Essays on Stock Price Crashes

A thesis presented in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Finance

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Abstract

This thesis comprises three essays that contribute to the literature on the consequences of stock price crashes. Essay One explores the post-crash responses of managers, the motives behind those responses, and the effects of those management responses on shareholders. The essay finds that managers of the crashed firms change their course of action to regain the trust of investors and improve firm value. Managers shift their attention towards enhancing transparency, optimizing investments, resolving internal conflicts, and investing in social capital and employee well-being. These initiatives contribute to enhancing the firm's value. Furthermore, this research proposes that management engages in these measures with consideration for their job security.

Essay Two investigates the extent to which firm systematic risk changes following stock price crashes. It shows that stock price crashes result in increased systematic risk. This is evident across firms with both low and high betas. The higher systematic risk following a crash primarily stems from heightened default risk and results in equity financing becoming more expensive.

Essay Three examines whether a firm price crash leads to the returns of the firm’s non-crash peer firms co-moving more with the returns of the market. The essay finds that this does occur. Investors focus more on firms that have experienced a crash while paying less attention to their non-crashed peer firms. This suggests that the investor trading behavior of these peer firms relies less on specific stock-related news

and more on general market trends. The essay does not find any evidence to consider internal as well as external monitoring and information asymmetry as possible mechanisms of investor distraction.

Overall, these essays provide contributions to the literature on stock price crash risk, financial markets, and corporate risk management. The thesis highlights how stock price crashes impact management responses, systematic risk, and the behavior of non-crashing peer firms, offering valuable insights for managers, investors, and market regulators to manage and respond to such events effectively. The thesis suggests that managers need to ensure their actions are taken post-crashes and potentially even before to prevent adverse events. Increased firm beta post-crash affects equity financing, portfolio management, risk assessment, and hedging decisions. Understanding firms' systematic risk holds implications for managers, portfolio managers, and market regulators to manage firm systematic risk effectively. This thesis also documents a new source of return co-movement distinct from market-level shocks.

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Chapter One

Introduction

This section provides a summary of the content covered in this thesis. It explores the rationale behind examining the firm-specific stock price crashes and outlines the contributions made by each of the three essays included in this thesis. The chapter concludes by presenting the structure of the thesis.

1.1 Introduction

Stock price crashes have attracted increasing attention from both academics and practitioners since the corporate scandals of the early 2000s such as Enron, Xerox, and WorldCom (Forbes, 2002). A stock price crash is typically linked to bad news hoarding by managers because of a) their numerous incentives (Ball, 2009; Kim, Li, and Zhang, 2011b; Kothari, Shu, and Wysocki, 2009), b) tax avoidance (Kim, Li, and Zhang, 2011a), c) earnings smoothing (Chen, Kim, and Yao, 2017; Khurana, Pereira, and Zhang, 2018), d) opaque earnings management and financial reporting (Hutton, Marcus, and Tehranian, 2009; Kim, Wang, and Zhang, 2019; Kim and Zhang, 2014), or e) information asymmetry and individualism (Jin and Myers, 2006; An, Chen, Li, and Xing, 2018). The information about these management practices accumulates beyond a critical threshold and suddenly becomes publicly available to investors, resulting in stock price crashes (Jin and Myers, 2006).

We expand this growing stock price crash-related literature by examining the impact of stock price crashes. The first essay investigates management actions and their grounds following crashes. It also explores the effect of management actions on shareholders. The second essay studies whether a firm's stock price crash affects its systematic risk and the cost of equity financing. Lastly, the third essay examines whether a stock price crash affects the prices of the firm's non-crash peer firms co-moving more with market returns.

The remainder of this chapter is organized as follows. The following three sections, namely Sections 1.2, 1.3, 1.4, and 1.5 present related literature, and a summary, containing the significant contribution to the extant literature, of each of the three essays. Research outputs from the thesis are outlined in Section 1.5. Subsequently, Section 1.6 describes the structure of the remainder of the thesis.

1.2 Related Literature

Many prior empirical studies document the determinants of stock price crashes. However, the consequences of these crash events remain underexplored. For instance, Hackenbrack, Jenkins, and Pevzner (2014) find that stock price crashes raise firms' audit fees. An, Li, and Yu (2015) observe that firms struggle to raise and adjust capital after their exposure to crashes. Kim, Lee, and Zhu (2022) document higher investor attention and analyst coverage after stock price crashes. Besides, studies examine the economic cost of stock return skewness. Jumps in both stock return and volatility affect option pricing (Eraker, Johannes, and Polson, 2003). Similarly, Cremers, Halling, and Weinbaum (2015) show economically significant evidence that expected stock returns drop due to high jump risk. Bollerslev and Todorov (2011) as well as Conrad, Dittmar, and Ghysels (2013) show that investors need compensation for this stock price crash risk. These prior findings in the literature show how costly stock price crashes are to firms and investors.

Investors suffer substantial capital loss (Callen and Fang, 2017) due to stock price crashes and panic about stock prices declining even further in the dawn of economic breakdown (Kim, Wang, and Zhang, 2016). Kim, Lee, and Zhu (2022) demonstrate that when a company's stock price undergoes a sudden extreme price drop, it grabs the attention of investors toward that firm. Investors can discount firm-level information from other firms and focus more on market-level information due to having a negative perception of crashed firms. Barberis and Shleifer (2003) suggest that investors possess categorical behavior and invest in stocks by grouping them rather than individual stocks. These circumstances usually put managers of crashed firms under substantial stress, pressing them to undertake crisis-management plans (Pearson and Clair, 1998).

Given these above arguments, this poses some questions i) how managers of crashed firms regain trust from investors following the bad news, ii) whether a firm’s stock price crash induces its systematic risk and higher costs for its equity financing, and iii) if a firm’s stock price crash takes investor attention away from its non-crashed peer firms, which can result in their stock return co-movement with the market. To address these empirical questions, this thesis provides a comprehensive discussion of associated literature, research designs, and key findings in Chapters Two, Three, and Four.

1.3 Essay One

While prior studies analyze the catalysts of a crash and post-crash responses of stakeholders, we concentrate on (1) managerial responses, (2) their motivations, and (3) the resultant impact on shareholders. Our contribution to the literature involves examining the extent to which stock price crashes influence managerial actions with the first essay.

As a result of stock price crashes, investors incur losses within their portfolios (Callen and Fang, 2017) and lose trust in the financial market (Lins, Servaes, and Tamayo, 2017). Managers who are exposed to crashes endure anxiety and are forced to take immediate crisis-management steps (Pearson and Clair, 1998). The first essay uses a sample of US data from 1950 to 2019 and examines management actions after stock price crashes. We find that management concentrates on enhancing transparency, optimizing the effectiveness of investment, minimizing agency problems, and rebuilding investor trust through ESG. We provide evidence of the causality of our results by utilizing the pressure from mutual fund flow hypothetical sale as an exogenous shock and an instrumental variable in two-stage least square regressions. This essay also investigates the intuition of management to undertake such actions and how these actions affect shareholders following crashes. We observe an increase in firm value because of these management actions. We also show that management engages in these actions due to their concerns about retaining their positions within the company.

This essay contributes to the literature on stock price crashes in several aspects. First, it contributes to the literature on the consequences of stock price crashes. Second, it contributes to the literature on crisis management after an adverse event. Moreover, this study on management actions following crashes has important economic implications, as crashed firms are more likely to experience improved firm performance.

1.4 Essay Two

The second essay investigates whether firm systematic risk increases after stock price crashes. Systematic risk is a major element in the Capital Asset Pricing Model (CAPM) and professionals still use this to estimate the cost of equity (Graham, 2022). Patton and Verardo (2012) mention that assessing the factors that influence a company's systematic risk, impacting the cost of equity holds significance for investors who manage portfolios and make hedging decisions.

Given stock price crashes occur due to hoarded bad news by managers (Jin and Myers, 2006), investors may pay less attention to firm-level news than market-level news. Besides, investors prefer grouping investments rather than investing in specific assets (Barberis and Shleifer, 2003). These conditions get us to explore the extent of systematic risk following a firm-specific crash. We use a comprehensive sample of U.S. firms that covers data from 1950 to 2021. We document higher firm systematic risk after firm-level crashes. Higher firm systematic risk is observed in both low- and high-beta firms following crashes. We implement two identification strategies, namely difference-in-differences and two-stage least squares regressions, and they support our core results. We also test whether systematic risk increases for crashed firms because of default risk or information asymmetry. Our evidence suggests that increased systematic risk following crashes is only due to higher default risk. Increased systematic risk leads to higher costs for equity financing.

The second essay adds to the existing knowledge in various ways. First, this essay is related to the literature that explores the outcome of firm-level price crashes. Second, it adds to the literature that investigates the impact of firm-level incidents on firm systematic risk. This study has important implications for the cost of equity, portfolio management, and hedging decisions. Therefore, it is important for practitioners and financial market regulators.

1.5 Essay Three

Researching the co-movement between stock returns and market returns holds significance as it influences diversification. Several studies by researchers highlight various factors influencing the stock return co-movement. Among them, some of the existing studies show evidence that market-specific shocks, which keep investor attention away from the capital market, lead to stock return co-movement (e.g., Eun, Wang, and Xiao, 2015; Huang, Huang, and Lin, 2019). However, this essay investigates whether a firm's price crash, considered to be a firm-specific shock, affects investor attention to non-crashed peer firms, leading to return co-movement of the peer firms with the market.

Kim, Lee, and Zhu (2022) show that when a company's stock price undergoes a sudden extreme price drop, it grabs the attention of investors toward that firm. Nevertheless, investor attention given to peer firms of a crashed firm has been underexplored and the direction of return co-movement of those firms is unclear. Using data from U.S. stocks from 1950 to 2021, the paper finds significant return co-movement between the non-crashed peer firms and the market. Investors pay more attention to a crashed firm and less focus on their non-crashed peer firms. Our main results are robust to peer-firm categorization, difference-in-differences test, and utilizing an exogenous shock. We further check whether internal as well as external monitoring and information asymmetry can be probable mechanisms for non-crashed peer firms' return co-movement. However, we do not find any evidence to consider them as possible mechanisms.

Essay three makes several contributions to the contemporary literature on stock price crashes. First, we document a negative shock specific to a firm that affects how the returns of other non-crashed firms in its peer group move together by shifting the focus of investors. Second, we add to the current literature where adverse firm-level events affect peer firms. Lastly, this essay is related to the informational consequence of a firm's crash on its non-crashed peer firms' co-movement.

1.5 Research Outputs from The Thesis

Essay One, "How does management respond to stock price crashes?", was published in the following journal:

Roy, S., Marshall, B. R., Nguyen, H. T., and Visaltanachoti, N. (2023). How does management respond to stock price crashes? International Journal of Managerial Finance. https://doi.org/10.1108/IJMF-05-2023-0250

Also, this essay has been presented at:

- School of Economics and Finance Seminar at Massey University (2022)
- Financial Markets and Corporate Governance Program (2022)
- Auckland Regional Accounting Conference (2022)

Essay Two, "Stock Price Crashes and Systematic Risk", is a working paper at the time of submitting the thesis.

Moreover, this essay has been presented at:

- School of Economics and Finance Seminar at Massey University (2023)

Essay Three, "Stock Price Crashes and Peer Firms' Return Co-movement", is a working paper at the time of submitting the thesis.

1.6 Structure of The Thesis

The remainder of the thesis proceeds as follows. Chapter Two examines the responses from the management after stock price crashes. Chapter Three investigates the impact of stock price crashes on systematic risk. The third essay, which explores how a firm's stock price crash influences its non-crashed peer firms' return co-movement, is presented in Chapter Four. Chapter Five concludes the thesis by presenting the important findings and meaningful implications of each of the three essays.

Chapter Two

How Does Management Respond to Stock Price Crashes?

This chapter introduces the first essay, which examines the responses from the management after stock price crashes, utilizing a sample of U.S. Stocks over the 1950-2019 period. Section 2.1 presents a brief overview of the essay and explains the motivation to conduct this study. Section 2.2 shows the research design of this essay. Section 2.3 describes the data sources and descriptive statistics. Section 2.4 reports the main results and related discussion. Section 2.5 addresses the endogeneity concerns for our main results. Section 2.6 reports managers' motives behind their actions and the outcome of those actions. Lastly, Section 2.7 concludes this chapter. Appendices and a reference list of this chapter are reported at the end of this thesis.

Abstract

The catalysts of stock price crashes are well documented, but much less is known about what happens following crashes. We consider how managers respond to stock price crashes. Management become more focused on improving transparency, raising investment efficiency, reducing agency conflicts, and regaining the trust of stakeholders by investing in social capital and employee welfare. These actions increase firm value. We also find evidence that management undertakes these actions out of concern for their tenure of employment.

JEL Classification Codes: D89, G14, G32, G34, M14, M40

Keywords: Crisis management, Information asymmetry, Crash risk, Investor trust, Agency conflict

2.1 Introduction

While extant literature has focused on the factors that cause stock price crashes,[1] less is known about what happens following crashes. Firms that have experienced stock price crashes (crashed firms hereafter) struggle to raise capital (e.g., An, Li, and Yu, 2015), experience an increase in audit fees (e.g., Hackenbrack, Jenkins, and Pevzner, 2014), and attract more investor attention (e.g., Kim, Lee, and Zhu, 2022). While the literature examines the stakeholders' actions following the crash, we focus on (i) what management do, (ii) why they do it, and (iii) how these actions affect the shareholders. We contribute to the literature by considering the impact of stock price crashes on management actions.

Our focus on management actions following crashes is of significant economic and social relevance for several reasons. First, a stock price crash leads to investors losing considerable wealth (e.g., Callen and Fang, 2017) and this incident is among the

[1] These include religion (e.g., Callen and Fang, 2015), liquidity (e.g., Chang, Chen, and Zolotoy, 2017), tax avoidance (e.g., Kim, Li, and Zhang, 2011a), equity incentives (e.g., Kim, Li, and Zhang, 2011b), opacity (e.g., Hutton, Marcus, and Tehranian, 2009; Jin and Myers, 2006; Kim, Wang, and Zhang, 2019, Kim and Zhang, 2014), insider trading (e.g., Marin and Olivier, 2008), credit expansion (e.g., Baron and Xiong, 2017), real earnings smoothing (e.g., Khurana, Pereira, and Zhang, 2018), accruals (e.g., Zhu, 2016), accounting conservatism (e.g., Kim and Zhang, 2016), adopting claw back provisions (e.g., Bao, Fung, and Su, 2018), CEO age (e.g., Andreou, Louca, and Petrou, 2017), CEO overconfidence (e.g., Kim, Wang, and Zhang, 2016), board diversity (e.g., Harakeh, Leventis, Masri, and Tsileponis, 2022), auditor-client relationship (e.g., Callen and Fang, 2017), analyst coverage (e.g., Kim, Lu, and Yu, 2019), mandatory IFRS adoption (e.g., DeFond, Hung, Li, and Li, 2015), financial statement comparability (e.g., Kim, Li, Lu, and Yu, 2016), product market threats (e.g., Li and Zhan, 2019), the level of institutional ownership (e.g., Callen and Fang, 2013), short interest (e.g., Callen and Fang, 2015b), geographically nearby major customers (e.g. Cao, Zhang, and Yuan, 2022), eco-innovation (e.g., Zaman, Atawnah, Haseeb, Nadeem, and Irfan, 2021), conditional conservatism (e.g., Andreou, Cooper, Louca, and Philip, 2017). Habib, Hasan, and Jiang (2018) provide an excellent literature review.

most unfavorable events in stock markets.[2] Second, crashes typically put management under considerable strain, forcing them to engage in crisis management (e.g., Pearson and Clair, 1998). Finally, the number of firms, exposed to stock price crashes, is increasing over time. Figure 2.1 shows that the proportion of U.S. firms that exhibit at least one stock price crash each year increases from 13% in 1950 to above 30% in 2019. Given the increasing percentage of crashed firms, our study on how corporate management responds to disruptive events has significant implications for practitioners and capital market regulators.

Figure 2.1 Percentage of Crashed Firms

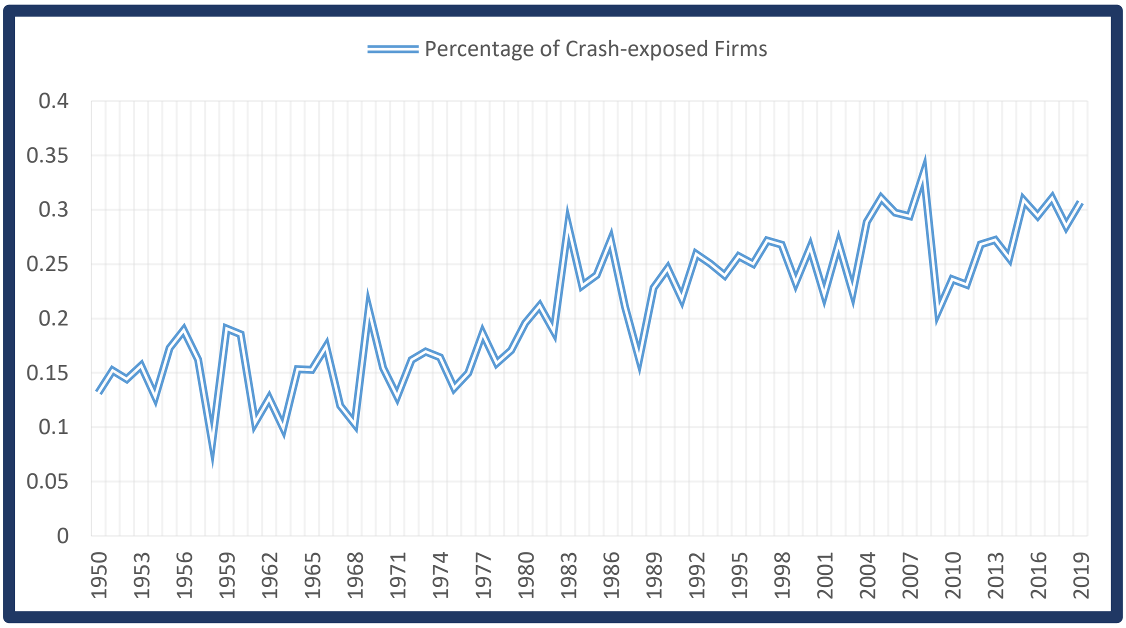

Figure 2.1 depicts the proportion of firms that have experienced crashes in our sample. We define crash firms as those that experience one or more firm-specific weekly residual returns obtained from expanded model regressions, falling 3.09 or more standard deviations below the mean residual return for its year and equal to zero otherwise. The sample period is from 1950 to 2019.

[2] The level of trust in firms and capital markets undergoes a negative shock due to crashes (e.g., Lins, Servaes, and Tamayo, 2017).

While management should act in shareholders' best interests, they, at times, make decisions that benefit themselves rather than shareholders (e.g., Jensen and Meckling, 1976). Management can successfully mask their poor performance via bad news hoarding until the amount of bad news crosses over the threshold and stock price crashes occur due to the accumulated bad news reaching the upper limit (e.g., Jin and Myers, 2006). However, following stock price crashes, firms' well-being, investor confidence, and management careers are at risk, so managers have a strong incentive to change their course of action to improve firm performance, regain investor trust, and reduce the chance of losing their jobs.[3] What remains unclear are the steps that managers take to improve stock price performance.

Previous literature attributes stock price crashes to deliberate information management (e.g., Bleck and Liu, 2007; Hutton, Marcus, and Tehranian, 2009; Khurana, Pereira, and Zhang, 2018; Kim, Li, Lu, and Yu, 2016; Kim and Zhang, 2014), so transparency improvements are desirable for shareholders. Improving transparency can cut the cost of external financing (e.g., Easley and O'hara, 2004; Myers and Majluf, 1984) and get managers to act more in the interests of shareholders (e.g., Ball, 2006) following crashes.[4] Through increased transparency and monitoring, firms' overinvestments are dampened (e.g., Biddle, Hilary, and Verdi, 2009; Francis, Huang,

[3] Understanding corporate crisis management practices following adverse events and addressing factors liable for primary transgression are one form of corrective action for managers, as Pearson and Mitroff (1993) suggest.

[4] Bushman and Smith (2001) provide a summary of the literature that records how shareholders and others use financial accounting information as a pivotal source of information to monitor managers.

Khurana, and Pereira, 2009).[5] Therefore, managers can curtail excess costs and invest efficiently to improve their career reputations after crashes.[6] Management also takes steps to reduce agency costs.[7] This includes distributing cash to shareholders through dividends to reduce the risk of over-investment (e.g., Bøhren, Josefsen, and Steen, 2012; Dittmar, Mahrt-Smith, and Servaes, 2003).

To make amends for the loss of shareholders' trust due to the stock price crash, managers are motivated to focus on environmental, social, and governance (ESG hereafter). Lins, Servaes, and Tamayo (2017) find that firms' ESG activities help maintain shareholder trust during periods of crisis. Gao, He, and Wu (2022) observe that firms under unfavorable price pressure engage more in ESG activities than other comparable firms. They also find that involvement in ESG activities attracts investors who believe in positive social impact. Hong and Kacperczyk (2009) document lower litigation risk for firms with high ESG ratings. Hence, an emphasis on ESG after the stock price crash can rebuild trust among shareholders. A specific area of ESG that

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[5] Bleck and Liu (2007) contend that managers' bad news hoarding precludes the board of directors and investors from discovering negative net present value (NPV) projects at a beginning phase. Consequently, the poor performance of negative NPV projects piles up and ultimately emerges, resulting in asset price crashes. Thus, we should observe managements' effort to increase investment efficiency along with information transparency if they would like to prevent future adverse events recurring.

[6] For example, Kinder Morgan built the company from Enron's spare parts. After Enron's scandal-plagued downfall, their former senior executive, Mr. Kinder, helped the company grow from its leftovers by cutting excess costs (Creswell, 2003). "People thought we were curmudgeons or stick-in-the-muds," Kinder told Fortune in 2003. "But we wanted to drive home one culture here: Cheap. Cheap. Cheap. We were tightwads."

[7] Managers are prone to make decisions for personal gain if they are less accountable to the investors, resulting in weak firm performance and eventually loss of shareholder value (e.g., Jensen, 1986; Jiraporn, Kim, Davidson, and Singh, 2006).

management may focus on, is employee well-being.[8] Employee-friendly treatment improves the effectiveness of internal controls (e.g., Guo, Huang, Zhang, and Zhou, 2016), which would help to mitigate agency issues after crashes.

On the other hand, following the crashes, managers may use accounting accruals to manipulate the stock price (e.g., Sloan, 1996). Managers may invest less in risky projects after a crash due to career consequences fears (e.g., Zwiebel, 1995), leading to under-investment. Managers may hold cash and not pay dividends to deal with uncertainty after crashes because higher cash holdings can assist with investor protection (e.g., Huang, Elkinawy, and Jain, 2013). Masulis and Reza (2015) infer negative market reactions to the announcements of corporate philanthropic contributions, indicating that investors do not always value ESG activity. Furthermore, an employee-friendly workplace may raise agency issues according to the agency theory.[9] So, we might not observe management's focus on ESG and employee treatment as well. Given the competing explanations and mixed evidence of previous studies, the impact of stock price crashes on management actions is an empirical question.

