The effect of peer information environment on stock price crash risk

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Abstract

This study explores how the peer information environment affects a focal firm's stock price crash risk. Using peer analyst coverage as a proxy, I find that the peer information environment is negatively associated with the focal firm's stock price crash risk. This result remains robust to alternative estimation techniques. This finding is consistent with the view that peer information plays a vital role in conveying information to managers and shareholders, reducing information asymmetry. The finding also supports the view that peer information serves as a monitoring mechanism in reducing principle-agent issues. Moreover, I find that larger peer firms and more relevant peer firms tend to strengthen the relationship between the peer information and focal firms' stock price crash risk. Peer information also tends to enhance the relationship between the focal firm's information environment and its crash risk. This study delivers meaningful insights into the emerging literature on peer effects in corporate finance by providing a different angle on the determinants of crash risk. This study also has important practical implications for corporate managers, investors, and regulators interested in the changes in corporate policies and decisions by incorporating peer information.

Keywords: Peer effects, Peer information environment, Stock price crash risk, Managerial learning, Agency theory.

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1. Introduction

A battery of literature documents how corporate managers make decisions based on their own information (Edmans, Goldstein & Jiang 2012; Dow, Goldstein & Guembel 2011; Foucault & Gehrig 2008; Bresnahan, Milgrom & Paul 1992), where the research on peer information has been overlooked. It has been documented that peer firms' information plays vital roles in shaping both the financing and investment decisions of a firm (Graham & Harvey 2001). Besides, the internal information of peer firms, such as stock price (Foucault & Fresard 2014; Ozoguz & Rebello 2013) and the quality of accounting information (Beatty, Liao & Yu 2013), are found to be positively associated with corporate decisions, such as investment decisions. Supported by this evidence, these studies highlight the learning motivation theory that corporate managers learn the information of their peers in their own firms' decision-making objective function.

Recent research finds evidence of such peer effects in corporate decisions across firms. In decision-making, managers often rely more on available peer information relative to their own information to form their decisions (Leary & Roberts 2014). Such a phenomenon highlights the importance of a peer information environment and views peer information as a substitute for own firm information (Shroff, Verdi & Yost 2017). This supports the learning from peer theory that managers use peer information to make decisions for their firms. Relying upon quantitative data of U.S. public firms, this empirical study establishes the connection between firms and their peers by examining the influence of peer information environment on a firm's stock price crash risk. Extensive research on stock market extreme negative events has been conducted in the last decade, suggesting crash risk theory as a result of managerial agency issues in concealing bad news. Crash risk represents a sudden and tremendous drop in the stock price of a firm, due to the tendency of management to hoard and accumulate bad news (Hutton, Marcus & Tehranian 2009). Such managerial behaviour leads to potential agency issues and conflicts, including the disclosure of private information especially bad news. While Kothari, Shu and Wysocki (2009) view career and compensation as the primary motivation for such behaviour, Ball (2009) suggests that the esteem of peers drives this tendency. The bad information is stockpiled to its upper limit, and it becomes too costly that the bad news can be further accumulated; all the hidden bad information will reveal itself all at once, resulting in a significant negative stock price movement, known as a crash (Jin & Myers 2006). This study is motivated by the aforementioned theory of peer learning motive, and the recent effort by academics in predicting the likelihood of stock price crashes. First, anecdotal evidence exists on corporates learning from peer information. There is also a battery of research predicting the negative news hoarding theory of crash risk, which relates to managerial agency behaviour when facing adverse information. This study extends the literature by combining these lines of research. Second, Ball (2009) suggests that peer firms tend to drive the incentives for managers to conceal negative information, implying that the peer-learning motive can be extended to such agency behaviour of bad news hoarding. While most of the literature focuses on the determinants of the crash risk of firms themselves, this study tends to attest to this possibility by examining whether the crash risk of a firm is, in part, driven by the information environment of peer firms.

With a large sample of U.S. public firms over the period 1996 – 2018, this study finds that a firm’s stock price crash risk is negatively associated with the information environment of its peer firms, after controlling for various firm characteristics and fixed effects. This indicates that a better peer information environment, measured by a higher level of peer analyst coverage, reduces the likelihood of a focal firm’s stock price crashes. This is consistent with the conjecture that information disseminated by peers serves as a monitoring mechanism, reducing the information asymmetry between managers and shareholders of a firm and disincentivizing managers to hide bad news. This result remains robust to the two-stage least square (2SLS) estimation technique, using the proportion of broker exit events experienced by the peer firms as instrumental variables. The main result also remains robust with alternative model specifications, alternative peer information measures, and alternative industry classification.

After establishing the negative relationship between peer information and the stock price crash risk of focal firms, this study further examines whether this relationship varies with peer characteristics. The cross-sectional tests reveal that the size of peer firms and the relevance of a peer firm with the focal firm tend to strengthen the relationship between peer information and a focal firm's stock price crash risk. This indicates that larger peer firms and more relevant peer firms tend to represent more effective information dissemination to influence the focal firms, compared to the smaller and less relevant peer firms. The results from the robustness test also discover weaker evidence of the relationship between peer information and focal firms' stock price crash risk when a larger number of highest-ranked TNIC peer firms are included as the proxy for peer information.

To shed light on the role of peers in information dissemination, this study also examines the effect of peer information on the relationship between a focal firm's information environment and its crash risk. The cross-sectional analysis discovers that focal information itself tends to have no effect in reducing a focal firm's crash risk. The information environment needs to be supplemented by peer information to reduce the exposure of stock price crashes. This indicates that peer information serves as supplementary information to focal firms, which enhances the information set of focal firms' managers and shareholders, and reduces focal firms' stock price crash risk.

This study contributes to the literature in two ways. First, linking peer information environment with stock price crash risk contributes to the literature on peer effects by providing an additional peer-driven angle on corporate financial management issues. This study also contributes to the stock price crash risk literature, by providing a different angle of crash risk determinants relating to peer firms. For instance, the existing literature to date has examined various determinants of stock price crash risk at an individual firm level, such as managerial incentives (Kim, Li & Zhang 2011b; Kothari et al. 2009; Ball 2009), financial reporting, and corporate disclosures (Kim, Li & Zhang 2011a; Desai & Dharmapala 2006), capital market transactions (Chang, Chen & Zolotoy 2017), competition (Li & Zhan 2019; Callen & Fang 2017) and social aspects (An et al. 2018; Chen et al. 2018; Callen & Fang 2015). However, these studies are conducted on a firm-level basis, focusing on the firm's characteristics and fundamentals on its own crash risk. To my best knowledge, the impact of the peer information environment on a firm's crash risk has not yet been explored.

Second, in the field of peer information environment, most of the relevant research employs industry averages as measures for peer information. For example, Shroff et al. (2017) measure peer information using the average earnings synchronicity within an industry and the percentage of public firms operating in the industry, treating all peer firms equally in their regression analyses. Subsequently, results reveal only the average impact of peer information, which can be biased when the less (more) relevant peers are over-weighted (under-weighted). Further, most literature classifies peers by a fixed industry classification such as the three-digit North American Industry

Classification System (NAICS) or Standard Industrial Classification (SIC) code industries. This approach may not capture the situation when firms move across industries in a timely manner. In identifying peer firms, the empirical design in this chapter will employ a variable industrial classification - Text-Based Network Industry Classification (TNIC) database provided by Hoberg and Phillip (2010, 2016).[1] This database differentiates the highly relevant peers from the less relevant peers, not only based on the same industry, but also similar product descriptions.[2] It is rational to expect that a firm tends to only follow the closely related peer firms, not all peer firms. One of the findings of this study suggests that more relevant peers enhance the relationship between peer information and focal firms' stock prices. The results from the robustness test also discover weaker evidence of the relationship between peer information and focal firms' stock price crash risk when a larger number of highest-ranked TNIC peer firms are included as the proxy for peer information. The frequently updated TNIC is a timely reflection of the competition among peers identified using this approach. Therefore, the empirical outcomes of this study are unique in providing a better understanding of the role of peer information on focal firms' stock price crash risk.

Lastly, this study also has useful practical implications. Managers tend to take peer information into consideration when making corporate decisions. Knowing this,

[1] TNIC is a time-varying peer classification, in which a pair of firms are classified as peer based on the product similarity score. The product similarity scores for each pair of firms are constructed based on the text-based analysis of 10-K's mandatory product description section, and thus take the consumer preferences and demand into account. This year-by-year peer classification is as opposed to the fixed industry classification such as SIC and NAICS industries, which react slower to industry or product changes in firms (Hoberg & Phillips 2016, 2010).

[2] With the feature of variable industry classification, each firm can have its own industry. For example, firm A and B are identified to be the peer firms (or competitors) to firm C separately, but at the same time both firm A and B are not classified as peer firm to each other. This is as opposed to the fixed industry classifications such as the SIC and NAICS which would classify all three firms as peers (Hoberg & Phillips 2010).

the study raises the investors' awareness of the importance of peer information and reflect them on their individual investment agenda. In a similar manner, it is critical that corporate managers obtain a deep understanding of the significance of peer information, which affects their firm value via information disclosure and reactions from market participants. Understanding market participants' responses to peer information is another important takeaway from this study. This study also delivers regulatory implications by demonstrating that information disclosure and decision of firms also affect their peers, which is potentially likely a source of systematic risk.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 states the research questions, hypotheses, and rationales. Section 4 describes the data. Section 5 outlines the empirical design. Sections 6 and 7 report the empirical results of the baseline regression and cross-sectional analyses, respectively. Section 8 discusses the additional tests and robustness checks. Section 9 concludes the study.

2. Literature review

The relevant literature is classified in three strands. The first is the peer effect literature that investigates the phenomena of “herding behaviour” in the way corporations “mimic” the actions or decisions of their peers rather than making independent decisions. Within the literature on peer effect, a smaller subset is the effect of peer information, which investigates the impact of information sharing and dissemination among peers on the financial markets, decisions, and firm behaviours. As such, the second strand of literature articulates the relevant studies that consider information provided by peers as well as information disseminated by peers’ external stakeholders. The third strand of literature focuses on studies pertinent to the issues of stock price crash risk.

2.1 Peer Effect – The Herding Behaviour

Peer firms tend to “mimic” the actions or decisions of each other, and studies have documented that such peer effects are more important in a firm’s decision-making process than other determinants (Leary & Roberts 2014; Foucault & Fresard 2014). Graham and Harvey (2001) highlight the importance of peer firms in shaping both the financing decisions and capital budgeting decisions of a firm. Frank and Goyal (2009) show that the industry average leverage, which reflects the leverage ratios of all peer firms, is an important factor in a firm’s capital structure. Further, Leary and Roberts (2014) extend the importance of peer firms' financing decisions by suggesting that the financing decisions are affected, to a larger extent, by the financing decision of peer firms and, to a lesser extent, by its existing fundamentals. Particularly, the authors find that peer firm equity shocks strongly negatively (positively) affect a firm’s debt (equity) issuance decisions, a result arising from managers’ learning motives. Kaustia and Rantala (2015) also report such peer effects in firms’ decisions to split their stocks. A relevant study by Bustamante and Fresard (2021) documents the complementarity of investment decisions among product market peers, showing that firms' investment decisions are influenced by the investment activities of their peers. Similarly, Machokoto, Gyimah, and Ntim (2021) highlight significant peer effects on corporate innovation, revealing leader-follower dynamics where firms tend to follow or adopt the innovation policies of their peers. In a further extension of this research, Machokoto et al. (2024) broaden the scope to include firms across different countries, examining how peer effects on innovation and investment transcend national boundaries.

