_{t-1}$_highcom* and *PEER_ACQ$_{t-1}$_lowcom*	0.037**	0.033**
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	12,104	11,376
Pseudo R^2	0.052	0.054

Panel B Purpose of acquisition

	Dependent variable= Δ*RPE$_t$*	
Independent variable	(1)	(2)
PEER_ACQ$_{t-1}$_competitionpurpose	**0.214*** **	**0.196*** **
	(3.30)	**(2.94)**
PEER_ACQ$_{t-1}$_otherpurpose	**0.018**	**-0.048**
	(0.11)	**(-0.27)**
Commonrisk		-1.028
		(-0.92)
Sizerkadj		-0.001
		(-0.04)
Industryconcentrate		-1.374
		(-1.02)
MTB		-0.004
		(-0.92)
Size	0.088***	0.093***
	(5.18)	(3.01)
Roaindadj		-0.034
		(-0.12)
Boardindepend		0.160
		(1.62)
Intercept	-2.719***	-2.745***
	(-9.33)	(-6.79)
p-value for coefficient inequality between *PEER_ACQ$_{t-1}$_competition purpose* and *PEER_ACQ$_{t-1}$_other purpose*	0.113	0.082*
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	11,648	10,845
Pseudo R^2	0.061	0.065

Table 7
Cross-Sectional Analyses: Firm-Characteristics
This table presents the results on the additional cross-sectional analyses for the effect of acquisitions on peer firms' RPE compensation. In Column (1), the conditioning variable is *D_ Marketfollower*$_{t-1}$ which equals one if the firm is a market follower in its industry in *t-1*, and zero otherwise. We define a firm as a market follower if the market share of the firm is not in the top decile in its industry. In Column (2), the cross-section is industry competition which is proxied by HHI. HHI is calculated by taking the market share of each firm in the industry, squaring it, and summing the result. The conditioning variable is *D_ Competitive* which equals one if the firm is in an industry with HHI value less than 2500 and zero if the firm is in an industry with HHI value over 2500 (Park et al., 2017). In Column (3), the conditioning variable is *D_Uniqueness* that equals one if a firm has fewer HP-competitors than its industry median level, and zero if a firm has more. HP-competitors are competitors based on product description word overlap. A firm with fewer HP-competitors means the firm's products are more unique, and thus the firm is less likely to be replicated (Hoberg and Phillips, 2014). Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

	Dependent variable= Δ*RPE*$_t$		
Independent variable	(1)	(2)	(3)
PEER_ACQ$_{t-1}$	-0.120	-0.241	0.151***
	(-1.08)	(-1.08)	(3.65)
D_Marketfollower $_{t-1}$	-0.157*		
	(-1.70)		
PEER_ACQ $_{t-1}$ **×** ***D_Marketfollower***$_{t-1}$	**0.287****		
	(2.45)		
D_Competitive $_t$		-0.111	
		(-0.33)	
PEER_ACQ $_{t-1}$ **×** ***D_Competitive***$_t$		**0.389***	
		(1.71)	
D_Uniqueness $_t$			-0.038
			(-0.28)
PEER_ACQ $_{t-1}$ **×** ***D_ Uniqueness***$_t$			**-0.318***
			(-1.94)
Commonrisk	-0.395	-0.146	-0.397
	(-0.63)	(-0.21)	(-0.64)
Sizerkadj	-0.014	-0.017	-0.015
	(-1.23)	(-1.41)	(-1.25)
Industryconcentrate	0.323	0.001	0.314
	(0.36)	(0.31)	(0.35)
MTB	-0.000	0.453	-0.000
	(-0.20)	(0.46)	(-0.20)
Size	0.120***	0.128***	0.121***
	(6.35)	(6.97)	(6.86)
Roaindadj	0.152	0.198	0.166
	(0.87)	(0.92)	(0.94)
Boardindepend	0.082	0.088	0.088
	(1.23)	(1.32)	(1.32)
Intercept	-3.168***	-3.288***	-3.333***

	(-8.79)	(-6.27)	(-10.12)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	18,409	18,409	18,409
Pseudo R^2	0.056	0.056	0.057

Table 8
Cross-Sectional Analyses: Board-Efficiency
This table presents the results on the cross-sectional analyses for the effect of acquisitions on peer firms' RPE compensation. The cross-sections are the board efficiency, measured by board independence, number of qualifications, years to retirement, and board compensation. In Column (1), *D_BoardEfficiency* equals one when the proportion of outside directors on a board exceeds the industry median level, and zero otherwise. In Column (2), *D_BoardEfficiency* equals one when the number of qualifications held by board members exceeds the industry median level, and zero otherwise. In Column (3), *D_BoardEfficiency* equals one when the board members are not close to retirement, and zero when board members are close to retirement. All regressions include industry and year fixed effects. Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

	Dependent variable= ΔRPE_t		
Independent variable	(1)	(2)	(3)
	Board independence	Number of qualifications	Years to retirement
PEER_ACQ$_{t-1}$	0.006	-0.016	0.046
	(0.10)	(-0.20)	(0.71)
D_BoardEfficiency	-0.013	-0.031	-0.022
	(-0.22)	(-0.44)	(-0.35)
PEER_ACQ$_{t-1}$×D_BoardEfficiency	**0.189****	**0.192****	**0.134***
	(2.47)	**(2.16)**	**(1.73)**
Commonrisk	-0.166	-0.145	-0.157
	(-0.23)	(-0.20)	(-0.22)
Sizerkadj	-0.017	-0.018	-0.017
	(-1.37)	(-1.45)	(-1.43)
Industryconcentrate	0.197	0.306	0.332
	(0.22)	(0.34)	(0.37)
MTB	0.001	0.001	0.001
	(0.27)	(0.33)	(0.28)
Size	0.120***	0.125***	0.127***
	(6.47)	(6.80)	(6.91)
Roaindadj	0.210	0.222	0.219
	(0.97)	(1.03)	(1.02)
Boardindepend		0.112*	0.113*
		(1.67)	(1.67)
Intercept	-3.219***	-3.334***	-3.367***
	(-9.80)	(-9.97)	(-10.08)
Industry fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Number of observations	18,409	18,409	18,409
Pseudo R^2	0.057	0.057	0.056

Table 9

The Effect of Using Relative Performance Evaluation on Competitive Aggressiveness

This table presents the association between relative performance evaluation (RPE) compensation and a firm's aggressive actions. In Panel A, the dependent variables is $ADEXP_t$, which is calculated as the advertising expenditure scaled by current total assets. In Panel B, the dependent variable is $OperatingMargin_t$, which is defined as the firm's sales revenue minus cost of goods sold and selling, general, and administrative expenditure, scaled by sales. We focus on peer firms of the acquirers, so the regression sample is restricted to the industry peer firms of an acquirer, assuming that the acquisition occurred in *t-1*. The independent variable ΔRPE_t equals one if the firm use RPE in its executive compensation in year *t* and dids not use RPE in year *t-1*, and zero otherwise. We use alternative measures to define the industry peers of an acquirer (the detailed discussion is in robustness test section). T-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

Panel A: The competitive aggressiveness: Advertisement expenditure

	Dependent variable= $ADEXP_t$				
Independent variable	(1) 2-digit SIC peers	(2) 3-digit SIC peers	(3) Chara.-matched peers	(4) 4-digit GICS peers	(5) 6-digit GICS peers
ΔRPE	**0.064***	**0.096****	**0.149*****	**0.068***	**0.074***
	(1.74)	**(2.13)**	**(2.73)**	**(1.66)**	**(1.83)**
Size	0.000***	0.000***	0.000***	0.000***	0.000***
	(42.11)	(38.19)	(32.60)	(41.46)	(39.31)
MTB	0.000	0.000	0.002	0.000	0.000
	(0.46)	(0.49)	(1.13)	(0.43)	(0.43)
Leverage	-0.054**	-0.039	-0.031	-0.056**	-0.056**
	(-2.33)	(-1.58)	(-0.69)	(-2.35)	(-2.36)
Salesgrowth	-0.000***	-0.000***	0.000***	-0.000**	-0.000*
	(-2.65)	(-2.88)	(2.82)	(-1.98)	(-1.93)
Pastreturn	-0.011	-0.013	-0.040	-0.011	-0.010
	(-0.89)	(-0.97)	(-1.58)	(-0.90)	(-0.85)
HHI	-0.005	-0.012**	-0.013**	-0.008*	-0.006
	(-1.23)	(-2.19)	(-2.28)	(-1.77)	(-1.27)
Intercept	0.062	0.094	0.065	-0.058	-0.063
	(0.41)	(0.58)	(0.43)	(-0.18)	(-0.20)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Number of observations	4,328	3,595	2,679	4,045	4,003
Pseudo R^2	0.373	0.368	0.502	0.379	0.360

Panel B: Competitive aggressiveness: Operating margin

	Dependent variable= $OperatingMargin_t$				
Independent variable	(1) 2-digit SIC peers	(2) 3-digit SIC peers	(3) Chara.-matched peers	(4) 4-digit GICS peers	(5) 6-digit GICS peers
ΔRPE	**-0.012***	**-0.016****	**-0.010**	**-0.014****	**-0.014****
	(-1.90)	**(-2.20)**	**(-1.47)**	**(-2.11)**	**(-2.23)**

Size	0.021***	0.022***	0.027***	0.021***	0.021***
	(20.50)	(19.71)	(24.44)	(20.97)	(20.95)
MTB	0.000**	0.000*	0.000	0.000**	0.000**
	(1.96)	(1.78)	(0.20)	(2.37)	(2.08)
Leverage	-0.030***	-0.029***	-0.043***	-0.029***	-0.030***
	(-5.27)	(-4.79)	(-6.39)	(-5.10)	(-5.23)
Salesgrowth	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***
	(-2.67)	(-2.33)	(-6.27)	(-3.62)	(-3.53)
Pastreturn	0.025***	0.023***	0.020***	0.021***	0.020***
	(7.58)	(6.34)	(5.18)	(6.37)	(6.26)
HHI	-0.000	0.000	-0.000***	-0.000	-0.000
	(-0.67)	(0.52)	(-2.69)	(-0.61)	(-0.85)
Intercept	-0.096	-0.106	-0.003	-0.028	-0.026
	(-1.20)	(-1.31)	(-0.09)	(-0.50)	(-0.47)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	7,932	6,891	5,350	7,434	7,346
Pseudo R^2	0.447	0.409	0.415	0.427	0.427

Table 10
Additional Analyses: The Effect of Acquisitions on Peer Firms' CEO Compensation
This table shows how peer firms respond to an acquisition by adjusting the CEO's compensation. Δ*Ln (Total Comp)*$_t$ is a logarithm of total compensation in the current year minus the logarithm of total compensation last year. Δ*Ln (Cash Comp)*$_t$ is the logarithm of cash compensation in the current year minus the logarithm of cash compensation last year. Total cash compensation refers to the sum of bonuses and salaries. Δ*Ln (Equity Comp)*$_t$ is the logarithm of equity compensation in the current year minus the logarithm of equity compensation last year. Total equity compensation is the sum of option value, stock value, and LTIP (long-term incentive payout) value (Dai et al., 2020). The explanatory variable of interest $PEER\_ACQ_{t-1}$ captures whether a firm is an industry peer of an acquirer, which is an indicator variable equal to one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise. All regressions include industry and year fixed effects. T-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