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[8] For example, when Delta was facing demise, one of the management's first moves was to better its customer experience by investing in its workforce to successfully turnaround. CEO Ed Bastian told The New York Times, "You've got to make certain that your employees know that they are the absolute best asset you have" (Gelles, 2019).

[9] Previous literature documents that employees have an incentive to develop coalition with management to obtain value from shareholders for more personal gains (e.g., Hilary, 2006; John, Knyazeva and Knyazeva, 2015; Pagano and Volpin, 2005).

We examine how corporate managers respond to stock price crashes using several approaches. We start with a panel regression with various firm-level controls, and firm- and year-fixed effects. We provide further evidence of the causality of our main results by exploiting mutual fund flow redemption pressure based on hypothetical sales as an exogenous variable to stock price crashes (e.g., Dessaint, Foucault, Frésard, and Matray, 2019; Kim, Lee, and Zhu, 2022). Mutual fund redemptions result in downward pressure on the price of impacted stocks and have little relationship with firm fundamentals (e.g., Bennett, Stulz, and Wang, 2020; Edmans, Goldstein, and Jiang, 2012). Our first-stage regressions prove that mutual fund flow pressure is positively associated with stock price crashes, confirming that this pressure significantly drives the incidence of stock price crashes. The F-statistics taken from the first-stage regressions pass the Stock and Yogo (2005) identification tests at the 1% level.

Our results indicate that discretionary accruals decline, and financial statement comparability increases. Following the crashes, management improves investment efficiency and reduces agency costs by paying higher dividends and holding less cash. Managers improve social capital and employee welfare, with firm ESG and employee treatment metrics (ETI hereafter) improving. These managers' actions increase firm performance for crashed firms. We also find evidence that the threat of a takeover has a positive impact on the management actions of crashed firms.

We contribute to the literature in several ways. First, we extend the literature on the consequences of stock price crashes. Kim, Lee, and Zhu (2022) focus on market information efficiency and find increased investor attention following crashes. Moreover, prior studies suggest that following the crash, auditors' fees increase (e.g., Hackenbrack, Jenkins, and Pevzner, 2014), and firms face difficulty in raising and adjusting capital (e.g., An, Li, and Yu, 2015). These studies focus on the external stakeholders' reactions following the crashes. However, we focus on how management, an important internal stakeholder, responds to stock price crashes. Particularly, we show a causal relationship between stock price crashes and management actions toward improving transparency, maintaining efficient investment, resolving agency conflicts, and investing in social capital and employee welfare. These management actions have economic effects, in that the performance of firms that have experienced stock price crashes is more likely to improve.

Second, we expand our understanding of corporate crisis management practices following negative information. Addressing factors liable for primary transgression is one form of corrective action, as Pearson and Mitroff (1993) suggest. Previous literature has paid attention not only to corrective action after a crisis but also to continuing and tactical attempts at crisis prevention and preparation (e.g., Mitroff, Shrivastava, and Udwadia, 1987; Mitroff, Pearson, and Harrington, 1996; Pauchant and Mitroff, 1992; Pearson and Mitroff, 1993). Researchers document a range of corrective actions to regain investor confidence, for instance, explaining misconduct publicly (e.g., Gillespie and Dietz, 2009), apologizing (e.g., Wynes, 2021), accepting punishment and penance, and paying compensation to victims (e.g., Dirks, Lewicki, and Zaheer, 2009).[10] We contribute to this strand of literature by considering management's corrective actions on the catalysts of stock price crashes to regain investor confidence and improve firm performance following stock price crashes, which remain under-investigated.[11]

The rest of the paper is organized as follows: Section 2.2 reports the research design. Section 2.3 contains data sources and descriptive statistics. Section 2.4 presents the general empirical results. Section 2.5 evaluates causality. Section 2.6 examines the management motive behind their actions, and Section 2.7 concludes the paper.

2.2 Research Design

To measure annual firm-specific crashes, we follow prior literature (e.g., Chen, Kim, and Yao, 2017; Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a,b) and compute weekly residual returns from running expanded model regressions. First, we estimate equation (1) below, using each firm's weekly return data for two consecutive years:

$$r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i.w} \quad (1)$$

[10] The Sarbanes-Oxley Act of 2002 is one of the corporate governance regulations designed to restore investor confidence or trust after the corporate scandals in the early 2000s, which lead to subsequent stock price crashes (e.g., Jain and Rezaee, 2006).

[11] Blanchard (2009) suggests that eliminating the perception of the probability of crash risk as well as realized crash risk is vital in re-establishing investors' trust and stabilizing the capital market.

where for the firm i and on the week w, $r_{i,w}$ is a firm's raw return; $r_{j,w}$ is the Fama and French value-weighted industry (j, to which firm i belongs) return; and $r_{m,w}$ is the CRSP value-weighted market return on the week w. We add in the lead and lag terms to take into account the non-synchronous trading (e.g., Dimson, 1979). The firm-specific weekly return ($R_{i,w}$) is the natural log of one plus the estimated residual return, i.e., $R_{i,w}$ = log (1 + $\varepsilon_{i.t}$) for the firm i on the week w.

We follow Hackenbrack, Jenkins, and Pevzner (2014) and compute a firm-specific crash measure for each firm i and year y. $Crash_{i,y}$ is a firm-specific annual crash variable, which is an indicator variable equal to one if within its year a firm experiences one or more firm-specific weekly $R_{i,w}$ falling 3.09 or more standard deviations below the mean ($R_{i,w}$) return for its year and equal to zero otherwise.

We use *ACCTCOMP* and *ACCRUALS* to proxy for a firm's transparency. *ACCTCOMP* indicates whether a firm with an identical financial statement has a comparable accounting system to another firm (De Franco, Kothari, and Verdi, 2011). *ACCRUALS* refers to discretionary accruals and shows a firm's earnings management activity (McNichols, 2002). To investigate investment efficiency, we utilize *INVEFFIC* and *INVEFFIC2*, which imply lower excess investment (Goodman, Neamtiu, Shroff, and White, 2014; McNichols and Stubben, 2008). We capture mitigating agency costs through *DIV* and *CASHHOLD*, which refer to a firm's dividend payment to common shareholders (Grullon and Michaely, 2002), and cash holdings (Opler, 1999), respectively. We employ *ESG* and *ETI* to examine management's investment in social capital and employee welfare. *ESG* indicates a firm's sustainable performance towards environmental, social, and governance (Di Giuli and Kostovetsky, 2014). *ETI* refers to the employee treatment index which is the difference between the sum of strength and concern scores of nine subcategories in ESG ratings (Mao and Weathers, 2019). We report detailed information on all variables, the construction of the dependent variables, and the remaining control variables in Appendix A.1.

To test the impact of stock price crashes on management actions, we estimate the multivariate regression model specified below:

$$MNGRACT_{i,y+1} = CRASH_{i,y} + Controls_{i,y} + \mu_i + \tau_y + e_{i,y+1} \quad (4)$$

where $MNGRACT_{i,y}$ represents the variable of interest, explained by stock price crashes, in the year $y + 1$. $MNGRACT_{i,y}$ denotes financial statement comparability, discretionary accruals, investment efficiency, dividend payment, cash holdings, ESG ratings, and employee treatment index. $CRASH_{i,y}$ is a firm-specific annual crash measure in the current year y. $Controls_{i,y}$ are appropriate control variables that have an impact on dependent variables to mitigate omitted variable concerns. μ_i and τ_y are the firm- and year-fixed effects. Following prior literature, we control for firm characteristics and risk to make sure of a robust causal effect from the stock price crashes (e.g., Cronqvist and Yu, 2017; Rashid, 2015). We lag all right-hand side variables by one year relative to the left-hand side variables to mitigate the concern of reverse causality. In addition, we apply year-fixed effects and firm-fixed effects to our model to control for any unobservable time- and firm-specific variations (e.g., Kim, Lee, and Zhu, 2022). Our robust standard errors are clustered by the firm (e.g., Petersen, 2009).

2.3 Data Sources and Descriptive Statistics

Our sample period is from 1950 to 2019.[12] We obtain daily stock return and market return data from the Center for Research in Security Prices (CRSP) database. We collect industry returns from Fama and French value-weighted industry index data from their website.[13] Our sample covers annual financial data from Compustat. In addition, we collect data from a broad range of databases to capture the impact of stock price crashes on managers' actions. We extract annual ESG rating data from the MSCI database to measure corporate social responsibility and employee treatment indices (ETI) for firms from 1991 to 2018. We obtain annual financial statement comparability data following De Franco, Kothari, and Verdi, (2011).[14] We obtain performance and mutual fund holdings data from CRSP. We collect data to capture executive compensation and the number of board members from the ExecuComp database. To calculate crash measurement by state, we collect both current and historical

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[12] We choose this period due to data availability of common beginning period from Compustat and CRSP databases. We end our sample in 2019, the latest year when writing the paper.

[13] We collect this daily industry return data from https://mba.tuck.dartmouth.edu. We thank Kenneth French for sharing the data.

[14] We thank Rodrigo Verdi for generously sharing the data which is available at https://mitmgmtfaculty.mit.edu/rverdi/. This financial statement comparability variable data is available from 1981 to 2013.

headquarters data from the Compustat database and Bai, Fairhurst, and Serfling (2020).[15] We obtain the hostile takeover index data from Cain, McKeon, and Solomon (2017) and use it as a takeover threat proxy (*TTHREAT*) in this paper.[16] Later, we include the US state-wide unemployment rate in our sample from the U.S. Bureau Of Labor Statistics.[17] Following Bollerslev, Patton, and Quaedvlieg (2022), we exclude all "penny stocks" with prices less than five dollars from our sample to alleviate biases arising from price discreteness. Finally, our sample is comprised of 101,532 firm-year observations with 11,727 unique firms.

We summarize the distribution of the variables in our sample in Table 1. We winsorize all the continuous variables at 1% and 99%. In our sample, the mean of *CRASH* is 0.2353. We find our stock price crash measure generally consistent with the literature. Consistent with the findings from Hutton, Marcus, and Tehranian (2009) and Chen, Kim, and Yao (2017), we find that firms experience extremely positive events more than extremely adverse events.

The mean (median) value for *ACCTCOMP* is −2.87 (−1.70), implying that the average (median) error in quarterly earnings between firm *i* and firm *j* functions is 2.87% (1.70%) of market value. The average and median values of discretionary accruals are 0.006 and 0.007, respectively. Transparency measures are similar to the

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[15] Bai, Fairhurst, and Serfling (2020) manually collect historical headquarters information from several sources. We thank John Bai for generously sharing the data.

[16] We are grateful to Stephen McKeon for making this data available on this website: https://pages.uoregon.edu/smckeon/. The availability of this measure begins in 1964 and ends in 2014.

[17] The unemployment rate data is available at https://www.bls.gov/web/laus/laumstrk.htm.

literature (e.g., De Franco, Kothari, and Verdi, 2011; McNichols, 2002). Around 50% of the firms in our sample invest efficiently and these investment measures are consistent with the literature (e.g., Goodman, Neamtiu, Shroff, and White, 2014; McNichols and Stubben, 2008). We find that a typical firm holds less cash based on the data distribution. We also find that *ESG* and *ETI* are slightly positive, with mean values of 0.286 and 0.005. Thus, the average firm has more ESG and employee treatment (ETI) strengths than concerns. Our ESG measures are generally consistent with the literature (e.g., Deng, Kang, and Low, 2013). We report descriptive statistics of other variables in Table 2.1.[18]

[18] These descriptive statistics are consistent with previous studies in the literature (e.g., Cain, McKeon, and Solomon, 2017; Chen, Kim, and Yao, 2017; Cronqvist and Yu, 2017; Johnson, 2003; McNichols and Stubben, 2008).

Table 2.1 Descriptive Statistics

Variables	Nobs	Mean	Std	Pctl.25th	Median	Pctl.75th
CRASH	101,532	0.2353	0.4242	0.0000	0.0000	0.0000
ACCTCOMP	52,585	-2.8691	3.0691	-3.6170	-1.7000	-0.8190
ACCRUALS	101,532	0.0043	0.1024	-0.0348	0.0044	0.0445
INVEFFIC	89,255	0.4884	0.4999	0.0000	0.0000	1.0000
INVEFFIC2	86,656	0.0000	0.0451	-0.0099	0.0035	0.0170
DIV	99,736	0.0128	0.0198	0.0000	0.0023	0.0199
CASHHOLD	99,758	0.2671	0.5729	0.0304	0.0846	0.2411
ESG	23,710	0.2857	1.6629	0.0000	0.0000	1.0000
ETI	23,111	0.0052	0.1438	0.0000	0.0000	0.0000
ADJMFHS	45,264	-0.0053	0.0224	-0.0062	-0.0019	-0.0004
State_Ncskew	101,532	0.1576	0.2179	0.0346	0.1515	0.2672
SIZE	101,532	6.1222	1.9547	4.6489	5.9752	7.4395
ROA	101,532	0.0190	0.1544	0.0097	0.0488	0.0847
MB	101,532	2.7485	3.6368	1.0812	1.8413	3.2272
DEBT	101,532	0.2237	0.1919	0.0528	0.2005	0.3384
RETVOL	101,532	-2.8458	0.4948	-3.1874	-2.8517	-2.5156
TOBINQ	101,532	2.5289	3.2091	1.1099	1.5870	2.5814
SALESGR	101,532	0.1192	0.3681	0.0077	0.0917	0.2008
TTHREAT	32,216	0.1544	0.0962	0.0775	0.1354	0.2151
CEOCOMPEN	93,143	0.2497	0.2376	0.0768	0.1666	0.3465
UNEMP	101,532	0.0605	0.0197	0.0465	0.0561	0.0718

This table presents descriptive statistics of variables employed in this study. We winsorize all continuous variables at the 1st and 99th percentiles to address potential outliners across pooled data. The sample period is from 1950 to 2019. Our sample contains 101,532 firm-year observations with 11,727 unique firms. Appendix A.1 provides variable descriptions.

2.4 Results

We report results in this section. We study the impact of stock price crashes on management actions. We present a range of robustness tests and their findings to support our results. Finally, we consider exploring managers' motives behind their actions following crashes.

2.4.1 Management's Focus on Transparency

We find that the management of crashed firms improves financial statement transparency by enhancing comparability with the financial statements of other firms within the same industry and reduces earnings management. Consequently, investors will gain more confidence and trust in these firms.

We observe a positive coefficient on financial statement comparability at a 1% level with the stock price crash proxy in Table 2.2. The estimate is 0.1525 (*t*-statistics = 6.80) in the specification with *CRASH*. This finding shows that the financial statements of the crash-exposed firms become more transparent and are comparable to other firms within the same industry. In this regard, our findings are relevant to standard setters who emphasize the significant role of financial statement comparability in nurturing and restoring investor confidence or trust (e.g., U.S. Securities and Exchange Commission, 2008).

The effect is both statistically and economically significant. Specifically, based on the coefficient on *CRASH* in Table 2.2, all else being equal, a one standard deviation surge in a crash reduces the discretionary accruals by -0.0011 (i.e., -0.0025 × 0.4242), which amounts to 24.59% (i.e., -0.0011/ 0.0043) lower than the sample mean. Our findings are consistently robust across two of our crash proxies. When financial disclosures, and monitoring mechanisms for investors improve in the firms, investors can connect managerial decisions to their firm performance (e.g., McCahery, Moerland, Raaijmakers, and Renneboog, 2002) and undertake optimal investment decisions.

Table 2.2 Transparency after Stock Price Crashes

Dependent variables:	*ACCTCOMP*	*ACCRUALS*
CRASH	0.1525***	-0.0025***
	(6.80)	(-3.11)
SIZE	0.2650***	-0.0086***
	(7.07)	(-9.33)
ROA	3.0348***	-0.0490***
	(19.78)	(-7.73)
MB	0.0078	0.0010***
	(1.45)	(4.84)
DEBT	-0.6891***	-0.0379***
	(-4.36)	(-8.57)
RETVOL	-0.5792***	0.0005
	(-13.07)	(0.43)
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No. of observations	52,585	101,532
Adj. R-Squared	56.06%	24.28%

Table 2.2 presents the results from regressions using financial statement comparability (*ACCTCOMP*), discretionary accruals (*ACCRUALS*), as the dependent variables, and *CRASH* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

2.4.2 Management's Focus on Investment Efficiency

Our multivariate regression results show that management's investment efficiency improves after crashes. This improvement is consistent with the managers' actions towards improving transparency because better financial reporting quality supports managers' optimal investment activities.

Table 2.3 Investment Efficiency after Stock Price Crashes

Dependent variables:	*INVEFFIC*	*INVEFFIC2*
CRASH	0.0092**	0.0013***
	(2.24)	(3.51)
SIZE	-0.0198***	0.0058***
	(-5.50)	(15.31)
ROA	-0.0065	-0.0061***
	(-0.39)	(-3.45)
MB	0.0066***	-0.0004***
	(10.51)	(-6.81)
DEBT	-0.0539***	0.0291***
	(-2.98)	(15.42)
RETVOL	0.0189***	-0.0007
	(3.09)	(-1.31)
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No. of observations	86,656	86,656
Adj. R-Squared	8.15%	9.71%

Table 2.3 reports the results from regressions using investment efficiency proxies (*INVEFFIC*), (*INVEFFIC2*), as the dependent variables, and *CRASH* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample

period is from 1950 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.3 presents the coefficient on *CRASH* for *INVEFFIC*, 0.0092 (*t*-statistic = 2.24). Our findings in Table 2.3 are not only statistically but also economically significant. A crash-exposed firm's investment efficiency (*INVEFFIC2*) is about 15% (i.e., (0.0013 × 0.4242)/0.0035) higher, compared to a median firm in our sample. Our results indicate that management raises investment efficiency following stock price crashes. As a result, crashed firms can make investors aware of positive net present value projects and attract capital from them. These findings are consistent with the results of the previous section. Healy and Palepu (2001) find that better accounting information increases investment efficiency by curtailing information asymmetry between managers and capital providers.

2.4.3 Management's Focus on Agency Conflicts

Management mitigates agency costs by distributing cash to investors through dividends and holding less cash following stock price crashes. These results illuminate the exclusive role of dividend payment and managers' less cash holding in curbing agency problems between managers and shareholders, resulting in higher investor confidence.

That is, when a firm faces a crash, our evidence indicates that the firm's dividend payment is about 6% (i.e., 0.0007/0.0128) higher afterward, compared to the sample mean. This corresponds to roughly 4% (i.e., 0.0007/0.0198) of one standard deviation of the *DIV* distribution. The signaling hypothesis implies that distributing dividends to investors is a favorable signal of a firm's future cashflows (e.g., John and Williams, 1985; Miller and Rock, 1985), and retail investors prefer stocks with dividends (e.g., Graham and Kumar, 2006).

Table 2.4 Agency Conflict after Stock Price Crashes

Dependent variables:	*DIV*	*CASHHOLD*
CRASH	0.0007***	-0.0104***
	(6.80)	(-3.51)
SIZE	0.0018***	-0.0251***
	(9.73)	(-5.16)
ROA	0.0058***	-0.0995***
	(8.28)	(-3.07)
MB	0.0001***	0.0038***
	(3.23)	(4.34)
DEBT	-0.0151***	-0.2993***
	(-15.94)	(-13.44)
RETVOL	-0.0044***	0.0276***
	(-18.58)	(4.52)
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No. of observations	99,692	99,692
Adj. R-Squared	63.77%	71.78%

This table presents the results from regressions using dividend (*DIV*) and cash holdings (*CASHHOLD*) as the dependent variables, and *CRASH* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1950 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Management holds less money to prevent overinvestment and usage of money for personal gains. In Table 2.4, the coefficient on *CRASH* is -0.0104 (*t*-statistics = -3.51) for crash holdings. This amounts to a nearly 0.4% (i.e., -0.0104 × 0.4242) decrease in cash holdings and about a one standard deviation increase in *CRASH*. This result is plausible because managers with 'empire-building' intentions invest more when they have more cash (e.g., Jensen, 1986). However, there is an alternative explanation for a firm having lower cash holdings following a crash.[19] A lower cash holding is not necessarily always better for the firm as cash provides the necessary cash reserves and safeguards in case the firm experiences negative shocks. If anything, these results appear to imply that managers increase payout using the firms' cash reserve to quickly stabilize the stock prices, thus putting the firms at higher risk.

2.4.4 Management's Focus on Trust

The positive coefficient in ESG ratings indicates that management invests in social capital and employee welfare to regain investor trust. So, management improves ESG ratings and employee treatment to cultivate trust among various shareholders after crashes.

[19] We are thankful to an anonymous reviewer for pointing out this alternative explanation.

When a firm has experienced a crash, our evidence shows that the firm's ESG ratings are about 16% (i.e., (0.1121 × 0.4242)/ 0.2857) higher than the sample mean. This corresponds to a nearly 3% (i.e., (0.1121 × 0.4242)/ 1.6629) of one standard deviation of the *ESG* distribution. If firms improve their reputations and develop moral capital through ESG, shareholders are less likely to assess them negatively in adverse events (e.g., Godfrey, 2005). Besides, these firms' actions towards ESG allure investors with positive social impacts and reduce signaling companies' cost of capital (e.g., Gao, He, and Wu, 2022).

Table 2.5 Trust after Stock Price Crashes

Dependent variables:	*ESG*	*ETI*
CRASH	0.1121***	0.0088***
	4.37	3.89
SIZE	2.0106***	0.1272***
	12.54	10.91
ROA	2.0634***	0.1391***
	8.27	7.84
MB	0.0531***	0.0031***
	8.00	6.74
DEBT	-5.8136***	-0.3426***
	-12.80	-10.19
RETVOL	0.1598**	0.0056
	2.41	1.16
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Inverse mills ratio	Yes	Yes
No. of observations	23,111	23,111
Adj. R-Squared	7.01%	7.10%

This table reports the results from regressions using environmental, social, and governance ratings (*ESG*), Employee treatment index (*ETI*) as the dependent variables, and *CRASH* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1991 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Employees' lenience for failure leads to an increase in innovation and firm value and can be built by focusing on employee wellbeing (e.g., Chen, Leung, and Evans, 2016; Mao and Weathers, 2019). In Table 2.5, we show that the coefficient on

CRASH, 0.0088 (*t*-statistics = 3.89), is positive and highly statistically significant. An employee is regarded as and is considered one of the highest critical factors for a firm's competitive success (e.g., Pfeffer, 1994). Management would like to improve firm innovation and value by treating employees well after stock price crashes. The number of ESG and employee treatment observations is significantly smaller due to fitting credit raters' criteria. Thus, we use the inverse mills ratio to control for sample selection bias in our baseline specification by following Heckman (1979).