There also exist peer effects in firms' dividend policy. Grennan (2019) demonstrates evidence of dividend policy changes by a firm in response to peer changes, which include payment increases and speed of implementing dividend changes. Besides, firms tend to mimic their peers' social aspects, such as CSR policies in Cao, Liang and Zhan (2019). The study establishes that the CSR policy and its adoption by a firm result in similar adoption by its peer firms, motivated by a strategic response to the competitive threat within the same product market (Cao et al. 2019). Further, such herding phenomena have also been discovered in the options market. Decaire, Gilje, and Taillard (2020) find that the likelihood that a firm exercises a real option is related to peer exercise behaviour. Gyimah, Machokoto, and Sikochi (2020) document the mimicking behaviour in formulating trade credit policies. Another stem of research documents the peer effect in CEO compensation policy. Several studies of peer effects in CEO compensation find that firms tend to pick peers that pay higher compensation to their CEO in benchmarking their compensation scheme against the chosen peers, known as the peer pay effect (Faulkender & Yang 2010; Bizjak, Lemmon & Naveen 2008). In the context of executive compensation contracts, Gong, Li, and Shin (2011) and Albuquerque (2009) examine the adoption of relative performance evaluation (RPE) in the selection of peers. Subsequently, Albuquerque, De Franco and Verdi (2013) decompose the peer selection effect and find that such peer pay effect not only reflects a self-serving behaviour but also represents a reward for unobserved CEO managerial talent.

Peer effect in disclosure policy is also evident. Evidence has demonstrated that a firm’s voluntary disclosure policy is driven not only by the firm’s information itself but also by the information about other firms operating within the same industry (Seo 2020; Dye & Sridhar 1995). Tuo, Yu and Zhang (2020) find that firms tend to increase their disclosure frequency and horizon in response to that of industry peers. Tse and Tucker (2010) document evidence of managerial herding instinct in disclosure decisions, especially during firms’ earnings shortfalls in response to the information and disclosure decisions of peer firms. Kedia, Koh, and Rajgopal (2015) suggest that firms tend to manage their earnings in response to the public announcements of accounting restatements by their peers within the same industry. Segmenting firms into regulated and unregulated firms, a recent study conducted by Breuer, Hombach, and Muller (2020) compares both firms’ mandatory and voluntary disclosures and reports that unregulated firms’ voluntary disclosures decrease with an increase in regulated peer firms’ voluntary disclosure. These studies illustrate the “herding” phenomenon that peer firms tend to mimic the actions, behaviours, and decisions undertaken by each other.

In terms of what constitutes a “peer”, there are a number of approaches used from the existing literature to this definition. While it is intuitively appealing to define peer groups by the firms’ three-digit SIC industry code, peer firms are most commonly identified using the Hoberg-Phillips industry classification in the last decade. This measurement is based on similarity in the firms' product text descriptions (Hoberg, Phillips & Prabhala 2014; Hoberg & Phillips 2010). This is arguably better in capturing competitive threats between the peer firms and shaping the firms' financial and social policies. Apart from the industry and product market classification, literature in the last decade has documented a variety types of links that classify peers in different definitions such as supply-customer chain (Menzly & Ozbas 2010), choices of sell-side analysts (De Franco, Hope & Larocque 2015), internet co-searches (Lee, Ma & Wang 2015) and a "crowd-of-crowds" approach (Lee, Ma & Wang 2016).[3] The most recent approach includes the common analysts by Kaustia and Rantala (2020) and news-based links that classify firms based on news co-coverage by Tao, Yim and Han (2020).

2.2 The Effect of Peer Information Environment

Within the literature on peer effect, a smaller subset focuses on the impact of peer information environment on focal firms (i.e., information spillover among peer firms). A firm's information environment refers to the collective body of information available, accessed, and utilized within and around the company, including both internal data possessed and controlled by the company such as accounting reports and disclosures, and the external sources disseminated by the important outside stakeholders, such as analysts and media. On the other hand, the peer information environment focuses on the information available and accessible to a focal company regarding its peers or counterparts in the same industry or product market.

[3] The "crowd-of-crowds" approach combines the internet co-searches and analyst co-coverages (Lee et al. 2016).

Prior research has extensively demonstrated that peer information significantly impacts the decision-making processes of focal firms. For example, corporate managers absorb new information released by their peers in making more informed investment decisions (Roychowdhury, Shroff & Verdi 2019). Using the industry averages, Shroff et al. (2017) find that a firm's cost of capital is negatively associated with the information environment of its peers, thereby improving investment decision-making. Further, there is also literature on such information spillover effect of rivals' tone of Management Discussion and Analysis (MD&A) disclosure (Durnev & Mangen 2020) and corporate restatement announcement (Durnev & Mangen 2009) for corporate investment.[4] Gordon, Hsu, and Huang (2020) find that peer voluntary disclosures about R&D are associated with greater innovation in firms. The studies mentioned earlier suggest that corporate investment decisions can also be influenced by peer accounting information and disclosures, apart from a firm's own accounting information and peer stock prices.

Foucault and Fresard (2014) examine the effect of peer firms' stock price informativeness on investment decisions. The authors find a positive relationship between a firm's investment and a peer's valuation, whereby the investment sensitivity to the peers' valuation is about half the sensitivity of their valuation. This implies that corporate executives learn from their peers and consider the peers' stock price information in their own investment decisions (Foucault & Fresard 2014). Regarding fraud in accounting reporting, Beatty et al. (2013) examine the potential spillover effect on the investment of high-profile firms and find greater capital expenditures by peers

[4] MD&A is a mandatory subsection of the annual financial report of a public-listed firm which reviews the company's performance. This subsection of the report often discusses the opinions and views of the management on the company and is not audited. Waymire (2004) provides a discussion on the usefulness of MD&A disclosures. The language and tone used in MD&A is used when measuring a company's report readability (Li 2008; Lo, Ramos & Rogo 2017).

during the scandal period with a larger magnitude of earnings overstatement by a firm, compared to the non-scandal period. However, this relationship only holds in firms with a poorer information environment. On the other side, Li (2016) finds that this effect does not necessarily apply only to high-profile firms, but it is also found to be similar in smaller firms. These results focus on firms across all sizes and suggest that larger peer firms also react to the accounting report quality of smaller firms. This argument is consistent with Fiegenbaum and Karnani (1991), who document that competitive advantage can present in smaller firms, which could flow from other channels such as output flexibility and innovation.

A spillover effect in corporate investment is also evident in the setting of mergers and acquisitions. McNichols and Stubben (2014) document that the quality of a target's disclosure of accounting information has a positive effect on the acquirer's profitability. In the event of a hostile takeover, the target firms tend to utilize their information disclosure strategy that emphasizes their own bad news in order to influence the potential peer acquirers (Chen, Miao & Valentine 2020). Apart from the studies mentioned above, there is also other related research on the effect of peer information, such as loan pricing (Bao 2020), audit pricing process (Fang et al. 2020), and corporate voting (Li, Ng & Wu 2018). Recent evidence uncovers a negative peer disclosure (NPD) phenomenon in peers, where firms tend to publicize bad information about their peers when facing a competitive threat, and such tendency of NPD increases with the degree of product market rivalry (Cao, Fang & Lei 2021).

Most research reviewed in this literature emphasizes the significance of peer firms' internal information, often possessed and disseminated by the firms themselves. However, external stakeholders also play a crucial role in providing valuable information about a company. This study examines the impact of the peer information environment, particularly information provided by peers' analysts, on stock price crash risk (resulting from bad news hoarding behaviour by management). The findings in this study about the effect of peer information tend to complement the recent and growing research about managerial learning, showing that managers rely on peer information in making their corporate decisions. This study also demonstrates the importance of peer information, particularly the information disseminated by peers' external stakeholders, such as analysts, that could also attenuate information asymmetry between the focal firm and external stakeholders.

2.3 Stock Price Crash Risk

Corporate scandals and financial crises such as Enron, WorldCom, Xerox, and Fannie Mae, have resulted in a tremendously sudden drop in firms' asset prices. Stock price crashes are viewed as a consequence of the accumulated firm-specific negative news previously concealed by management until it reaches its tipping point and is released all at once into the market, leading to large and sudden price drops (Hutton et al. 2009; Bleck & Liu 2007; Jin & Myers 2006). There exists a battery of research conducted in exploring the determinants of crash risk. Habib, Hasan, and Jiang (2018) provide a systematic review of the relevant literature and synthesize various crash risk determinants into the following categories: (i) managerial incentives; (ii) financial reporting and corporate disclosures; (iii) competition threats; (iv) capital market transactions; and (v) social aspects which include political connections and religiosity.

Managerial incentives could drive bad news hoarding behaviour. While Kothari et al. (2009) suggest that managers hide bad information to keep their current jobs. Ball (2009) indicates that the tendency to hoard bad news results from peers' esteem.

Kim et al. (2011b) investigate equity-based executive compensation as a determining factor of crash risk, and find that the strength of CFO's option incentives is significantly and positively related to the firm's future stock price crash risk. However, studies of CEO's option incentives report only weak positive evidence (Kim et al. 2011b; Burns & Kedia 2006), implying that CFOs are more influential in firms' bad news hoarding decisions than CEOs. This is consistent with the survey evidence in Graham, Harvey, and Rajgopal (2005). In the same spirit, He (2015) examines the impact of CEO inside debt on crash risk. A higher proportion of inside debt relative to equity provides CEOs with more incentive to manage their firms better and commit to a higher level of reporting quality. Consistently, He (2015) finds a negative relation between the inside debt and stock price crash risk.[5]

The quality of the financial reporting environment is linked with stock price crash risk. Studies have demonstrated that stock price crash risk decreases with a higher quality reporting environment as a result of mandatory accounting reporting standard (DeFond et al. 2015), adoption of CSR policy (Kim et al. 2014), and a reduced magnitude of earnings management (Callen & Fang 2015). Tax avoidance activities facilitate managerial opportunism in bad news hoarding by management also result in higher future crash risk (Kim et al. 2011a; Kim & Zhang 2010; Desai & Dharmapala 2006). Besides firms' reporting environment, there exists ample evidence that relates crash risk to external corporate governance mechanisms. Callen and Fang (2013) document a negative association between institutional investor stability and crash risk. An and Zhang (2013) distinguish between long-term dedicated institutional investors and short-term transient institutional investors and find that corporate managers tend

[5] Inside debt represents a firm's exogenous obligation of future payments to CEOs, usually exists in the form of pensions and deferred compensation. Such compensation is viewed as motivation for managers to exert high level of efforts and commit to high-quality financial reporting (He 2015).

to conceal bad news to prevent short-termism transient investors from disposing of shares. Financial analysts also play an important role as a governance mechanism in gathering and synthesizing information about the firms they follow. However, studies on the effect of financial analysts on crash risk reach mixed conclusions. With analysts gathering and disseminating firm-specific information, which then mitigates information asymmetry between the insider managers and outside investors, Kim et al. (2011a) find evidence of crash risk exacerbation in companies with less analyst coverage. On the other hand, both passive and active managers face pressure to meet and beat analysts' expectations. This creates opportunities for managers to display short-termism behaviors and conceal bad news (Irani & Oesch 2016; He & Tian 2013). Using media coverage as an alternative proxy for a firm's information environment, An et al. (2020) document its negative impact on crash risk.