	Dependent variable=		
Independent variable	(1)	(2)	(3)
	Δ*Ln(Total Comp)*$_t$	Δ*Ln(Cash Comp)*$_t$	Δ*Ln(Equity Comp)*$_t$
PEER_ACQ$_{t-1}$	**0.024*** **	**0.017*** **	**0.009**
	(2.72)	**(3.17)**	**(0.78)**
Size	-0.005**	-0.006***	-0.008***
	(-2.00)	(-4.04)	(-2.66)
Volatility	-0.155**	-0.021	0.061
	(-1.99)	(-0.45)	(0.56)
ROA	0.118***	0.027**	0.232***
	(6.12)	(2.46)	(7.88)
MTB	0.001	-0.002*	0.001**
	(0.99)	(-1.79)	(2.12)
Cash	0.063**	0.052***	0.049
	(2.42)	(3.27)	(1.38)
Leverage	-0.003	-0.002	-0.059**
	(-0.15)	(-0.21)	(-2.42)
Capex	0.036	0.034	0.362***
	(0.35)	(0.55)	(2.65)
Age	-0.003***	-0.001***	-0.004***
	(-5.67)	(-3.95)	(-6.00)
Ownership	-0.000	0.000	0.000
	(-0.24)	(0.09)	(0.07)
Intercept	0.158	-0.378***	0.883***
	(1.45)	(-5.76)	(6.16)
Industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	27,240	27,118	21,760
Adjusted R^2	0.011	0.061	0.031

Table 11
The Effect of Acquisitions on Peer Firms' Overlapping Relative Performance Evaluation
This table presents the effect an acquisition on peer firms' overlapping relative performance evaluation (RPE). The dependent variable $\Delta OverlapRPE_t$ is and indicator variable equals one if the firm used overlap RPE in its executive compensation in year *t* and did not use overlap RPE in year *t-1*, and zero otherwise. The explanatory variable of interest $PEER\_ACQ_{t-1}$ captures whether a firm is an industry peer of an acquirer, which is an indicator variable equal to one if at least one acquisition activity is announced by another firm in the same 2-digit SIC industry in *t-1*, and zero otherwise. From Columns (2) to (5), we analyse the governance-aspect of the association between $\Delta OverlapRPE_t$ and $PEER\_ACQ_{t-1}$. In Column (2), *Goodgovdummy* equals one if the firm's E-index is above the industry median level in year *t*, and zero otherwise. In Column (3), *Goodgovdummy* equals one if the equity compensation ratio of a firm in year *t* is above the industry median, and zero otherwise. In Column (4), *Goodgovdummy* equals one if the percentage of independent board directors in year *t* is above the industry median level, and zero otherwise. N denotes the number of observations, Z-statistics shown in parentheses are based on standard errors clustered at the firm level. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Appendix A gives definition of all variables.

	Dependent variable= $\Delta OverlapRPE_t$			
Independent variable	(1)	(2) E-index	(3) Equity-comp ratio	(4) Director independence
$PEER\_ACQ_{t-1}$	0.03920	-0.048	-0.031	-0.166
	(0.56)	(-0.55)	(-0.41)	(-1.56)
Goodgovdummy		-0.184	-0.559***	-0.005
		(-1.56)	(-3.50)	(-0.05)
$PEER\_ACQ_{t-1}$×*Goodgovdummy*		**0.232***	**0.365***	**0.317****
		(1.72)	**(1.92)**	**(2.44)**
Commonrisk	-0.247	-0.209	-0.311	-0.268
	(-0.20)	(-0.17)	(-0.25)	(-0.21)
Sizerkadj	-0.006	-0.006	-0.008	-0.006
	(-0.27)	(-0.29)	(-0.37)	(-0.29)
Industryconcentrate	0.333	0.373	0.580	0.326
	(0.20)	(0.22)	(0.33)	(0.20)
MTB	0.003	0.003	0.003	0.003
	(0.62)	(0.65)	(0.67)	(0.63)
Size	0.105***	0.104***	0.088***	0.098***
	(3.32)	(3.27)	(2.72)	(3.07)
Roaindadj	0.010	-0.014	-0.077	0.012
	(0.03)	(-0.04)	(-0.19)	(0.03)
Boardindepend	0.228*	0.253**	0.247*	
	(1.82)	(1.99)	(1.95)	
Intercept	-3.627***	-3.524***	-3.233***	-2.900***
	(-6.69)	(-6.33)	(-5.73)	(-5.59)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Number of observations	16,065	16,065	16,065	16,065
Pseudo R^2	0.069	0.071	0.078	0.075

Chapter 4: The Spillover Effects of Exogenous Events on Managerial Disclosure of Earnings Forecasts: Evidence from U.S. Major Hurricanes

ABSTRACT

We examine how peer firms located in nonaffected areas respond to major hurricane events by issuing management forecasts. We build our argument on the premise that a hurricane-hit firm's loss strengthens the competitive position of its industry peers, incentivizing them to take advantage of the loss in market share experienced by the hurricane-hit firm. We show that, after a major hurricane, industry peers issue more management forecasts. We also find a positive association between management forecast frequency and firm visibility and shifts in market share. This implies that by issuing more management forecasts, industry peers can potentially attract more attention from investors and enhance their market share. Our research findings underscore the significant impact a firm's adverse event can have on its peers' disclosure strategy, despite the peers not being directly affected by the event.

JEL classification:

Keywords: natural disasters, hurricanes, disclosure, management forecasts, spillover effects, competitive advantages

1. Introduction

How exogenous events directly affect firms has attracted considerable attention from accounting and finance researchers. Recent researchers (e.g., Dessaint, and Matray, 2017; Garg, 2020; Loughran and McDonald, 2020; Massa and Zhang, 2021;) show interest in "the spillover effect" instead of "the direct effect" of such events and they demonstrate that exogenous shocks such as hurricanes, cyberattacks, and pandemics spread out and indirectly affect a large number of firms. In this study, we use an exogenous event, major hurricanes in the U.S., to examine how it affects the management forecasts of firms located in non-hurricane areas, i.e., the spillover effect of hurricanes. In the event of a major hurricane strike, hurricane-hit firms are exposed to more public scrutiny, forcing them to at least take action to reassure their investors. We focus on industry peers located outside the area directly impacted by hurricane strikes because those firms have more autonomy to respond strategically. Lang and Stulz (1992) illustrate that industry peers can benefit from the difficulties of a bankrupt peer. Intuitively, how industry peers react to a major hurricane largely depends on whether they can benefit from the difficulties of their hurricane-hit peer.

This study investigates how a major hurricane influences industry peers' voluntary disclosure. According to strategy-based voluntary disclosure theory (Verrecchia, 1983; Dye, 2001), firms with superior performance will try to distinguish themselves by providing a higher level of voluntary disclosure. Conversely, the legitimacy theory (e.g., Patten, 2002) predicts that firms with poorer environmental performance have an incentive to make more disclosure to address threats to their legitimacy. Fundamentally, the strategy-based theory emphasizes affirmations of firms' advantageous position, whereas the legitimacy theory emphasizes the role of disclosure as a legitimizing tool. Our study is based on the strategy-based theory: though the literature finds major hurricanes impose enormous, disruptive impacts on firms located in the affected area in terms of operating performance and market functioning (e.g., Sydnor et al., 2017; Rehse et al., 2019), increased disclosure helps unaffected peers to: (1) reinforce their favourable position compared with a hurricane-hit firm; and (2) successfully improve visibility by distinguishing themselves from other nonaffected firms with insufficient disclosure.

We focus our analysis on management forecasts because management forecasts are one of the most pervasive and widely studied forms of voluntary disclosure (Hirst et al., 2008). Management forecasts convey forward-looking, value-relevant information on future performance, market demand and operating costs. Consequently, issuing more management forecasts functions as an ideal mechanism by which firms can increase their visibility (Manski, 2000; Bushee and Miller, 2012), and build a reputation for transparency in the capital market (Leland and Pyle, 1977; Trueman, 1986; Merton, 1987).

Major hurricanes in the U.S. provide a promising setting for examining the spillover effect of exogenous events on management forecasts. Hurricanes are regular events in the U.S.; since the 1850s, an average of two hurricanes have struck the U.S. mainland every year. Hurricanes usually cause widespread destruction, major collateral damage, and loss of life. An increasing body of literature (e.g., McKnight and Linnenluecke, 2016) has sought to explore the negative consequences of hurricanes, and how affected firms participate in building community resilience to hurricanes. Firms, however, do not operate in isolation and their strategies and market position must be examined in the context of and vis-à-vis peer firms' positions (Chen and Miller, 2012). Surprisingly, there has been relatively little research investigating the spillover effects of major hurricanes on nonaffected peer firms' behaviour. Our study fills this gap by analysing the spillover effects of major hurricanes on management forecast decisions of industry peers located outside the affected area.

Our study is based on the premise that between rival firms, the gain (loss) for a firm is often matched with the loss (gain) for its peer. We use a sample of 138,780 firm quarters for firms available in the I/B/E/S Guidance database from 2001 to 2020. Empirically, we examine how a major hurricane affects industry peers' decisions on issuing management forecasts, and find that industry peers issue more management forecasts following a major hurricane. We provide the following explanation for the observed effect. A hurricane-hit firm's considerable damage potentially strengthens the competitive position of industry peers in nonaffected areas. Industry peers have strong incentives to capitalize on their competitive advantage after a major hurricane. One such incentive is the desire to expand investor base and gain a larger market share to reduce the cost of capital and increase firm value (Merton 1987). Investors and customers are attention-constrained and firms strategically use management forecasts to attract their attention (e.g., Cohen and Frazzini, 2008; Seo, 2021). Furthermore, management forecasts serve as a signalling mechanism that establishes a reputation for transparency in the capital market (Leland and Pyle, 1977; Trueman, 1986). Therefore, a peer firm would respond to a major hurricane by issuing more management forecasts, aiming to better leverage its competitive position and reap the aforementioned benefits in the capital market. This strategic behaviour is driven by the fact that a peer firm's higher forecast frequency can shift investors' and customers' attention toward itself and lead them to perceive that another peer with lower forecast frequency is being less transparent and of lower quality (Seo, 2021).