2.5 Mutual Fund Flow Hypothetical Sale as an Exogenous Variable

We address the endogeneity concerns by utilizing an exogenous variable to stock price crashes. Specifically, we use the mutual fund flow hypothetical sale as an exogenous variable to stock price crashes. We find robust evidence that management works on improving information transparency and investment efficiency, solving agency problems, and regaining investor trust by enhancing ESG ratings, and employee treatment.

To this end, we provide further evidence of the causality of our main results by exploiting mutual fund flow redemption pressure based on hypothetical sales (e.g., Dessaint, Foucault, Frésard, and Matray, 2019; Kim, Lee, and Zhu, 2022) as an exogenous variable to stock price crashes. Mutual fund redemptions exert downward pressure on the price of impacted stocks and have little relationship with firm fundamentals (e.g., Bennett, Stulz, and Wang, 2020; Edmans, Goldstein, and Jiang, 2012). However, Wardlaw (2020) illustrates that the standard application to calculating outflow-prompted price force creates a variable that is unintentionally a straight function of a stock's actual realized return during the outflow year or quarter, casting skepticism about its independence to fundamentals. So, we follow Wardlaw (2020) and use their suggested refinement of the mutual fund flow redemption pressure based on hypothetical sales.[20] We measure *ADJMFHS* from a mutual fund's earlier disclosed portfolio rather than actual sales. Thus, it captures the decline of a fund's position, which investors' fund outflows are directly responsible for. As investor opinions on firm fundamentals are more likely to influence immediate trading in the firm's stock rather than a mutual fund share, these fund outflows are exogenous to a specific firm held by the fund. Edmans, Goldstein, and Jiang (2012) contend that *ADJMFHS* can establish the causality of the impact of the stock price on a firm due to satisfying the exclusion restriction (e.g., Roberts and Whited, 2013) and only affects firms through its influence on the stock price.[21]

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[20] We are thankful to an anonymous referee for suggesting us to exploit this adjusted hypothetical mutual fund sales.

[21] For instance, *ADJMFHS* is associated with only stock price movements, however, not associated with firm fundamentals.

Table 2.6 Mutual Fund Flow Hypothetical Sale as an Exogenous Variable

	First-stage Regression	Second-stage Regressions							
Dependent variables:	*CRASH*	*ACCTCOMP*	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
ADJMFHS	0.1030***								
	(2.79)								
Fitted_Crash		6.2982***	-0.2021***	0.1736**	0.0632***	0.0232***	-0.4386***	0.9879***	0.1221***
		(10.91)	(-8.36)	(2.15)	(9.79)	(8.13)	(-4.78)	(3.45)	(4.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weak identification test:									
F-Statistic		8.00***	19.49***	29.61***	28.03***	22.08***	22.17***	8.89***	7.54***
Hausman endogeneity test:									
p-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
No. of observations	45,264	16,737	32,827	37,209	37,209	31,354	31,354	17,976	17,976

Table 2.6 presents the robustness tests that draw on mutual fund flow redemption pressure based on hypothetical sales (*ADJMFHS*) as an exogenous variable to *CRASH*. We use *CRASH*, which refers to an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise, as the dependent variable in the first stage of linear probability model by following Kim, Li, and Zhu (2022). We include the same control variables as in the baseline model (equation 4). All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. In the second stage regressions, we regress *Fitted_Crash*, which is obtained from the first stage regression model, on *ACCTCOMP*, *ACCRUALS*, *INVEFFIC*, *INVEFFIC2*, *DIV*, *CASHHOLD*, *ESG*, and *ETI*. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6 provides the results of two-stage least square regressions adopting mutual fund flow hypothetical sale as an exogenous variable. We follow Kim, Lee, and Zhu, 2022 and exploit a linear probability regression (i.e., OLS) with *CRASH* (a stock price crash proxy) as the dependent variable. We find that mutual fund flow hypothetical sale pressure (*ADJMFHS*) has a significantly positive (coefficient = 0.103, *t*-statistics = 2.79) relationship with stock price crashes from the 1st stage regression result in Table 2.6. This proves that exogenously occurring mutual fund flow pressure significantly drives the incidence of stock price crashes. The model has all the control variables like our prior models and both firm and year fixed effects, and standard errors are clustered by firm. The Hausman endogeneity test statistics indicate that our endogeneity concern is substantiated. The F-statistics taken from the first-stage regressions pass the Stock and Yogo (2005) weak identification tests at the 1% level.

Our findings from a fitted crash, obtained from the 1st stage regression, support our baseline specification results and pass the conventional *t*-statistics. Heath, Ringgenberg, Samadi, and Werner (2023) discuss the potential concerns arising from the same instrument being used for multiple objectives. We follow Heath, Ringgenberg, Samadi, and Werner (2023) and use their suggested heuristic that our results should pass the *t*-statistics of 3.00. Heath, Ringgenberg, Samadi, and Werner (2023) use the correction method from Romano and Wolf (2005, 2016) and suggest adjusting *t*-statistics to address the multiple testing concerns. Our results pass the adjusted *t*-statistics except for *INVEFFIC*, one of the proxies for measuring investment efficiency.

However, we find partial results that the other investment efficiency measure passes the adjusted *t*-statistics of the multiple-testing approach. Therefore, we conclude that stock price crashes compel management to improve transparency, increase investment efficiency, reduce agency conflicts, and invest in social capital and employee welfare.

2.6 Management's Motive Behind Their Actions

In this section, we investigate the reasons for managers of crashed firms, undertaking the aforementioned actions. We observe improvement in the performance of crashed firms due to these management actions. We also find some evidence for the self-interest hypothesis that the threat of takeover has a positive impact on the management actions of crashed firms.

2.6.1 Firm Performance and Management Actions

As firms' well-being and investor confidence undergo negative shocks after crashes, managers might have a strong motivation to improve firm performance. To check whether management acts to regain shareholder trust, we create a composite management action score based on seven management actions discussed in the previous sections, including financial statement comparability, discretionary accruals, investment efficiency, dividend payment, cash holdings, ESG ratings, and employee treatment index. Following Lang, Lins, and Maffett (2012), we calculate the management action score (denoted as *MNGRACT*) by ranking each action in deciles and averaging the scores each year. Afterward, we use the interaction term of management action score (*MNGRACT*) and a crash proxy (*CRASH*) on firm performance (*TOBINQ, ROA, SALESGR*) to examine the impact of management actions on crashed firms' performance.

Table 2.7 Management Actions and Firm Performance

Dependent variables:	*TOBINQ*	*ROA*	*SALESGR*
*CRASH*MNGRACT*	0.0385***	0.0017***	0.0061***
	(5.11)	(4.43)	(4.81)
CRASH	-0.0189***	-0.0077***	-0.0377***
	(-5.20)	(-3.81)	(-5.87)
MNGRACT	0.0243***	0.0013***	0.0015
	(3.86)	(4.10)	(1.54)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of observations	101,532	101,532	101,532
Adj. R-Squared	47.14%	54.31%	15.73%

This table reports the results from regressions using a financial market-based measure of firm performance (*TOBINQ*) and an accounting-based measure of firm performance (*ROA, SALESGR*) as the dependent variables, and *CRASH* interacted with *MNGRACT* (i.e., *CRASH*MNGRACT)* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. *MNGRACT*, management action score, we rank each action in deciles and average the scores of management actions each year. Management actions refer to actions towards improving transparency (i.e., *ACCTCOMP*, *ACCRUALS*), actions toward improving investment efficiency (i.e, *INVEFFIC*, *INVEFFIC2*), actions towards resolving agency conflict (i.e., *DIV, CASHHOLD*), and actions toward improving trust (i.e., *ESG,* and *ETI*). All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1950 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7 presents the coefficient on *CRASH* × *MNGRACT* for *TOBINQ* is significantly positive (coefficient = 0.039, *t*-statistics = 5.11). Similarly, we observe that coefficients of interaction terms of management action score and the crash proxy are positive for all firm performance proxies, including market-based (*TOBINQ*) and accounting-based (*ROA*, *SALESGR*) measures, at the 1% significance level. These findings suggest if a firm has experienced a crash, it can enhance its firm value through these management actions.

2.6.2 Managers' Actions and Their Self-interest

Management careers are at stake following crashes, so they have a strong incentive to alter their course of action to reduce the chance of losing their job. To this end, we consider the threat of takeover (*TTHREAT*), CEO compensation (*CEOCOMPEN*), and state-wide unemployment rate (*UNEMP*) in the USA as the self-interest drivers (*SELFINT*) that motivate managers to perform crisis management practices. We sort the sample into 5 groups based on the value of each self-interest variable (*SELFINT*). We filter the sample and keep the top and bottom groups. We create a dummy variable for each self-interest variable. The dummy variable (*SELFINT*) is 1 if a firm falls in the top group and 0 otherwise.

Table 2.8 Impact of Managers' Self-interests on Their Actions

SELFINT	*TTHREAT*	*CEOCOMPEN*	*UNEMP*
Dependent variable:	*MNGRACT*		
*CRASH*SELFINT*	0.1059***	0.0035	0.0375
	(3.24)	(0.09)	(1.19)
CRASH	-0.0602**	0.0191	0.0084
	(-2.41)	(0.62)	(0.39)
SELFINT	0.4398**	0.0119	-0.0426
	(2.53)	(0.25)	(-0.69)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of observations	36,171	11,876	41,656
Adj. R-Squared	55.01%	44.43%	50.61%

Table 2.8 presents the results from regressions using management action score (*MNGRACT*) as the dependent variable, and *CRASH* interacted with takeover threat, CEO compensation, and unemployment rate (i.e., *TTHREAT*, *CEOCOMPEN*, *UNEMP*) as the main independent variables. The sample is sorted into 5 groups based on each group that represents a motive for management self-interests (i.e., *TTHREAT*, *CEOCOMPEN*, *UNEMP*) and then filter by top and bottom group, the dummy is 1 if a firm falls in the top group, and 0 otherwise. *MNGRACT*, management action score, we rank each action in deciles and average the scores of management actions each year. Management actions refer to actions towards improving transparency (i.e., *ACCTCOMP*, *ACCRUALS*), actions toward improving investment efficiency (i.e, *INVEFFIC*, *INVEFFIC2*), actions towards resolving agency conflict (i.e., *DIV*, *CASHHOLD*), and actions toward improving trust (i.e., *ESG*, and *ETI*). *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1950 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

The first column in Table 2.8 reports the impact of the threat of takeover on crashed firms' management actions. We use the management action score (*MNGRACT*) as the dependent variable. We observe that the coefficient on *CRASH* × *SELFINT* for *MNGRACT* is significantly positive (coefficient = 0.1059, *t*-statistics = 3.24). Although the coefficient for "*CRASH*" is negative, this is offset by the positive coefficient from an interaction "*CRASH***SELFINT*" variable. The net impact for the managerial actions is 0.1059 - 0.0602 + 0.4398 = 0.4855. Taken together, this result confirms that managers from a high crash-intensive firm perform the actions more in a high takeover threat situation. Managers can be at risk of getting fired or redundant after the risk of the threat of takeover rises. We do not observe any significant results for the other columns in Table 2.8. That indicates that CEO compensation and unemployment rate risk do not incentivize managers enough to take those actions following crashes. We also examine whether CFO compensation has any impact on management actions. Like CEO compensation results, we do not find any significant impact of CFO compensation as an incentive to motivate managers to do corporate crisis management practices.[22]

We conduct some additional analyses and report the results in Appendix A.2, A.3, A.4, and A.5. Motivated by Raffestin (2017), we exclude observations during financial crises or uncertain times. We would like to ensure that our findings are not impacted by extreme variations during uncertain times. Uncertain times in our sample

[22] We do not report the results of CFO compensation impact, however, the results are available upon request.

include the Kennedy slide of 1962, Black Monday in 1987, Friday the 13th Mini crash in 1989, the Early 1990s recession, the Dot-com bubble in 2000, the United States Bear Market of 2007-2009, the Global Financial Crisis of 2008 – 2009, 2010 Flash crash, August 2011 stock markets fall, and 2015-2016 stock market sell-off. Appendix A.2 provides consistent results relative to the results from our baseline specification results. We also find that management makes long-term efforts to improve transparency, investment efficiency, solving agency problems, and investing in social capital as these factors contribute to crash risk. These findings are plausible based on our results in Table 2.7. We report the results from our analyses of the managers' long-term actions in Appendix A.3.

We also use alternative measures of stock price crashes. Panel A and B of Appendix A.4 provide similar results to our previous findings and support our claims. Further, we use a state-level crash as an alternative instrumental variable. Firms located close by geographically are exposed to similar conditions (e.g., Gao, Ng, and Wang, 2011; John, Knyazeva, and Knyazeva, 2011; Thomadsen, 2005). Motivated by Addoum, Kumar, Le, and Niessen-Ruenzi (2020), we use a state-level crash, measured as the average number of crashes of all firms located in the same state excluding firm *i*, as an instrument variable. An unfavorable event can propagate and generate adverse spillover effects on local firms (e.g., Brunnermeier and Pedersen, 2009; Kaminsky, Reinhardt, and Vegh, 2003), suggesting that a firm's likelihood of exhibiting a stock price crash can be correlated with the crash likelihood of geographically proximate firms. In contrast, there is no clear link between a firm's management practices and the state-level crash. Therefore, the state-level crash appears to meet the relevance and exclusion conditions for an identification test (e.g., Roberts and Whited, 2013). We first show that state-level crashes are associated with an increase in firm crashes. The F-statistics obtained from the first-stage regressions pass the Stock and Yogo (2005) identification tests at the 1% level. Our findings from the instrumented crash proxy support our level regression results and are consistently significant. We present these results in Appendix A.5.

Additionally, we conduct pre- and post-crash difference and difference-in-differences analyses for further robustness checks.[23] First, we investigate how crashed firms perform in pre- and post-crash analyses. We compare the difference in performance in pre- and post-crash to check if there is any significant difference. We check the difference in their performance one year before and one year after the crash. The differences in management actions are statistically significant except *ACCTCOMP* and *INVEFFIC*.

We find similar consistent statistically significant results to our main findings except for partial evidence on the performance in transparency and investment efficiency categories. We report these results in Appendix A.6. We also conduct difference-in-differences tests based on entropy balancing by equating two groups, such as treatment and control groups. Treatment and control pairs indicate crash and non-

[23] We are thankful to an anonymous referee for the suggestion to conduct these analyses.

crash pairs. The 'After' variable is '1' if the manager actions occur after the crash event, otherwise '0' if they occur before the crash event. Our main variable of interest is the interaction variables (*Treatment*×*After*).

Our results from DiD analyses suggest that managers undertake the actions that we observe from our main results. We present the results in Panel A of Appendix A.7. We, therefore, conclude that crashed firms influence the actions of managers in specific ways. Panel B, Appendix A.7 provides the statistics of the standardized mean differences and their thresholds of all covariates in pre-match and before entropy balancing. It also presents the statistics of the standardized mean differences and their thresholds of all covariates in post-match and after entropy balancing. As the standardized mean differences of all covariates are greater than .05 in pre-match, they are imbalanced. However, we find that the standardized mean difference is less than .05 for all covariates in post-match, so, they are balanced.

Following the suggestion of an anonymous referee, we include additional control variables for further robustness checks and also examine whether the firms make any changes to the board of directors because these results could be driven by strong governance measures. We control for *R&D* (Research and development expenditure), *CAPEX* (Capital expenditure), and *GSCORE* (Overall governance score) and report the results in Appendix A.8.[24] The results are consistent with the main

[24] We collect the overall governance score data from DataStream. The sample period is from 1991 to 2019. We follow Donders, Van Der Heijden, Stijnen, and Moons (2006) and replace the missing values of this variable under each firm with the mean values of each firm so that we have similar observations

results. To rule out the alternative explanation for the main results, we also present the results from regressions using change of board of directors (*BOARDCH*) and change of independent board of directors (*INDBOARDCH*) as the dependent variables, and CRASH as the main independent variable in Appendix A.9. *BOARDCH* or *INDBOARDCH* indicates an indicator variable that is equal to '1' if a firm changes its board or independent board member within its year, respectively, and '0' otherwise. We observe no statistically significant results to the board of directors change following crashes.

2.7 Conclusions

Most prior empirical studies document the determinants of stock price crashes rather than what happens following stock price crashes. Given the adverse shock on investors' trust in firms and capital markets following crashes, it is essential to examine what happens following stock price crashes. In this study, we investigate how corporate management responds to stock price crashes.

We show that managers undertake corrective actions by addressing the catalysts of stock price crashes. Managers improve transparency by decreasing discretionary accruals and enhancing comparability with the financial statements of other firms within the same industry after stock price crashes. Managers of crash-exposed firms avoid engagement in over- and under-investment projects to improve their firms'

to our baseline specifications to run regressions.

investment efficiency. Management also pays higher dividends and holds less cash to promote an agency conflict-free environment after crashes. Furthermore, managers improve social capital and employee welfare, with firm general ESG and employee treatment metrics improving.

We adopt an identification strategy to establish a causal relationship between stock price crashes and management actions. We exploit the mutual fund flow hypothetical sale as an exogenous shock to do our main robustness check. Our identification tests confirm the positive relationship between stock price crashes and management corrective actions. Managers undertake these actions with the motive of improving firm performance. Moreover, we find that a manager of a firm with a high probability of being taken over undertakes these corrective actions out of a career consequence concern following a crash.

Chapter Three

Stock Price Crashes and Systematic Risk

This section introduces the second essay, focusing on stock price crashes and systematic risk. Section 3.1 outlines the main discoveries briefly with related literature. The essay proceeds to Section 3.2, which documents data sources, main variable construction, and summary statistics, followed by Section 3.3, presenting the methodologies employed and primary outcomes along with associated discussions. Section 3.4 presents the robustness test results in this essay. Section 3.5 describes the mechanisms of increased beta after crashes. Finally, Section 3.6 concludes this chapter. Appendices and the essay's reference list are placed at the end of the thesis.

Abstract

We show that firm systematic risk increases following stock price crashes. This occurs in both low- and high-beta companies and is robust to alternate proxies of systematic risk. Crashed firms face difficulty raising capital or obtaining loans, exacerbating default risk. Our results indicate that the increased systematic risk is due to increased default risk. There is no evidence to support information asymmetry as a channel for higher beta following crashes. We show that the increase in systematic risk results in higher costs for equity financing.

JEL Classification Codes: G11, G12, G14

Keywords: Crash risk, Systematic risk, Default risk, Information asymmetry

3.1 Introduction

Firm systematic risk is an important component of the Capital Asset Pricing Model (CAPM). Firms with higher betas (i.e., more systematic risk) are seen as being riskier than firms with lower betas. Asset pricing research typically uses multi-factor models (e.g., Fama and French, 2015). However, Graham (2022) finds that practitioners continue to rely on the CAPM when generating estimations of the cost of equity. Given the importance of firm beta, researchers have focused on how to estimate it as accurately as possible (Levi and Welch, 2017; Welch, 2022). The literature has also considered the causes of variation in firm betas. These include factors such as capital structure (Hamada, 1972), size, and dividends (Ben-Zion and Shalit, 1975).

We contribute to the literature by exploring whether there is a link between firm stock price crashes and systematic risk. Measuring the determinants of firm systematic, which affects the cost of equity, is important for investors managing portfolios and undertaking hedging decisions (Fama and French, 1993; Patton and Verardo, 2012).[25] Thus, our study on whether a firm's market risk increases after stock price crashes has implications for practitioners and capital market regulators.

Releasing previously concealed or distorted firm-specific information triggers stock price crashes (Jin and Myers, 2006), as a result, investors may i) discount firm-specific information from crashed firms and assign more weight to the market-level

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[25] For instance, prior literature demonstrate buy-sell strategies that show the abnormal performance of beta-sorted portfolios (Black, Jensen, and Scholes, 1972; Cederburg and O'Doherty, 2016; Friend and Blume, 1970).

information due to a trust issue,[26] or ii) develop negative sentiment in the broader market, leading to market-wide stock price declines. Investors tend to often group assets and allocate their investment to category-level stocks rather than individual stocks (Barberis and Shleifer, 2003). As a result, investors can discount firm-specific information and prefer market-level information on a group of stocks. This suggests that firm-specific stock price crashes can lead to higher systematic risk.

On the other hand, we may not observe an increase in systematic risk following a stock price crash because a crash typically occurs because of managers' bad news hoarding (Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009), and that implicates this adverse event as an idiosyncratic event. Firm-level news, simply idiosyncratic, has no or minimal implications for systematic risk variation (Engelberg, Mclean, and Pontiff, 2018), so it cannot trigger spillover or contagion effect. Investors can consider firm-specific stock price crashes as distinct events and acknowledge fundamental risk as well as the uncertainty of expected cash flows only for these crashed firms. So, investors give more attention to firm-level information than market-specific information,[27] resulting in decreases in stock beta. Given the conflicting arguments and evidence of prior literature, the effect of adverse events like firm price crashes on firm beta probes an empirical investigation.

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[26] For instance, if investors observe stock price crashes, which damage investor wealth (Callen and Fang, 2017) and confidence in companies and capital markets (Lins, Servaes, and Tamayo, 2017), they may not trust what managers of crashed firms or other firms report.

[27] For instance, stock price crashes can attract increased investor attention by increasing the earnings response coefficient (Kim, Lee, and Zhu, 2022).

We begin with a baseline specification with firm- and year-fixed effects. Using a large sample of U.S. firms covered by both the Center for Research in Security Prices (CRSP) and the Compustat databases between 1950 and 2021, our results imply that firm beta increases due to firm-specific crashes. For further robustness checks, we implement a difference-in-differences (DiD hereafter) identification approach. The firm-level crash event creates multiple treatment effects over time. We form two groups: i) a treatment group, which includes stocks with a price crash the previous year but not in the present or following year, and a control group, which includes stocks that do not experience a crash during the aforementioned time at all. We utilize propensity score matching and two multivariate reweighting procedures, namely i) inverse probability weighting; and ii) entropy balancing, to improve the covariate stability between the control and the treatment pairs having very similar fund characteristics. We follow Brogaard, Li, and Xia (2017) and Joshi (2020) and use propensity score matching, entropy weighting, and inverse probability weighting techniques to run DiD analyses. These test results support our conjecture that firms experience higher beta following crashes.

We follow Dessaint, Foucault, Frésard, and Matray (2019) and Kim, Lee, and Zhu (2022) and use the redemption pressure (*MFHS* hereafter) from mutual fund flow established on expected trades as an instrumental variable to firm price crashes. The redemption pressure from mutual funds causes downward pressure on the value of affected shares but as noted by Bennett, Stulz, and Wang (2020) and Edmans, Goldstein, and Jiang (2012), it has little connection with company fundamentals. This endogeneity check confirms that firm systematic risk increases following stock price crashes. This occurs in both low- and high-beta firms and is robust to alternative beta proxies.