Competition threats posed by rivals exert influence on stock price crash risk. Li and Zhan (2019) find that firms with more threats face higher competitive pressures and are more prone to stock crashes. On the contrary, a competing view suggests that higher competition may reduce crash risk due to lower agency costs, as it may be more difficult for managers to conceal bad information (Schmidt 1997). In examining how crash risk is related to the auditor-client relationship, Callen and Fang (2017) find that auditor tenure is negatively related to the firm's crash risk. This supports the monitoring-by-learning theory that a longer relationship enables auditors to 'know their client' better and detect and deter any bad news-hoarding behaviour by the management. Dai, Duan, and Ng (2019) find that intense competition from rivals with similar products supplied to common clients contributes to a higher stock price crash risk. This suggests that supplying firms that face greater threats from peers with common clients have more incentives to hoard bad news, increasing their stock price crash risk.

In capital markets, stock liquidity also plays a role in determining crash risk. Maug (1998) and Edmans (2009) discover a higher level of monitoring activity of firm management by blockholders in firms with higher stock liquidity, thereby reducing bad news hoarding and crash risk. Higher stock liquidity improves the flow of information, thus limiting managers in concealing bad news for a period of time (Holden, Jacobsen & Subrahmanyam 2014; Holmstrom & Tirole 1993). On the other hand, Chang et al. (2017) find that stock liquidity exacerbates the crash risk. Managers strategically withhold bad news to prevent downward stock price pressure exerted by short-term institutional investors, attracted by stocks with higher liquidity as the trading costs are low (Fang, Tian & Tice 2014; Porter 1992). According to Chang et al. (2017), this short-term investor channel prevails the blockholder channel for this relationship.

On a social level, religion plays a role in social norms and can influence economic behaviour. Callen and Fang (2015) suggest that religion helps reduce managers' bad news hoarding activities, thereby reducing the stock price crash risk. According to Kothari et al. (2009), individualism is positively related to crash risk. Individualistic managers usually have greater career and compensation concerns, enjoy a higher degree of autonomy, which provides them with self-governance flexibility (Han et al. 2010; Gray 1988), and have a strong self-enhancement tendency (Markus & Kitayama 1991), which motivates managerial bad news hoarding. In an international study, An et al. (2018) document that individualism can be transmitted by foreign investors from their home countries. The authors also examine other cultural dimensions such as power distance countries, masculine/feminine countries, and uncertainty-avoidance countries, and all yield consistent results.

Most of the literature summarized above emphasizes analysing factors contributing to stock price crash risk within individual firms. These studies primarily investigate firm-specific characteristics and fundamentals that influence the firm's crash probabilities. However, there is a notable gap in exploring the impact of external information from peer firms, disseminated by significant external parties, which has received limited research attention. This study aims to address this gap by investigating how the external information from peer firms, especially that provided by financial analysts, impacts the managerial behaviour of withholding negative news by focal firms, thereby adding to the crash risk literature by introducing a unique perspective on crash risk determinants relating to peer firms.

3. Research Questions, Hypothesis Development, and Rationales

Managers are hired as the key decision-makers on behalf of the shareholders. Underpinning this feature is the agency theory, which suggests that conflicts could occur when managers' decisions deviate from the general interest of shareholders. Driven by various factors such as managerial incentives (Kothari et al. 2009), information environment (An et al. 2020; Irani & Oesch 2016), and rival threats (Dai et al. 2019), managers tend to retain and hoard bad news. When the accumulated bad news reaches its capacity for which the bad news could contain, it reveals itself all at once, resulting in stock price crashes (Hutton et al. 2009). Information asymmetry plays a significant role in stock price crashes. For example, Kim et al. (2014) find that a less transparent information environment, characterized by a drop in financial analyst coverage, could significantly increase the risk of stock price crashes. This is because financial analysts are expected to reduce information asymmetry between investors and managers by disseminating their forecasts, drawn from both public and private sources to the broader market.

On the opposite side of the argument, greater analyst coverage attracts increased investor attention. It elevates the significance of analyst forecasts as benchmarks for managers, which could create market pressure for corporate managers to meet or beat the forecasts, fostering a culture of hoarding bad news. This heightened coverage might intensify the pressure on managers to prioritize short-term performance overly (Habib et al. 2018; Irani & Oesch 2016; He & Tian 2013). The effect of analysts' coverage on bad news hoarding activities can be twofold. Is there a role played by the peer information environment in the bad news hoarding activities of a company? This study examines the cross-firm crash analysis on whether the crash risk of a firm is, in part, driven by the information environment of peer firms. Therefore, the research question is as follows:

Research Question (RQ1): Does the peer information environment affect the crash risk of a firm?

While most of the literature focuses on discovering the determinants of bad news hoarding at the firm level, which results in the firm's stock price crashes, the question of whether such bad news hoarding behaviour could be influenced by peer information environment, is under-researched. Peer firms are interconnected and exposed to similar economic forces, including market demand and supply shocks. To maintain competitiveness, decisions made by a firm's manager can affect the decisions made by the managers of peer firms via the learning motive.[6] Peer information provides deeper insights into the competitive product market in which these firms function. Arguably, this information about the peers provided by external entities such as the analysts could further mitigate information asymmetry between focal firms' investors and managers, thereby reducing managerial bad news hoarding activities.[7]

On the other side of the argument, peer firms operating in the same product market face intense competition. Analysts providing insights about these peer firms might inadvertently intensify market pressure on corporate finance. This pressure arises from the comparison between the focal firm's performance and the forecasts or

[6] For example, it has been widely researched that managers learn from their peers' information in forming their own investment decisions (Foucault & Fresard 2014), capital structure (Leary & Roberts 2014), cash holdings (Hoberg et al. 2014), executive compensation (Albuquerque et al. 2013) and fraudulent activities in financial reporting (Li 2016; Beatty et al. 2013). Moreover, ample evidence highlights the importance of firms' disclosure on the economic consequences for their peers. Shroff et al. (2017) find that a firm's cost of capital can be affected by peer information.

[7] Analysts' forecasts regarding peer firms are often considered more reliable than the firms' own disclosures. While managers might manipulate earnings or disclosures, analysts are less likely to manipulate their research findings (Bushee, Gow & Taylor 2018).

performance of its peers outlined by the analysts. The need to match or outperform the analysts' forecasts for peer firms can create an environment where managers are driven to meet or exceed these external benchmarks. Ultimately, this perpetuates a culture where managers feel pressured to withhold negative news, fearing potential market repercussions or comparisons with the performance of their peers. To examine the effect of peer information environment on a firm's crash risk, the hypotheses (H1) of this study are established as follows:

H1(a): Ceteris paribus, the crash risk of a firm is negatively associated with the information environment of its peer firms.

H1(b): Ceteris paribus, the crash risk of a firm is positively associated with the information environment of its peer firms.

4. Data

This section describes the data handling and sample selection process. This study presents a panel data analysis focusing on U.S. public firms identified from the Wharton Research Data Services (WRDS) database. The initial sample period spans from 1996 to 2018.[8] Stock price data used to construct various crash risk measures are sourced from CRSP – the Center for Research in Security Prices. The firm-level accounting data are sourced from Compustat. Analyst data are sourced from the Institutional Brokers' Estimate System (I/B/E/S) Detail database via Datastream.[9] The media coverage data is sourced from RavenPack.

In identifying peer firms, this study follows Hoberg and Phillip's (2010) Text-Based Network Industry Classification (TNIC).[10] TNIC identifies pairs of peers based on the textual similarity scores in the product description established in the firms' 10-K annual filed with the Securities and Exchange Commission (SEC).[11] Since the product market is highly dimensional, each firm can have its distinct industry, which can vary in time, analogous to a circle of friends in an individual social media account.[12] Firms are classified as peers for a firm when all these firms belong to its TNIC industry in a given year. Therefore, this peer classification provides time-varying pairs of peers, reflecting the dynamic product market space that changes over time. This is opposed

[8] TNIC data provided by Hoberg-Phillips Data Library is available from 1996 to 2018 when I downloaded it.
[9] Following Kaustia and Rantala (2015), I consider analyst following for a firm in a particular year only if the analyst has provided estimates for the firm in that particular year.
[10] TNIC database is provided by the Hoberg and Phillips Data Library (link: https://hobergphillips.tuck.dartmouth.edu/.)
[11] TNIC is a time-varying peer classification, in which a pair of firms are classified as peer based on the product similarity score. The product similarity scores for each pair of firms are constructed based on the text-based analysis of 10-K's mandatory product description section, and thus take the consumer preferences and demand into account (Hoberg & Phillips 2016, 2010)
[12] For example, it can be possible that firm A and B are identified to be the peer firms (or competitors) to firm C separately, but not directly related to each other.

to fixed industry classifications, such as those of the SIC and NAICS industries, which react slower to industry product changes in firms (Hoberg & Phillips 2016; 2010).

Even though the TNIC database provides a full list of peer firms of a focal firm, in a given year, it is rational to expect that only the highly related peers with higher-ranked TNIC scores are more relevant in the contribution of peer information transfer than the less-related peers with lower-ranked TNIC scores.[13] Analysing the full set of identified peer firms may be biased. Therefore, this study primarily focuses on the top three highest-ranked TNIC peer firms. An identified peer with missing data for analyst coverage is excluded and replaced by the next highest-ranked TNIC peer. In robustness tests, all analyses will be repeated by the following choices of the number of peers: (i) top TNIC peer firm, (ii) top five TNIC peer firms, (iii) top ten TNIC peer firms, and (iv) top 20 TNIC peer firms. Peer classification by three-digit SIC codes will also be tested for robustness.[14]

The data-handing and sample selection process involves a few important criteria. The sample retains (i) firms that are incorporated in the U.S. (i.e., fic = "USA"); (ii) firms with positive book values and total assets; (iii) firms with year-end stock price is $1 or greater; (iv) firms with at least 26 weeks of stock return data available. Only the top three highest-ranked TNIC pairs of the peer are retained. This yields 97,378 firm-peer-year observations over the sample period of 1996 to 2018. After calculating the equal-weighted average of the peer information variable for each focal firm in a

[13] The TNIC scores of firm pairs utilises a minimum threshold of similarity to identify peers that need to be included in the database. The higher the scores, the higher the similarity between the firm pairs. Scores that are close to the lower boundary of zero also means that the firm has exceeded the minimum similarity threshold to be identified as peer firms (Hoberg & Phillips 2016, 2010).