We then dissect these effects in the cross-section to shed light on the validity behind the association between major hurricanes and industry peers' disclosure decisions. First, we show that the positive effect of a hurricane on industry peers' management forecast issuance is particularly pronounced when the hurricane-hit firm is a market leader. Given that natural disasters disrupt affected firms' performance and, thus, cause a drop in market share (e.g., Meier et al., 2010), therefore peer firms (located in non-affected regions) have the potential to take market share from the affected firms. An affected market leader has a higher potential loss of market share than an affected non-market leader, providing stronger incentives for industry peers to take the market share because there are potentially more benefits from such an impaired market leader. Next, we hypothesize that the positive relationship between a major hurricane and industry peers' management forecasts is particularly pronounced in competitive industries. Generally, a major hurricane can enable peer firms to prey on the hurricane-hit firms because hurricane-hit firms' products have become less attractive because of the hurricane-induced disruption, in relation to peers' products. Thus, a major hurricane represents a demand shift for a given total market value in the industry (Lang and Stulz, 1992). Firms in a competitive industry compared with those in a concentrated industry, find it more difficult to benefit from the increased demand unless they take actions that make themselves distinguishable in the industry. In line with this view, we find that industry peers are more likely to increase management forecasts after a hurricane when they are in a competitive industry rather than a concentrated industry.

This study contributes to the literature in several ways. First, this study adds to the growing literature on the spillover effects of exogenous events. Prior work highlights the spillover effects of cyberattacks, earthquakes, and bankruptcies (e.g., Zhang, 2010; Garg, 2020; Carvalho et al., 2021). For example, Garg (2020) finds that the damage caused by a cyberattack is contagious in the industry and along the supply chain. Carvalho et al. (2021) find that the disruption caused by an earthquake is contagious up- and down-stream along the supply chain. Zhang (2010) finds that Chapter 11 bankruptcy provides competitive advantages to the re-organized firm at the expense of its industry peers, representing a competition effect. To our knowledge, despite the significant and disruptive impact of hurricanes in the U.S., there is little research focusing on the spillover effects of major hurricanes. A recent exception is the study by Massa and Zhang (2021) that focused on the insurance industry. They find that Hurricane Katrina generated an externality spillover effect on firms' financing decisions in the insurance industry, even for firms not directly impacted by the hurricane. Our study complements that study by investigating the spillover effect of a major hurricane on peer firms' voluntary disclosures. We find industry peers increase management forecasts after a hurricane, suggesting that industry peers are motivated to attract investors and take up a greater market share by issuing management forecasts when a peer suffers from hurricane-induced disruption.

Secondly, our study contributes to the literature on related firms learning from each other. Most prior studies find that a firm's action matters for its related firms' actions, including capital budget, investment, and corporate disclosure decisions (e.g., Foucault and Fresard, 2014; Grennan, 2019; Seo, 2021). Our study complements these studies by documenting that firms make real decisions on disclosure not only by learning from related firms' actions but also by learning from related firms' events. For example, Garg (2020) shows that a peer firm adjusts its cash holding strategy as a precautionary action when a cyberattack hits another firm in the same industry. Li and Tang (2016) show that a firm's financial policies are influenced by its customers' credit default swaps. Our analysis extends prior literature by showing that firms strategically make forecast decisions when another firm in the industry is hit by a major hurricane.

Last, our study contributes to the accounting literature on voluntary disclosure motives. Management forecasts are voluntary disclosures about future earnings expectations. Managers have a large amount of discretion over issuing management forecasts (Hirst et al., 2008). Existing theories propose that the decision to issue a forecast is influenced by pre-existing conditions or antecedents. Some antecedents are external to the firm (such as legal, regulatory, investor, and analyst environment) whereas others are internal and firm-specific (such as issuer characteristics) (e.g., Healy, et al. 1999; Ajinkya, et al. 2005; Hirst et al., 2008). Our study provides large-sample evidence of how a sudden shift in competitive position shapes a firm's management forecasts issuance. We treat a major hurricane as an exogenous shock to a non-affected peer firm's competitive position. Our findings suggest that beyond the traditional motives, firms strategically issue management forecasts to leverage the wealth re-distribution when other firms in the same industry are impaired by a major hurricane.

The remainder of the chapter is organized as follows. Section 2 reviews the literature and develops the hypotheses; Section 3 describes sample selection and the data, Section 4 presents the results, Section 5 provides additional tests, and Section 6 summarizes our main findings.

2. Literature and Hypotheses

2.1 Related literature

Firms do not operate as independent entities. Previous studies (e.g., Cohen and Frazzini, 2008) have pointed out that any shock to one firm affects its linked firms' real activities, indicating a spillover effect of the shock. In this study, we focus on the industry-wide spillover effect of a major hurricane. Our argument is based on the premise that any adverse (favourable) shock strengthens (weakens) peers' competitive position in an industry (e.g., Lang and Stulz, 1997; Erwin and Miller, 1998; Hsu et al., 2010). Consistent with such a competitive effect, Hsu et al. (2010) find, as an IPO is expected to allow the issuing firm to compete more successfully against industry peers, the successful completion of an IPO should have a negative impact on peers' stock prices. Erwin and Miller (1998) find that firms announcing open market share repurchase programmes experience a significantly positive stock price reaction at the announcement, but their peers in the same industry experience a significant, contemporaneous negative stock price reaction. Lang and Stulz (1997) argue that a bankruptcy announcement can reveal that the bankrupt firm has become less efficient and the competitive position of other firms in the industry has improved. It is widely believed that competitive interdependence represents an essential nature of rivalry and, thus, to gain a competitive advantage, a firm must constantly gauge what happens to its peers and deploy competitive actions in response. Prior studies have examined how industry peers make real decisions in response to a sudden change in their competitive position. For example, a firm under Chapter 11 protection may emerge from bankruptcy in a more advantageous competitive position in the industry to the detriment of its peers. When WorldCom was under Chapter 11 protection, its peer firms such as AT&T, SBC, and Verizon, spent considerable resources to prevent WorldCom's emergence from bankruptcy (Dattner, 2004; Zhang, 2010). Lei et al. (2018) argue that a firm's financial slump and potential exit resulting from credit risk may strengthen industry peers' competitive position; industry peers could have incentives to accumulate cash and invest to take advantage of firms suffering from a credit risk. A common feature of natural disasters is their intensely regional economic and social impact (West and Lenze, 1994). It is generally believed that industry peers, provided they are located in non-disaster areas, experience an enhanced competitive position compared with affected firms, because their operations and performance remain undisturbed. Prior literature largely focuses on estimating the economic impact of natural disasters and evaluating the recovery and rebuilding actions and has been silent on how industry peers interpret post-disaster changes in their competitive environment. Specifically, we examine how industry peers strategically respond to a major hurricane shock through management forecast decisions.

Over the last several decades, studies on management forecasts have largely focused on various rationales for firms to issue management forecasts. For example, Trueman (1986) finds that firms make earnings forecasts to reveal their ability in identifying changes in their underlying economics. Barry and Brown (1985) and Merton (1987) show that firms increase voluntary disclosures to reduce the cost of capital arising from information asymmetry. Healy and Palepu (1993, 1995) indicate that firms disclose information to communicate their superior knowledge to investors. Bergman and Roychowdhury (2008) suggest that voluntary disclosure reflects a firm's desire to strategically maintain investor optimism about future earnings.

How market competition influences firms' management forecasts has also attracted considerable attention. For example, Ali et al. (2014) find that firms in more competitive industries tend to disclose more. In contrast, Huang et al. (2017) use large reductions in U.S. import tariff rates to identify an exogenous increase in market competition. They find that the increase in market competition is associated with a decrease in management forecasts. As the tariff reductions primarily increase competition from existing foreign rivals against domestic firms, management forecasts issued by domestic firms potentially face higher proprietary costs. This, in turn, is likely to reduce domestic firms' incentives to issue such forecasts. These studies largely emphasize whether overall competition affects management forecast issuance. However, to our knowledge, very few prior studies have focused on the role that a change in competitive position plays in management forecast decisions. According to strategy-based theory, firms with superior performance tend to disclose more information, thereby acclaiming their favourable position relative to their peers (Verrecchia, 1983; Dye, 2001). Consequently, peer firms of hurricane-hit firms are likely to issue more forecasts to highlight their competitive advantage following a hurricane.

2.2 Unpredictability of hurricanes

Hurricanes are frequent, costly events throughout U.S. history. On average, a hurricane strikes the U.S. mainland every six months. Indeed, hurricane risk randomly affects firms throughout the U.S., but it is nearly impossible to predict the potential amount of damage. Hurricanes present a situation of heightened firm operating uncertainty and local economic uncertainty (Knight, 1921). Extant studies in finance and climate show that the distribution of hurricanes in the U.S. has been stationary for all hurricanes and major hurricanes at both country and regional levels (e.g., Landsea et al., 2006; Blake et al., 2011). Despite hurricanes tending to cluster in certain areas with particular climate conditions, we cannot deny the fact that the exact time, location, and intensity of future hurricanes are "largely determined by the weather patterns in place as the hurricane approaches, and those patterns are only predictable when the storm is within several days of making landfall" (NOAA 2021 Atlantic Hurricane Season Outlook). In this case, predicting a specific hurricane is nearly impossible. This view has been confirmed by Dessaint and Matray (2017, pp 98) who state that "Estimating the marginal increase in the local probability of hurricane landfall in response to the occurrence of a hurricane over the past two years produces a statistically insignificant coefficient that is negative or equal to zero". The unpredictability, together with the exogenous nature of hurricanes, provides us with a setting of a natural experiment in which a small subset of firms is directly exposed to hurricanes.

2.3 Hypothesis development

Prior literature and anecdotal evidence[19] show that firms operating in the same industry are interdependent. Competitive dynamic research contends the competitive interdependence between rival firms is such that the gain (loss) for one firm is often matched with the loss (gain) for its peers (e.g., Lang and Stulz 1992; Lien et al., 2021). Lang and Stulz (1992) show that a firm-specific negative event can potentially increase the value of other firms in the industry by redistributing wealth from the affected firm to nonaffected ones. Prior literature (e.g., Kong et al., 2021) shows that severe natural disasters exert a significant negative effect on firms' operations and local economic development. Compared with hurricane-hit firms, industry peers located in nonaffected areas are naturally assumed to benefit from a hurricane by an improved competitive position. For example,

Given that a hurricane creates a competitive advantage for industry peers, industry peers potentially have incentives to exploit the difficulties of the hurricane-hit firms. For example,

[19] For example, when Caterpillar formulated its strategy to compete with Komatsu in the international construction and mining industry, Caterpillar formed an alliance with Mitsubishi to undercut Komatsu, because Mitsubishi was Komatsu's primary rival in Japan. Similarly, when Hewlett-Packard formulated its strategy to compete against Dell, comprehending Dell's perception of Lenovo as a main rival enhanced HP's ability to determine an opportune time to attack Dell (Tsai et al., 2011).

Rehse et al. (2019) find that uncertainty- or ambiguity- aversion leads investors to decide not to transact with a hurricane-hit firm. This seems a good time for industry peers to expand their investor base to reduce the cost of capital and increase firm value (Seo, 2020). Prior literature documents that firms rely on voluntary disclosures to attract investors' attention and keep investors informed about them (e.g., Barber and Odean, 2008; Cohen and Frazzini, 2008; Engelberg and Parsons, 2011). Trueman (1986) theorizes that a manager's ability to identify changes in the firm's underlying economics is value relevant. A peer's voluntary disclosure can serve as a signal to the market that the manager has identified changes in the firm's competitive position. Therefore, industry peers with more disclosures are perceived as being more transparent and of higher quality (Seo, 2021). We formally test the follow hypothesis.