We consider default risk as a channel that could be driving the association between stock price crashes and systematic risk. Callen and Fang (2017) mention that firm price crashes damage investor wealth and that the situation triggers negative sentiment market-wide (Lins, Servaes, and Tamayo, 2017).[28] Negative investor sentiment can cause firms' stock price to fall in the wider capital markets.[29] As a consequence, firms may face difficulty raising capital or obtaining loans, exacerbating default risk (An, Li, and Yu, 2015; Myers, 1977). Also, a crash leads to a significant drop in equity which in turn leads to higher financial leverage (Christie, 1982). Financial leverage is related to default risk (Cathcart, Dufour, Rossi, and Varotto, 2020). Lang and Stulz (1992) and Denis and Denis (1995) show that default risk is related to aggregate factors like industry leverage, economic recession, low asset-market liquidity, and regulatory developments, which indicate that default risk could be positively related to systematic risk. There is a strong positive relationship between forecasted stock returns and the default risk, as documented by Chava and

[28] A related case of this is the crumble of Lehman Brothers in 2008 and this firm-specific event caused a systemic financial crisis (Rodini, 2023).

[29] Existing literature show that investor sentiment can affect asset valuation (Brown and Cliff, 2005; Lemmon and Portniaguina, 2006).

Purnanandam (2010). Thus, we predict that default risk can explain the firm-level systematic risk.

We also consider information asymmetry as a cross-sectional channel to increase a firm's systematic risk after a crash. Crashed firms are considered to be opaque (Hutton, Marcus, and Tehranian, 2009) and information asymmetry is a part of systematic risk (Easley and O'hara, 2004). Information asymmetry influences risk incentives (Hughes, Liu, and Liu, 2007).[30] Brockman, Liebenberg, and Schutte (2010) document more information asymmetry during uncertain periods like recession and suggest that this results in higher stock return co-movement. Therefore, information asymmetry can be an explanation for higher systematic risk after a stock price crash.

The firm beta increases through the default risk channel following crashes. Firms encountering stock price crashes face the probability of increased default risk that results in the positive relation between stock price crashes and firm betas. On the other hand, we do not observe any evidence to establish that information asymmetry serves as a channel for higher beta following crashes. Furthermore, we observe an increase in the cost of equity due to crashed firms' higher beta. It explains the important implications of systematic risk increase because it makes equity financing more expensive for crashed firms.

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[30] Previous studies also observe the positive relationship between information asymmetry and risk premiums (Bhattacharya, Daouk, and Welker, 2003; Bhattacharya and Daouk, 2002; Jain, 2005).

Our paper is related to several empirical studies that investigate the aftermath of stock price crashes. Stock prices instigate management's decision in resource allocation and corporate news affects company governance and valuation in market-directed economics (Beyer, Cohen, Lys, and Walther, 2010; Goldman, 2004), hence, the effects of firm price crashes should matter to a broad range of stakeholders, for instance, investors, management, suppliers, and regulators. Previous literature documents that after the crash, auditors' fees surge (Hackenbrack, Jenkins, and Pevzner, 2014), and companies encounter hardship in increasing and remodeling capital for investment (An, Li, and Yu, 2015), or an increase in market information efficiency (Kim, Lee, and Zhu, 2022). Roy, Marshall, Nguyen, and Visaltanachoti (2023) find that managers take several steps like transparency and investment efficiency improvement, agency concern alleviation, and building up investor trust after crashes. This paper further investigates how informational consequences of stock price crashes influence investors to act further on market-specific information than firm-specific information, leading to a rise in firm beta.

We also add to the prior literature that explores return adjustments in the covariance formation amid a firm-level incident. For instance, the impact of earning earnings announcement news (Patton and Verardo, 2012; Savor and Wilson, 2016), investigation around adding stocks to indexes (Barberis, Shleifer, and Wurgler, 2005; Greenwood, 2008), repurchasing and offering shares (Denis and Kadlec, 1994), or increasing number of shares by splitting (Green and Hwang, 2009) on firm beta. Kelly and Jiang (2014) find that firm-specific price crashes have a strong ability to predict aggregate market returns. We link variations in betas to firms and adverse events, such as stock price crashes, to effectively comprehend the contributing factors of beta around information movements.

In the following Section 2, we describe the data and main variable construction. Section 3 provides the research design and the core findings. Section 4 reports the results of robustness checks. In Section 5, we discuss the mechanism of increased systematic risk after crashes and supplementary analyses. Section 6 concludes the paper.

3.2 Data and Variable Construction

This segment discusses the data and the composition of the main measures. We also report the summary statistics for our sample and compare them with the other experiments utilized in the previous research studies.

3.2.1 Data Source

Our sample consists of a comprehensive list of U.S. firms covered by both the Center for Research in Security Prices (CRSP) and the Compustat databases between 1950 and 2021.[31] We obtain daily stock returns and value-weighted market returns data

[31] The sample begins in 1950 as this is when the Compustat database begins. The sample ends in 2021, which is the latest data available at the time of writing this paper.

from CRSP and annual financial data from Compustat. Further, we obtain daily industry return and risk-free return data from Kenneth French's website.[32] We obtain beta estimation based on a market model from the WRDS' Beta Suite database. Following Bollerslev, Patton, and Quaedvlieg (2022), we exclude "penny stocks" whose values are below five dollars from the analyses to lessen concerns.[33] We also collect analysts' forecasted mean one-year-ahead annual earnings per stock and forecasted mean two-year-ahead annual earnings per stock from I/B/E/S on the Thomson Reuters Datastream database.[34]

3.2.2 Main Variable Construction

We capture systematic risk by employing beta (*BM*) measure based on the market model from the WRDS database. The formula for *BM* calculation based on the market model (Fama and MacBeth, 1973) is given as:

$$BM_{i,y} = \frac{cov[r_{i,d}, r_{m,d}]}{var[r_{m,d}]} \qquad (1)$$

where $BM_{i,y}$ is the systematic risk of the firm i in year y. $r_{i,d}$ is a firm's daily excess return in year y; $r_{m,d}$ is a daily market's excess return in year y. We require each year

[32] We collect Fama and French value-weighted industry index data from https://mba.tuck.dartmouth.edu. We are grateful to Kenneth French for generously handing out the data.

[33] Our findings are not affected if we include the penny stocks in the sample.

[34] I/B/E/S data starts from 1981 (Mohanram and Gode, 2013), hence, we include the data available for our sample.

y to have a valid $r_{i,d}$ for at least 126 daily observations when estimating the market model to minimize measurement errors (Fama and MacBeth, 1973).

We consider two more beta measures to proxy for systematic risk. We follow Welch (2022) and calculate the winsorized daily stock return, $r_{i,d}^{sw}$, by restricting the daily stock return, $r_{i,d}$, to be between -200% and 400% of the daily market return, $r_{m,d}$ as in equation 2 below:

$$r_{i,d}^{sw} \in (1 + [-\Delta_s + \Delta_s])r_{m,d} \qquad (2)$$

where Δ_s = 3; $r_{i,d}^{sw}$ is a firm's slope winsorized excess return on the day d. We estimate the slope winsorized annual beta, $BSW_{i,y}$, by following the model below:

$$BSW_{i,y} = \frac{cov[r_{i,d}^{sw}, r_{m,d}]}{var[r_{m,d}]} \qquad (3)$$

Welch (2022) mentions the applications of historical return decay with age and proposes a weighted least-squares specification to address the issue of historical return decay with the increasing number of years. Following Welch (2022), we winsorize the slope and employ age decay to calculate the other systematic risk measure, $BSWA_{i,y}$. In the first step, we execute model (2) to obtain slope winsorized excess return. In the second step, we estimate the beta by running the proposed market specification, in which the weight of individual observation declines with age. The decay parameter is set to $p = 2/252$ per day, which reflects a semi-lifespan of nearly 90 trading days.

Next, we estimate the crash indicator variable as follows. Following Hutton, Marcus, and Tehranian, (2009) and Kim, Li, and Zhang (2011a,b), we first estimate the firm-idiosyncratic excess return, $R_{i,w}$, as follows:

$$r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i.w} \quad (4)$$

where $r_{i,w}$ is a firm's return for an individual firm i on the week w; $r_{j,w}$ and $r_{m,w}$ are the value-weighted industry (Fama and French) and market returns. We incorporate lead and lag periods to control for the effect of non-synchronous trading. We extract the residual returns from Equation (4) and employ the natural logarithm method, $\text{i.e.}, R_{i,w} = log(1 + \varepsilon_{i,w})$.

We then define $CRASH_{i,y}$ as an indicator variable, which is one if there is any week w in the year y that the $R_{i,w}$ is less than the Mean($R_{i,w}$) - 3.09 SD($R_{i,w}$), otherwise zero. We utilize the subsequently extended model regression and produce firm-level returns $R_{i,w}$ on a weekly basis.

Appendix B.1 describes the definition of the remaining dependent variables, control variables, and the other variables.

3.2.3 Summary Statistics

Table 3.1 states the summary statistics of the key measures used in our empirical study. The continuous measures in our sample are winsorized at 1% and 99%. The mean of *CRASH* is 0.215. We observe that our main measure for identifying crashed firms is usually similar to the literature.[35] We show that firms encounter massively positive incidents more than awfully adverse incidents.[36]

Table 3.1 Summary Statistics

Variables	Nobs	Mean	Std	Pctl.25th	Median	Pctl.75th
CRASH	115,695	0.2150	0.4108	0.0000	0.0000	0.0000
BM	111,277	0.8658	0.5891	0.4230	0.8121	1.2303
BSW	115,695	0.8414	0.4892	0.4807	0.8129	1.1611
BSWA	115,695	0.8409	0.4970	0.4741	0.8111	1.1660
EDF	115,695	0.0318	0.1597	0.0000	0.0000	0.0000
ZSCORE	115,695	0.1609	0.3674	0.0000	0.0000	0.0000
EFFSPREAD	115,695	-3.9483	0.6417	-4.3376	-3.9406	-3.5227
AMIHUD	115,695	0.4042	0.9935	0.0041	0.0433	0.2875
PIN	20,739	0.1170	0.0611	0.0701	0.1114	0.1549
RPEG	48,069	0.0615	0.0681	0.0289	0.0466	0.0730
RGM	49,373	0.0729	0.1019	0.0315	0.0502	0.0818
MFHS	66,569	-0.0705	0.0964	-0.0940	-0.0351	-0.0075
SIZE	115,695	5.8541	2.0598	4.3291	5.7205	7.2426
BTM	115,695	0.6620	0.5666	0.2904	0.5263	0.8742
LEV	115,695	0.2255	0.1975	0.0532	0.1929	0.3468
VOL	115,695	0.7440	1.5250	0.1528	0.3068	0.6364
LIQ	115,695	2.8275	2.5715	1.4159	2.1195	3.2049
AGE	115,695	17.5157	13.7269	7.0000	14.0000	25.0000

Table 3.1 reports summary statistics of the variables utilized in this paper. Appendix B.1 provides variable descriptions. Our sample period is from 1950 to 2021. We winsorize all continuous variables at the 1st and 99th percentiles to address potential outliers within the pooled data. Our sample covers 115,695 firm-year observations along with 20,776 unique companies.

[35] For instance, the average crash is 0.161 for a sample of 1995-2008 (Kim, Li, and Zhang, 2011a). The average crash in another paper is 0.225 for a sample of 1994-2014 (Kim, Wang, and Zhang, 2019).

[36] These findings are comparable to the results of Hutton, Marcus, and Tehranian (2009) and Chen, Kim, and Yao (2017).

A typical firm has a mean (0.8980) value and a median (0.8409) value of systematic risk or beta (*BM*) in our sample. The other beta measures based on slope winsorization and age decay are comparable to our main beta proxy. An average firm has an expected default frequency (*EDF*) of 2%, while the median is zero. The mean (median) of *EFFSPREAD* is -3.948 (-3.941). The average firm has a cost of equity of 6.15% and 7.29%, which we measure through *RPEG* and *RGM* respectively. We present summary statistics of the remaining measures in Table 3.1.

3.3 Stock Price Crashes and Beta

3.3.1 Research Design

To examine the effect of firm price crashes on systematic risk, we utilize the following multivariate baseline specification:

$$Beta_{i,y+1} = \beta CRASH_{i,y} + \sum_{k=1}^{K} \gamma_k Controls_{i,k,y} + \mu_i + \tau_y + e_{i,y+1} \qquad (4)$$

where the $Beta_{i,y+1}$ denotes our main dependent variable, justified by crashed-firm proxies, in the following year $y+1$. $Beta_{i,y+1}$ indicates systematic risk, is proxied by *BM*, *BSW*, *BSWA*. $CRASH_{i,y}$ is a dummy variable for identifying crashed firms in the current year y. We add suitable control variables, $Controls_{i,k,y}$, which can explain $Beta_{i,y+1}$ and lessen omitted variable problems. We follow Kim, Lee, and Zhu (2022) and employ firm-fixed effects and year-fixed effects, μ_i and τ_y, to the Equation (4) to control for unidentifiable firm and time-specific changes. We include firm characteristics in the baseline specification (Gomes, Kogan, and Zhang, 2003; Hong and Sarkar, 2007; Livdan, Sapriza, and Zhang, 2009). We make an inference based on the firm-clustered standard errors (Petersen, 2009).

3.3.2 Baseline Results

We begin by estimating the baseline specification in Equation (4) for systematic risk increasing following stock price crashes. Table 3.2 covers the main findings. Columns (1) through (3) present estimates for the main proxy and alternative proxies for systematic risk, respectively, in our sample. These estimates provide strong evidence of increased firm beta after stock price crashes. For instance, the coefficient that we observe from *CRASH* for systematic risk, *BM*, is 0.0278 (*t*-statistic = 9.34). These results are robust to alternative beta proxies, which are reported in columns (2) to (3). We observe that the findings in Table 3.2 are consistent and statistically significant at a 1% level.

We observe not only statistically but also economically significant outcomes in Table 3.2. The extent of the coefficient on *CRASH* shows that a standard deviation shift in *CRASH* increases *BM* by 1.14 (i.e, (0.0278 × 0.4108) × 100) percent, which amounts to 1.40% (i.e., 1.14/ 0.812) of the sample median of *BM*. These results support our conjecture that stock price crashes cause firm beta to increase. Nevertheless, these findings are subject to typical endogeneity concerns like omitted variables and reverse causality issues. We require an approach to address these issues so that we can establish a causal effect of stock price crashes on systematic risk.

Table 3.2 Firm Beta after Stock Price Crashes

Dependent variable:	*BM*	*BSW*	*BSWA*
CRASH	0.0278***	0.0245***	0.0232***
	(9.34)	(10.17)	(9.21)
SIZE	0.0361***	0.0369***	0.0331***
	(6.32)	(8.02)	(7.18)
BTM	-0.0985***	-0.0781***	-0.0738***
	(-17.58)	(-17.56)	(-16.36)
LEV	0.0041	-0.0049	0.0049
	(0.20)	(-0.29)	(0.29)
VOL	0.0102***	0.0092***	0.0087***
	(5.39)	(6.26)	(5.84)
LIQ	-0.0004	-0.0002	-0.0011
	(-0.28)	(-0.17)	(-0.87)
AGE	0.011**	0.0067*	0.0048
	(2.53)	(1.82)	(1.28)
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of observations	111,277	115,695	115,695
Adj. R-Squared	50.37%	49.99%	47.74%

This table reports the results from specifications using systematic risk or beta (*BM*, *BSW*, and *BSWA*) as the dependent variables, and *CRASH* as the main independent variable. *CRASH* is a dummy variable that indicates '1' if, within its year, a company faces one or more firm-specific crashes and '0' otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4 Robustness Tests

3.4.1 Difference-in-differences Analyses

In this segment, we implement a difference-in-differences (DiD hereafter) identification strategy. The firm-level crash event creates multiple treatment effects over time. We form two groups: i) a treatment group, which does not exhibit a crash in the present and the following year but exhibits a crash in the previous year, and a control group, which does not experience a crash during the aforementioned time at all. We utilize propensity score matching (PSM hereafter) and two multivariate reweighting procedures, like i) inverse probability weighting; and ii) entropy balancing, to improve the covariate stability between the control and the treatment pairs having very similar fund characteristics. We follow Brogaard, Li, and Xia (2017) to utilize the propensity score matching to do a DiD analysis.[37] We also follow Joshi (2020) and use multivariate weighting techniques to run DiD analyses.

We provide the results of the difference-in-differences analyses in Table 3.3. *Treatment* implies whether firms fall in the treatment group and is equal to 1, or else '0', and *After* specifies '1' if the year is following the event of a crash, '0' if not. The

[37] First, we run pre-match regression on the treatment and control pairs. In the pre-match specification, firms do not have similar characteristics and are not comparable. That is why we find statistically significant coefficients for some control variables in pre-match regression. Due to matching process, we select firms that have similar propensity scores. As a result, we do not find any significant results for post-match regression and that confirms that the characteristics of the treatment pair are same as the characteristics of the control pair. These results along with propensity score distribution are reported in Appendix B.4.

estimate on *Treatment*After* for *BM*, 0.0407 (*t*-statistic = 5.98) in PSM DiD analysis. In entropy weighting, we observe the statistically significant and positive estimate of 0.0369 for *Treatment*After*, implying that crashed firms experience higher beta compared to the control group. In Table 3.3, the coefficients for all beta measures are positive and statistically significant at a 1% level, advocating that firms experience higher beta following crashes. The results from the DiD analyses are in line with the findings from our baseline specification.

Table 3.3 Difference-in-differences Analysis of the Effect of Stock Price Crashes on Beta

	Propensity Score Matching			Entropy Weighting			Inverse Probability Weighting		
Dependent variable:	*BM*	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*
*Treatment*After*	0.0407***	0.0374***	0.0341***	0.0369***	0.0276***	0.0244***	0.0327***	0.0278***	0.0251***
	(5.98)	(7.80)	(6.83)	(4.28)	(4.88)	(4.14)	(4.51)	(4.78)	(4.11)
Treatment	-0.0138***	-0.0142***	-0.0105***	-0.0112***	-0.0121***	-0.0094***	-0.0129***	-0.0115***	-0.0089***
	(-3.16)	(-4.00)	(-2.89)	(-2.75)	(-4.35)	(-3.27)	(-3.68)	(-4.03)	(-3.01)
After	0.0194***	0.0127***	0.0098***	0.0096**	0.0108***	0.017***	0.0112***	0.0065**	0.0122***
	(4.54)	(3.71)	(2.75)	(2.20)	(3.57)	(5.37)	(3.04)	(2.21)	(3.94)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	39,284	39,284	39,284	108,374	108,374	108,374	108,374	108,374	108,374
Adj. R-Squared	51.10%	52.68%	50.91%	53.06%	53.82%	52.05%	53.53%	54.70%	52.88%

Table 3.3 presents difference-in-differences analyses of the effect of stock price crashes on firm beta. We examine whether changes in firm beta are different in the post-crashes compared to the pre-crash periods. Systematic risks or betas (*BM*, *BSW*, and *BSWA*) act as the dependent variables, and *Treatment*After* as the main independent variable. *Treatment* implies whether firms fall in the treatment group and is equal to 1, otherwise '0', and *After* indicates '1' if the year is after the crash event, '0' otherwise. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We use three methods to run DiD analyses, namely propensity score matching (PSM), entropy balancing (EB), and inverse probability weighting (IPW). Following PSM specification, we report pre-match and post-match

regression results along with propensity score distribution in Appendix B.4. We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.2 Mutual Fund Flow Expected Sale as an Exogenic Shock

Motivated by Dessaint, Foucault, Frésard, and Matray (2019) and Kim, Lee, and Zhu (2022), we present additional evidence to reinforce the validity of our main findings by utilizing *MFHS* established on expected trades as an exogenic shock to the crashes of share prices. We compute *MFHS* from a mutual fund's formerly revealed portfolio instead of real trades. Hence, it tracks the fall of a fund's holdings, and investors' fund outflows are immediately accountable for that decrease. Bennett, Stulz, and Wang (2020) and Edmans, Goldstein, and Jiang (2012) mention that *MFHS* causes a downward force on the value of affected shares and has an insignificant correlation with company fundamentals. These mutual fund flows are exogenous to a particular firm, whose shares are owned by the funds since the views of investors on company fundamentals potentially affect instant transactions in the company's shares instead of a mutual fund's shares. Edmans, Goldstein, and Jiang (2012) assert that *MFHS* can prove the causation effect of the share price on a company because of fulfilling the exclusion constraint (Roberts and Whited, 2013) and simply influencing companies via its effect on the share price.

In Table 3.4, we observe from the first-stage specification that *MFHS* is positively correlated with crash events, proving that this force notably raises the occurrence of firms' crash events. We show that the coefficient on *MFHS* for stock price crashes is 0.2442 (*t*-statistic = 7.27). We use all the control variables corresponding to our previous specifications. We find the F-statistics obtained from our first-stage specification passing the Stock and Yogo (2005) identification checks at the 1% level. The second-stage regressions (columns 2 to 4) in Table 3.4, provide consistent and statistically significant results to our panel regression results in section 3.3. Thus, we conclude that firm systematic risk increases following stock price crashes.

Table 3.4 2SLS Specification with Mutual Fund Flow Hypothetical Sale

Dependent variable:	*CRASH*	*BM*	*BSW*	*BSWA*
MFHS	0.2442***			
	(7.27)			
Fitted_Crash		1.0571***	0.7562***	0.7021***
		(7.17)	(6.16)	(5.74)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Weak identification test:				
F-Statistic		54.28	60.15	60.15
Hausman endogeneity test:				
p-value		0.00	0.00	0.00
No. of observations	39,129	35,002	36,478	36,478

Table 3.4 reports the endogeneity tests that derive from mutual fund flow redemption pressure depending on hypothetical sales (*MFHS*) as an exogenous shock to *CRASH*. Following Kim, Li, and Zhu (2022), we employ *CRASH*, implying a dummy variable that indicates '1' if, within its year, a firm faces one or more firm-specific crashes and '0' otherwise, as the dependent variable in the first-stage regression. We add the constant control variables used in the baseline specification. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). In the second-stage models, we regress *Fitted_Crash* acquired from the first-stage specification, on firm beta, for instance, *BM*, *BSW*, and *BSWA*. We parenthesize t-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

3.4.3 Beta Increase after Crashes Irrespective of Their History

In this part, we check whether historically high- and low-beta firms have consistently higher systematic risk following crashes. Companies with higher equity risk can continue to have higher equity risk. So, we investigate both historical high and low beta firms to investigate that firm beta increases after crashes irrespective of their past beta conditions. We create four sub-samples based on the historical beta. For instance, our first and second sub-sample groups are constructed depending on the average beta of lag 3 years, which is higher and lower than the beta 1 value respectively. Similarly, we create two more groups based on an average beta of lag 5 years. Then, we run a panel regression using equation (4) for each sub-sample.