[14] Although derived from conventional SIC code industries, the time-varying TNIC industries are better in capturing competition among peers within the same peer group. Further, TNIC pairwise similarity score is constructed with different intensities; as such, TNIC defined pairwise peer firms may not necessarily be direct competitors to each other (Hoberg & Phillips 2016, 2010).

given year, the sample is left with 34,454 firm-year observations over the sample period of 1996 to 2018.

5. Research Design

This section describes the research design to explore the influence of peer information environment on the stock price crash risk of a focal firm. The primary estimation model employed in this study is the Ordinary Least Square (OLS) regression model.

5.1 Crash risk variables

To construct the crash risk measures, for each firm-year observation, I first obtain the daily stock prices of all U.S. public firms. Next, I estimate the firm-specific weekly returns, which is the natural logarithm of one plus the residuals from the expanded market model (Kim et al. 2011a):

$$r_{i,\tau} = \alpha + \beta_1 r_{m,\tau-2} + \beta_2 r_{m,\tau-1} + \beta_3 r_{m,\tau} + \beta_4 r_{m,\tau+1} + \beta_5 r_{m,\tau+2} + \varepsilon_{i,\tau} \quad (1)$$

where $r_{i,\tau}$ and $r_{m,\tau}$ are the returns on stock *i* and value-weighted market index in week τ, respectively. The weekly returns are calculated based on the individual stock price and market index on Wednesday (Jin & Myers 2006). $r_{m,\tau-2}$ and $r_{m,\tau-1}$ ($r_{m,\tau+2}$ and $r_{m,\tau+1}$) are the two lag (lead) terms for annual market return. These lead and lag terms are included to allow for nonsynchronous trading (Dimson 1979). For each firm-week observation, the firm-specific weekly return, $W_{i,\tau}$, is calculated by taking the natural logarithm of one plus the residual return, $\varepsilon_{i,\tau}$, from Eq. (1) (i.e., $W_{i,\tau} = \ln(1 + \varepsilon_{i,\tau})$). Following Hutton et al. (2009), in each firm-year, I define crash (jump) weeks as those weeks during which the firm has firm-specific weekly returns 3.09 standard deviations below (above) the mean firm-specific weekly returns over the year. This level of standard deviation is selected to generate a weekly crash frequency of 0.1% in a normal distribution.

Next, I calculate three commonly used crash risk measures. The first crash risk measure is a variable $COUNT$, which is the difference between the number of crash weeks and jump weeks over a fiscal year. A higher $COUNT$ indicates a higher stock price crash risk, as it represents a higher number of crash weeks relative to jump weeks.

The second crash risk measure is the negative conditional return skewness ($NCSKEW$), which is calculated by taking the negative of the third moment of firm-specific weekly returns for each sample year, divided by the standard deviation of firm-specific weekly returns raised to the third power, for a given firm in a fiscal year. Specifically, $NCSKEW$, for each firm i in year t, is computed as follows:

$$NCSKEW_{i,t} = -\frac{\left[n(n-1)^{\frac{3}{2}} \sum W_{i,\tau}^{3}\right]}{\left[(n-1)(n-2)\left(\sum W_{i,\tau}^{2}\right)^{\frac{3}{2}}\right]} \qquad (2)$$

where $W_{i,\tau}$ is the firm-specific weekly returns; n is the number of firm-specific weekly returns for firm i in a year. The higher the $NCSKEW$, the more left-skewed the distribution of weekly returns, hence the higher the stock price crash risk.

The third crash risk proxy is the down-to-up volatility ($DUVOL$) of firm-specific weekly returns. To measure $DUVOL$, for each firm-year, all weeks with firm-specific weekly returns below the annual mean (i.e., down weeks) and those with firm-specific weekly returns above the annual mean (i.e., up weeks) are separated into two groups, for which standard deviation for these two groups are calculated. $DUVOL$ is then calculated by taking the natural logarithm of the ratio of the standard deviation on the “down” weeks to the standard deviation on the up weeks, as follows:

$$DUVOL_{i,t} = log\left[\frac{(n_u-1)\sum W_{i_d,\tau}^{2}}{(n_d-1)\sum W_{i_u,\tau}^{2}}\right] \qquad (3)$$

where $W_{i_d,\tau}$ ($W_{i_u,\tau}$) represents the firm weekly return of down (up) weeks and n_d (n_u) is the number of down (up) weeks for firm i in year t. In the same spirit with $NCSKEW$, a higher value of $DUVOL$ means a more left-skewed return distribution and reflects a higher stock price crash risk.

5.2 Baseline regression model

H1 links the stock price crash risk of a firm with its peer information environment. To examine this hypothesis, the following Ordinary Least Square (OLS) regression model is employed:

$$FIRM\_CRASH_{i,t} = \alpha_0 + \beta_1 ANALYST\_3PEER_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (4)$$

where $FIRM\_CRASH$ takes one of the crash risk measures, including $COUNT$, $NCSKEW$, and $DUVOL$, as described in Section 5.1. Peer analyst coverage is used as a proxy for the peer information environment. $ANALYST\_3PEER$ is the average information of the top three highest-ranked TNIC peers of focal firm i, identified in year $t-1$, and is calculated as the equal-weighted average of analyst coverages of all three peer firms. Analyst coverage is calculated as the natural logarithm of one plus the number of analysts following.[15]

$\boldsymbol{Controls}$ is a vector of firm-level control variables. Following Kim et al. (2011a), I include (i) Detrended turnover ($DTURN$); (ii) past negative skewness of firm-specific weekly returns ($NCSKEW$); (iii) the standard deviation of firm-specific weekly return ($SIGMA$); (iv) the mean of firm-specific weekly return (RET); (v) firm size ($SIZE$); (vi) market-to-book ratio (MB); (vii) leverage (LEV); (viii) return on asset (ROA); (ix) a

[15] Analyses of top, top five, top ten, and top 20 highest-ranked TNIC peer firms are expanded as robustness tests in Section 2.8.

measure of accrual manipulation ($ACCM$), (x) analyst coverage of the focal firm ($ANALYST\_FOCAL$).[16] All firm-level control variables employed are lagged by one year. $Industry\ FE$ and $Year\ FE$ represent industry and year fixed effects, respectively. The standard errors are clustered at the firm level.

5.3 The expectation for the sign of coefficients

H1(a) conjectures that all else being equal, the crash risk of a firm is negatively associated with its peer information environment; whereas *H1(b) posits the opposite*. Increased peer analyst coverage signifies an elevated level of peer information environment. If this information is effectively transferred to the focal firm, reducing the information asymmetry between the investors and managers, it may lead to a decrease in managerial tendencies to withhold negative news, subsequently reducing stock price crash risk. In this situation, the coefficient of $ANALYST\_3PEER$ is predicted to be negative. However, if this information generates market pressures and in turns encourages bad news hoarding activities in focal firms, it could elevate the risk of a stock price crashes in focal firm. In this situation, the coefficient of $ANALYST\_3PEER$ is predicted to be positive.

For the bucket of control variables, a larger difference among shareholders' opinions is expected to increase the stock price crash risk (Chen, Hong & Stein 2001). It is also expected that firms with a higher past return skewness are likely to have a high return skewness in the subsequent year (Chen et al. 2001). A higher degree of both average firm-specific weekly returns and its standard deviation is expected to affect crash risk positively. This is because stocks with a higher level of return and

[16] The definitions of all variables, including the control variables, are provided in Appendix A.

volatility are more prone to future crashes (Kim et al. 2011a; Chen et al. 2001). The higher the earnings management, the higher the probability of stock price crash risk. The larger the firm, the higher the probability of stock price crashes (Hutton et al. 2009). Growth stocks have a higher future crash risk (Kim et al. 2011a; Hutton et al. 2009). Therefore, crash risk is expected to be positively associated with a higher market-to-book ratio. According to Hutton et al. (2009), leverage and return on asset ratio are negatively associated with crash risk. A higher analyst coverage represents a better information environment of a firm, and hence this is expected to reduce crash risk. For these control variables, I expect a positive coefficient for $DTURN$, $NCSKEW$, $SIGMA$, RET, $SIZE$, MB, and $ACCM$; and a negative coefficient for LEV, ROA, and $ANALYST\_FOCAL$.

6. Empirical Results

6.1 Descriptive statistics

Table 1 reports the key summary statistics for all variables used in the baseline model. The sample contains firm-year observations from 1996 to 2018. As shown in Table 1, the mean values for the dependent variables $NCSKEW$, $DUVOL$, $COUNT$ and $CRASH$ are 0.136, 0.031, 0.065, and 0.260, respectively. These statistics are reported to be larger than that of Chen et al. (2001), indicating that the data sample employed in this study generally has a higher chance of crashes.

This study employs peer analyst coverage as a measure of the peer information environment. It is rational to expect that only the highly related peers (with higher-ranked TNIC scores) are more relevant in contributing peer information transfer than the less-related peers (with lower-ranked TNIC scores). Therefore, this study focuses on the top three highest-ranked TNIC peers. An identified peer with missing data for analyst coverage is excluded and replaced by the next highest-ranked TNIC peer. $ANALYST\_3PEER$ is defined as the equal-weighted average analyst coverage of the top three highest-ranked TNIC peers, identified in year $t-1$, for a focal firm i. The mean value of this variable is reported to be 1.987, suggesting that each focal firm, in year t, has, on average, approximately seven analysts (i.e., $e^{1.987} = 7.3$) covering its peer firms identified by the TNIC database in year $t-1$.

As robustness tests, all regression models are repeated by analyzing the peer effect from the top peer, top five, top ten, and top 20 highest-ranked TNIC peer firms. Table 1 shows that the descriptive statistics for these measurements are similar. The analyst coverage of focal firm, $ANALYST\_FOCAL$, is averaging approximately 1.906, which is higher than that of Kim et al. (2011a) (i.e., 1.217), which replaces the missing analyst data with zero values.

The statistics are generally similar to Kim et al. (2011a) for other control variables. $DTURN$ has a mean value of 0.003, suggesting that the opinion among investors differs about 0.3% on average for each firm. $SIGMA$ and RET are averaging about 5.3% and -17.3%, respectively. These figures are consistent with Kim et al. (2011a), which report 6% and -22.3%, respectively, for both the standard deviation and mean of the firm's weekly returns. $SIZE$ has a mean value of 6.72, which is slightly larger than that of Kim et al. (2011a) (i.e., 5.55), indicating that the firms contained in the sample are generally larger in market capitalization. Market to book ratio (MB), firm leverage (LEV), and return on assets (ROA) have mean values of 3.72, 0.18, and -0.006, respectively (compared to 2.80, 0.21, and 0.01 of Kim et al. (2011a), respectively).