H1. *Industry peers of hurricane-hit firms increase the frequency of management forecasts after a major hurricane.*

3. Sample and data

We obtain detailed information about major hurricane landfalls in the U.S. since 2000 from the report of U.S. billion-dollar disaster events available in the National Center for Environmental Information (https://www.ncdc.noaa.gov/). This information includes major hurricanes' names, dates and locations. To ensure that the event is sufficiently severe, we focus on hurricanes with a total estimated cost (adjusted for the CPI in 2020) above five billion dollars (Dessaint et al., 2017). Table 1 summarises the statistics for 20 hurricanes.

[Insert Table 1 here]

We obtain management forecast data from the I/B/E/S Guidance, which reports the monthly number of management forecasts, including forecasts of earnings, EBITDA, sales, dividends, CAPEX, and margins (Reiter, 2021). We count the number of management forecasts disclosed by a firm during the quarter as the frequency of management forecasts. We obtain financial data from Compustat Quarterly. We define a firm as hurricane-hit if the firm's headquarters is located in a state hit by a hurricane in a given quarter. Ideally, we would like to know where the facilities (plants) are located to avoid a misclassification problem. For example, if a firm's headquarters is in the affected area but its facilities are in a nonaffected area, the firm would be misclassified as a hurricane-hit firm. Following Chaney et al. (2012) and Dessaint et al. (2017), we assume that facilities are located in the same area as a firm's headquarters. This approximation should not affect our results for the following reasons. First, Kalnins and Lafontaine (2013) document that the longer the distance between headquarters and plants, the less likely a business will survive into the future, thus, around 40 percent of plants have a zero distance from their headquarters. Even if it is possible that a firm's plant and headquarters are located in different areas, most firm plants are likely to cluster around their headquarters.

In the main analysis, we obtain a firm-quarter panel dataset of 138,780 observations from 2001-2020. We do not include forecasts made before 2001 to avoid any confounding effects of disclosure regulations (i.e., Reg FD) on management forecasts because Reg FD was passed by the SEC in 2000[20]. Before testing the empirical hypothesis, we first aim to provide evidence supporting the premise that a major hurricane is viewed negatively for hurricane-hit firms but positively for their industry peers. Alternatively, a behavioural story may predict investors' pessimism after a natural disaster (e.g., Kong et al., 2021). Although hurricanes do not significantly influence the operations of peer firms, investors may overreact to news of hurricanes. This reaction, stemming from feelings of fear, dread, and anxiety, could lead to negative stock price reactions for both the hurricane-impacted firms and their industry peers. Therefore, we observe the stock price reactions of both the hurricane-hit firms and their industry peers around the hurricane's occurrence date. Table 2 reports the univariate analysis

[20] Regulation FD (Fair Disclosure), ordinarily referred to as Regulation FD or Reg FD, is a regulation that was promulgated by the U.S. Securities and Exchange Commission (SEC) in August 2000 in an effort to prevent selective disclosure by public companies to market professionals and certain shareholders. It aims to increase transparency and accountability. Heflin et al. (2003) and Bailey et al. (2003) find that number of forecast issuances increased after Reg FD.

of the hurricane-hit firms and their industry peers' average cumulative abnormal returns (CAR, hereafter) around the beginning date of the major hurricane. Our key event window of interest is day -1 (the hurricane landfall date) and the next trading day after the event day +1. For hurricane-hit firms, the mean (median) CAR over the window (-1, +1) is -0.139% (-0.280%). For the industry peers, the mean (median) CAR over the window (-1, +1) is 0.094% (0.042%). Univariate tests show that though hurricane-hit firms suffer from negative stock price reactions around the hurricane event, nonaffected peer firms' stock price reactions are positive around the event, providing some preliminary evidence of the competitive effect of a hurricane strike. In other words, though a major hurricane is viewed negatively for hurricane-hit firms, it is viewed positively for nonaffected industry peers.

[Insert Table 2 here]

4. Results

4.1 Baseline results

First, we examine the effect of major hurricanes on management forecasts issued by industry peers located in nonaffected areas using the following OLS regression model:

$$FREQ_t = \beta_0 + \beta_1 Peer_{t-1} + \beta_2 SIZE + \beta_3 MTB + \beta_4 Goodnews + \beta_5 Loss + \beta_6 Leverage + \beta_7 RevVol + \beta_8 Big4 + Firm\ FE + Time\ FE + \varepsilon \quad (1)$$

where: the dependent variable *FREQ* is the number of management forecasts issued in a given quarter *t*. We define a firm as a hurricane-hit firm if the firm's headquarters is in an area (at the state-level) hit by a major hurricane in a given quarter. The explanatory variable of interest, *Peer*, is used to capture whether a firm is an industry peer firm of hurricane-hit firms. $Peer_{t-1}$ is an indicator variable that equals one if a firm is operating in the same 2-digit SIC industry as a hurricane-hit firm in quarter *t-1*, and zero otherwise (e.g., Leary and Roberts, 2014). The coefficient on *Peer*, β_1, captures the spillover effect of a last-quarter hurricane on management forecast frequency of industry peers. A positive, significant β_1 is consistent with our prediction that industry peers increase the frequency of management forecasts after a hurricane. We select the following additional independent variables to control for other possible determinants of management forecasts: *Size* (the natural logarithm of a firm's book value of total assets); *MTB* (the ratio of market value-to-book value of common equity); *Goodnews* (an indicator variable equal to one if the current-period total income is greater than or equal to the previous-period total income, and zero otherwise); *Loss* (an indicator variable equal to one if the firm reports losses, and zero otherwise); *Leverage* (the ratio of total debt to total assets); *RevVol* (the volatility of the firm's revenue); and *Big4* (an indicator variable equal to one if a firm's auditor is a Big 4 auditor, and zero otherwise (e.g., Ajinkya et al.2005; Tsang et al. 2019). We include firm fixed effects to control for time-invariant differences among firms and the quarterly time-fixed effects to adjust the analysis for time-specific shocks between different time periods because hurricane activity is seasonal (e.g., Dessaint et al., 2017; Lee, 2017). We winsorize continuous variables at the 1st and 99th percentiles before estimating the regression.

Table 3 reports the results. Column (1) shows that *FREQ* is significantly positively associated with *Peer* (coef.= +0.066, t-stat= 2.26), which implies that industry peers increase their management forecast frequency following a hurricane event (consistent with **H1**). These results suggest that the industry peers of a hurricane-hit firm disclose, on average, 0.07 more management forecasts than firms that are not industry peers of the hurricane-hit firm. We use a Poisson model to re-estimate Equation (1) where *FREQ* is a count-dependent variable. The same inference applies if we use the Poisson model because the results presented in Column (2) (coef.= +0.082, t-stat= 2.20) are consistent with the OLS results.

[Insert Table 3 here]

4.2 The effect of management forecasts on firm visibility

The fact that industry peers issue more management forecasts after a major hurricane suggests potential benefits associated with disclosures. In this section, we analyse the implications of issuing more management forecasts, to provide a more textured understanding of the reasons why industry peers respond to a major hurricane by increasing management forecast issuance.

Many firms face significant challenges in improving their visibility to attract investors. A key motivation for studying strategies to increase firm visibility draws on Merton (1987) who suggests that an increase in the size of a firm's customer base (i.e., the number of investors that are aware of the firm's existence) reduces the cost of capital. This result is intuitively appealing, since it indicates that firms take full advantage of their lower cost of capital by raising enough financing to cover their investment opportunities for the next several years. Consistently, Lehavy and Sloan (2008) find that firm visibility is even more important than news about firm fundamentals, such as earnings, in explaining stock prices. Though our main results show a positive relationship between a major hurricane and industry peers' management forecasts, we posit that one of the primary goals in increasing management forecasts is to improve firm visibility. We test if frequent issuers indeed benefit from improved firm visibility. Prior studies argue that institutional ownership increases with firm visibility (e.g., Chen et al., 2002; Lehavy and Sloan, 2008). Accordingly, in our analysis, the dependent variable *Firmvisibility* is measured by total institutional ownership during quarter *t* (e.g., Arbel et al., 1983; Bushee and Miller, 2012). Our key independent variable of interest, *FREQ*, is the frequency of management forecast for a firm during quarter *t*. We restrict the initial sample to peer firms of hurricane-hit firms. The sample consists of firm-quarter observations with available data.

Table 4, Panel A, presents the results. In Column (1), we include firm fixed effects to control for time-invariant differences in institutional ownership among firms and year-quarter time fixed effects to control for differences between time periods. In Column (2), we add a set of control variables. We include the fundamental characteristics of firms such as firm size (*Size*), leverage (*Leverage*) and market-to-book ratio (*MTB*). We also include a market-adjusted returns (*Mret*) proxy for firm performance, the level of trading volume in the stock (*Tvol*) as a control for institutional investor preferences for more liquid stocks, and the log of outstanding shares (*Shrs*) to proxy for stock issuance. We include several variables to capture the fundamental growth and income ratios on which institutions might base their trading decisions, including dividend yield (*DP*), the earnings-price ratio (*EP*), and sales growth (*Sgr*) (e.g., Lang and McNichols, 1997; Bushee and Noe, 2000). All variables are measured quarterly. We find the coefficient on *FREQ* is positive and significant in both Columns (1) and (2). This result indicates that firms issuing more management forecasts experience a significant improvement in firm visibility.

In response to visibility concerns, firms provide enhanced forecasts to attract the attention of institutional investors. Though prior work finds that institutional investors often exhibit a preference for large firms as a way to reduce information processing and search costs (e.g., Abarbanell et al., 2003; Bushee and Miller, 2012), the remaining question is, compared with large and highly-visible firms, whether small and less-visible firms are better able to attract institutions by increasing forecasts. This gap provides a key motivation to examine further the role of management forecasts based on different firm size subsamples. We re-estimate the OLS model separately for the large- and small-size subsamples, defined as firms with above and below the industry-median total assets, respectively. The results are reported in Table 4 Columns (3) and (4).The coefficient of *FREQ* is significantly positive for the small subsample, and the coefficient of *FREQ* for the large subsample lacks significance at conventional levels. Moreover, the coefficient of *FREQ*, 0.019, for the small firm subsample, is higher than the coefficient of *FREQ*, 0.004 for the large subsample. The difference between coefficients for small- and large-size firm subsamples is significant at the 1 percent level indicating that increasing management forecast functions as a more efficient mechanism for small firms to overcome their visibility barriers. Overall, the findings align with the literature that indicates that institutional investors often exhibit a preference for larger firms (Abarbanell et al., 2003). The results suggest that, though large firms have limited scope to enhance their visibility through increased management forecasts, it is important for smaller firms to strategically issue more of these forecasts to attract institutional investors.