In Panel A of Table 3.5, we observe that either high- or low-beta firms, based on lag 3 years, face consistently high beta after stock price crashes. For example, the coefficient on *CRASH* for *BM* on sub-sample whose historical beta is more than 1 (historical beta less than 1) based on lag 3 years, 0.0285 with *t*-statistic = 5.65 (0.0257 with *t*-statistic = 7.14). We observe constantly statistically significant results throughout the entire columns at the 1% level in both Panel A and B in Table 3.5. These results imply that firms' systematic risks increase following crashes irrespective of their high or low historical betas.

Table 3.5 The Effect of Crashes on Betas Based on Their History

Panel A: A beta split analysis based on lag 3 years						
	Lag 3 years beta > 1			Lag 3 years beta < 1		
	BM	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*
CRASH	0.0285***	0.0265***	0.0264***	0.0257***	0.0217***	0.0205***
	(5.65)	(6.51)	(6.22)	(7.14)	(7.24)	(6.52)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	37,030	38,293	38,293	55,018	57,046	57,046
Adj. R-Squared	38.55%	37.50%	35.82%	44.07%	43.71%	42.08%

Panel B: A beta split analysis based on lag 5 years						
	Lag 5 years beta > 1			Lag 5 years beta < 1		
	BM	*BSW*	*BSWA*	*BM*	*BSW*	*BSWA*
CRASH	0.0261***	0.0234***	0.0228***	0.0302***	0.0261***	0.0252***
	(4.98)	(5.44)	(5.09)	(7.94)	(8.20)	(7.53)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	32,031	33,081	33,081	48,285	49,972	49,972
Adj. R-Squared	39.25%	38.14%	36.58%	45.58%	45.00%	43.29%

Table 3.5 presents the results from specifications using systematic risk or beta (*BM, BSW,* and *BSWA*) as the dependent variables, and CRASH as the main independent variable. However, the purpose of these tests is to check whether historically high- and low-beta firms have consistently higher systematic risk following crashes. Panel A reports the beta split analysis based on lag 3 years and Panel B reports the beta split analysis based on lag 5 years. CRASH is a dummy variable that indicates '1' if, within its year, a company faces one or more firm-specific crashes and '0' otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

3.5 Mechanism of Beta Increase after Crashes and Additional Analyses

3.5.1 Default Risk as a Channel

We conjecture default risk as a channel that can steer the association between stock price crashes and systematic risk. A stock price crash leads to a significant drop in equity which in turn leads to higher financial leverage (Christie, 1982). Higher financial leverage results in higher stock return co-movement (Do, Nguyen, Nguyen, and Truong, 2023) and higher stock return volatility (Li, 2011).[38] Firms experience challenges to raise capital amid extreme price declines (An, Li, and Yu, 2015), this situation can induce default risk. Default risk could be positively related to systematic risk as Denis and Denis (1995) argued that default risk is related to aggregate factors. The average beta of failing firms increases as their financial situations worsen (Castagna and Matolcsy, 1981; Ro, Zavgren, and Hsieh, 1992). Therefore, firms encountering stock price crashes face the probability of increased default risk that results in the positive relation between stock price crashes and firm betas.

We report our estimation, 0.0945 (t-statistics = 2.02), on *CRASH* × *EDF* for *BM* in Table 3.6 and find the estimation positively and statistically significant at the 5% level. Likewise, we see that the coefficient of interaction terms of *ZSCORE* and *CRASH* is positive and highly statistically significant for our main systematic risk measure

[38] Appendix B.6 provides results that correlation and relative volatility, the ratio of the standard deviation of a firm returns and the standard deviation of market returns, go up after the crash.

(*BM*). Our results indicate if a firm faces a crash event, it can increase its beta through its default risk.

Table 3.6 Default Risk Channel

Dependent variable:	*BM*	
*CRASH*EDF*	0.0945**	
	(2.02)	
*CRASH*ZSCORE*		0.0341***
		(3.34)
CRASH	0.0249***	0.0213***
	(7.55)	(6.06)
EDF	0.1601***	
	(8.47)	
ZSCORE		0.0042
		(0.45)
Control variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No. of observations	81,170	81,170
Adj. R-Squared	52.14%	52.05%

Table 3.6 reports the results from specifications utilizing the main firm beta measure (*BM*) as the dependent variable, and *CRASH* interacted with default risk proxies like *EDF* and *ZSCORE* (i.e., *CRASH*EDF* and *CRASH*ZSCORE*) as the main independent variables. *CRASH* is a dummy variable that indicates '1' if, within its year, a company faces one or more firm-specific crashes and '0' otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

3.5.2 Information Asymmetry as a Channel

We also study information asymmetry as another channel, which can rationalize the relationship between firm price crashes and firm betas. Prior literature shows that information asymmetry is a part of systematic risk (Easley and O'hara, 2004; Hughes, Liu, and Liu, 2007). Stock price crashes invoke uncertainty, and this situation may lead to less accessible firm-specific information. Thus, we predict that the information asymmetry can explain the firm-level systematic risk. We use information asymmetry proxies like *EFFSPREAD*, *AMIHUD*, and *PIN*. We follow Easley, Kiefer, O'hara, and Paperman (1996) to use the probability of private information trade (*PIN*).[39]

[39] We thank Duarte, Hu, and Young (2020) for making annual data available to calculate *PIN* in their website, https://edwinhu.github.io/pin/. The data is available from 1993 to 2012.

Table 3.7 Information Asymmetry Channel

Dependent variable:	*BM*		
*CRASH*EFFSPREAD*	1.3195		
	(1.46)		
*CRASH*AMIHUD*		-0.0355***	
		(-3.95)	
*CRASH*PIN*			-0.0617
			(-0.53)
CRASH	-0.0046	0.0276***	0.0477***
	(-0.24)	(7.20)	(3.40)
EFFSPREAD	4.2946***		
	(4.33)		
AMIHUD		-0.0355***	
		(-7.50)	
PIN			-0.7502***
			(-5.28)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of observations	64,887	64,887	14,205
Adj. R-Squared	50.13%	52.05%	59.08%

Table 3.7 presents the results from specifications utilizing the main firm beta measure (*BM*) as the dependent variable, and *CRASH* interacted with information asymmetry proxies like *EFFSPREAD*, *AMIHUD*, and *PIN* (i.e., *CRASH*EFFSPREAD*, *CRASH*AMIHUD*, and *CRASH*PIN*) as the main independent variables. *CRASH* is a dummy variable that indicates ‘1’ if, within its year, a company faces one or more firm-specific crashes and ‘0’ otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3.7 presents the findings of interaction terms between *CRASH* and information asymmetry proxies, such as *EFFSPREAD*, *AMIHUD*, and *PIN*. Here, we do not find any consistent significant results to conclude that information asymmetry can explain the relationship between the crashes and betas. Thus, we rule out information asymmetry as a channel for a stock price crash to cause a beta increase.

3.5.3 Additional Analyses

We also test whether an increase in firm beta after crashes has any implication on the firm cost of equity. We begin with two proxies for the cost of equity. Motivated by Heckman (1979), we employ the inverse mills ratio to address any concern for sample selection bias in the panel regressions.[40] We find that the cost of equity increases after the crashes. Table 3.8 provides the coefficient of 0.0033 (*t*-statistics = 1.95) on *CRASH* for *RPEG*. We also observe a positive coefficient, 0.0069, for *RGM* at the 1% significance level. Our results from Table 3.8 explain the important implications of systematic risk increase because it makes equity financing more expensive for crashed firms.[41]

We also run some additional tests to confirm the impact of stock price crashes on systematic risks and report the results in Appendices B.2 and B.3. We employ additional crash measures to verify the robustness of the reported main results.

[40] The reason is that I/B/E/S coverage starts from 1981 for this dataset.

[41] We also report results for the cost of equity measures by using alternative crash proxies in Appendix B.5 and find similarly statistically significant results.

Table 3.8 Cost of Equity Following Stock Price Crashes

	RPEG	*RGM*
CRASH	0.0033*	0.0069**
	(1.95)	(2.41)
Control variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Inverse mills ratio	Yes	Yes
No. of observations	19,360	20,705
Adj. R-Squared	6.50%	7.06%

Table 3.8 presents the results from specifications using the cost of equity (*RPEG,* and *RGM*) as the dependent variables, and *CRASH* as the main independent variable. *CRASH* is a dummy variable that indicates '1' if, within its year, a company faces one or more firm-specific crashes and '0' otherwise. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Additionally, we use an instrumental measure approach by exploiting state-specific crash events. Geographically neighboring firms are subjected to parallel circumstances (Gao, Ng, and Wang, 2011; John, Knyazeva, and Knyazeva, 2011; Thomadsen, 2005). Inspired by Addoum, Kumar, Le, and Niessen-Ruenzi (2020) and following Roy, Marshall, Nguyen, and Visaltanachoti (2023), we calculate the mean of occurrences of all firm price crashes in the matching state disregarding firm *i* to employ a state-specific crash measure. An adverse incident can spread and create undesirable spillover impacts on regional companies (Brunnermeier and Pedersen, 2009; Kaminsky, Reinhardt, and Vegh, 2003), implying that the probability of price-crash incidents from geographically neighboring firms can be associated with that of an individual firm in the matching state. On the other hand, we do not see any apparent connection between the systematic risk of a firm and the state-specific crashes. Thus, the state-specific crash measure seems to fulfill the requirement of exclusion and relevance robustness checks (Roberts and Whited, 2013). Our findings indicate that state-specific crashes are correlated with a rise in firm-specific crashes. Our results from the fitted crash proxy uphold our main panel specification findings and are constantly robust. Thus, we conclude that crashed firms affect the firm beta.

3.6 Conclusion

Systematic risk plays a vital role in the Capital Asset Pricing Model (CAPM). Financial market experts remain attached to the CAPM while estimating the cost of equity. Generally, riskier firms are the firms with higher systematic risk. Judging the critical role of firm beta, academics have leaned on investigating its precise estimate and determinants. In this paper, we examine i) whether stock price crashes affect firm beta ii) why firm beta increases, and iii) whether an increase in crashed firm beta makes equity financing more expensive.

We find that firm beta increases after stock price crashes. This result is robust to other beta measures and is persistent in low- and high-beta firms. The evidence suggests that the beta increase occurs because of increased default risk. Our evidence does not support that information efficiency is an explanation for the beta increase.

Finally, we find that the cost of equity increases after the crashes. We adopt difference-in-differences analysis to check the beta change after crashes by comparing the states of before- and after-crash beta. We also utilize the redemption pressure from mutual fund flow as an exogenic shock to perform the core identification test. The robustness checks in this paper verify the robust positive association between stock price crashes and firm beta.

Chapter Four

Stock Price Crashes and Peer Firms' Return Co-movement

In this chapter, the third essay explores the relationship between stock price crashes and peer firms' return co-movement. Section 4.1 introduces this essay's findings and associated literature. Section 4.2 describes the data, calculation of main variables, and research designs employed in the essay. Section 4.3 presents the summary as well as primary findings and relevant discussions. The essay discusses several identification strategies in Section 4.4. Lastly, Section 4.5 offers the conclusion for this chapter. Appendices and a reference list of the essay can be found at the end of the thesis.

Abstract

We show that a stock price crash results in the prices of the stock's non-crash peer firms co-moving more with market returns. The stock price crash causes investors to focus more on affected firms and pay less attention to peer firms. This results in the peer firms trading less on firm-specific information and more on market information. This result is robust to different peer-firm classifications and an exogenous shock. The evidence does not support either internal and external monitoring or information asymmetry as alternative mechanisms to distraction as the driver of the results.

JEL Classification Codes: G11, G12, G14

Keywords: Crash risk, Co-movement, Investor attention, Information environment

4.1 Introduction

Stock return co-movement with the market is an important area to study due to its implications for diversification, and many researchers document several catalysts for changes in this co-movement. For instance, Eun, Wang, and Xiao (2015) show that stock return co-movement occurs due to cultural factors. Huang, Huang, and Lin (2019) observe stronger stock return co-movement during large lottery jackpots. Ma, Marshall, Nguyen, Nguyen, and Visaltanachoti (2022) note that stock return co-movement is higher during extreme climate events.

Extant literature investigates market-level shocks that distract investor attention, leading to increased stock return co-movements. For example, Huang, Huang, and Lin (2019) find that large lotteries divert investor attention from the financial market, while Peress and Schmidt (2020) document that climate disasters distract investors. We consider whether and to what extent, a firm-specific shock impacts investor attention given to peer firms. Kim, Lee, and Zhu (2022) show that stock price crashes attract investor attention to the firm experiencing the crash.[42] However, it is not clear whether the crash event takes attention away from peer firms. Investigating this issue is the purpose of this study.

[42] Adverse news like overstatement, displacement and scandal (Darnton, 1975; Gibson and Zillmann, 1994; Shoemaker and Reese, 1996) appeals to readers more than positive news (Tetlock, 2007). Besides, media prioritizes poorly managed firms over well-managed ones in terms of covering stories (Core, Guay, and Larcker, 2008).

Human attention is a limited cognitive resource (Kahneman, 1973). Paying attention to one job inherently involves reallocating cognitive reserves from other jobs. Peng and Xiong (2006) suggest that scarce attention triggers category-learning behavior. As a result, investors typically analyze more market- and sector-level data than firm-specific data.[43] This suggests that a stock price crash may draw attention away from other peer firms in the same industry. On the other hand, an adverse event may result in more attention being paid to the firm experiencing the event and to related peer firms. For instance, the BP oil spill impacted the stock price of BP and the stock prices of the other oil businesses (Bergin, 2010). Gleason, Jenkins, and Johnson (2008) document that accounting restatements cause stock price declines among non-stating firms in the same industry. Given this, a crashed firm may also attract more investor attention to its non-crashed peer firms. The degree to which a stock price crash in one firm leads to more or less investor attention for peer firms is therefore an empirical question.

We investigate the effect of firm-level price crashes on peer firms' co-movement with market returns in the U.S. during the 1950-2021 period. We observe strong evidence of increased return co-movement between crashed firms' peer firms and the market. We conduct a difference-in-differences test by exploring the change in non-crashed peer firms' return co-movement in pre- and post-crash of stock in the same

[43] For example, companies that altered their names to dot-com without making basic strategic changes experienced considerable above-average returns following their announcements of name changes in the era of the Internet bubble (Cooper, Dimitrov, and Rau, 2001).

industry. We also run two-stage least squares (2SLS hereafter) regression analyses by using mutual fund flow hypothetical sale (*MFHS* henceforth) as an instrumental variable (Kim, Lee, and Zhu, 2022). *MFHS* exerts a downhill pressure on the stock price and has little correlation with fundamental aspects of companies, as noted by Dessaint, Foucault, Frésard, and Matray (2019). Our core result is robust to the difference-in-differences and 2SLS tests. We find that investors pay more attention to a crashed firm and less attention to its non-crashed peer firms. Our evidence also suggests that the relationship between a firm's stock price crash and its peer firms' return co-movement becomes stronger with the association of less investor attention at the industry level.

We also consider additional possible mechanisms by which a firm's stock price crash affects its peer firms' return co-movement. First, we investigate the external monitoring channel. Prior studies suggest that analyst following can act as an external monitoring mechanism and improve information quality for companies (Farrell and Whidbee, 2003; Gentry and Shen, 2013). Companies that are followed by a larger number of financial analysts typically gain increased visibility, leading to heightened interest and closer scrutiny by investors (Bushee and Miller, 2012). Our results indicate that a crashed firm attracts more analyst following, but there is no significant impact on the analyst following non-crash peer firms. Therefore, we rule out analyst following as a potential driver of a non-crashed peer firms' return co-movement.

Second, we investigate whether internal monitoring affects the relationship between a firm's stock price crash and its peer firms' return co-movement. Institutional investors incentivize management to monitor and improve the internal governance system (Li, Moshirian, Pham, and Zein, 2006; Shleifer and Vishny, 1986). Internal managerial monitoring and information quality improve due to increased institutional ownership, as documented by Chung, Elder, and Kim (2010) and Easley and O'hara (2004). We expect institutional owners of non-crashed peer firms to invest more in their stocks to increase managerial monitoring and information quality to avoid unexpected crashes. Our analysis shows that institutional ownership rises following a crash, however, no significant relationship is observed between a crashed firm and its peer firms' institutional ownership.

Lastly, we consider information asymmetry as a feasible mechanism for non-crashed peer firms' return co-movement. Brockman, Liebenberg, and Schutte (2010) observe higher stock return co-movement during uncertainty caused by the recession. Similarly, stock price crashes cause uncertainty in the stock market (Lins, Servaes, and Tamayo, 2017). A firm's price crash may provoke an uncertain future and higher information asymmetry for its non-crashed peer firms, leading to peer firms' return co-movement. However, our results indicate no association between a firm's share price crash and its non-crashed peer firms' information asymmetry.

Our article adds to several strands of the literature. Prior studies document market-level shocks that affect investor attention, resulting in increased stock return co-movements. For instance, Huang, Huang, and Lin (2019) document higher return co-movement when large lotteries distract investors from the financial market. Brockman, Liebenberg, and Schutte (2010) find stronger co-movement during ambiguity or recession. Ma, Marshall, Nguyen, Nguyen, and Visaltanachoti (2022) document higher stock return co-movements during climate disasters. Do, Nguyen, Nguyen, and Truong (2023) show that aerospace competition causes investor inattention and increases return co-movements. Our paper investigates a firm-specific adverse shock that impacts return co-movements of a crashed firm's peer firms by diverting investor attention.

Second, we present a fresh perception in the existing literature on the adverse firm-specific events that affect peer firms. For example, Beatty, Liao, and Yu (2013) find that financial misreporting increases peer firms' investment, and Li (2016) shows more investment in R&D and advertising by peer firms during fraud periods. Jia and Zhao (2020) observe that accounting restatements released by foreign firms induce negative stock market returns for home country peer firms.

Our paper is also related to the effect of a firm's stock price crash on its peer firms' co-movement and financial markets. Stock price crashes are becoming one of the adverse events nowadays and inflict investor-wealth damage (Callen and Fang, 2017). Among other things, stock price crashes cause firms to face trouble adjusting and raising capital (An, Li, and Yu, 2015) and rising auditor fees (Hackenbrack, Jenkins, and Pevzner, 2014). Roy, Marshall, Nguyen, and Visaltanachoti (2023a) show that management undertakes several actions to regain investor trust and firm value.

Kim, Lee, and Zhu (2022) document that stock price crashes can distort or accelerate information efficiency. We suggest that the returns of a crashed firm's peer firms coincide more with the market returns.

The remainder of the article proceeds as follows. In Section 4.2, we discuss our data sources, main dependent variable construction, and empirical specification of our study. Section 4.3 describes the summary statistics and core results. Section 4.4 conducts identification strategies to check for the robustness of our core results. Section 4.5 oversees the test results from channels that drive the stock return co-movements. In Section 4.6, we conclude the paper.

4.2 Research Design

In this section, we discuss the details of the data in our sample, the calculation of the main dependent variables, and the empirical model for our investigation.

4.2.1 Sample Data

Our initial sample of return co-movement and stock price crash data covers from 1950 through 2021.[44] The data contains US firms and is obtained from the Center for Research in Security Prices (CRSP) and Compustat database. We include all common stocks (SHRCD = 10 or 11) and exclude all "penny stocks" with prices less than five

[44] Our sample commences in 1950, coinciding with the beginning of the Compustat database and finishes in 2021, representing the most recent data accessible at the time of writing this article.

dollars to control for attraction from particular investors by following Bollerslev, Patton, and Quaedvlieg (2022).[45] We obtain analyst following data and institutional ownership data from I/B/E/S on the Thomson Reuters Datastream database and the Thomson Reuters Institutional Holdings database, respectively. We download monthly search volume indexes from Google Trends for each firm in our sample.[46] We follow Da, Engelberg, and Gao (2011) and search for a stock using its ticker. We exclude tickers with 35 ticker symbols with potential alternative and universal meanings (e.g., "GPS", "CAT", "BAT", "DNA", "TOY", "BABY", "MAT", "ALL", "A", "B"). We manually go through all the US stock tickers in our sample and mark such "noisy" tickers, consistent with Da, Engelberg, and Gao (2011).

4.2.2 Main Dependent Variable

We follow Huang, Huang, and Lin (2019) and utilize two measures to proxy for return co-movement. First, we calculate the Pearson correlation coefficient as follows:

$$CORR_{-i,j,y} = \overline{\left[\frac{\sum(ret_{i,j,y}-\overline{ret}_i)-(ret_{m,y}-\overline{ret}_m)}{\sqrt{\sum(ret_{i,j,t}-\overline{ret}_i)^2-(ret_{m,y}-\overline{ret}_m)^2}}\right]} \tag{1}$$

where the above equation is formed in two steps. First, we calculate the correlation between stock return and market return using the time series of return within year *y*. Second, we calculate a cross-sectional average of a correlation, which is the cross-

[45] Our results are not different from the sample if we add the penny stocks.

[46] Google Trends provides search term frequency data, which begins in January 2004 (Da, Engelberg, and Gao, 2011).

sectional mean of industry j, excluding firm i in year y. $CORR_{-i,j,y}$ indicates peer firm (non-crash firms) average co-movement (excluding crashed firms i in the same industry) of industry j in year y and we add a bar on top of the correlation equation to indicate the cross-sectional average within the industry.[47] $ret_{i,j,y}$ is the excess return for individual firm i in industry j in y year, and $\overline{ret}_i$ is the average excess return of for firm i over y years. $mret_{m,y}$ and $\overline{ret}_m$ denote market excess return and the average of market excess return, respectively, in y year.

Second, we calculate the adjusted R^2. We obtain the adjusted R^2 from the following equation:

$$ret_{i,j,y} = \beta_0 + \beta_1 mret_{m,y} + \varepsilon_{i,j,y} \qquad (2)$$

here, we obtain the adjusted R^2 from the regression in two steps. First, we extract the adjusted R^2 from the regression using time series daily return within year y. Second, we calculate a cross-sectional average of the adjusted R^2, which is the cross-sectional mean of industry j excluding firm i in year y. $ADJR2_{-i,j,y}$ denotes the average peer firm (excluding crashed firms i in the same industry) co-movement of industry j in year y.