Table 2 presents the Pearson r correlation coefficients of key variables. The crash risk measures are highly correlated with each other, with a minimum ratio of 62.6% among $DUVOL$ and $CRASH$. Both $DUVOL$ and $NCSKEW$, are reported to have the highest correlation (95.6%). The correlation coefficients of the peer information variables are reported to be positive, which seems to contradict the conjecture in H1(a) and in support of H1(b). Nevertheless, the low correlation coefficients of the peer information variables suggest that there is no distinct pattern in the correlation between peer information variables and crash risk variables. Moreover, these correlation statistics do not control for other confounding variables and, therefore, cannot infer a relation. Controlling for other variables, the multivariate analysis following this section will reveal the relation between peer information and stock price crash risk. Among other control variables, the correlation coefficients are expected and generally similar to the literature.

Looking closer at the main independent variable, Table 3 presents the yearly distribution of how $ANALYST\_3PEER$ varies over time. The average value generally increases over time from 1.80 in 1996 to 2.11 in 2017, indicating an improving analyst coverage for the peer firms. This reconciles with Figure 1, illustrating an increasing trend of $ANALYST\_3PEER$. This figure also presents the time series analysis for the alternative measures for peer information, $ANALST\_1PEER$, $ANALST\_5PEER$, $ANALST\_10PEER$, and $ANALST\_20PEER$, for similar increasing patterns, are discovered.

Table 1. Descriptive statistics for RQ1.

This table presents the descriptive statistics for the variables used in the baseline regression. The sample contains firm-year observations from 1996 to 2018 and is based on non-missing values of all variables. To measure peer information environment, $ANALYST\_1PEER$ is defined as the analyst coverage of the highest-ranked TNIC score identified in year $t-1$, for a focal firm i. $ANALYST\_3PEER$, $ANALYST\_5PEER$, $ANALYST\_10PEER$, and $ANALYST\_20PEER$ represent the average analyst coverage of top three, five, ten, and 20 highest-ranked TNIC peers, respectively, identified in year $t-1$, for a focal firm i. All other variables are defined in Appendix A.

Variables	N	Mean	Std. Dev.	5^{th} Percentile	$Q1$	Median	$Q3$	95^{th} Percentile
Crash risk measures								
$NCSKEW$	34454	0.136	1.045	-1.152	-0.413	-0.002	0.476	1.869
$DUVOL$	34454	0.031	0.422	-0.577	-0.238	-0.004	0.252	0.752
$COUNT$	34454	0.065	0.678	-1.000	0.000	0.000	0.000	1.000
$CRASH$	34454	0.260	0.439	0.000	0.000	0.000	1.000	1.000
Peer information variables (one-year lagged)								
$ANALYST\_3PEER$	34454	1.987	0.542	1.099	1.612	1.985	2.367	2.883
$ANALYST\_1PEER$	34454	1.994	0.770	0.693	1.386	2.079	2.565	3.218
$ANALYST\_5PEER$	34454	1.981	0.481	1.177	1.660	1.981	2.308	2.773
$ANALYST\_10PEER$	34454	1.965	0.426	1.258	1.697	1.976	2.245	2.642
$ANALYST\_20PEER$	34454	1.954	0.396	1.309	1.721	1.965	2.202	2.570
Control variables (one-year lagged)								
$DTURN$	34454	0.003	0.095	-0.136	-0.030	0.001	0.032	0.152
$NCSKEW$	34454	0.151	1.047	-1.106	-0.406	-0.001	0.475	1.869
$SIGMA$	34454	0.053	0.028	0.018	0.032	0.047	0.069	0.106
RET	34454	-0.173	0.181	-0.544	-0.234	-0.109	-0.049	-0.016
$SIZE$	34454	6.721	1.824	3.795	5.440	6.664	7.951	9.942
MB	34454	3.723	5.416	0.750	1.455	2.294	3.886	10.374
LEV	34454	0.175	0.175	0.000	0.002	0.141	0.289	0.507
ROA	34454	0.006	0.156	-0.306	-0.006	0.039	0.078	0.159
$ACCM$	34454	0.623	1.062	0.050	0.145	0.306	0.648	2.152
$ANALYST\_FOCAL$	34454	1.906	0.784	0.693	1.386	1.946	2.485	3.178

Table 2. Correlation matrix for RQ1.

This table reports the Pearson r correlation coefficients for the pair-variables. The sample contains firm-year observations from 1996 to 2018 and is based on non-missing values of all variables. To measure peer information environment, $ANALYST\_1PEER$ is defined as the analyst coverage of the highest-ranked TNIC score identified in year $t-1$, for a focal firm i. $ANALYST\_3PEER$, $ANALYST\_5PEER$, $ANALYST\_10PEER$, and $ANALYST\_20PEER$ represent the average analyst coverage of top three, five, ten, and 20 highest-ranked TNIC peers, respectively, identified in year $t-1$, for a focal firm i. All other variables are defined in Appendix A.

		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
$NCSKEW_t$	A	1.00																		
$DUVOL$	B	0.96	1.00																	
$COUNT$	C	0.72	0.72	1.00																
$CRASH$	D	0.64	0.63	0.78	1.00															
$ANALYST\_3PEER$	E	0.02	0.02	0.00	0.01	1.00														
$ANALYST\_1PEER$	F	0.01	0.02	0.01	0.01		1.00													
$ANALYST\_5PEER$	G	0.02	0.03	0.01	0.01			1.00												
$ANALYST\_10PEER$	H	0.02	0.03	0.00	0.02				1.00											
$ANALYST\_20PEER$	I	0.02	0.02	0.00	0.02					1.00										
$DTURN$	J	0.03	0.04	0.03	0.03	-0.01	-0.01	-0.01	-0.01	-0.02	1.00									
$NCSKEW_{t-1}$	K	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.05	1.00								
$SIGMA$	L	-0.05	-0.05	0.00	-0.03	-0.25	-0.19	-0.26	-0.27	-0.28	0.13	0.19	1.00							
RET	M	0.05	0.05	0.00	0.04	0.21	0.17	0.22	0.24	0.25	-0.14	-0.1	-0.96	1.00						
$SIZE$	N	0.12	0.13	0.06	0.06	0.34	0.28	0.36	0.35	0.35	0.04	0.08	-0.53	0.46	1.00					
MB	O	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.05	0.00	0.02	-0.04	0.19	1.00				
LEV	P	-0.02	-0.01	-0.02	-0.03	0.03	0.03	0.40	0.04	0.04	0.03	-0.01	-0.16	0.14	0.16	0.12	1.00			
ROA	Q	0.03	0.02	-0.01	0.00	0.09	0.07	0.09	0.10	0.10	-0.01	0.03	-0.32	0.31	0.30	-0.02	0.03	1.00		
$ACCM$	R	0.00	0.00	0.01	0.01	-0.02	-0.02	-0.03	-0.03	-0.04	0.01	-0.01	0.14	-0.13	-0.06	0.11	-0.10	-0.17	1.00	
$ANALYST\_FOCAL$	S	0.09	0.10	0.05	0.05	0.36	0.30	0.37	0.36	0.35	0.01	0.10	-0.35	0.32	0.78	0.13	0.12	0.17	-0.03	1.00

Table 3. Sample distribution for peer information.

This table presents the yearly distribution of observations and the descriptive statistics for the average analyst coverage of the top three highest-ranked TNIC peer firms, $ANALST\_3PEER$. The sample contains 34,454 firm-years observations from 1996 to 2018.

Fiscal year	Number of firms	Mean of $ANALST\_3PEER$
1996	1,423	1.80
1997	1,540	1.77
1998	1,548	1.80
1999	1,616	1.80
2000	1,608	1.77
2001	1,533	1.82
2002	1,706	1.82
2003	1,654	1.93
2004	1,637	2.00
2005	1,608	2.00
2006	1,571	2.06
2007	1,514	2.00
2008	1,603	1.95
2009	1,633	2.03
2010	1,573	2.10
2011	1,541	2.15
2012	1,562	2.19
2013	1,544	2.20
2014	1,523	2.17
2015	1,506	2.16
2016	1,511	2.13
2017	1,500	2.11
Total	34,454	1.99

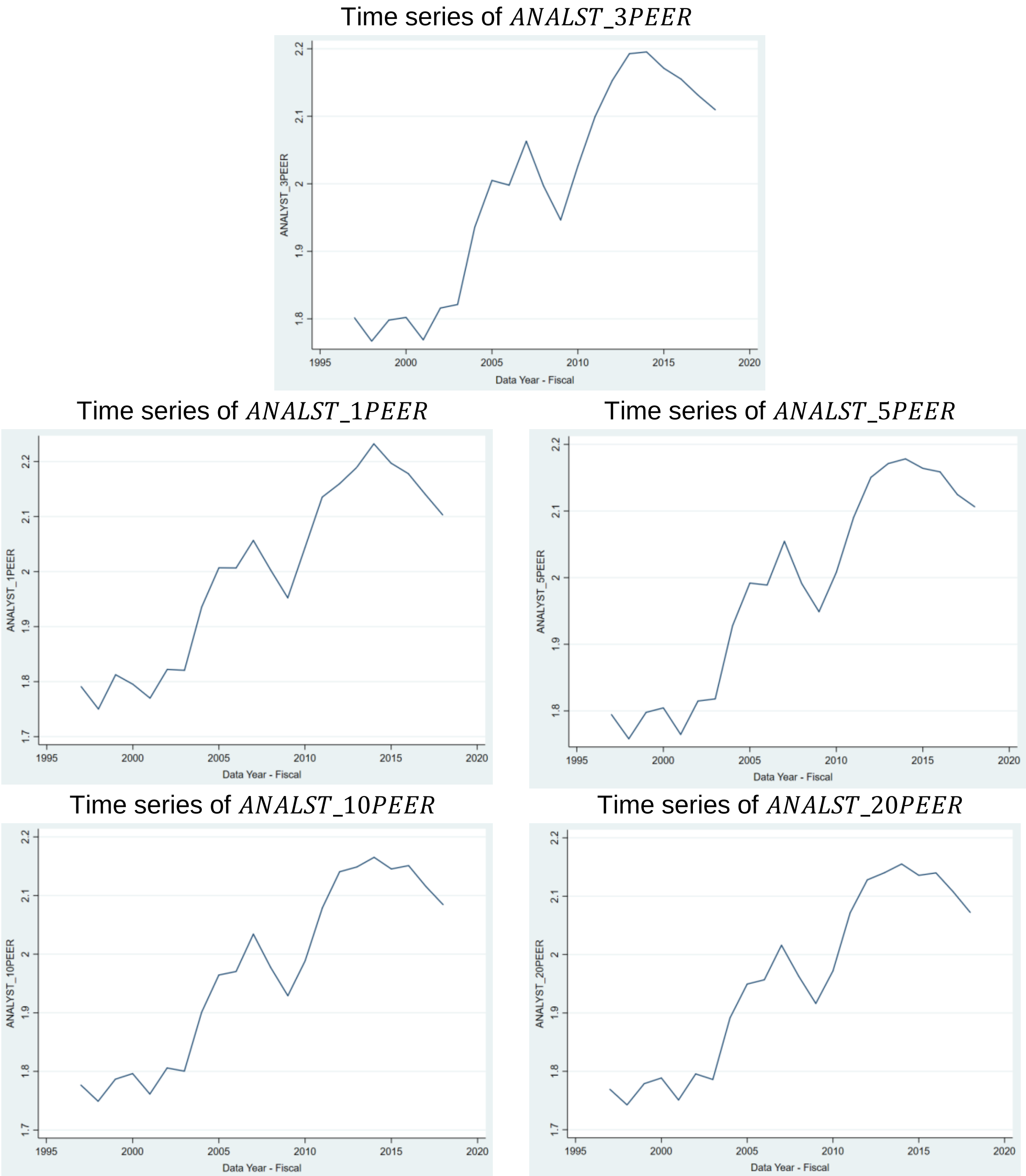

Figure 1. Time series analysis of peer information measures. This figure presents the yearly distribution of the main independent variable, peer information environment. Peer information is measured by the average analyst coverage of the top ($ANALST\_1PEER$), top three ($ANALST\_3PEER$), top five ($ANALST\_5PEER$), top ten ($ANALST\_10PEER$), and top 20 ($ANALST\_20PEER$), highest-ranked TNIC peer firms. The sample contains 34,454 firm-year observations from 1996 to 2018.