[Insert Table 4 here]

4.3 The effect of management forecasts on market share

Considering that natural disasters disrupt the performance of affected firms and lead to reductions in their market shares (e.g., Meier et al., 2010), therefore peer firms have incentives to seize these shares. In this subsection, we propose and empirically test an alternative explanation for why industry peers respond to a major hurricane by increasing their management forecast issuance. Specifically, we investigate whether this disclosure strategy helps peer firms in capturing more market shares. We use an OLS model where the dependent variable Δ*Marketshare* is the difference between the market share in the next quarter and the current market share (market share is calculated as the firm's sales over the total sales of the industry during a quarter). The independent variable is *FREQ*. Table 5 reports the results. In Column (1), we only include industry-fixed effects and year-quarter time fixed effects. The coefficient on *FREQ* is positive but lack of significance. Column (2) presents the full regression as we include additional determinants of market share. To be specific, we add in the fundamental firm characteristics (i.e., *Size*, *MTB*, *Leverage*), market structure variables (i.e., *HHI*, *Mgrrate*), competitive strategy variables (i.e., *RD*, *SG*A), and firm-specific resource (i.e., *Intangible*). In Column (2), we find that *FREQ* is positively associated with Δ*Marketshare,* and significant at the 5 percent level (coef.=+0.005, t-stat=2.09). This suggests that after a major hurricane, industry peers can capture more market shares by issuing management forecasts. Lang and Stulz (1992) suggest that a negative event causing a firm's product to become less attractive can decrease demand for that firm. Conversely, this situation is advantageous for peer firms in the same industry, as they have experienced or can anticipate an increase in demand. We complement Lang and Stulz (1992) by finding that peer firms can benefit from such shift in demand by issuing more management forecasts[21].

[Insert Table 5 here]

5. Additional analyses

5.1 Alternative explanations

Having established that firms are more likely to issue management forecasts if they are industry peers of hurricane-hit firms, we conduct additional sensitivity tests to assess the robustness of our findings. There is overwhelming evidence suggesting that macroeconomic shocks have an impact on firm performance and voluntary disclosure policies (e.g., Loughran and McDonald, 2020). Therefore, we argue that other macroeconomic shocks during our sample period, such as the 2007-2008 financial crisis and the COVID-19 outbreak, may also influence management forecast decisions because of the economic downturn and increased uncertainty caused by these events. On the one hand, we argue that, in times of these shocks, firms might not be able to afford the costly process of additional voluntary disclosure costs because of the poor information environment. Hence, firms provided fewer management forecasts. On the other hand, macroeconomic shocks might force firms to be involved in more voluntary disclosure to legitimize their existence. Investors' information demand may increase during periods of uncertainty (Kim et al., 2016), leading to higher expectations of firms to disclose more information. In response to this increased information need, firms may need to

[21] We acknowledge that, in additional to firm visibility and market share, the importance of advertising expenses and pricing campaigns in gauging a firm's competitive position. We made an effort to examine if peer firms' management forecast frequency affect their competitive strategies such as advertising and pricing campaigns. However, Compustat does not provide quarterly advertising expenditure data, we are not able to test if advertising expenses of peer firms vary with the frequency of management forecasts. Following Mouzas (2006), we understand that increased costs associated with competitive aggressiveness, such as temporary price reductions or trade promotions, can often compress operating margins. In untabulated results, we find that peer firms with a higher frequency of management forecasts indeed, report a reduced operating margin. This provides some evidence that, following a hurricane, peer firms intensify their competitive stance, potentially through pricing campaigns, aiming to reinforce their favorable position in the market.

increase their issuance of management forecasts. To test this possibility, we control for the effect of a financial crisis and COVID-19 in Equation (1) and report the results in Table 7. The coefficients on *Financial Crisis* are significantly positive, suggesting that firms tend to provide more forecasts in response to investors' heightened information demands during a financial crisis. Although the coefficients on *Covid-19* are also positive, they are not statistically significant at conventional levels. We find the coefficient of $Peer_{t-1}$ is still positive and statistically significant at the 5% level (see Table 6, Columns (1) and (2). The stability of the baseline finding that peer firms increase management forecast frequency following a major hurricane is not affected by the inclusion of macroeconomic shocks.

Second, it can be argued that disclosure decisions made by peer firms in response to a major hurricane could be influenced by a CEO's personal characteristics. The literature indicates that voluntary disclosure decisions may be associated with CEO characteristics. For example, empirical evidence on the relationship between voluntary disclosure and CEO characteristics is mixed. Anderson and Anthony (1986) argue that a unified leadership structure, such as CEO duality, can reduce information sharing costs and the conflict of interests between the CEO and non-CEO chairman. Rhoades et al. (2001) assert that CEO duality's clear lines of authority and unity of command can mitigate internal conflicts and enhance decision-making. Given the reduced information sharing costs and enhanced decision-making, a CEO holding dual roles might be more confident and inclined to provide more voluntary disclosures. Other studies, such as Cheng and Courtenery (2006), Li et al. (2008) and Allegrini and Greco (2013), document a negative or insignificant association between CEO duality and voluntary disclosure. Regarding CEO tenure, Park and Yoo (2016) propose that CEOs with a shorter tenure may be more motivated to do voluntary disclosure, aiming to signal their abilities to the labour market and establish a solid reputation. Conversely, CEOs with long tenure could potentially increase the issuance of management forecasts because of their deep understanding of their firm's operations that enables them to provide higher quality disclosures (Brockman et al., 2019). Therefore, CEO tenure may affect disclosure decisions. To rule out this possibility, we control for several fundamental CEO characteristics including tenure, compensation, age, and duality. Consistent with Brockman et al.'s (2019) argument that the frequency of management forecasts increases with CEO internal experience, we find the coefficients of *CEOTENURE* are significantly positive at the 1 percent level. The coefficient of $Peer_{t-1}$ is still positive and statistically significant at the 1% level (see Table 6, Columns (3) and (4)), indicating that the stability of the baseline results is not affected by the inclusion of CEO characteristics.

Third, we are concerned that external governance mechanisms may bias our main results. External governance mechanisms can play an important role in determining the voluntary disclosure policy of firms. Disclosures, especially management forecasts, are closely watched by market participants. Prior work (e.g., Healy et al. 1999; Bushee and Noe, 2000) suggests that institutions prefer to buy stocks in firms that have superior disclosure. In line with this, managers who act in the best interests of the firm should recognize the benefits of transparency and choose to issue more frequent management forecasts. However, managers may act in their own-self-interest and can decide to issue fewer forecasts than what might be optimal for the firm for various reasons such as insider trading opportunities. External governance mechanisms can help foster an environment that encourages greater transparency. Therefore, we re-estimate Equation (1) controlling for two external governance mechanisms (i.e., total institutional ownership and analysts' following) and find that the baseline effect of a major hurricane on peers' forecast frequency is still positive and significant at the 5 percent level (see Table 6, Columns (5) and (6)). In addition, we find that the coefficients of *Insown* are significantly positive at the 1 percent level, but the coefficient of *Analystfollowing* is insignificant. It seems reasonable that, once institutions invest in a particular firm, they are likely to have added incentive to encourage further improvement in forecast issuance. Overall, the stability of our baseline results is not affected by the inclusion of external governance mechanisms.

One remaining concern is peer effects on corporate disclosure decisions. Peer effects suggest that the average behaviour of a group influences the behaviour of individual members (Manski, 1993). In our study, it is plausible that industry peers' increase in issuing management forecasts could be induced by other firms in the same industry increasing management forecasts rather than the result of a major hurricane. In Table 6, Columns (7) and (8), we control for peer effects (*P_FREQ*= the average frequency of management forecasts by other firms in the same 2-digit SIC industry in quarter *t*). The loadings on *P_FREQ* are significantly positive at the 1 percent level, which is generally consistent with Seo (2021), providing strong evidence of peer effects in disclosure. After controlling for the peer effect of disclosure decision, the coefficients of $Peer_{t-1}$ are still positive and significant at the 1 percent level (see Table 6, Columns (7) and (8)). The stability of our baseline results is not affected by the inclusion of peer effects in disclosure decisions.

[Insert Table 6 here]

5.2 Robustness tests

In previous sections, we define peer firms as those located in non-hurricane areas and operating in the same 2-digit SIC industry as the hurricane-hit firms. Although existing SIC industry classification is convenient and frequently used in research, it is important to acknowledge its limitations. For example, although the SIC categories are established by the Federal Census Bureau, the responsibility for assigning the primary industry code to a specific firm falls to the data vendor, which may result in inconsistent assignments across vendors (Bhojraj et al., 2003). Clarke (1989) examined the similarity of firms in the same SIC classification and concludes that SIC codes are not effective in identifying firms with similar characteristics. In this section, we perform several robustness checks by using other definitions of industry peers and present the results in Table 7. First, to select peer firms that are most similar to hurricane-hit firms in terms of fundamental firm characteristics, we use a 1:3 nearest-neighbour matching approach to identify character-matched industry peers. We match each hurricane-hit firm in our sample to three nonaffected firms in the same industry (2-digit SIC) and year-quarter. The set of matching variables includes fundamental firm characteristics: size, sales, MTB, and leverage. The results are presented in Table 7, Columns (1) and 5). We find a significantly positive coefficient of $Peer_{t-1}$ at the 5 percent level (coef.=+0.098, t-stat=2.39, and coef.=+0.114, t-stat=2.35), consistent with the baseline results. Secondly, Bhojraj et al. (2003) indicate that, among the broadly available industry classification schemes, the advantages of Global Industry Classifications Standard (GICS) system is consistent from year to year[22], because the GICS classification explains a much greater proportion of the variation in firm-level operating characteristics. Therefore, we use 4- and 6-digit GICS classifications to allow the possibility that the different classification systems may potentially impact the empirical results (Bhojraj et al., 2003; Katselas et al., 2019)[23]. The results are presented in Table 7, Columns (2), (3), (6), and (7). We find that, in line with the baseline results, 4- and 6-digit GICS-matched industry peers increase their management forecasts after a hurricane. In addition, the overall magnitude of the results in the robustness tests does not vary significantly from that in Section 4. Thirdly, Hoberg and Phillips (2016) highlight the limitations inherent in using existing industry classifications like SIC and GICS. Though these classifications are widely used because of their convenience, they fail to adjust frequently over time in response to the evolution of product markets. To overcome these issues, Hoberg and Phillips (2016) introduced the Text-Based Network Industry Classification (TNIC) based on text-based

[22] Bhojraj et al. (2003) compare four broadly available industry classification schemes (e.g., GICS, SIC, NAICS, and Fama and French). They argue that the GICS classification is significantly better at explaining various operating characteristics and key financial ratios. The other three methods differ little in most applications.

analysis of product descriptions from firm 10-K statements filed yearly with the Securities and Exchange Commission. This year-by-year set of industry classification allows for a new set of industries where firms can have their own distinct set of competitors. We define peer firms as those located in non-hurricane areas and operating in the same TNIC industry as the hurricane-hit firms. As presented in Table 7, Columns (4) and (8), our baseline results remain consistent when using TNIC to define industry peers.