4.2.3 Empirical Model

Our approach to investigating the impact of a firm's crash on its peer firms' co-movement is to employ a model that includes fundamental firm- and industry-specific

[47] We choose SIC3 code and Fama-French 48 industry classification to identify peer firms (Fama and French, 1993; Leary and Roberts, 2014).

factors to explain the co-movement under investigation. We utilize the following baseline specification in Equation (3):

$$COMOVEMENT_{-i,j,y+1} = \beta_0 + \beta_1 CRASH_{i,j,y} + \beta_2 \sum_{k=1}^{K} \gamma_k X_{i,k,j,y} + \beta_3 \sum_{k=1}^{K} \gamma_k \bar{X}_{-i,k,j,y} + \mu_i + \tau_y + \epsilon_{i,j,y+1} \quad (3)$$

where $COMOVEMENT_{-i,j,y+1}$ represents $CORR_{-i,j,y+1}$ or $ADJR2_{-i,j,y+1}$, which are the proxies of stock return co-movement defined in the above equations. $CRASH_{i,j,y}$ is an indicator variable, which indicates 1 if a firm *i* in industry *j* faces a crash during year y, otherwise, 0. To identify a crash for a firm in a year, we follow Hutton, Marcus, and Tehranian (2009) and Kim, Li, and Zhang (2011a) to extract the firm-level weekly log of residual return from an expanded regression model. If the firm-level weekly return drops 3.09 or more standard deviations lower the mean of that return for a year, we use a dummy variable 1 to indicate a price crash or zero otherwise. $X_{i,j,y}$ refers to firm-specific characteristics. $\bar{X}_{-i,j,y}$ denotes peer firm average of firm characteristics by excluding crashed firms and firm i. We implement firm-fixed effects and year-fixed effects, μ_i and τ_y, in the model to address any unobservable firm and time-specific variations. Following Petersen (2009), we cluster our estimated standard errors by firms. We provide a comprehensive discussion on the measurement of the other independent variables in Appendix C.1.

4.3 Empirical Results

This section presents the descriptive statistics of some of the main variables in our sample. We also discuss the core results of our baseline specification in detail.

4.3.1 Descriptive Statistics

We report the descriptive statistics for the full sample in Table 4.1 from 1950 to 2021. To control for outlier influences, we winsorize continuous variables at the 1 and 99 percent levels. Panel A in Table 4.1 presents the industry-level summary statistics for the dependent variables. The means of *CORR* and *ADJR2* based on SIC3 industry classification are 35 and 16 percent respectively. We observe similar means and medians of the peer firm co-movement based on the Fama-French 48 industry classification. Panel B in Table 4.1 reports the firm-level summary statistics of the main independent variable and firm characteristics. The mean of *CRASH* is 21 percent. A high percentage of firms face positive events rather than extremely adverse events as per our observation in our sample. These statistics are similar to the results of previous literature (Chen, Kim, and Yao, 2017; Hutton, Marcus, and Tehranian, 2009).

Table 4.1 Descriptive Statistics

Panel A: Industry-level summary characteristics						
Variables	Nobs	Mean	Std	Pctl.25th	Median	Pctl.75th
SIC3						
CORR	143,198	0.3488	0.1412	0.2497	0.3377	0.4409
ADJR2	143,198	0.1551	0.1114	0.0737	0.1294	0.2092
Fama-French48						
CORR	143,198	0.3500	0.1578	0.2436	0.3403	0.4530
ADJR2	143,198	0.1561	0.1227	0.0668	0.1276	0.2189
Panel B: Firm-level summary characteristics						
Variables	Nobs	Mean	Std	Pctl.25th	Median	Pctl.75th
CRASH	143,198	0.2103	0.4075	0.0000	0.0000	0.0000
SIZE	143,198	5.4825	2.0334	3.9727	5.3311	6.8116
BTM	143,198	0.6617	0.5669	0.2901	0.5260	0.8740
VOL	143,198	16.0227	2.4006	14.2388	15.9681	17.7784
SDRET	143,198	0.0676	0.1340	0.0364	0.0535	0.0782
LGAGE	143,198	2.5321	0.8728	1.9459	2.6391	3.2189
MFHS	43,488	-0.0710	0.0992	-0.0940	-0.0351	-0.0075

Table 4.1 presents the descriptive statistics for all main variables utilized in the regression analyses. Panel A and Panel B provide the statistics at industry and firm levels, respectively. All continuous variables are winsorized at the 1st and 99th percentiles to control for possible outliers within our sample. Our sample covers 143,198 firm-year observations. Appendix C.1 presents the detailed variable definitions.

4.3.2 Core Results

Table 4.2 provides the regression results employing the baseline specification of Equation (3). The first two columns and the last two columns report the regression results of peer firms' co-movement based on the SIC3 classification and Fama-French 48 industry classification, respectively. The evidence in all columns in Table 4.2 supports our conjecture that increased return co-movement between a crashed firm's peer firm and the market. A stock price crash event can be a firm-specific shock on investor attention as Kim, Lee, and Zhu (2022) document increased investor attention to firm-specific crashes. Besides, investors can distrust news from crashed firms' peer firms because they can similarly expect bad news-hoarding behavior from them. As a result, investors of crashed firms' non-crashed peer firms can prefer market-level information to firm-level information, resulting in return co-movement.

The estimate on *CRASH* for peer firms' co-movement, *CORR*, is 0.002 (*t*-statistic = 3.91) in the first column of Table 4.2. This result is both statistically and economically significant. For example, the extent of the estimate on *CRASH* appears that a standard deviation change in *CRASH* increases peer firms' co-movement by 0.082 (i.e, (0.002 × 0.408) × 100) percent, which quantities to .24% (i.e., 0.082 / 0.338) of the sample median of *CORR* under SIC3 classification. Similarly, the estimate on *CRASH* for *ADJR2* under the Fama-French 48 industry classification is 0.002 (*t*-statistic = 4.02) in the last column of Table 4.2. The remaining columns in the table are significantly positive at the 1% level. Overall, the results suggest that a stock price crash of a firm causes its peer firms' return to comove with the market return.

Table 4.2 Impact of a Firm's Crash on Its Peer Firms' Co-movements

	SIC3		Fama-French48	
Dependent variable:	*CORR*	*ADJR2*	*CORR*	*ADJR2*
CRASH	0.0020***	0.0015***	0.0029***	0.0020***
	(3.91)	(3.80)	(4.33)	(4.02)
SIZE	0.0038***	0.0024***	0.0064***	0.0041***
	(6.26)	(4.83)	(8.60)	(6.98)
BTM	-0.0035***	-0.0029***	-0.0030***	-0.0028***
	(-3.86)	(-4.06)	(-2.58)	(-3.20)
VOL	0.0014***	0.0009***	0.0027***	0.0017***
	(3.51)	(2.90)	(5.33)	(4.61)
SDRET	0.0051**	0.0032*	0.0029	0.0038*
	(2.01)	(1.74)	(0.82)	(1.72)
LGAGE	-0.0051***	-0.0062***	-0.0055***	-0.0079***
	(-3.80)	(-5.67)	(-3.30)	(-5.96)
INDSIZE	0.0128***	0.0096***	0.0098***	0.0083***
	(12.19)	(12.00)	(8.94)	(9.82)
INDBTM	-0.0197***	-0.0130***	-0.0187***	-0.0110***
	(-10.73)	(-9.51)	(-9.72)	(-7.89)
INDVOL	0.0160***	0.0112***	0.0162***	0.0115***
	(18.43)	(16.89)	(17.17)	(16.91)
INDSDRET	0.0290***	0.0178***	0.0179***	0.0077*
	(3.92)	(3.37)	(2.72)	(1.67)
INDLGAGE	0.0029**	0.0030***	0.0111***	0.0084***
	(1.97)	(2.61)	(6.61)	(6.53)
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of Observations	143,198	143,198	143,198	143,198
Adj. R-Squared	67.70%	69.46%	60.29%	62.43%

Table 4.2 reports the results from Equation (3) using non-crashed peer firms' co-movement (*CORR,* and *ADJR2*) as the dependent variables, which are divided into two groups by the SIC3 and Fama-French48 industry classifications, and *CRASH* as the main independent variable. *CRASH* denotes '1' if within its year, a firm encounters one or more firm-specific crashes and '0' otherwise. To prevent possible reverse causality issues, all independent variables are lagged by one year relative to the dependent variables. We include firm- and year-fixed effects to address the concern for time- and firm-specific invariant omitted factors. We parenthesize *t*-

statistics under each coefficient. Our robust standard errors are clustered by firm (Petersen, 2009). *, **, and *** suggest statistical significance at the 10%, 5%, and 1% levels, correspondingly.

4.4 Identification Strategies

This section supplements the results in Section 4.3 with a difference-in-differences test and the use of mutual fund flow hypothetical sale as an exogenous variable.

4.4.1 Difference-in-differences Test

We consider firm-specific stock price crash events as multiple treatment shocks over time. Following Joshi (2020), we employ a multivariate weighting method to conduct the difference-in-differences (DiD hereafter) test. We examine whether there is a difference in the co-movement of a firm's peer firms with the market before and after a crash event. We initially generate treated and control groups, whereas, '*TREATED'* indicates '1' if a firm suffers from a price crash at year *t* and does not suffer a price crash the year before and after that, otherwise '0'. '*AFTER'* denotes '1' if the year is after the crash event, '0' otherwise. We utilize entropy balancing on the firm characteristics of the treatment and the control pairs to improve the covariate balance.

Panel A, Table 4.3 presents the results of the DiD test. In Panel A, our main variable of interest is *TREATED*AFTER*, which implies the change in return co-movement of a crashed firm's peer firms. The coefficient on *TREATED*AFTER* for

CORR based on SIC3 is 0.003 (*t*-statistic = 2.02). We also observe consistent statistically significant positive coefficients across all the columns in Panel A. These results indicate that return co-movement of crashed firms' peer firm rises related to the control group. In Panel B, we present the statistics for standardized mean differences and their associated thresholds for all covariates both before the entropy balancing process and afterward. Before the balancing, the standardized mean differences for all covariates exceeded 0.05, indicating an imbalance. Nevertheless, after the entropy balancing, we observed that the standardized mean differences for all covariates were less than 0.05, signifying that they were successfully balanced.

Table 4.3 Difference-in-differences Test

Panel A: Difference-in-differences analysis based on entropy balancing				
	SIC3		Fama-French48	
Dependent variable:	*CORR*	*ADJR2*	*CORR*	*ADJR2*
*TREATED*AFTER*	0.0026**	0.0019*	0.0032*	0.0030**
	(2.02)	(1.94)	(1.93)	(2.35)
TREATED	-0.0003	-0.0001	0.0000	-0.0001
	(-0.44)	(-0.15)	(0.01)	(-0.24)
AFTER	-0.0006	-0.0006	-0.0029***	-0.0019***
	(-0.88)	(-1.05)	(-3.13)	(-2.77)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of Observations	131,762	131,762	131,762	131,762
Adj. R-Squared	74.35%	75.22%	67.15%	68.12%

Panel B: Covariate balance before entropy balancing and after entropy balancing				
	Pre-Match		Post-match	
	Mean Differences	Mean Threshold	Mean Differences	Mean Threshold
SIZE	0.3242	> 0.05	-0.006	<0.05
BTM	-0.3389	> 0.05	-0.0019	<0.05
VOL	0.1623	> 0.05	-0.0033	<0.05
SDRET	-0.0521	> 0.05	0.0016	<0.05
LGAGE	-0.0987	> 0.05	-0.0059	<0.05

In this table, Panel A reports difference-in-differences test results of the impact of a firm's stock price crash on its peer firms' co-movements. We utilize peer firms' co-movement (*CORR,* and *ADJR2*) as the dependent variables, which are divided into two groups by the SIC3 and Fama-French48 industry classifications and *TREATED*AFTER* as the main independent variable. *TREATED* denotes '1' if firms belong to the treatment group and '0' otherwise. *AFTER* denotes '1' if the year is after a stock price crash, otherwise '0'. We include firm- and year-fixed effects to address the concern for time- and firm-specific invariant omitted factors. We parenthesize *t*-statistics under each coefficient. Our robust standard errors are clustered by firm (Petersen, 2009). Panel B presents the statistics of the standardized mean differences and their thresholds of all covariates in pre-match (before entropy balancing) and post-match (after entropy balancing). *, **, and *** suggest statistical significance at the 10%, 5%, and 1% levels, correspondingly.

4.4.2 2SLS Model with an Exogenous Variable

We perform two-stage least square regressions with mutual fund flow projected sale (*MFHS* hereafter) as an exogenous variable to a crash event (Kim, Lee, and Zhu, 2022; Roy, Marshall, Nguyen, and Visaltanachoti, 2023a, b). We compute *MFHS* based on a mutual fund's disclosed portfolio, not on actual transactions. *MFHS* exerts a downhill pressure on the stock price and has little correlation with fundamental aspects of companies, as noted by Dessaint, Foucault, Frésard, and Matray (2019). These flows of money into or out of mutual funds are external to the specific companies whose shares are held by the fund, as investors' views on company fundamentals primarily affect immediate trading in the company's shares, not the mutual fund's shares. *MFHS* can demonstrate the causal impact of a stock's price on a company, satisfying the exclusion constraint, and it primarily affects companies through its impact on share prices (Edmans, Goldstein, and Jiang, 2012).

Table 4.4 Mutual Fund Flow Hypothetical Sale as An Exogenous Variable

		SIC3		Fama-French48	
Dependent variable:	*CRASH*	*CORR*	*ADJR2*	*CORR*	*ADJR2*
MFHS	0.1827***				
	(6.10)				
Fitted_Crash		0.0754**	0.0945***	0.0903*	0.1146***
		(2.08)	(3.30)	(1.94)	(3.18)
Control variables	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Weak identification test:					
F-Statistic		88.19***	88.19***	5.49***	5.49***
Hausman endogeneity test:					
p-value		0.00	0.00	0.00	0.00
No. of Observations	43,488	42,226	42,226	42,226	42,226

Table 4.4 reports the results from two-stage least square specifications that employ mutual fund flow hypothetical sale as an exogenous variable to stock price crashes. In the first-stage regression, we use *CRASH* as the main dependent variable. In the second-stage regression, we use peer firms' co-movement (*CORR,* and *ADJR2*) as the dependent variables, which are divided into two groups by the SIC3 and Fama-French48 industry classifications. We utilize *Fitted_Crash*, obtained from the first-stage regression, as the main independent variable. *CRASH* denotes '1' if within its year, a firm encounters one or more firm-specific crashes and '0' otherwise. To prevent possible reverse causality issues, all independent variables are lagged by one year relative to the dependent variables. We include firm- and year-fixed effects to address the concern for time- and firm-specific invariant omitted factors. We parenthesize *t*-statistics under each coefficient. Our robust standard errors are clustered by firm (Petersen, 2009). *, **, and *** suggest statistical significance at the 10%, 5%, and 1% levels, correspondingly.

Table 4.4 reports a positive coefficient on *MFHS* for *CRASH*, 0.183 (*t*-statistic = 6.10). This first-stage regression result indicates that this pressure notably increases crash events. We use the same control variables used in Equation (3) in these specifications. We report second-stage regression results from column number 2 to column number 5. We observe positive and statistically significant coefficients from the second-stage regressions. For instance, the estimate on the 2nd column is 0.075 and is statistically significant at the 5% level. Our results in this part support our conjecture that a stock price crash of a firm increases its peer firms' return co-movement with the market. The F-statistics obtained from the 2SLS model meet the identification tests established by Stock and Yogo (2005) with a significance level of 1%.

4.4.3 Further Analysis

We also test our baseline specification with two more crash proxies, *NCSKEW* and *DUVOL*, depending on the methods Khurana, Pereira, and Zhang (2018) and Kim, Li, and Zhang(2011) use for their crash measures. We report the results in Appendix C.2. We find that the coefficients on *NCSKEW* and *DUVOL* for industry-level co-movements are positive and statistically significant at the 1% level. Both Panel A and Panel B provide evidence to support peer firms' return co-movement after a stock price crash, presented in our core results.

4.5 Mechanisms for Core Results

In this section, we investigate various mechanisms, for instance, investor attention, external monitoring, internal monitoring, and information asymmetry, by which a firm's stock price crash can affect its peer firms' return co-movement.

4.5.1 Investor Attention Channel

As noted by Huang, Huang, and Lin (2019), large lotteries divert investor attention from the financial market and cause higher return co-movement. A firm's stock price crash is not a market-specific shock, but it can attract investor attention (Kim, Lee, and Zhu 2022). Therefore, we expect investors of a crashed firm's peer firms to be distracted and that leads to peer firm's return co-movement. We utilize a search volume index for individual stocks, which is a proxy for investor attention. It is a total search frequency from Google Trends based on stock ticker (Da, Engelberg, and Gao, 2011). We calculate the average monthly search frequency as an annual search volume index measure in a year. Then, we capture the industry-level investor attention, *ATTENIND*, as the average of the log of Google search volume index on non-crashed peer firms. In Table 4.5, Panel A provides consistent results with the above argument. We observe higher attention at the firm level but document lower attention at the industry level during a crash. Panel B supports our view that investor attention significantly impacts our core results.

Table 4.5 Investor Attention Channel

Panel A: Investor attention during crashes			
	SIC3	Fama-French48	Firm-level
Dependent variable:	*ATTENIND*	*ATTENIND*	*ATTEN*
CRASH	-0.0238***	-0.0479***	0.0218***
	(-5.95)	(-10.20)	(4.14)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of Observations	140,106	140,106	44,043
Adj. R-Squared	97.46%	96.46%	72.65%

Panel B: Investor attention as a channel				
	SIC3		Fama-French48	
Dependent variable:	*CORR*	*ADJR2*	*CORR*	*ADJR2*
*CRASH*ATTENIND*	-0.0006***	-0.0005***	-0.0008***	-0.0007***
	(-4.33)	(-4.52)	(-3.64)	(-4.01)
CRASH	0.0030***	0.0024***	0.0038***	0.0029***
	(5.06)	(5.53)	(4.89)	(5.19)
ATTENIND	-0.0113***	-0.0082***	-0.0094***	-0.0068***
	(-12.86)	(-11.52)	(-8.97)	(-8.00)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of Observations	129,228	129,228	129,228	129,228
Adj. R-Squared	67.87%	69.61%	60.39%	62.52%

In this table, Panel A reports the regression results that use both industry- and firm-level investor attention as the dependent variables, *ATTENIND* and *ATTEN*, and *CRASH* as the main independent variable at the contemporary level. Panel B reports the results from the regressions that use peer firms' co-movement (*CORR*, and *ADJR2*) as the dependent variables, which are divided into two groups by the SIC3 and Fama-French48 industry classifications, and *CRASH* interacted with the industry-level investor attention, *ATTENIND* (i.e., *CRASH*ATTENIND*), as the main independent variable. *CRASH* denotes '1' if within its year, a firm encounters one or more firm-specific crashes and '0' otherwise. We capture the industry-level investor attention, *ATTENIND*, as the average of the log of Google search volume index on non-crashed peer firms. To prevent possible reverse causality issues, all independent variables are lagged by one year relative to the dependent variables. We include firm- and year-fixed effects to address the concern for time- and firm-specific invariant omitted factors. We parenthesize *t*-statistics under each coefficient. Our robust standard errors are clustered by firm (Petersen, 2009). *, **, and *** suggest statistical significance at the 10%, 5%, and 1% levels, correspondingly.

4.5.2 External Monitoring Channel

We test our conjecture that analyst following at the industry level can impact the link between a firm's stock price crash and its peer firms' return co-movement. Analyst following can work as an external monitoring channel and better information quality for companies (Ma, Marshall, Nguyen, Nguyen and Visaltanachoti, 2022). As a result, firms with lower analyst following can increase their return co-movement with the market due to less investor attention to their news. We calculate *INDANAF* as the average of the log of the number of analysts following for non-crashed peer firms of a crashed firm. Panel A of Table 4.6 shows that industry-level analyst following does not have significant change during a stock price crash, whereas firm-level analyst following goes up amid a crash. Considering there is no statistically significant relationship between a firm's crash and its peer firms' analyst following, we do not consider it as a channel that drives our core results.

4.5.3 Internal Monitoring Channel

We also explore the role of internal monitoring on our core results. Higher institutional ownership raises managerial monitoring and information quality (Chung, Elder, and Kim, 2010). So, increased institutional ownership for a firm can lead to increased investor attention. The variable *INDINSOW* is the average percentage of institutional ownership for non-crashed peer firms of a crashed firm. We do not observe the strong contemporary link between a stock price crash and industry-level institutional ownership in Panel B, Table 4.6. Our findings indicate that industry-level institutional ownership can function as a potential mechanism for our main results.

Table 4.6 Other Potential Channels

Panel A: Analyst following as an external monitoring channel			
	SIC3	Fama-French48	Firm-level
Dependent variable:	*INDANAF*	*INDANAF*	*ANAF*
CRASH	0.0025	0.0001	0.0247***
	(0.73)	(0.03)	(5.94)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of Observations	36,181	36,181	26,490
Adj. R-Squared	68.33%	71.29%	87.04%
Panel B: Institutional ownership as an internal monitoring channel			
	SIC3	Fama-French48	Firm-level
Dependent variable:	*INDINSOW*	*INDINSOW*	*INSOW*
CRASH	-0.0006	-0.0011	0.0149***
	(-0.95)	(-1.13)	(14.23)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of Observations	121,545	121,545	126,082
Adj. R-Squared	89.10%	84.64%	80.05%
Panel C: Illiquidity as an information asymmetry channel			
	SIC3	Fama-French48	Firm-level
Dependent variable:	*INDILLIQ*	*INDILLIQ*	*ILLIQ*
CRASH	-0.0003	0.0024	-0.0432***
	(-0.13)	(0.70)	(-10.57)
Control variables	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
No. of Observations	135,760	135,760	123,631
Adj. R-Squared	59.83%	54.38%	56.34%

In this table, Panel A presents the regression results that use both industry- and firm-level analysts following, *INDANAF* and *ANAF*, as the dependent variables, and *CRASH* as the main independent variable at the contemporary level. Panel B reports the regression results that use both industry- and firm-level institutional ownership as the dependent variables, *INDINSOW* and *INSOW*, and *CRASH* as the main independent variable at the contemporary level. Panel C provides the regression results that use both industry- and firm-level accruals as the dependent variables, *INDILLIQ* and *ILLIQ*, and *CRASH* as the main independent variable at the contemporary level. Industry-level measures are divided into two groups by the SIC3 and Fama-French48 industry classifications. *CRASH* denotes '1' if within its year, a firm encounters one or more firm-specific crashes and '0' otherwise. We calculate *INDANAF* as the average of the log of the number of analysts following for non-crashed peer firms of a crashed firm. We calculate *INDINSOW* as the average percentage of institutional ownership for non-crashed peer firms of a crashed firm. *INDILLIQ* is the average of firm-level illiquidity for non-crashed peer firms. The sample period for only analysts following data is from 1973 to 2019. We include firm- and year-fixed effects to address the concern for time- and firm-specific invariant omitted factors. We parenthesize *t*-statistics under each coefficient. Our robust standard errors are clustered by firm (Petersen, 2009). *, **, and *** suggest statistical significance at the 10%, 5%, and 1% levels, correspondingly.