6.2 Baseline results

Hypothesis H1 relates a firm's stock price crash risk to the peer information environment, proxied by the analyst coverage of its peer firms. Table 4 presents the OLS regression results. The dependent variable is stock price crash risk, measured by $NCSKEW\ DUVOL$, and $COUNT$, as described in Section 5.1. The independent variable of interest is peer analyst coverage, $ANALYST\_3PEER$, which is defined in Section 5.2.

In Table 4, Columns (1), (3), and (5) document the parsimonious results using $NCSKEW$, $DUVOL$, and $COUNT$ as the dependent variables, without including industry- and year-fixed effects, respectively. Columns (2), (4), and (6) report the regression results by incorporating the industry and year fixed effects. All model specifications are based on standard errors clustered by firm. As shown in Columns (1) to (6), the estimated coefficients for $ANALYST\_3PEER$ are all negative and statistically significant at less than 5% level (t-statistics of -4.562, -3.050, -4.027, -2.859, -3.220, and -2.127, respectively), consistent with H1(a). These results indicate that holding all else constant, more informative peer firms are associated with lower stock price crash risk of a focal firm. This result is consistent with the story of information asymmetry mitigation, that a higher level of peer information, characterized by higher analyst coverages, tends to alleviate information opaqueness in the environment of focal firm, thereby reducing the probability of stock price crashes.

Table 2 reports positive correlations between peer information variables and crash risk measures. This could be due to a high correlation between peer analyst coverage and focal analyst coverage. To address this potential multi-collinearity issue, the regression models in columns (2), (4), and (6) are re-estimated without the focal analyst coverage variable. In an untabulated result, it is found that the estimated coefficients for $ANALYST\_3PEER$ remain negative and statistically significant (t-statistics of -3.242, -2.976, and -2.067), thus alleviating the concerns of multi-collinearity.

All control variables employed in this study are focal-related. In Table 4, it is shown that the coefficient of $DTURN$ is statistically and significantly positive across all models (t-statistics of 5.463, 5.402, 5.733, 5.668, 4.128, and 4.085), indicating that a larger difference among shareholders' opinions increases the stock price crash risk of a firm. This result is consistent with Chen et al. (2001). Besides, consistent with Kim et al. (2011a) and Chen et al. (2001), the coefficients of $SIGMA$ and RET are both positive and significant, suggesting that stocks with higher past returns and volatility are more prone to future crashes. Results also show that $SIZE$ and MB are positively related to the crash risk of a firm. Consistent with Hutton et al. (2009), I find negative and significant coefficients for both LEV and ROA, suggesting that firms with lower leverage and return on assets are more prone to future crashes. Finally, a significant positive coefficient for $ACCM$ suggests that firms with higher earnings management are more likely to crash in the future.[17]

Overall, the results tabulated in Table 4 strongly support H1(a), that holding all else constant, the crash risk of a firm is negatively associated with the information environment of its peer firms. The results are robust to alternative proxies of stock price crash risk, various potential determinants of crash risk as control variables, and the inclusion of fixed effects with standard errors corrected for firm clustering.

[17] The adjusted R^2 across different models are relatively small. The omitted variable bias test by Oster (2019) have been conducted and results are found to be similar.

Table 4. The impact of peer information environment on stock price crash risk.

This table shows the OLS results of the impact of the peer information environment on stock price crash risk. The dependent variables are $NCSKEW$ in Columns (1) and (2), $DUVOL$ in Columns (3) and (4); and $COUNT$ in Columns (5) and (6). The peer information environment is measured by $ANALYST\_3PEER$, which is defined as the average analyst coverage of the top three highest-ranked TNIC peer firms. Other variables are given in Appendix A**.** Columns (2), (4) and (6) include the industry and year fixed effects, whereas columns (1), (3), and (5) do not. The sample covers firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm clustering. ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NCSKEW$		$DUVOL$		$COUNT$	
$ANALYST\_3PEER_{i,t-1}$	-0.052***	-0.036***	-0.018***	-0.013***	-0.024***	-0.016**
	(-4.562)	(-3.050)	(-4.027)	(-2.859)	(-3.220)	(-2.127)
$DTURN_{i,t-1}$	0.288***	0.293***	0.127***	0.129***	0.159***	0.161***
	(5.463)	(5.402)	(5.733)	(5.668)	(4.128)	(4.085)
$NCSKEW_{i,t-1}$	-0.001	-0.001	-0.001	-0.001	-0.005	-0.005
	(-0.140)	(-0.204)	(-0.277)	(-0.308)	(-1.306)	(-1.301)
$SIGMA_{i,t-1}$	2.447***	0.867	1.329***	0.802**	2.419***	1.717***
	(2.858)	(0.963)	(3.851)	(2.195)	(4.536)	(2.999)
$RET_{i,t-1}$	0.364***	0.272**	0.185***	0.165***	0.237***	0.207***
	(3.317)	(2.435)	(4.407)	(3.547)	(3.319)	(2.796)
$SIZE_{i,t-1}$	0.084***	0.085***	0.038***	0.037***	0.036***	0.036***
	(13.727)	(13.393)	(15.263)	(14.436)	(9.145)	(8.704)
$MB_{i,t-1}$	0.004***	0.004***	0.001**	0.002***	0.002**	0.002***
	(3.319)	(3.632)	(2.558)	(3.385)	(2.054)	(2.435)
$LEV_{i,t-1}$	-0.240***	-0.218***	-0.085***	-0.086***	-0.122***	-0.113***
	(-7.519)	(-6.178)	(-6.389)	(-5.855)	(-5.601)	(-4.685)
$ROA_{i,t-1}$	-0.058**	-0.141***	-0.055***	-0.090***	-0.106***	-0.143***
	(-1.733)	(-3.864)	(-3.797)	(-5.814)	(-4.120)	(-5.125)
$ACCM_{i,t-1}$	0.004	0.022***	-0.000	0.009***	0.002	0.013***
	(0.621)	(3.468)	(-0.018)	(3.508)	(0.537)	(3.107)
$ANALYST\_FOCAL_{i,t-1}$	-0.008	-0.015	-0.003	-0.004	0.005	0.005
	(-0.637)	(-1.227)	(-0.563)	(-0.727)	(0.701)	(0.571)
Industry FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
N	34454	34454	34454	34454	34454	34454
Adjusted R^2	0.018	0.027	0.022	0.031	0.008	0.013

6.3 Identification Strategy

Thus far, the results show a negative relation between peer information and the stock price crash risk of the focal firm. However, this finding could be subjected to endogeneity problems. For instance, there could be a bias in analyst coverage when analysts select their coverages based on certain characteristics such as firm size (Bhushan 1989) and features such as favourable opinions of prospects (McNichols & O'Brien 1997). Besides, the problems of reverse causality and unobservable firm heterogeneity correlated with both analyst coverage and crash risk could result in biased estimation.

6.3.1 Exogenous shocks

To establish the causal relation between peer information and the focal firm's stock price crash risk, this section attempts to address the endogeneity issue by adopting natural experiments that cause broker exits. In such an event, analyst coverage of peer firms, followed by the exited broker houses, is expected to decrease. Such reduction in analyst following is beyond the control of peer firms and is orthogonal to the crash risk of the focal firm.

This section employs two natural experiments. First, broker house closures are identified as an ideal source of exogenous shocks to analyst coverage as these events are less likely to be driven by the heterogeneous characteristics of firms followed (Kelly & Ljungqvist 2012). Second, broker house mergers are also widely used as exogenous shocks to analyst coverage, initiated by Hong and Kacperczyk (2010). The mergers of two broker houses would result in redundant employees. Wu and Zang (2009) find that other factors contributing to a reduction in the number of analysts include the uncertainty resulting in post-merger and potential culture clash. If both combining broker houses have two or more analysts following the same firm, at least one analyst is likely dismissed post-merger. Subsequently, firms followed by both combining broker houses pre-merger experience a reduction in analysts following post-merger (Chen, Harford & Lin 2015). Therefore, both broker house mergers and closures provide an exogenous reduction to a firm's analyst coverage. In this study, the instrumental variables (IVs) are calculated based on these natural experiments, which generate an exogenous reduction in peer firm analyst coverage.[18]

6.3.2 Identifying broker house exits

Following the methods used by Chen et al. (2015), the hand collection process commences by identifying the event of broker exits. First, to identify broker house closures, a list of U.S. firms whose price estimation was stopped by the respective broker estimator is obtained from the I/B/E/S database. This provides a list of broker houses that stopped providing price estimates to U.S. firms. Due to data coverage issues, the sample coverage spans from 2000 to 2018. This results in a total of 700 observations of potential broker exits. Press releases in Factiva are searched, supplemented by Google search and FINRA. The outcome of 60 events of broker house closures is identified across 2000-2018. The 2000-2008 and 2000-2010 sample outcomes are cross-checked and reconciled against Kelly and Ljungqvist (2012) and Chen et al. (2015). Results are found to be similar.

Next, to identify broker house mergers, I follow the procedures conducted by Hong and Kacperczyk (2010) using SDC Platinum. The following constraints are applied: First, only broker houses (both acquirers and targets) with primary SIC codes

[18] Broker closures are identified from I/B/E/S and broker mergers are sourced from Thomson's SDC Mergers and Acquisition database. The identified broker closure and merger events are confirmed from the search of press release in Factiva.

of 6211 (including but not limited to investment banks and brokerage firms) and 6282 (including but not limited to independent research firms) are retained. Second, only the completed deals and deals in which 100% of target shares are acquired are retained. Third, only those deals that the combining broker houses analyzing at least two of the same stocks are retained. Finally, in line with the sample period of this study, only deals that occur within the sample period of 2000 – 2018 are retained.[19] The outcome is then manually compared with the I/B/E/S data and the press releases from Factiva, Google search, and FINRA.