[Insert Table 7 here]

5.3 Cross-sectional analyses

In this section, we conduct several cross-sectional analyses for further insights. We begin by examining how the characteristics of hurricane-hit firms can influence the strength of the effect. We expect that industry peers have stronger incentives to issue more management forecasts after a hurricane when the hurricane-impaired firm is a market leader. Shi (2021) focuses on the predatory activities of peers when an industry leader is financially impaired and illustrates that, in the case when an industry leader becomes vulnerable, gains from predation are potentially large for peers. Intuitively, if a hurricane-hit firm is a market leader in an industry, peers have stronger incentives to exploit the change in competitive position because they have potentially more to gain by doing so. In Table 8, Panel A, we define an indicator variable *D_Marketleader* as equal to one if the market share of a hurricane-hit firm exceeds 90% of industry peers in the industry, and zero otherwise. Our main variable of interest is the interaction term *Peer*× *D_Marketleader*, which indicates how nonaffected industry peers' management forecast frequency after a hurricane differs depending on whether the hurricane-hit firm is a market leader. Panel A, Columns (1) and (2) show positive coefficients of the interaction of *Peer* with *D_Marketleader* are significant at the 5 percent level. These findings are consistent with Shi (2021) and indicate that industry peers are more incentivized to capitalize on the circumstances of a hurricane-affected market leader rather than a market follower affected by the same event. This is because the potential for larger gains (such as increased market share) that can be realized is greater from a market leader's predicament.

Next, we consider how the relationship between a hurricane and industry peers' management forecast frequency varies with industry competition. Assume that hurricane-hit firms experience an unexpected decrease in demand because their product has become less attractive through the disruption to their operations. If a major hurricane conveys information about the demand shift, this information is positive for industry peers located in nonaffected areas because they either experience or can be expected to have increased demand (Lang and Stulz, 1997). Compared with peer firms in concentrated industries, peer firms in competitive industries have more difficulty in benefitting from an increased in demand unless it can distinguish itself from other nonaffected firms. We, therefore, expect the positive relationship between a major hurricane and industry peers' management forecasts to be more pronounced in a more competitive environment. We use the Herfindahl-Hirschman index (HHI) [24] to proxy for industry competition. Following Park et al. (2017), an HHI of less than 2500 represents an industry with high and moderate competition; an HHI value of over 2500 represents a concentrated industry. In Table 8, Panel B, we define an indicator variable as equal to one if a firm is in a highly or moderately competitive industry, and zero otherwise. In Column (1), the estimated results using the OLS model show coefficient estimates of the interactions of *Peer* with *D_Competitive Industry* are significant at the 5 percent level (coef.=+0.042, t-stat=2.04). This indicates that, after a hurricane, firms in a competitive industry are more likely to increase their management forecast frequency. The coefficient estimates on the interactions of *Peer* with *D_Competitive Industry* are positive as expected but statistically insignificant; the results are not robust when using the Poisson model.

[24] To calculate HHI, we take the percentage market share of each firm in an industry, square that number, and then add all the squares together.

When a major disruption occurs, the magnitude of the impact across different industries may be different. The underlying premise in our last cross-sectional analysis is that some industries are particularly sensitive to extreme weather and some are not. Altay and Ramirez (2010) investigated the disaster impact on firms in different industries focusing on the extraction, manufacturing, wholesale, and retail industries - representative of four echelons of a typical supply chain. Their results show that affected firms in all sectors, with the exception of extraction industries, dramatically suffer from time-persistent and significant damage caused by the disasters such as earthquakes and floods. Hsiang (2010) provides confirmation that certain industries, such as agriculture, wholesale, and retail, are highly vulnerable to the negative impacts of cyclones. In the light of this, we categorize agriculture, manufacturing, wholesale, and retail industries as highly-sensitive industries in our analysis. We aim to determine whether the influence of a major hurricane on the frequency of management forecasts among industry peers is more pronounced in highly-sensitive industries. In Table 8, Panel C, we define an indicator variable *D_Highsensitive* as equal to one if a firm is operating in a highly-sensitive industry and zero otherwise. In Column (1), the estimates using the OLS model show coefficient estimates of the interactions of *Peer* with *D_Highsensitive* are significant at the 5 percent level (coef.=+0.028, t-stat=2.13). The results provide some evidence that the main effect of a major hurricane on the frequency of management forecasts is more pronounced in highly-sensitive industries, where firms are more susceptible to the effects of hurricanes. It is notable that the results are not robust when using the Poisson model in Column (2), as coefficient estimates of the interactions of *Peer* with *D_Competitive Industry* is positive as expected but statistically insignificant.

[Insert Table 8 here]

6. Conclusion

Recent studies document that firms initiate actions that depend very much on actions initiated by related firms operating in the same industry. Explaining a firm's behaviour often requires seeing what happens to other firms in the industry. In this chapter, we explore how firms located outside the affected area respond to major hurricanes that hit other firms in the industry. Our study builds on the concept of competition effect; between rival firms, the gain (loss) for a firm is often matched with the loss (gain) for its peers. The fallout from a major hurricane typically involves the disruption of business operations, thereby weakening the position of hurricane-hit firms and creating potential competitive advantage for their industry peers. As a result, industry peers have incentives to capitalize on the changes in competitive position following a hurricane. The baseline result suggests that industry peers strategically increase the issuance of management forecasts in the aftermath of a hurricane. By doing so, these firms can leverage this adverse event to shift investor attention and favourability towards themselves. Our findings show a positive association between the frequency of management forecasts and firm visibility and shifts in market share. This indicates that industry peers can effectively use these forecasts as a strategic tool to enhance their visibility among investors and so capture a larger market share. The study also reveals that industry peers are more likely to increase their management forecasts after a hurricane if they operate in industries that are highly sensitive to hurricane strikes, if they face a more competitive environment, and if the hurricane-affected peer is an industry leader.

In conclusion, the study provides the first, large-sample evidence to show how a sudden shift in competitive position, triggered by an exogenous shock such as a hurricane, prompts firms to issue more management forecasts. This novel finding enriches our understanding of strategic decision-making in the face of environmental changes and competitive dynamics.

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Appendix A

Variable	Description
Analystfollowing	Average analysts following a firm during a quarter.
Big4	An indicator variable equal to one if the firm is audited by one of the Big 4 auditors, and zero otherwise.
CEOAGE	Natural logarithm of the CEO's age
CEOCOMP	Total CEO compensation
CEODUAL	An indicator variable equal to one if a CEO is also a chair of the board, and zero otherwise.
CEOTENURE	Natural logarithm of the number of years that a CEO continuously holds this position in the firm.
COVID -19	An indicator variable equal to one if quarter *t* is during the COVID-19 breakout period, and zero otherwise. As the U.S. government declared COVID-19 a national emergency on March 13, 2020, we identify the time periods 2020Q2, 2020Q3, and 2020Q4 as COVID-19 breakout period in our study.
D_Analystfollowing	An indicator variable equal to one if the number of analysts following a firm in a given quarter exceeds the industry median, and zero otherwise
D_Marketleader	An indicator variable equal to one if the market share of a hurricane-hit firm exceeds 90% of firms in the industry, and zero otherwise.
DP	Ratio of dividend to market value of equity
Earnings Volatility	The standard deviation of earnings (earnings before extraordinary deflated by average total assets) over the most recent 5 quarters since quarter *t*.
EP	The ratio of income before extraordinary item to market value of equity
Financial Crisis	An indicator variable equal to one if quarter *t* is during a financial crisis period (i.e., 2007Q3, 2007Q4, and 2008), and zero otherwise.
Firmvisibility	Total institutional ownership
$FREQ_t$	The frequency of management forecasts issued in a given quarter *t*.
HHI	The percentage market share of each firm in an industry, square that number, and sum of all the squares together.
Insown	Total institutional ownership during a quarter
Intangible	An indicator variable equal to one for a firm with positive intangible assets, and zero otherwise.
Leverage	The ratio of total debt to total assets
Loss	An indicator variable equal to one if the firm reports losses in the current period, and zero otherwise.
Marketshare	A firm's sales over a quarter divided by the total sales of the industry over the same quarter.
Δ*Marketshare*	$Marketshare_{t+1} - Marketshare_t$
Mgrrate	Market growth rate is calculated by the difference between market size in quarter *t* and quarter *t-1*divided by market size in quarter *t-1*.
Mret	Market-adjusted return
MTB	The ratio of market value-to-book value of common equity
Goodnews	An indicator variable equal to one if the current-period total income is greater than or equal to the previous-period total income, and zero otherwise.
RD	R&D expenditure
RevVol	The volatility of the firm's revenue
$Peer_{t-1}$	An indicator variable equal to one if the firm is the 2-digit SIC (character, 4-digit GICS, 6-digit GICS) matched industry rival of a hurricane-hit firm in quarter *t-1*, and zero otherwise.
SGA	SG&A expenditure
Sgr	Percentage change in quarterly sales

Shrs	The natural logarithm of shares outstanding
Size	The natural logarithm of a firm's book value of total assets
Tvol	Total trading volume

Tables

Table 1
Major hurricane landfalls in the US Mainland over the 2001-2020 period
This table describes the 20 major hurricanes according to total damage adjusted for inflation that occurred in the US mainland after 2000. The CPI-adjusted cost is the estimated value of total damages expressed in billions of dollars adjusted for the Consumer Price Index as of 2021. Category measure refers to the Saffir–Simpson hurricane wind scale (SSHWS). The scale separates hurricanes into five different categories based on wind, ranging from one (lowest intensity) to five (highest intensity). The information about the hurricanes is available in National Centers for Environmental Information (https://www.ncdc.noaa.gov/).