4.5.4 Information Asymmetry Channel

We next explore information asymmetry as the prospective channel. The primary factor leading to crashes is often attributable to opacity (Hutton, Marcus, and Tehranian, 2009). Investors may not want to follow a crashed firm's peer firms, which are like to be opaque. As a consequence, we can observe that investors focus more on the news from the market instead of potential opaque firms. To capture the industry-level information asymmetry, we construct an aggregate measure, *INDILLIQ*, based on the average illiquidity for non-crashed peer firms of a crashed firm. Panel C, Table 4.6 reports the weak contemporary relationship between a stock price crash and industry-level information asymmetry. However, we find that firm-level information asymmetry falls significantly during a crash. Our evidence in the first two columns of Panel C suggests that we need to drop information asymmetry as a probable channel for the main hypothesis.

4.6 Conclusion

Numerous researchers have explored several market-level shocks that cause stock return co-movements due to investor distraction. In this paper, we investigate the impact of firm-specific shock on investor attention and peer firms' return co-movements. We focus on a stock price crash as an important firm-specific event that attracts investor attention (Kim, Lee, and Zhu, 2022). Our results suggest that a firm's stock price crash causes the returns of the non-crashed peer firms to coincide more with the returns of the market. Two identification strategies, namely difference-in-differences and mutual fund flow hypothetical sale as an exogenous variable, strengthen the robustness of our core results.

To examine the underlying mechanisms through which a firm's stock price can impact its peer firms' co-movements, we investigate the role of investor attention as a possible driver of the results. We find evidence that less investor attention at the industry level can boost the relationship between a firm-level crash and peer firms' co-movement. We further explore several other potential mechanisms at the industry level, namely analyst following, institutional ownership, and illiquidity, to explain our core results. However, our initial findings suggest that there are no consistent relationships between a firm's stock price crash and analyst following, institutional ownership, and illiquidity at the industry level. Therefore, we rule out the possibility of external and internal monitoring as well as information asymmetry influencing the return co-movements of a crashed firm's peer firms.

Chapter Five

Conclusion

In this chapter, the thesis wraps up by outlining the key discoveries and their significance within each of the three essays discussed in Section 5.1. Furthermore, it proposes potential avenues for future research in Section 5.2.

5.1 Major Findings and Implications

In this section, we provide a summary of the major findings for each essay in this thesis. We also discuss the potential economic implications for investors, professionals, and financial market regulators.

5.1.1 Essay One

Most existing literature about stock price crashes focuses on the factors of firm-level crashes, but little is known about their consequences. Firm-specific price crashes can damage investor confidence in the financial markets and put a lot of strain on the management. The first essay examines how stock price crashes affect management responses given to crashed firms, the intuition behind those responses, and the outcomes of those responses to shareholders.

Utilizing a comprehensive sample of the U.S. capital market between 1950 and 2019, the first essay shows that managers reduce earnings management and improve financial statement comparability within the industry. It also finds that managers improve firms' investment efficiency following crashes. Improved transparency is instrumental in restoring investor confidence and increasing investment efficiency (Healy and Palepu, 2001; US Securities and Exchange Commission, 2008). Besides, managers alleviate agency costs by paying dividends and slashing cash holdings after crashes. This finding implies signaling a good sign of future cash flow for the firms (John and Williams, 1985). Lastly, managers of crashed firms improve ESG ratings and employee treatment to grow confidence among shareholders. These actions can have a positive social impact and create better values for the firms. Managers carry out these actions out of career concern.

Overall, the essay provides evidence that stock price crashes incentivize management to undertake actions to improve crashed firms' performance and the trust given to them. The essay adds more knowledge to the understanding of corporate crisis management procedures after adverse events. The implications for managers would be making sure these actions are taken after unexpected crashes and even beforehand to prevent such adverse events.

5.1.2 Essay Two

The second essay investigates the impact of a stock's price crash on its systematic risk using a sample of U.S. stocks between 1950 and 2021. Given the growing significance of identifying firm beta catalysts in recent years, the essay considers to which extent firm beta increases after crashes and what is the mechanism for increased firm beta.

The key empirical findings of Essay Two are as follows. First, we find that a standard deviation movement in our crash proxy results in an increase in firm beta by 1.14 percent. High- and low-beta firms exhibit similar findings after crashes. The essay attributes default risk to the main mechanism for a crashed firm's increased beta. There is no evidence for an alternative explanation that information asymmetry can be a channel for higher beta after these adverse events. Higher firm beta makes equity financing more expensive.

Firm beta is instrumental in equity financing, managing portfolios, risk assessment, and hedging decisions. The empirical findings of this essay suggest that stock price crashes become a contributing factor to firm beta. Given the significance of firm systematic risk, this study can provide significant implications for professionals and financial market regulators. For instance, firm managers of crashed firms can undertake an alternative option for financing costs. Portfolio managers can make appropriate decisions to include or exclude these crashed stocks based on their funds' risk tolerance levels. Market regulators can implement rules and regulations to maintain firm systematic risk under control so that it does not lead to contagion effects.

5.1.3 Essay Three

Prior literature documents increased stock return co-movement due to various market-level shocks (Huang, Huang, and Lin, 2019; Ma, Marshall, Nguyen, Nguyen, and Visaltanachoti, 2022). Essay Three conducts an empirical test to show whether firm-level shock causes stock return co-movement. Specifically, this essay examines a crashed firm's impact on the return co-movement of its non-crashed peer firms and investors' focus given to those peer firms.

There are some important findings obtained from analyzing a large sample of data from the U.S. financial market between 1950 and 2021. First, the essay shows that when a stock exhibits a price crash, the prices of other non-crashing stocks within its peer group seem to move more closely with market fluctuations. This situation occurs because investors pay more attention to crashed firms than their non-crashed peers. Along with investor attention, the essay investigates three more potential mechanisms to explain our main results. We do not find any significant relationship between crashed firms and their peer firms' internal or external monitoring. Similarly, there is no evidence of existing peer firms' information asymmetry following a crash.

The key findings from this study can have significant implications for investors. For example, investors can make appropriate decisions regarding managing a portfolio or hedging a particular set of investments after experiencing firm-specific crashes. The essay demonstrates a new firm-specific source of return co-movement and shows this is different from current market-level shocks to co-movement.

5.2 Future Areas of Research

This thesis explores various aspects of the aftermath of stock price crashes. It is promising for future research to empirically investigate how management actions affect other stakeholders after crashes, such as bondholders, who might prefer a higher cash buffer. It will be meaningful empirical analyses to get a sense of how bondholders or other stakeholders are affected by the managerial actions following crashes as a future research avenue. There is literature studying the threat of takeover or hedge fund activism that discusses this transfer of wealth from bondholders to shareholders toward off potential bidders or activists. Future researchers may want to refer to that literature to formulate further analyses of whether such transfer also exists in the setting of this essay.

There is also another potential avenue for future research about the post-crash reactions from mutual fund managers. For instance, researchers can investigate what mutual fund managers do with stocks with immediate firm-specific crash events. This poses multiple questions: i) do they buy them or sell them? ii) why do they buy or sell them? iii) does it depend on their investing style (value vs growth investing style), window dressing, and characteristics (for example, having previous experience in downturn markets, young or inexperienced managers)? Investigating these empirical questions can have important implications for professional investors and market regulators.

Future studies may examine to what extent crashed firms suffer to fund projects and fail to utilize growth opportunities. Given the higher systematic risk after crashes, researchers can explore how institutional investors conduct other risk assessments on the crashed firms. In addition, future researchers can explore the causal effect of stock price crashes in international settings to examine whether the effect is a global phenomenon or specific to the U.S.

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Appendix A

For Chapter One

Appendix A.1 Variable definition

Variables	Description
CRASH	An indicator variable that is equal to one if within its year, a firm experiences one or more firm-specific weekly $R_{i,w}$ falling 3.09 or more standard deviations below the mean ($R_{i,w}$) return for its year and equal to zero otherwise. $R_{i,w}$ = log (1 + $\varepsilon_{i.w}$) for firm *i* on the week w, estimated on weekly return data between each firm's two head-to-head years: $$r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i.w}$$ where for firm i and on week w, $r_{i,w}$ is a firm's raw return; $r_{j,w}$ is the Fama and French value-weighted industry (*j*, to which firm *i* belongs) return; and $r_{m,w}$ is the CRSP value-weighted market return on the week w (Chen, Kim, and Yao, 2017; Hutton, Marcus, and Tehranian, 2009).
ACCTCOMP	Financial statement comparability, the absolute value of the difference of the predicted value of regression of firm *i*'s earnings on firm *i*'s return using the estimated coefficients for firms *i* and *j*, respectively. It is calculated for each firm *i* − firm *j* pair, (*i* _= *j*), *j* = 1 to *j* firms in the same two-digit SIC industry as firm *i* (De Franco, Kothari, and Verdi, 2011).
ACCRUALS	Discretionary accruals, estimated for each two-digit SIC code industry and year pair: $$ACC_{i,y}/A_{i,y-1} = \lambda_0 + \lambda_1 CFO_{i,y-1}/A_{i,y-2} + \lambda_2 CFO_{i,y}/A_{i,y-1} + \lambda_3 CFO_{i,y+1}/A_{i,y} + \lambda_4 \Delta REV_{i,y}/A_{i,y-1} + \lambda_5 PPE_{i,y}/A_{i,y-1} + \epsilon_{i,y}$$

where $ACC_{i,y}$, defined as earnings before extraordinary items (IB) minus cash flow from operations (OANCF after 1987 or IB-ΔACT+ΔCHE+ΔLCT-ΔDLC+DP before 1987), is the accruals of firm i in year y, $A_{i,y-1}$ is the total asset (AT) of firm i at the beginning of year y. $CFO_{i,y}(CFO_{i,y-1}, CFO_{i,y+1})$ is the cash flow from operations in year y $(y-1, y+1)$. $\Delta REV_{i,y}$ is the change in revenue (SALE) in year y. $PPE_{i,y}$ is the gross property, plant, and equipment (PPEGT) at the beginning of year y (McNichols, 2002).

INVEFFIC Investment efficiency is our first proxy to indicate lower unexpected investment. The model to capture investment efficiency can be estimated as follows:

$$Inv_{i,y} = \alpha + \beta_1 Q_{i,y-1} + \beta_2 CF_{i,y} + \beta_3 GROWTH_{i,y-1} + \beta_4 Inv_{i,y-1} + \varepsilon_{i.y}$$

where the $Inv_{i,y}$ is the investment ($CAPEX_{i,y}/AT_{i,y-1}$) for firm *i* in year *y*. $Q_{i,y-1}$ is market to book ratio, a proxy for Tobin's q. $CF_{i,y}$ is the firm's cash flow. $GROWTH_{i,y-1}$ equals to the log of total assets at the end of year *y – 1* divided by total assets at the end of year *y – 2*. The unexpected investment is the absolute value of the residual from the above industry-year regressions. We multiply the absolute value of the residual by -1 to make our variable increase in efficiency. We set an indicator variable that takes a value of 1 if the absolute value of a firm's level of unexpected investment falls below the median absolute value of the unexpected investment distribution, and 0 otherwise (Goodman, Neamtiu, Shroff, and White, 2014).

INVEFFIC2 Our second investment efficiency proxy implies lower excess investment. The model to capture investment efficiency can be expressed as follows:

$$Inv_{i,y} = \alpha + \beta_1 Q_{i,y-1} + \beta_2 Q_{Qry2_{i,y-1}} + \beta_3 Q_{Qry3_{i,y}} + \beta_4 Q_{Qry4_{i,y}} + \beta_5 CF_{i,y} + \beta_6 GROWTH_{i,y-1} + \beta_7 Inv_{i,y-1} + \varepsilon_{i.y}$$

	where $Inv_{i,y}$ is the investment ($CAPEX_{i,y}/AT_{i,y-1}$) for firm *i* in year *y*. $Q_{i,y-1}$ is market to book ratio, a proxy for Tobin's q. ${Q_{Qrt2}}_{i,y-1}$(${Q_{Qrt3}}_{i,y}$, ${Q_{Qrt4}}_{i,y}$) equals $Q_{i,y-1}$ times an indicator variable that equals 1 if $Q_{i,y-1}$ is in the second (third, fourth) quartile of its industry-year distribution. $CF_{i,y}$ is the firm's cash flow. $GROWTH_{i,y-1}$ equals to the log of total assets at the end of year *y – 1* divided by total assets at the end of year *y – 2*. The residual from the regression measures the investment inefficiency. We multiply the residual by -1 to ensure that higher values always indicate higher investment efficiency (McNichols and Stubben, 2008).
DIV	Dividends (DVC) for common shareholders (Grullon and Michaely, 2002), are scaled by total assets (AT).
CASHHOLD	Log of the ratio of cash and marketable securities (CHE) to total assets (AT) minus cash and marketable securities (CHE) as the cash holdings variable (Opler, 1999).
ESG	Total ESG score for firm *i*, at the end of year *y*, computed by adding up the net scores (strengths minus concerns) for the community, diversity, employee relations, environment, human rights, and product categories in the MSCI database (Di Giuli and Kostovetsky, 2014).
ETI	The raw employee treatment index is the difference between the sum of strength and concern scores of nine subcategories in ESG ratings (Mao and Weathers, 2019). Then, the strength and concern scores are scaled by the corresponding number of dimensions available each year, and the adjusted employee treatment index is computed as the difference between the adjusted total strength score and the adjusted total concern score (Deng, Kang, and Low, 2013).
SIZE	Firm size is the natural logarithm of the market value of equity (CSHO*PRCC) at the end of each year (Kim, Lee, and Zhu, 2022).
ROA	Return on asset is the ratio of net income (NI) to total assets (AT) (Cronqvist and Yu, 2017).
MB	The market-to-book ratio is the ratio of the market value (PRCC_F) to the book value (BKVLPS) of a firm (Cronqvist and Yu, 2017).

DEBT	Book value of debt (DLC + DLTT) divided by total asset (AT) (Johnson, 2003).
RETVOL	Log of the standard deviation of stock price return weekly in a year (Rashid, 2015).
ADJMFHS	We follow Edmans, Goldstein, and Jiang (2012) to measure mutual fund flow redemption pressure based on hypothetical sales. It is a measure of hypothetical sales of the stock of firm *i* each year *y* by mutual funds experiencing large outflows. Dessaint, Foucault, Frésard, and Matray (2019) give a detailed description of the process of calculating this variable in Appendix C. However, we adjusted mutual fund flow redemption pressure based on hypothetical sales by following Wardlaw (2020), and the detailed description of calculating this variable is reported in the Internet Appendix under section, II. Adjusted Flow Estimation. A higher value of *ADJMFHS* corresponds to the higher redemption pressure.
State_Ncskew	We use *NCSKEW* to calculate yearly state-level crash proxy by averaging the crash risks of firms, excluding firm *i*, in a year *y*. Unlike *CRASH*, which is a dummy variable, *NCSKEW* is a continuous variable. This continuous value setting helps us to measure the magnitude of more than one crash incident, which is suitable for capturing state-level crashes.
TOBINQ	The market value of the equity plus the book assets minus the sum of the book value of common equity and deferred taxes is divided by the beginning book value of assets (Kim and Nguyen, 2019).
SALESGR	The natural logarithm of total sales (SALE) in the current year to the previous year (Opler and Titman, 1994).
MNGRACT	It refers to a composite management action score based on seven management actions, including financial statement comparability, discretionary accruals, investment efficiency, dividend payment, cash holdings, ESG ratings, and employee treatment index. Following the approach of Lang, Lins, and Maffett (2012), we calculate this score by ranking each action in deciles and averaging the scores each year.

TTHREAT	A takeover threat proxy refers to the hostile takeover index data from Cain, McKeon, and Solomon (2017).
CEOCOMPEN	Measured as ONEPCT/ (ONEPCT + SALARY + BONUS) for a firm *i* in year *y*, where ONEPCT = (0.01*share price*option delta*number of options). Similarly, we calculate CFO compensation (*CFOCOMPEN*) based on CFO salary, bonus, and their compensation through options (Kim, Li, and Zhang, 2011b).
UNEMP	It refers to the state-wide unemployment rate in decimals obtained from the U.S. Bureau Of Labor Statistics.
NCSKEW	The negative coefficient of skewness of $R_{i,y}$ over a year y. $Ncskew_{i,y} = (-(n(n-1)^{\frac{3}{2}} \sum R_{i,y}{}^{3}) / ((n-1)(n-2)(\sum R_{i,y}{}^{2})^{\frac{3}{2}})$ (Chen, Kim, and Yao, 2017; Kim, Li , and Zhang, 2011a).
DUVOL	The down-to-up volatility of $R_{i,y}$ during the year y. $Duvol_{i,y} = \log\{((n_{up}-1)\sum_{down} R_{i,y}{}^{2})/((n_{down}-1)\sum_{up} R_{i,y}{}^{2})\}$ (Khurana, Pereira, and Zhang, 2018).

Appendix A.2 Robustness Check by Excluding Uncertain Times

Dependent variables:	*ACCTCOMP*	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
CRASH	0.1382***	-0.0034***	0.0101**	0.0013***	0.0007***	-0.0096***	0.1396***	0.0092***
	(5.52)	(-3.76)	(2.10)	(2.82)	(6.41)	(-2.95)	(4.40)	(3.25)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inverse mills ratio	No	No	No	No	No	No	Yes	Yes
No. of observations	38,687	82,406	66,234	66,234	80,648	80,648	14,865	14,865
Adj. R-Squared	25.33%	53.94%	8.58%	8.21%	66.32%	72.39%	5.81%	7.23%

This table presents the results from regressions on a sub-sample, using management actions as the dependent variables and *CRASH* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1950 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A.3 Management's Long-term Actions Following Crashes

Panel A: Management actions in the 2nd year following crashes

Dependent variables:	*ACCTCOMP*	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
	y+2	y+2	y+2	y+2	y+2	y+2	y+2	y+2
CRASH	0.1173***	-0.0014*	0.0093**	0.0014***	0.0005***	-0.0102***	0.0597**	0.0004
	(5.16)	(-1.73)	(2.18)	(3.85)	(4.21)	(-3.65)	(2.11)	(0.15)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inverse mills ratio	No	No	No	No	No	No	Yes	Yes
No. of observations	51,662	91,075	80,001	80,001	90,975	90,975	22,212	22,212
Adj. R-Squared	55.72%	22.92%	8.02%	8.21%	63.60%	70.73%	6.89%	6.04%

Panel B: Management actions in the 3rd year following crashes

Dependent variables:	*ACCTCOMP*	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
	y+3	y+3	y+3	y+3	y+3	y+3	y+3	y+3
CRASH	0.0447*	-0.0004	0.0004	0.0006*	0.0004***	-0.0056**	0.0647**	0.0014
	(1.91)	(-0.47)	(0.09)	(1.84)	(3.21)	(-1.99)	(2.10)	(0.50)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inverse mills ratio	No	No	No	No	No	No	Yes	Yes
No. of observations	50,296	83,294	73,501	73,501	83,186	83,186	21,358	21,358
Adj. R-Squared	54.82%	22.67%	7.69%	7.02%	63.47%	70.13%	7.22%	5.31%

This table presents managers' long-term actions following crashes. We re-estimate equation (4) when all dependent variables are one year and two years ahead of management actions (*ACCTCOMP*, *ACCRUALS*, *INVEFFIC*, *INVEFFIC2*, *DIV*, *CASHHOLD*, *ESG*, and *ETI*) at year *y+1*. Our main independent variable, *CRASH*, is lagged by one year relative to dependent variables in equation (4) in year *y*. *CRASH* denotes an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to dependent variables in the equation at year *y*. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1950 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A.4 Alternative Measures of Crash

Panel A: Impact of crashes with NCSKEW								
	ACCTCOMP	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
NCSKEW	0.0657***	-0.0003	0.0035**	0.0003**	0.0004***	-0.0031***	0.0122*	0.0020***
	(8.18)	(-1.21)	(2.25)	(2.39)	(9.83)	(-3.06)	(1.77)	(2.95)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	52,519	101,395	86,523	86,523	99,612	99,634	23,093	23,093
Adj. R-Squared	55.98%	24.33%	8.15%	9.69%	63.60%	70.73%	55.02%	43.20%
Panel B: Impact of crashes with DUVOL								
	ACCTCOMP	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
DUVOL	0.0973***	-0.0011**	0.0076***	0.0009***	0.0006***	-0.0075***	0.0236*	0.0035***
	(6.55)	(-2.21)	(2.77)	(3.58)	(9.35)	(-4.01)	(1.86)	(2.89)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	52,585	101,527	86,653	86,653	99,687	99,687	23,110	23,110
Adj. R-Squared	56.06%	24.28%	8.38%	9.71%	63.80%	71.82%	55.05%	43.17%

This table reports the results from regressions using management actions as the dependent variables, and *NCSKEW* and *DUVOL* as the main independent variables. *NCSKEW* denotes the negative coefficient of skewness of residual return obtained from the expanded model regressions. *DUVOL* refers to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from the expanded model regressions. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A.5 State-level Crash as an Exogenous Shock

	1st Stage Regression	2nd Stage Regressions							
	NCSKEW	*ACCTCOMP*	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
State_Ncskew	0.0820***								
	(4.05)								
Fitted_Ncskew		1.3391***	-0.0425***	0.0691***	0.0193***	0.0086***	-0.0619***	0.3290***	0.0293***
		(14.40)	(-11.04)	(5.30)	(13.63)	(16.82)	(-4.06)	(4.72)	(3.90)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weak identification test:									
F-Statistic		288.04***	209.43***	200.87***	192.51***	201.70***	201.24***	62.37***	60.29***
Hausman endogeneity test:									
p-value		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
No. of observations	101,382	51,332	92,898	80,709	80,709	91,171	91,171	22,270	22,270

This table presents the estimation of the two-stage least square (2SLS) equation. We use *NCSKEW*, which refers to the negative coefficient of skewness of residual return obtained from the expanded model regressions, as the dependent variable in the first stage of regression. We include control variables as in the baseline model (equation 4). All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. In the second stage regressions, we regress fitted crash, which is obtained from the first stage regression model, on *ACCTCOMP*, *ACCRUALS*,

INVEFFIC, INVEFFIC2, DIV, CASHHOLD, ESG, and *ETI*. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A.6 Pre- and Post-crash Managerial Actions of Crashed Firms

	Post-crash	Pre-crash	Difference	*t*-statistics
ACCTCOMP	-2.5052	-2.5393	-0.0249	-0.97
ACCRUALS	0.0012	0.0073	-0.0057	-5.54
INVEFFIC	0.4856	0.4779	0.0053	0.92
INVEFFIC2	0.0010	-0.0008	0.0019	3.80
DIV	0.0133	0.0124	0.0002	2.39
CASHHOLD	0.2717	0.3223	-0.0283	-8.68
ESG	0.3274	0.3186	0.0812	4.01
ETI	0.0091	0.0081	0.0102	4.92

This table reports the results from pre- and post-crash difference analysis. It provides the explanation for any existing differences in management actions one year before and one year after the crash for crashed firms. We parenthesize t-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A.7 Difference-in-differences Analyses Based on Entropy Balancing Method

Panel A: Difference-in-differences analyses

Dependent variable:	*ACCTCOMP*	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
Treatment×After	0.1509	-0.0041	0.0183	0.0018	0.0005	-0.0169	0.0904	0.0480
	2.82	-2.14	1.82	2.14	2.07	-2.65	1.74	1.66
Treatment	0.0223	0.0028	-0.0073	-0.0016	-0.0003	0.0023	0.0672	0.0193
	0.85	3.23	-1.50	-3.90	-2.12	0.75	2.33	1.21
After	-0.0423	0.0021	-0.0076	-0.0029	0.0001	-0.0017	0.0390	-0.0175
	-1.50	2.05	-1.36	-6.01	0.09	-0.49	1.35	-1.10
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	48,248	91,028	78,502	78,502	90,973	90,973	20,847	20,847
Adj. R-Squared	57.62%	27.35%	10.63%	13.17%	65.35%	72.73%	9.98%	10.98%

Panel B: Covariate balance before entropy balancing and after entropy balancing

	Pre-Match		Post-match	
	Mean Differences	Mean Threshold	Mean Differences	Mean Threshold
SIZE	0.2589	> 0.05	-0.0124	<0.05
ROA	0.2214	> 0.05	0.0036	<0.05
MB	0.1548	> 0.05	-0.0049	<0.05

DEBT	-0.1384	> 0.05	-0.0045	<0.05
RETVOL	-0.1640	> 0.05	0.0062	<0.05

This table reports the results from difference and difference-in-differences analyses. Panel A conducts difference-in-differences tests based on entropy balancing by comparing two groups, such as treatment and control groups. Treatment and control pairs indicate crash and non-crash pairs. '*Treatment'* equals '1' if a firm faces a crash, otherwise '0'. 'After' indicates '1' if the manager's actions occur after the crash event, otherwise '0' if they occur before the crash event. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively. Panel B provides the statistics of the standardized mean differences and their thresholds of all covariates in pre-match and before entropy balancing. It also presents the statistics of the standardized mean differences and their thresholds of all covariates in post-match and after entropy balancing.