When multiple identities are listed for one broker, we reconcile the effective date of the transaction completed with the I/B/E/S stop price estimate file. More specifically, to identify the more accurate estimator code/id, we first sort the stop price estimate data according to the stop price date in descending order and reconcile that with the transaction date.[20] In situations when a single target broker firm appears as a target more than once, the decision on which to retain depends on news sourced.[21] When there are multiple records of deals from the same acquirer and target, these separate deal records are combined as one.[22]

After matching the data, the procedure produces 120 events of broker mergers for the sample period of 2000 – 2018. The outcomes are cross-checked and are found

[19] Lehman is excluded from the sample of this study because it is explained as an inappropriate source of exogenous shock, since Barclays took over Lehman's entire U.S. research department to be its own equity (Kelly & Ljungqvist 2012).

[20] For example, on 3rd July 2017, Wunderlich Investment Co was acquired by B. Riley Financial Inc. There are two possible estimator code/id that matches the company, which are 3039 and 1412. After sorting the stop price date, we notice that the estimator code 1421 only covers firms up to the year of 2005, and estimator code 3039 covers firms from November 2008 and stopped at July 2017. Therefore, 3039 is the more accurate estimator id for this target firm in this business exits event.

[21] For example, SDC record shows Yuanta Core Pacific Sec Co Ltd (with matching id/code as 29879/FANTACOR) was acquired on 31 December 2002 by CTB Financial Holding Co., and on 2 April 2007 (with same matching id/code) by Fuhwa Financial Holding Co Ltd. The latter is retained since there is a confirming news sourced from Factiva.

[22] For example, on 1 May 2010, there were two separated records of Morgan Stanley Japan (CUSIP: 61801Y) and Morgan Stanley Japan – IB Div (CUSIP 61801X) as target, acquired by Mitsubishi UFJ Securities; A unique estimator id/code (628/MGNSTFJ) was found for both deals, so we decided to delete the deal related to Morgan Stanley Japan – IB division.

to be the same as, for the subsample period used, that reported in Hong and Kacperczyk (2010) and Chen et al. (2015). Combined with the 60 events of broker closure, this yields a total of 180 brokerage exits over the 2000 – 2018 sample period.[23]

6.3.3 Two-stage Least Square (2SLS) results

To address the endogeneity concerns related to analyst coverage, this section employs the instrumental variables (IV) approach using a two-stage least squares procedure.

I construct two continuous IVs, both representing the average proportion of peer coverage losses due to broker closures and mergers. For each focal firm i, at a given year t, the first IV, $\overline{CovLoss_1}$, calculates the proportion of coverage loss for each peer firm j, then takes the average of this proportion for all n peers identified, as follow:

$$\overline{CovLoss_1}_{i,t} = \frac{1}{n}\sum_{j=1}^{n}\frac{(\# \ of \ peer \ coverage \ loss \ due \ to \ CMA)_{j,t}}{(total \ \# \ of \ peer \ analyst)_{j,t}} \tag{5}$$

The second IV, $\overline{CovLoss_2}$, for each focal firm i, at a given year t, first sums up the coverage losses experienced by n peers and divides this total with the total number of analyst coverages of n peers, as follow:

$$\overline{CovLoss_2}_{i,t} = \frac{\sum_{j=1}^{n}(\# \ of \ peer \ coverage \ loss \ due \ to \ CMA)_{j,t}}{\sum_{j=1}^{n}(total \ \# \ of \ peer \ analyst)_{j,t}} \tag{6}$$

The second IV is a less conservative calculation than the first because it does not differentiate peers who do not experience broker exit events from those who do.

The broker exit events are almost surely orthogonal to a firm's stock price crash risk, thereby satisfying the exclusion condition. Next, we conduct the relevance condition in the first stage to establish the relationship between the instrument variable

[23] Refer to Appendix C for the list of 180 broker house exits identified over the sample period of 2000 – 2018.

and peer analyst coverage. I estimate an OLS model of the determinants of peer analyst coverage, controlling for all other peer firm variables. The first-stage model is as follow:

$$ANALYST\_3PEER_{i,t} = \alpha_0 + \alpha_1 \overline{CovLoss}_{i,t} + \gamma \overline{Controls}_{i,t} + Year\ FE + \varepsilon_{i,t} \qquad (7)$$

where the dependent variable ($ANALYST\_3PEER$) is the equal-weighted average of peer analyst coverage for a focal firm i, in year t; $\overline{CovLoss}$ is the instrument variable defined as above; $\overline{\boldsymbol{Controls}}$ is a vector of the averages of various peer-level control variables. $Year\ FE$ represents year fixed effect. Industry fixed effect is not included because not all three peer firms belong to the same industry classification. The standard errors are clustered at the firm level. As the average of peer analyst coverage is expected to decrease when there is a broker exit, α_1 is expected to be negative.

In the second stage, I re-run the baseline regression model using the predicted value of peer analyst coverage, $\widehat{ANALYST\_3PEER}$. The second-stage model is as follow:

$$\begin{aligned} FIRM\_CRASH_{i,t} & \\ &= \alpha_0 + \beta_1 \widehat{ANALYST\_3PEER}_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE \\ &+ Year\ FE + \varepsilon_{i,t} \qquad (8) \end{aligned}$$

where all variables are defined as previous. The coefficient estimates β_1 is expected to be negative.

Table 5 documents the results of the first-stage procedure, which clearly shows that the average proportion of broker exits experienced by the top three highest-ranked TNIC peers is negatively related to the peer analyst coverage. This relation is statistically significant at the 1% level. The F-tests (251.42 in Column (1) and 250.10 in Column (2)) is statistically significant, indicating that the IVs employed, $\overline{CovLoss}_1$ and $\overline{CovLoss}_2$ are both convincingly strong instrument variables.

Table 5. Peer analyst coverage and focal crash risk: The first-stage procedure of 2SLS.

This table documents the results from the first-stage procedure for peer analyst coverage, using the following instrument variables:

$$\overline{CovLoss_1}_{i,t} = \frac{1}{n}\sum_{j=1}^{n}\frac{(\#\ of\ peer\ coverage\ loss\ due\ to\ CMA)_{j,t}}{(total\ \#\ of\ peer\ analyst)_{j,t}}$$ in Column (1); and

$$\overline{CovLoss_2}_{i,t} = \frac{\sum_{j=1}^{n}(\#\ of\ peer\ coverage\ loss\ due\ to\ CMA)_{j,t}}{\sum_{j=1}^{n}(total\ \#\ of\ peer\ analyst)_{j,t}}$$ in Column (2).

The sample covers firm-year observations with non-missing values for all variables from 2000 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for firm clustering. The year fixed effects are included in all regressions. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively. Variables are defined in Appendix A**.**

	(1)	(2)
	Dependent variable = $ANALYST\_3PEER_{i,t}$	
$\overline{CovLoss_1}_{i,t}$	-0.256***	
	(-11.97)	
$\overline{CovLoss_2}_{i,t}$		-0.275***
		(-9.20)
$\overline{DTURN\_P}_{i,t}$	-0.038	-0.035
	(-1.21)	(-1.12)
$\overline{NCSKEW\_P}_{i,t}$	0.006**	0.006**
	(1.96)	(1.96)
$\overline{SIGMA\_P}_{i,t}$	1.779***	1.780***
	(2.97)	(2.98)
$\overline{RET\_P}_{i,t}$	0.176**	0.177**
	(2.28)	(2.29)
$\overline{SIZE\_P}_{i,t}$	0.239***	0.239***
	(64.59)	(64.71)
$\overline{MB\_P}_{i,t}$	-0.001**	-0.001*
	(-2.00)	(-1.91)
$\overline{LEV\_P}_{i,t}$	0.060**	0.060**
	(2.08)	(2.06)
$\overline{ROA\_P}_{i,t}$	-0.077***	-0.076***
	(-2.97)	(-2.92)
$\overline{ACCM\_P}_{i,t}$	0.007**	0.008**
	(2.34)	(2.42)
Industry FE	No	No
Year FE	Yes	Yes
N	27,838	27,838
Adjusted R^2	0.456	0.455
F-test	251.42***	250.10***
	(0.00)	(0.00)

In the second-stage regression, all models in Table 4 are re-estimated with the peer analyst coverage $ANALYST\_3PEER$ being substituted by the fitted peer analyst coverage $ANALY\widehat{ST}\_3PEER$, estimated from the first-stage procedure. The results of the second-stage procedure are reported in Table 6, which documents statistically significant negative coefficients for $ANALY\widehat{ST}\_3PEER$ across all models. These results indicate that holding all else constant, an exogenous drop in peer analyst coverage results in ha higher stock price crash risk for the focal firm. The t-statistics reported across Columns (1) to (3) are -4.056, -3.923, and -2.693, respectively, which is stronger than the previously reported baseline result, providing robust evidence of the relation between peer analyst coverage and focal crash risk. The results in Columns (4) to (6) are similar.

Table 6. Peer analyst coverage and focal crash risk: The second-stage procedure of 2SLS.

This table reports the second-stage results using the predicted peer analyst coverage estimated from the first stage. The fitted peer analyst coverage in Columns (1) to (3) (Columns (4) to (6)) are estimated by using $\overline{CovLoss_1}_{i,t}$ ($\overline{CovLoss_2}_{i,t}$) as the IVs. All model specifications are based on the OLS regressions. The sample covers firm-year observations with non-missing values for all variables from 2000 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for firm clustering. Industry and year fixed effects are included in all regressions. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively. Variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$	$NCSKEW$	$DUVOL$	$COUNT$
$\widehat{ANALYST\_3PEER}_{i,t-1}$	-0.088***	-0.034***	-0.039***	-0.086***	-0.033***	-0.038***
	(-4.056)	(-3.923)	(-2.693)	(-3.974)	(-3.837)	(-2.638)
$DTURN_{i,t-1}$	0.278***	0.121***	0.157***	0.278***	0.121***	0.157***
	(4.675)	(4.886)	(3.585)	(4.672)	(4.884)	(3.583)
$NCSKEW_{i,t-1}$	-0.009	-0.004	-0.007	-0.009	-0.004	-0.007
	(-1.319)	(-1.486)	(-1.529)	(-1.321)	(-1.488)	(-1.530)
$SIGMA_{i,t-1}$	0.663	0.739*	1.424**	0.668	0.741*	1.426**
	(0.676)	(1.831)	(2.233)	(0.681)	(1.837)	(2.237)
$RET_{i,t-1}$	0.233*	0.153***	0.196**	0.233*	0.153***	0.196**
	(1.881)	(2.931)	(2.373)	(1.886)	(2.936)	(2.376)
$SIZE_{i,t-1}$	0.081***	0.037***	0.035***	0.081***	0.037***	0.035***
	(11.619)	(12.870)	(7.497)	(11.602)	(12.854)	(7.485)
$MB_{i,t-1}$	0.004***	0.002***	0.002***	0.004***	0.002***	0.002***
	(3.154)	(2.878)	(2.135)	(3.155)	(2.878)	(2.135)
$LEV_{i,t-1}$	-0.159***	-0.062***	-0.081***	-0.159***	-0.062***	-0.081***
	(-4.127)	(-3.788)	(-2.980)	(-4.132)	(-3.793)	(-2.983)
$ROA_{i,t-1}$	-0.212***	-0.121***	-0.191***	-0.212***	-0.121***	-0.191***
	(-4.977)	(-6.667)	(-5.744)	(-4.972)	(-6.662)	(-5.741)
$ACCM_{i,t-1}$	0.020***	0.008***	0.012**	0.020***	0.008***	0.012**
	(2.819)	(2.820)	(2.544)	(2.819)	(2.819)	(2.544)
$ANALYST\_FOCAL_{i,t-1}$	-0.027**	-0.011*	-0.004	-0.027**	-0.011*	-0.004
	(-1.980)	(-1.923)	(-0.430)	(-1.974)	(-1.918)	(-0.427)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	27,838	27,838	27,838	27,838	27,838	27,838
Adjusted R^2	0.023	0.028	0.011	0.023	0.028	0.011

7. Cross-sectional Analyses

It has been established that the peer information environment is negatively related to focal firms' stock price crash risk. This section tends to conduct further tests to understand how peer information could alter the impact of focal firms' characteristics on their stock price crash risk. This further shed light on the role of peer firms in transmitting the incremental value of information.