Name	Year	Begin date	End date	CPI-adjusted Estimated cost (in billions)	Deaths	Category	State
Laura	2020	27/08/2020	28/08/2020	$19.2	42	4	Louisiana, Texas
Sally	2020	15/09/2020	17/09/2020	$7.3	5	2	Alabama, Florida
Michael	2018	10/10/2018	11/10/2018	$26.0	49	5	Alabama, Florida, Georgia
Florence	2018	13/09/2018	16/09/2018	$25.0	53	1	North Carolina
Harvey	2017	25/08/2017	31/08/2017	$133.8	89	4	Texas
Maria	2017	19/09/2017	21/09/2017	$96.3	2,981	4	Puerto Rico, United States Virgin Islands
Irma	2017	6/09/2017	12/09/2017	$53.5	97	4	Florida, United States Virgin Islands
Matthew	2016	8/10/2016	12/10/2016	$11.1	49	1	Florida, Georgia, South Carolina
Sandy	2012	30/10/2012	31/10/2012	$75.4	159	1	New York
Irene	2011	26/08/2011	28/08/2011	$16.1	45	1	North Carolina
Ike	2008	12/09/2008	14/09/2008	$37.5	112	2	Texas
Gustav	2008	31/08/2008	3/09/2008	$7.5	53	2	Louisiana
Katrina	2005	25/08/2005	30/08/2005	$172.5	1,833	5	Alabama, Florida, Louisiana, Mississippi
Wilma	2005	24/10/2005	24/10/2005	$26.2	35	3	Florida
Rita	2005	20/09/2005	24/09/2005	$25.5	119	3	Florida, Louisiana, Texas
Ivan	2004	12/09/2004	21/09/2004	$29.1	57	3	Alabama, Florida
Charley	2004	13/08/2004	14/08/2004	$22.7	35	4	Florida, South Carolina,
Frances	2004	3/09/2004	9/09/2004	$13.9	48	2	Florida
Jeanne	2004	15/09/2004	29/09/2004	$10.6	28	3	Florida
Isabel	2003	18/09/2003	19/09/2003	$8.0	55	2	North Carolina, Virginia

Table 2
Market reactions around the hurricane beginning date

This table presents mean and median cumulative abnormal returns (CARs) across event windows from day -1 to day +1 around the beginning date for major hurricanes for firms located in nonaffected areas. CARs are obtained by subtracting the value-weighted CRSP market return from the raw returns of the issuing firms (Kim and Purnanandam, 2014). We partition those firms into two groups based on how they connected to hurricane-hit firms. Peers are 2-digit SIC industry peers of hurricane-hit firms. p-values are presented in parentheses, p-values for means and medians are based on standard t-tests and Wilcoxon signed-rank tests, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Hurricane-hit firms N= 2,219		**Peers N=70,962**	
	Mean	Median	Mean	Median
CAR (-1, +1) (%)	- 0.139**	-0.280***	0.094***	0.042
	(0.05)	(0.00)	(0.00)	(0.27)

Table 3
Analysis of Major Hurricane Strikes on the Industry Peer's Frequency of Management Forecast Issuance

This table presents baseline OLS and Poisson regressions that examine how peers of a hurricane-hit firm adjust their frequency of management forecasts after the hurricane. The dependent variable is the number of management forecasts issued in quarter *t*. All independent variables are measured in quarter *t* unless otherwise specified. Details on the construction of all variables are provided in the Appendix. t-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable= $FREQ_t$	**OLS**	**Poisson**
Independent variable	(1)	(2)
$Peer_{t-1}$	**0.066****	**0.082****
	(2.26)	**(2.20)**
Size	0.135***	0.118***
	(5.74)	(5.65)
MTB	-0.002	-0.001
	(-1.45)	(-1.12)
Goodnews	-0.021***	-0.017***
	(-3.95)	(-3.36)
Loss	-0.025*	-0.016
	(-1.88)	(-1.41)
Revenue volatility	0.000	0.001
	(0.05)	(0.54)
Leverage	-0.015	-0.005
	(-0.26)	(-0.10)
Big4Auditor	-0.058*	-0.043*
	(-1.92)	(-1.70)
Constant	-0.072	
	(-0.43)	
Year-quarter time fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Number of observations	138,780	129,668
Adjusted R^2	0.017	

Table 4
Management Forecast Frequency and Firm Visibility
This table presents OLS regressions that examine the relationship between firms' management forecast frequency and visibility. The dependent variable *Firmvisibility* is proxy by total institutional ownership during quarter *t*. The independent variable is the number of management forecasts issued in quarter *t*. Columns (3) and (4) report large- and small-size subsample analyses of estimating the OLS model. The large- (small-) size subsample consists of firms above (below) industry median firm size. All variables are measured in quarter *t* unless otherwise specified. The definitions of other variables are provided in the Appendix. We report t-statistics in parentheses below the coefficients. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable= Firmvisibility	**OLS**			
Independent variable	(1)	(2)	(3) Large-size firm Subsample	(4) Small-size firm Subsample
$FREQ_t$	**0.018***** **(6.06)**	**0.007***** **(3.21)**	**0.004** **(1.61)**	**0.019***** **(5.33)**
Size		0.000*** (4.10)		
MTB		-0.244*** (-5.41)	0.000 (0.32)	0.000*** (2.97)
Leverage		0.003 (0.22)	-0.070 (-1.40)	-0.153** (-2.42)
Mret		0.025*** (5.49)	-0.010 (-0.55)	-0.021 (-1.20)
Tvol		0.079** (2.13)	0.010 (1.38)	0.039*** (5.81)
EP		-0.316 (-0.63)	0.118*** (3.01)	0.068 (1.06)
DP		0.736*** (18.08)	0.745 (0.97)	-1.087* (-1.85)
Shrs		-0.000*** (-4.71)	0.917*** (30.63)	0.725*** (8.92)
Sgr		0.241*** (10.85)	0.000 (1.50)	0.000 (1.39)
Constant	16.996*** (228.00)	12.448*** (80.62)	13.709*** (90.64)	13.503*** (48.53)
p-value for test of the difference in the coefficients for $FREQ_t$			0.000***	
Quarterly Time Fixed Effects	yes	yes	yes	yes
Firm Fixed Effects	yes	yes	yes	yes
Number of observations	52,941	48,749	23,884	23,866
Adjusted R^2	0.114	0.333	0.364	0.241

Table 5

Management Forecast Frequency and Market Share

This table presents the OLS regressions that examine the relationship between firms' management forecast frequency and change in market share. The dependent variable is the difference between the market share in the next quarter and the current market share (market share is calculated as firm's sales over the total sales of the industry during a quarter). The independent variable is the number of management forecasts issued in quarter *t*. All variables are measured in quarter *t* unless otherwise specified. Definitions of control variables are provided in the Appendix. t-statistics are reported in parentheses below the coefficients. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable= ΔMarketshare$_{t+1}$	**OLS**	
Independent variable	(1)	(2)
FREQ$_t$	**0.003**	**0.005****
	(1.16)	**(2.09)**
Size		0.000***
		(3.09)
MTB		0.000
		(0.90)
Leverage		0.002
		(0.10)
HHI		-0.000***
		(-17.23)
Mgrrate		1.642***
		(60.12)
RD		0.748**
		(2.53)
SGA		-0.408***
		(-3.79)
Intangible		-0.022
		(-1.49)
Constant	-0.232	0.055
	(-1.28)	(0.31)
Quarterly Time Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Number of observations	50,318	24,596
Adjusted R^2	0.020	0.227

Table 6
Further possible explanations
This table reports possible explanations that may influence the baseline results. The dependent variable is the number of management forecasts issued in quarter *t*. All independent variables are measured in quarter *t* unless specified. Details of the construction of all variables are provided in the Appendix. T-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable=FREQ$_t$	**Additional controls for unexpected shocks**		**Additional controls for CEO characteristics**		**Additional controls for external governance**		**Additional controls for peer effect in disclosure**	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	Poisson	OLS	Poisson	OLS	Poisson	OLS	Poisson
Peer$_{t-1}$	**0.066****	**0.082****	**0.140*****	**0.170*****	**0.076****	**0.090****	**0.214*****	**0.226*****
	(2.26)	**(2.20)**	**(3.52)**	**(3.13)**	**(2.26)**	**(2.18)**	**(7.10)**	**(6.05)**
Size	0.135***	0.118***	0.089***	0.079***	0.132***	0.117***	0.135***	0.112***
	(5.74)	(5.65)	(2.76)	(2.67)	(4.66)	(4.61)	(6.61)	(6.49)
MTB	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001*	-0.001
	(-1.45)	(-1.12)	(-0.63)	(-0.45)	(-1.62)	(-1.05)	(-1.71)	(-1.45)
Goodnews	-0.021***	-0.017***	-0.014*	-0.011	-0.021***	-0.016***	-0.020***	-0.015***
	(-3.95)	(-3.36)	(-1.73)	(-1.43)	(-3.45)	(-2.92)	(-3.80)	(-3.11)
Loss	-0.025*	-0.016	-0.008	-0.009	-0.018	-0.009	-0.024*	-0.016
	(-1.88)	(-1.41)	(-0.40)	(-0.52)	(-1.21)	(-0.74)	(-1.80)	(-1.35)
Revenue volatility	0.000	0.001	-0.001	-0.000	0.000	0.001	0.000***	0.000***
	(0.05)	(0.54)	(-0.45)	(-0.38)	(0.23)	(0.70)	(3.01)	(3.62)
Leverage	-0.015	-0.005	0.024	0.045	0.002	0.004	-0.005	0.001
	(-0.26)	(-0.10)	(0.25)	(0.55)	(0.03)	(0.06)	(-0.11)	(0.01)
Big4Auditor	-0.058*	-0.043*	-0.085	-0.055	-0.077**	-0.050**	-0.055*	-0.042*
	(-1.92)	(-1.70)	(-1.43)	(-1.15)	(-2.45)	(-2.06)	(-1.81)	(-1.67)
Financial Crisis	0.343***	0.286***						
	(5.98)	(5.16)						
Covid-19	0.091	0.053						

	(1.29)	(0.74)						
CEOTENURE			0.026***	0.022**				
			(2.73)	(2.50)				
CEOCOMP			-0.005	-0.005				
			(-0.48)	(-0.45)				
CEODUAL			0.118	0.099				
			(1.45)	(1.51)				
CEOAGE			0.401	0.409*				
			(1.43)	(1.73)				
Analystfollowing					-0.000	-0.003		
					(-0.14)	(-1.47)		
Insown					0.063***	0.064***		
					(3.44)	(3.43)		
P_FREQ							0.064***	0.056***
							(12.51)	(12.56)
Constant	-0.072		-1.454		-1.148***		-0.182	
	(-0.43)		(-1.29)		(-3.66)		(-1.14)	
Year Quarter Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	138,780	129,668	55,709	50,500	112,024	103,707	138,780	129,668
Adjusted R^2	0.017		0.022		0.019		0.019	

TABLE 7
Robustness tests

This table presents the robustness tests that examine how peers of a hurricane-hit firm adjust their frequency of management forecasts after a hurricane. We use different ways to identify the peers of a hurricane-hit firm. In Columns (1) and (5), we use a 1:3 nearest neighbour matching approach. We match each hurricane-hit firm in our sample to nonaffected firms in the same industry (2-digit SIC) and year-quarter. The set of matching variables includes fundamental firm characters: size, sales, MTB, and leverage; in Columns (2) and (6), we define the industry peers as firms share the same 4-digit GICS industry code with hurricane-hit firms (i.e., *Peer*=1); in Columns (3) and (7), we define the industry peers as firms share the same 6-digit GICS industry code with hurricane-hit firms (i.e., *Peer* =1); in Columns (4) and (8), we define the industry peers as firms with the 10 highest similarity scores to a hurricane-hit firm (i.e., *Peer*=1) according to the Hoberg-Phillips Text-Based Network Industry Classification (TNIC). TNIC data are downloaded from: https://hobergphillips.tuck.dartmouth.edu/. The dependent variable is the number of management forecasts issued in quarter *t*. All independent variables are measured in quarter *t* unless otherwise specified. Details of the construction of all variables are provided in the Appendix. T-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent variable: $FREQ_t$	**OLS**				**Poisson**			
Independent variable	(1) Character-matched	(2) GICS 4-Digit	(3) GICS 6-Digit	(4) TNIC	(5) Character-matched	(6) GICS 4-Digit	(7) GICS 6-Digit	(8) TNIC
$Peer_{t-1}$	**0.098****	**0.093*****	**0.067*****	**0.041*****	**0.114****	**0.094*****	**0.064*****	**0.033****
	(2.39)	**(7.52)**	**(5.99)**	**(2.71)**	**(2.35)**	**(7.02)**	**(5.43)**	**(2.54)**
Size	0.163***	0.138***	0.138***	0.147***	0.156***	0.121***	0.121***	0.127***
	(4.46)	(5.84)	(5.82)	(5.68)	(4.93)	(5.72)	(5.70)	(5.53)
MTB	-0.002	-0.002*	-0.002*	-0.002	-0.001	-0.002	-0.002	-0.002
	(-0.97)	(-1.69)	(-1.70)	(-1.57)	(-0.42)	(-1.38)	(-1.41)	(-1.20)
Goodnews	-0.019**	-0.018***	-0.018***	-0.018***	-0.015**	-0.014***	-0.014***	-0.013**
	(-2.29)	(-3.36)	(-3.37)	(-3.03)	(-2.00)	(-2.82)	(-2.84)	(-2.53)
Loss	-0.005	-0.023*	-0.023*	-0.022	-0.003	-0.016	-0.016	-0.013
	(-0.26)	(-1.74)	(-1.76)	(-1.49)	(-0.19)	(-1.31)	(-1.32)	(-1.03)
Revenue volatility	0.000	0.000	-0.000	0.000	0.001	0.001	0.001	0.001
	(0.05)	(0.01)	(-0.01)	(0.31)	(0.39)	(0.50)	(0.48)	(0.81)
Leverage	-0.143	-0.003	-0.002	0.003	-0.103	0.006	0.006	0.009