Appendix A.8 Including R&D, CAPEX, and Overall Governance Score as Additional Controls for Robustness Check

	ACCTCOMP	*ACCRUALS*	*INVEFFIC*	*INVEFFIC2*	*DIV*	*CASHHOLD*	*ESG*	*ETI*
CRASH	0.1442***	-0.0025***	0.0071*	0.0008**	0.0008***	-0.0101***	0.1094***	0.0086***
	(6.43)	(-3.09)	(1.73)	(2.25)	(7.08)	(-3.37)	(4.27)	(3.80)
R&D	-0.3330**	0.0060***	-0.0325	-0.0065**	0.0001*	0.0208	0.8925***	0.0559***
	(-2.23)	(3.74)	(-1.51)	(-2.07)	(1.67)	(0.89)	(3.38)	(2.88)
CAPEX	0.8174***	0.0076	0.7487***	0.1693***	-0.0086***	-0.1693***	-8.8397***	-0.6821***
	(3.64)	(1.02)	(23.40)	(26.44)	(-9.03)	(-6.27)	(-11.16)	(-9.93)
GSCORE	0.0109***	-0.0001	-0.0011***	-0.0001	0.0001***	0.0011***	-0.0123***	-0.0010***
	(4.05)	(-1.46)	(-3.41)	(-0.30)	(3.46)	(3.24)	(-3.62)	(-4.34)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	52,083	101,532	86,652	86,652	98,703	98,703	20,603	20,603
Adj. R-Squared	56.25%	24.41%	8.95%	14.59%	63.94%	71.91%	8.54%	7.94%

This table presents the results from regressions by including two more control variables, such as *R&D* (Research and development expenditure), *CAPEX* (Capital expenditure), and *GSCORE* (Overall governance score) to our baseline specifications, using management actions as the dependent variables and *CRASH* as the main independent variable. *CRASH* indicates an indicator variable that is equal to '1' if, within its year, a firm experiences one or more firm-specific crashes, and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A.9 Board of Directors Change after Stock Price Crashes

Dependent variables:	*BOARDCH*	*INDBOARDCH*
CRASH	-0.0010	-0.0075
	(0.12)	(-0.87)
Controls	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
No. of observations	18,925	18,925
Adj. R-Squared	6.78%	6.22%

This table presents the results from regressions using change of board of directors (*BOARDCH*) and change of independent board of directors (*INDBOARDCH*) as the dependent variables, and *CRASH* as the main independent variable. *BOARDCH* or *INDBOARDCH* indicates an indicator variable that is equal to '1' if, within its year, a firm changes its board or independent board member, respectively, and '0' otherwise. *CRASH* indicates an indicator variable that is equal to '1' if within its year, a firm experiences one or more firm-specific crashes and '0' otherwise. All independent variables are lagged by one year relative to the dependent variables to avoid potential reverse causality issues. Our robust standard errors are clustered by firm (Petersen, 2009). All regressions contain firm- and year-fixed effects to account for time- and firm-specific invariant omitted variables. The sample period is from 1996 to 2019. We parenthesize *t*-statistics under each coefficient. *, **, and *** refer to statistical significance at the 10%, 5%, and 1% levels, respectively.

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In which chapter is the manuscript/published work?	Chapter Two		
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Appendix B

For Chapter Two

Appendix B.1 Variable Definition

Variables	Description
BM	*BM* refers to systematic risk. We collect this beta data from Beta Suite by WRDS database. The formula for *BM* calculation based on the market model is given as: $BM_{i,y} = \frac{cov[r_{i,d}, r_{m,d}]}{var[r_{m,d}]}$ (Fama and MacBeth, 1973).
BSW	*BSW* is a proxy for systematic risk. We use the slope winsorization method to firms' excess returns, topped within the constrained factors of market returns, as follows: $r_{i,d}^{sw} \in (1 + [-\Delta_s + \Delta_s]). r_{m,d}$, $BSW_{i,y} = \frac{cov[r_{i,d}^{sw}, r_{m,d}]}{var[r_{m,d}]}$ where Δ_s = 3; $r_{i,d}^{sw}$ is a firm's slope winsorized excess return on the day d (Welch, 2022).
BSWA	*BSWA* refers to a firm's systematic risk. We execute model (2) to obtain slope winsorized excess return and then estimate the beta by running a weighted least squares market model, in which the weight of each observation decays with age. The decay parameter is set to ρ = 2/252 per day, which reflects a half-life of nearly 90 trading days (Welch, 2022).
CRASH	An indicator variable that is equal to one if within its year, a firm experiences one or more firm-specific weekly $R_{i,w}$ falling 3.09 or more standard deviations below the mean ($R_{i,w}$) return for its year and equal to zero otherwise. $R_{i,w}$ = log (1 + $\varepsilon_{i.w}$) for firm i on the week w, estimated on weekly return data: $r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i.w}$

	where for firm i and on the week w, $r_{i,w}$ is a firm's raw return; $r_{j,w}$ is the Fama and French value-weighted industry (j, to which firm i belongs) return; and $r_{m,t}$ is the CRSP value-weighted market return on the week *w* (Hutton, Marcus, and Tehranian, 2009).
EDF	*EDF* refers to the expected default frequency. We follow below the model and use the cumulative standard normal distribution function on *DD*: $EDF_{i,y} = N(-DD_{i,y})$ (Brogaard, Li, and Xia, 2017).
ZSCORE	We follow Altman (1968) and calculate defaults from five accounting ratios. Please refer to their paper or see details of this default risk measure, a type of accounting measure, from (Abinzano, Gonzalez-Urteaga, Muga, and Sanchez, 2020). We use an indicator variable from this score to denote the default risk. *ZSCORE* equals 1 if the score is below 1.8 as it observes a firm's default risk, otherwise 0.
EFFSPREAD	We apply the natural logarithm to the annual average of daily effective spreads, calculated as twice the absolute difference between the trading price and the bid-ask midpoint, divided by the trading price (Anderson, Duru, and Reeb, 2009).
AMIHUD	It refers to the annual mean of the daily ratio of the absolute value of stock return and trading volume and then multiplied by one million (Brogaard, Li, and Xia, 2017).
PIN	The probability of private information trade = $\alpha\mu\alpha\mu$+2ε (Easley Kiefer, O'hara and Paperman, 1996).
RGM	It is the implied cost of equity depending on the Ohlson-Juettner model. The calculation is based on the following equation: $RGM = A + \sqrt{A^2 + \frac{EPS_1}{P_0} * (STG - (\gamma - 1))}$, $A = \frac{1}{2}\left((\gamma - 1) + \frac{DPS_1}{P_0}\right)$ and $STG = \frac{EPS_2}{EPS_1} - 1$ where EPS_1 and EPS_2 are forecasted one-year and two-year ahead earnings per share, respectively.
RPEG	It represents the implied cost of equity. We calculate *RPEG* based on the following equation:

	$RPEG = \sqrt{\frac{EPS_1}{P_0} * STG}$ (Mohanram and Gode, 2013).
SIZE	Log of total assets (AT) (Gomes, Kogan, and Zhang, 2003).
BKMKT	The book-to-market ratio is the ratio of the book value (BKVLPS) to the market value (PRCC_F) of a firm (Gomes, Kogan, and Zhang, 2003).
LEV	Book value of debt (DLC + DLTT) divided by total asset (AT) (Livdan, Sapriza, and Zhang, 2009).
VOL	Refers to earnings volatility. It represents the standard deviation of fractional changes in the earnings stream and is calculated for a five-year period (Hong and Sarkar, 2007).
LIQ	The current ratio of a firm (ACT/LCT) (Beaver and Manegold, 1975).
AGE	Log of the number of years since the stock's first listing on the stock market (McAlister, Srinivasan, and Kim, 2007).

Appendix B.2 Alternative Measures of Crashes

	BM		*BSW*		*BSWA*	
NCSKEW	0.0179***		0.0182***		0.0172***	
	(18.35)		(22.88)		(20.74)	
DUVOL		0.0264***		0.0286***		0.0271***
		(14.12)		(18.9)		(17.20)
SIZE	0.0337***	0.0348***	0.0344***	0.0352***	0.0307***	0.0315***
	(5.89)	(6.08)	(7.47)	(7.65)	(6.66)	(6.83)
BTM	-0.0955***	-0.0975***	-0.0751***	-0.0768***	-0.071***	-0.0726***
	(-17.03)	(-17.39)	(-16.93)	(-17.3)	(-15.78)	(-16.12)
LEV	0.0117	0.0079	0.0044	0.0004	0.0139	0.0100
	(0.57)	(0.38)	(0.27)	(0.02)	(0.83)	(0.60)
VOL	0.0102***	0.0103***	0.0093***	0.0093***	0.0088***	0.0087***
	(5.40)	(5.42)	(6.34)	(6.31)	(5.90)	(5.88)
LIQ	-0.0004	-0.0004	-0.0002	-0.0002	-0.001	-0.0011
	(-0.24)	(-0.27)	(-0.14)	(-0.17)	(-0.84)	(-0.88)
AGE	0.0108**	0.0107**	0.0067*	0.0065*	0.0048	0.0046
	(2.50)	(2.47)	(1.82)	(1.76)	(1.28)	(1.22)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	111,114	111,273	115,524	115,691	115,524	115,691
Adj. R-Squared	50.54%	50.43%	50.32%	50.20%	48.04%	47.93%

Appendix B.2 presents the results from specifications using systematic risk or beta (*BM*, *BSW*, and *BSWA*) as the dependent variables, and *NCSKEW* and *DUVOL* as the main independent variables. *NCSKEW* and *DUVOL*, crash proxies, refer to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from expanded model regressions, respectively. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B.3 2SLS Analysis with State-level Crash as an Instrument

	NCSKEW	*BM*	*BSW*	*BSWA*
State_Ncskew	0.1087***			
	(4.66)			
Fitted_Crash		0.225***	0.1906***	0.1662***
		(3.70)	(3.83)	(3.22)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Weak identification test:				
F-Statistic		446.20	465.10	465.10
Hausman endogeneity test:				
p-value		0.00	0.00	0.00
No. of observations	115,391	110,975	115,384	115,384

Appendix B.3 reports the estimation of the two-stage least square (2SLS) specification. In the first stage of regression, we employ *NCSKEW*, which implies the negative coefficient of skewness of residual return acquired from the expanded model specifications, as the dependent variable and *State_Ncskew*, which we calculate through yearly state-level *NCSKEW* by averaging the crashes of firms, excluding firm *i*, in a year *y*, as the main independent variable. In the second-stage models, we regress *Fitted_Crash* acquired from the first-stage specification, on firm beta, for instance, *BM*, *BSW*, and *BSWA*. We add the constant control variables used in the baseline specification. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B.4 Probit Regressions and Propensity Score Distribution following PSM

Panel A: Probit regressions with pre-matched and post-matched samples

	Pre-match	Post-match
SIZE	0.0324***	0.0011
	(12.29)	(0.29)
BTM	-0.3681***	-0.0078
	(-40.93)	(-0.55)
LEV	-0.7409***	0.0088
	(-29.7)	(0.24)
VOL	-0.0317***	0.0037
	(-10.06)	(0.60)
LIQ	-0.0307***	0.0014
	(-15.83)	(0.47)
AGE	-0.1573***	-0.0033
	(-25.5)	(-0.36)
No. of observations	108,374	39,284
p-value of $\chi 2$	0.0001	0.9806
Pseudo R2	0.1630	0.0000

Panel B: Propensity score distribution

Group	Nobs	Mean	Min.	Median	Max.	Std Dev
Treatment	19,642	0.2304	0.0359	0.2341	0.4136	0.0540
Control	19,642	0.2301	0.0359	0.2339	0.4170	0.0538
Difference	19,642	0.0003	0.0000	0.0002	-0.0034	0.0002

Appendix B.4 reports the findings from a probit specification, following which we run regressions on pre-matched and post-matched firms in the treatment and control groups. The dependent variable of the probit specification indicates “1” if the firm falls in the treatment group and “0” if the firm comes under the control group. We employ the constant control variables used in the baseline specification. We present the statistical distribution of the propensity scores of the firms in both treatment and control groups along with their differences.

Appendix B.5 Alternative Measures of Crashes to Check its Effect on Cost of Equity

	RPEG		*RGM*	
NCSKEW	0.0005***		0.0005**	
	(3.14)		(2.21)	
DUVOL		0.0013***		0.0014***
		(3.77)		(2.95)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of observations	25,943	25,961	27,582	27,605
Adj. R-Squared	43.89%	43.84%	39.79%	39.72%

Appendix B.5 presents the results from specifications using cost of equity (*RPEG*, and *RGM*) as the dependent variables, and *NCSKEW* and *DUVOL* as the main independent variables. *NCSKEW* and *DUVOL*, crash proxies, refer to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from expanded model regressions, respectively. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix B.6 Decomposed Beta

	CORR			*RVOL*		
CRASH	0.0061***			0.1690***		
	(5.35)			(4.02)		
NCSKEW		0.0048***			0.0746***	
		(12.62)			(6.34)	
DUVOL			0.0065***			0.0998***
			(9.06)			(4.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	115,691	115,522	115,689	115,691	115,525	115,691
Adj. R-Squared	44.75%	44.83%	44.78%	21.20%	23.04%	21.20%

Appendix B.6 shows the results from specifications using correlation and relative volatility (*CORR*, and *RVOL*) as the dependent variables, and *CRASH*, *NCSKEW*, and *DUVOL* as the main independent variables. *CORR* refers to the correlation between stock and market returns, whereas *RVOL* refers to the ratio of the standard deviation of a stock return and the standard deviation of a market return. *CRASH* denotes '1' if, within its year, a firm encounters one or more firm-specific crashes, and '0' otherwise. *NCSKEW* and *DUVOL*, crash proxies, refer to the negative coefficient of skewness and the down-to-up volatility of residual return obtained from expanded model regressions, respectively. To avert probable reverse causality concerns, we lag independent variables by one year compared to the dependent variables. All specifications utilize firm- and year-fixed effects to control for time- and firm-specific invariant omitted variables. Our robust standard errors are clustered by firm (Petersen, 2009). We parenthesize *t*-statistics under each coefficient. *, **, and *** imply statistical significance at the 10%, 5%, and 1% levels, respectively.

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In which chapter is the manuscript/published work?	Chapter Three		
Describe the contribution that the student and members of the supervisory team have made to the manuscript/published work:[1] Roy and his supervisors mutually agreed on the topic in Chapter UPDATE. Roy gathered and cleaned the datasets. The supervisors advised on appropriate empirical analysis, and Roy conducted this analysis and produced results. In weekly meetings, Roy's supervisors reviewed his findings, answered questions, and provided improvement suggestions. Roy wrote the draft working paper, with his supervisors providing improvement suggestions. Roy wrote the draft working paper, with his supervisors providing improvement suggestions to arrive at the final working paper.			
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Appendix C

For Chapter Three

Appendix C.1 Variable Definition

Variables	Description
CORR	We calculate the Pearson correlation coefficient as follows: $$CORR_{j,y} = \overline{\left[\frac{\sum(ret_{i,j,y}-\overline{ret_i})-(ret_{m,y}-\overline{ret_m})}{\sqrt{\sum(ret_{i,j,y}-\overline{ret_i})^2-(ret_{m,y}-\overline{ret_m})^2}}\right]}$$ where $CORR_{j,y}$ indicates peer firm (non-crash firms) average co-movement (excluding crashed firms in the same industry) of industry *j* in year *y* and we add a bar on top of the correlation equation to indicate the cross-sectional average within the industry. We choose the SIC3 code and Fama-French 48 industry classification to identify peer firms (Fama and French, 1993; Leary and Roberts, 2014). $ret_{i,j,y}$ is the excess return for individual firm *i* in industry *j* in *y* year, and $\overline{ret_i}$ is the average excess return of for firm *i* over *y* years. $ret_{m,y}$ and $\overline{ret_m}$ denote market excess return and the average of market excess return, respectively, in *y* year (Huang, Huang, and Lin, 2019).
ADJR2	We calculate the adjusted R^2. We obtain the adjusted R^2 from the following equation: $$ret_{i,j,y} = B_0 + \beta_1 mret_{m,y} + \varepsilon_{i,j,y}$$ here, we choose the SIC3 code and Fama-French 48 industry classification to identify peer firms (Fama and French, 1993; Leary and Roberts, 2014). We obtain adjusted R^2 from the regression and measure the average peer firm (excluding crashed firms in the same industry) co-movement, which we denote as $ADJR2_{j,t}$, of industry *j* in year *y* (Huang, Huang, and Lin, 2019).

CRASH	It denotes '1' if, within its year, a firm encounters one or more firm-specific weekly $R_{i,y}$ dropping 3.09 or more standard deviations below the mean ($R_{i,y}$) return for its year and '0' otherwise. $R_{i,y}$ = log (1 + $\varepsilon_{i,y}$) for firm i on the week y, projected on weekly return data: $r_{i,w} = \alpha + \beta_1 r_{j,w-1} + \beta_2 r_{m,w-1} + \beta_3 r_{j,w} + \beta_4 r_{m,w} + \beta_5 r_{j,w+1} + \beta_6 r_{m,w+1} + \varepsilon_{i.w}$ where, for firm *i* and on the week w, $r_{i,w}$ is a firm's unadjusted return; $r_{j,w}$ is the Fama and French value-weighted industry (j, to which firm *i* belongs) return; and $r_{m,w}$ is the CRSP value-weighted market return on the week *w* (Hutton, Marcus, and Tehranian, 2009).
SIZE	Log of market capitalization (Kim, Lee, and Zhu, 2022).
BTM	It represents the ratio of the book value (BKVLPS) to the market value (PRCC_F) of a firm (Gomes, Kogan, and Zhang, 2003).
VOL	It denotes the log of trading volume (Ma, Marshall, Nguyen, Nguyen, and Visaltanachoti, 2022).
SDRET	It captures the standard deviation of weekly returns in a year (Huang, Huang, and Lin, 2019).
LGAGE	It measures the log of the number of years since the stock's initial recording on the financial market (McAlister, Srinivasan, and Kim, 2007).
ATTENIND	It refers to the search volume index for individual stocks and is a proxy for investor attention. It is a total search frequency from Google Trends based on stock ticker (Da, Engelberg, and Gao, 2011). We calculate the average monthly search frequency as an annual search volume index measure in a year. To capture industry-level investor attention, we measure the log of the Google search volume index on non-crashed peer firms.
INDANAF	It denotes the average of the log of an average number of analysts following for non-crashed peer firms. We follow Fang and Peress (2009) and calculate the firm-level analyst following.
INDINSOW	It measures the average percentage of institutional ownership for non-crashed peer firms.

INDILLIQ	It denotes the average of firm-level illiquidity for non-crashed peer firms. We follow Brogaard, Li, and Xia (2017) and compute the yearly mean of the daily ratio between the absolute stock return value and the dollar trading volume. Then, we multiply that by a million.
MFHS	We adopt the methodology proposed by (Edmans, Goldstein, and Jiang, 2012) to assess mutual fund outflow pressure, which relies on hypothetical stock sales. This approach quantifies the hypothetical yearly sales of a firm *i*'s stock by mutual funds facing substantial outflows during each year *y*. A comprehensive explanation of the variable's calculation process can be found in Appendix C of Dessaint, Foucault, Frésard, and Matray's (2019) work.

Appendix C.2 Alternative Measures of Crash

Panel A: *NCSKEW* as an alternative crash proxy				
	SIC3		Fama-French48	
Dependent variable:	*CORR*	*ADJR2*	*CORR*	*ADJR2*
NCSKEW	0.0012***	0.0008***	0.0015***	0.0010***
	(6.99)	(5.94)	(6.62)	(5.72)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of Observations	142,968	142,968	142,968	142,968
Adj. R-Squared	67.66%	69.43%	60.25%	62.42%

Panel B: *DUVOL* as an alternative crash proxy				
	SIC3		Fama-French48	
Dependent variable:	*CORR*	*ADJR2*	*CORR*	*ADJR2*
DUVOL	0.0019***	0.0011***	0.0023***	0.0014***
	(5.97)	(4.61)	(5.45)	(4.54)
Control variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
No. of Observations	143,193	143,193	143,193	143,193
Adj. R-Squared	67.61%	69.38%	60.20%	62.37%

This table presents the results from equation (3) using peer firms' co-movement (*CORR*, and *ADJR2*) as the dependent variables, which are divided into two groups by the SIC3 and Fama-French48 industry classifications, and *NCSKEW* and *DUVOL* as the main independent variables. *NCSKEW* and *DUVOL* represent the negative coefficient of skewness and the down-to-up volatility of residual return captured from expanded model specifications, respectively. To prevent possible reverse causality issues, all independent variables are lagged by one year relative to the dependent variables. We include firm- and year-fixed effects to address the concern for time- and firm-specific invariant omitted factors. We parenthesize *t*-statistics under each coefficient. Our robust standard errors are clustered by firm (Petersen, 2009). *, **, and *** suggest statistical significance at the 10%, 5%, and 1% levels, correspondingly.

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