	(-1.60)	(-0.06)	(-0.04)	(0.05)	(-1.42)	(0.11)	(0.11)	(0.16)
Big4Auditor	-0.022	-0.079*	-0.079*	-0.087*	-0.020	-0.057	-0.057	-0.062*
	(-0.51)	(-1.92)	(-1.92)	(-1.95)	(-0.62)	(-1.61)	(-1.62)	(-1.69)
Constant	-0.003	-0.088	-0.085	-0.148				
	(-0.77)	(-0.52)	(-0.50)	(-0.80)				
Year Quarter Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	55,931	135,554	135,554	118,815	48,785	126,698	126,698	110,400
Adjusted R^2	0.016	0.018	0.018	0.018				

Table 8
Spillover Effects of Hurricanes on Industry Peers' Management Forecasts: Cross-Sectional Analyses

This table presents OLS and Poisson results on whether the association between a major hurricane and peers' frequency of management forecasts varies with different cross sections. The dependent variable is the number of management forecasts issued in quarter *t*. All independent variables are measured in quarter *t* unless otherwise specified. In Panel A, the channel is the hurricane-hit firm's market power proxied by the firm's market share. The conditional variable is *D_ Marketleader*$_{t-1}$ *that* equals one if the market share of a hurricane-hit firm in quarter *t-1* exceeds 90% of firms in its industry and zero otherwise. In Panel B, the third channel is industry competition which is proxied by HHI. HHI is calculated by taking the market share of each firm in the industry, squaring that, and summing the results. The conditional variable is *D_ Competitive Industry* that equals one if a firm is an industry with HHI value less than 2500 and zero if a firm is an industry with HHI value more than 2500 (Park et al., 2017). In Panel C, the last channel is firm sensitivity to hurricanes. Following Altay and Ramirez (2010) and Hsiang (2010), the highly-sensitive group consists of firms in industries that are particularly sensitive to hurricanes: the agriculture (SIC: 100-999), manufacturing (SIC: 2000-3999), wholesale (SIC: 5000-5199) and retail (SIC: 5200-5999) industries. The less-sensitive group consists firms in other industries. The conditioning variable is *D_ High sensitive that* equals one if a firm is in the highly-sensitive group, and zero if a firm is in the less-sensitive group. Details of the construction of all variables are provided in the Appendix. T-statistics are reported in parentheses below the coefficients. Standard errors are clustered by firm. Continuous variables are winsorized at the 1st and the 99th percentile. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: hurricane-hit firm's market power

Dependent variable= FREQ$_t$	**OLS**	**Poisson**
Independent variable	(1)	(2)
Peer $_{t-1}$	-0.001	-0.004
	(-0.04)	(-0.09)
D_ Marketleader $_{t-1}$	-0.085***	-0.110***
	(-3.82)	(-4.02)
Peer* $_{t-1}$ **D_ Marketleader*** $_{t-1}$	**0.059****	**0.072****
	(2.45)	**(2.43)**
Controls	Yes	Yes
Quarterly Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	138,462	129,395
Adjusted R^2	0.017	

Panel B: Industry competition

Dependent variable= FREQ$_t$	**OLS**	**Poisson**
Independent variable	(1)	(2)
Peer$_{t-1}$	0.036	0.055
	(1.06)	(1.34)
D_ Competitive Industry	0.062*	0.063
	(1.82)	(1.53)
Peer* $_{t-1}$ **D_ Competitive Industry***	**0.042****	**0.035**

	(2.04)	**(1.61)**
Controls	Yes	Yes
Quarterly Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	112,702	104,359
Adjusted R^2	0.018	

Panel C: *Firm sensitivity to hurricanes*

Dependent variable= $FREQ_t$	**OLS**	**Poisson**
Independent variable	(1)	(2)
$Peer_{t-1}$	0.051*	0.072*
	(1.74)	(1.92)
D_ High-sensitive[25]		
$Peer_{t-1}$* D_ High-sensitive Industry	**0.028****	**0.015**
	(2.13)	**(1.26)**
Controls	Yes	Yes
Quarterly Time Fixed Effects	Yes	Yes
Firm Fixed Effects	Yes	Yes
Number of observations	138,780	129,668
Adjusted R^2	0.017	

[25] *D_ High sensitive* is omitted because of collinearity.

Chapter 5: Conclusion

This study conducted an in-depth analysis of the spillover effects of external shocks and competitive pressures on firms. In Chapter 2, we examine whether a cyberattack affects the target firm and its industry peer firms' decisions on equity issuance. The findings show that both the cyberattack target and the target's peer firms conduct fewer, smaller SEOs following a cyberattack and this effect persists for up to three years. Our findings are largely consistent with the contagion effect of a cyberattack, showing that attacked firms and their industry peers suffer from the adverse information revealed by a cyberattack, hence refrain them from equity issuance because of the increased cost of finance. In addition, the adverse information incorporated by peer firms is reflected in a higher likelihood of becoming the next victims of a future cyberattack. It is notable that not all peer firms in an industry are equally affected by a cyberattack. The spillover effect of a cyberattack on peer firms' SEO decisions is more pronounced when the peer has a higher probability of being attacked, and when the peer is a more visible firm. The spillover effect of a cyberattack on peer firms' SEO decisions is more pronounced when peers have sufficient IT investment and cash reserves because of their lesser dependence on external financing.

Chapter 2 makes several contributions. First, it sheds light, for the first time, to the best of our knowledge, on the impact of unexpected events (i.e., cyberattacks) on equity issuance. Though the literature largely focuses on the motivations behind firms undertaking SEOs, this study introduces a novel perspective on how such unexpected events deter firms, either directly or indirectly affected, from issuing equity because of increased reputation loss. Second, this study broadens our understanding of the aftermath of a cyberattack. Empirical and anecdotal evidence suggests a cyber incident increases a firm's financing needs if it is in the affected industry, primarily for investing in remedial/precautionary activity to ensure that cyber risk is contained. However, we highlight that, when it comes to making SEO decisions, firms prioritize avoiding increased SEO costs over meeting their increased financing needs. Finally, this study contributes to the literature on spillover effects. Given that the negative information signalled by a cyberattack spills over to industry peers of the attacked firm, we highlight that such negative information, incorporated by peer firms, manifests as an increased likelihood of becoming the next cyberattack target.

In Chapter 3, we examine the spillover effect of an acquisition on the RPE compensation package of peer firms of the acquirer. Extant studies suggest acquirers gain advantage from acquisitions that negatively impact their peers, prompting peers to behave more aggressively to defend their competitive position. We treat an acquisition as a shock to peer firms' competitive pressures and find that peer firms exhibit an increased propensity to adopt RPE-based compensation in response to an acquisition. The results suggest that RPE compensation serves as a mechanism to motivate firms to actively compete and strive in the face of increased competitive pressures. Consistently, the empirical evidence shows that peer firms adjust their use of RPE compensation and exhibit a higher level of competitive action including higher advertising expense and lower operating margins than peer firms not doing so. In addition, we find that the spillover effect of an acquisition on peer firms' RPE use is particularly pronounced if the peer firm's stock return co-moves closely with the acquirer before the acquisition, and if the acquisition is driven by a competition-related purpose.

Chapter 3 makes several contributions. First, this study contributes to the RPE literature. Though there is an increasing interest in RPE literature, there is a lack of consistent evidence supporting the use of RPE in executive compensation. Some studies argue that RPE-based compensation is superior to traditional compensation based on absolute performance evaluation. That is because RPE allows the risk-averse agent to bear less risk and the principal to better evaluate and motivate the agent's effort, thereby offering risk-sharing benefits. The tournament theory proposes the competition benefits of RPE. However, some studies suggest that the adoption of RPE-based compensation could incur significant costs by creating adverse incentives for agents such as sabotaging peer performance, colluding with peers, and/or choosing inappropriate reference groups. Our study supports the competition benefits of RPE compensation, indicating that it functions as a mechanism for shareholders to incentivize firms to withstand competitive pressures. Second, this study contributes to the literature on spillover effects. Our findings show that the competitive advantages gained by an acquirer result in competitive pressures for peers, representing a competitive spillover effect that, thus, motivates peer firms to strategically defend their competitive position following the acquisition.

In Chapter 4, we examine how hurricane-hit firms' peers located in nonaffected areas respond to major hurricane events by issuing management forecasts. Our argument is built on the premise that a hurricane-hit firm's loss strengthens the competitive position of its peers, so the peers are incentivized to take action to capitalize on the hurricane-hit firm's misfortune. We find that the peer firms issue more management forecasts following a major hurricane. This increased management forecast frequency enables peer firms to gain some capital market benefits such as improving their visibility and taking the market share from the impaired hurricane-hit firm(s).

Chapter 4 makes several contributions. First, it contributes to the literature on spillover effects by exploring another unexpected event: a major hurricane. Different unexpected events may generate different types of information spillover. For example, a cyberattack creates negative information contagion in an industry. A major hurricane, as a regional event, can create a competitive advantage for industry peers located in non-affected areas. Second, this chapter contributes to the discourse on inter-firm learning. Though most prior research recognizes that firms learn from their industry peers' disclosure strategies to make disclosure decisions, our study complements these studies by documenting that firms not only learn from the actions of other firms, but they also adapt based on specific events happening to peer firms.

Finally, this study introduces a fresh perspective on the motives behind management forecasts, demonstrating that firms tend to issue more management forecasts when they hold a more advantageous competitive position. This finding complements the strategy-based voluntary disclosure theory that suggests that high-performing firms strive to distinguish themselves through increased levels of voluntary disclosure.