7.1 Focal firms' information environment

Kim, Lu, and Yu (2019) document that an exogenous drop in a firm's analyst coverage increases the firm's expected crash risk. Such a negative relation between information environment and crash risk is also found in An et al. (2020), who use media coverage as a proxy for information. Moreover, there exists anecdotal evidence about peer effects in information, that the information of a firm is partly driven by the information of its peers, suggesting that peer information tends to complement the focal firm's information (Seo 2020; Shroff et al. 2017). Therefore, a better information acquisition from peers serve as an additional monitoring mechanism that is expected to enhance the firms' information environments. As managers and shareholders obtain more information about the industry, less information asymmetry will result in less incentive for managers to hoard bad news, thereby reducing the stock price crash risk. Based on this argument, I expect that peer information, by adding value to the current existing information set of a focal firm, can enhance the relationship between the information environment of a focal firm and its crash risk.

I conduct cross-sectional tests to examine whether peer information enhances the relationship between the information environment of a focal firm and its crash risk.

I use both the analyst and media coverages of focal firms to measure their overall information environment. I include the interaction terms of $ANALYST\_3PEER \times ANALYST\_FOCAL$ and $ANALYST\_3PEER \times MEDIA\_FOCAL$ separately into the baseline regression, and also separately controlling for the analyst and media coverages of focal firms. The regression models to test this conjecture is as follow:

$$FIRM\_CRASH_{i,t} = \alpha_0 + \alpha_1 ANALYST\_3PEER_{i,t-1} \times ANALYST\_FOCAL_{i,t-1} + \alpha_2 ANALYST\_3PEER_{i,t-1} + \alpha_3 ANALYST\_FOCAL_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (9)$$

$$FIRM\_CRASH_{i,t} = \alpha_0 + \alpha_1 ANALYST\_3PEER_{i,t-1} \times MEDIA\_FOCAL_{i,t-1} + \alpha_2 ANALYST\_3PEER_{i,t-1} + \alpha_3 MEDIA_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (10)$$

where $MEDIA\_FOCAL$ represents the media coverage of focal firm i, in year $\mathrm{t}-1$, which is computed as the average of the natural logarithm of one plus the number of news articles coverage. All other variables are defined as previous. If peer information adds value to the information of a focal firm, which further mitigates information asymmetry between shareholders and manager of the focal firm and subsequently reducing focal firm's stock price crash risk, the coefficients for both interaction terms in Eq. (9) and Eq. (10) are expected to be negative and statistically significant.

Table 7 provides the estimated results. Columns (1) to (3) report the results where focal firms' analyst coverage is used to interact with peer information, whereas Columns (4) to (6) provide the results where focal firms' media analyst coverage is used to interact with peer information. As shown across the columns, the estimated coefficients for the interaction terms are all negative and statistically significant at the 1% level. On average, an increase of one unit in $ANALYST\_3PEER$ above its average (i.e., from 1.987 to 2.987) results in $ANALYST\_FOCAL$ contributing to a further decrease in crash risk of 0.07 units in $NCSKEW$, 0.027 unit in $DUVOL$, and 0.030 unit in $COUNT$.[24] These imply that peer information enhances focal information environment, which then reduces focal firms' stock price crash risk. These findings support my conjecture that peer information enhances the information environment of focal firms, ultimately reducing the stock price crash risk of focal firms.

Focusing on the relationship between the focal information environment and the focal firm's stock price crash risk, Kim et al. (2019) find a negative relationship between a firm's analyst coverage and the ex-ante expected crash risk of the firm. This result is not found in the baseline result reported in Table 4, suggesting no evidence that focal information itself has an effect in reducing crash risk. However, with the inclusion of $ANALYST\_3PEER \times ANALYST\_FOCAL$ in the model, the coefficients of the interaction term reported in Columns (1) to (3) of Table 7 are estimated to be negative and statistically significant. This indicates that the information environment of focal firms needs to be supplemented by peer information to reduce the exposure of stock price crashes. These findings suggest that peer information enhances the firms' information environments, thereby reducing the probability of price crashes.

It is also documented in An et al. (2020) that media coverage reduces stock price crash risk. Columns (4) to (6) of Table 7 also confirm that peer information exacerbates the negative relation between a firm's media coverage and its stock price

[24] Interpreting the coefficient of interaction term requires consideration of the joint effect. $ANALYST\_3PEER$ has a mean of 1.987. Using model in Column (1) of Table 7 as an example, at the mean level (i.e., when $ANALYST\_3PEER$ = 1.987), the new coefficient of $ANALYST\_FOCAL$ becomes $-0.07 \times 1.987 + 0.128$, which is -0.011. An additional unit increase in $ANALYST\_3PEER$ to 2.987 will further reduce the coefficient of $ANALYST\_FOCAL$ from -0.011 to -0.081, a decrease of 0.07 unit in crash risk measure of $NCSKEW$.

crash risk. From the reported adjusted R^2, these models with the interaction term result in a better fit. These findings support my conjecture, indicating that peer information serves as supplementary information, enhancing the information set of focal managers and shareholders and reducing the stock price crash risk.

Table 7. Focal information environment and stock price crash risk: The role of peer information.

This table presents the OLS results of the effect of the peer information on the association between focal firm information environment and its stock price crash risk. The dependent variables are $NCSKEW$ in Columns (1) and (4), $DUVOL$ in Columns (2) and (5); and $COUNT$ in Columns (3) and (6). The peer information environment is measured by $ANALYST\_3PEER$, which is defined as the average analyst coverage of the top three highest-ranked TNIC peer firms. Other variables are given in Appendix A**.** All regressions control for the industry and year fixed effects. The sample covers firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_3PEER_{i,t-1} \times ANALYST\_FOCAL_{i,t-1}$	-0.070***	-0.027***	-0.030***			
	(-5.319)	(-5.112)	(-3.557)			
$ANALYST\_3PEER_{i,t-1} \times MEDIA\_FOCAL_{i,t-1}$				-0.035***	-0.015***	-0.022***
				(-3.509)	(-3.522)	(-3.195)
$ANALYST\_3PEER_{i,t-1}$	0.098***	0.038***	0.041**	0.138***	0.060***	0.095***
	(3.757)	(3.578)	(2.299)	(2.700)	(2.825)	(2.618)
$ANALYST\_FOCAL_{i,t-1}$	0.128***	0.051***	0.066***	-0.016	-0.005	0.003
	(4.387)	(4.413)	(3.570)	(-1.135)	(-0.933)	(0.287)
$MEDIA_{i,t-1}$				0.041*	0.016	0.036**
				(1.702)	(1.616)	(2.207)
$DTURN_{i,t-1}$	0.285***	0.126***	0.158***	0.296***	0.130***	0.164***
	(5.258)	(5.534)	(3.998)	(4.793)	(5.036)	(3.656)
$NCSKEW_{i,t-1}$	-0.002	-0.001	-0.005	-0.013*	-0.006*	-0.009**
	(-0.259)	(-0.362)	(-1.339)	(-1.842)	(-1.945)	(-1.994)
$SIGMA_{i,t-1}$	0.476	0.653*	1.548***	0.984	0.863**	1.398**
	(0.527)	(1.781)	(2.697)	(0.955)	(2.020)	(2.044)

	(1)	(2)	(3)	(4)	(5)	(6)
$RET_{i,t-1}$	0.215*	0.144***	0.182**	0.296**	0.172***	0.199**
	(1.920)	(3.074)	(2.459)	(2.239)	(3.070)	(2.178)
$SIZE_{i,t-1}$	0.085***	0.037***	0.036***	0.081***	0.037***	0.033***
	(13.455)	(14.499)	(8.743)	(9.982)	(11.164)	(6.109)
$MB_{i,t-1}$	0.004***	0.002***	0.002**	0.003**	0.001**	0.001
	(3.618)	(3.368)	(2.422)	(2.390)	(2.374)	(1.125)
$LEV_{i,t-1}$	-0.221***	-0.087***	-0.115***	-0.163***	-0.068***	0.088***
	(-6.252)	(-5.935)	(-4.736)	(-3.975)	(-3.974)	(-3.076)
$ROA_{i,t-1}$	-0.138***	-0.089***	-0.142***	-0.244***	-0.130***	-0.207***
	(-3.802)	(-5.763)	(-5.089)	(-5.241)	(-6.633)	(-5.856)
$ACCM_{i,t-1}$	0.021***	0.008***	0.012***	0.017**	0.007**	0.012**
	(3.291)	(3.338)	(2.987)	(2.500)	(2.482)	(2.534)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34,454	34,454	34,454	26,330	26,330	26,330
Adjusted R^2	0.028	0.032	0.013	0.022	0.026	0.010

7.2 Focal firms' opinion dispersion among shareholders

Next, I consider the role of peer information in transmitting value-added information from the perspectives of shareholders. A higher degree of disagreement in opinion among the shareholders within a firm is associated with a higher stock price crash risk for the firm (Kim et al. 2019). A large difference in opinion among shareholders can result in information asymmetry in stock prices, causing negatively skewed trades, especially during market declines, which forces the hidden information to be revealed (Chen et al. 2001). A better information set supplemented by peers' analysts can help the shareholders of a firm to understand the product market in which the firm they invest operates. This can alleviate information asymmetry and reduce disagreement in opinion, which eventually discourages managerial bad news hoarding activities. Therefore, I expect that peer information tends to mitigate the relationship between the opinion dispersion of a focal firm and its crash risk.

To test this, I include an interaction term $ANALYST\_3PEER \times DTURN$ into the baseline regression. The regression model then becomes:

$$FIRM\_CRASH_{i,t} = \alpha_0 + \alpha_1 ANALYST\_3PEER_{i,t-1} \times DTURN_{i,t-1} + \alpha_2 ANALYST\_3PEER_{i,t-1} + \alpha_3 DTURN_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (11)$$

where $DTURN$ is measured as the difference between the average monthly stock turnover over the current fiscal year minus the average monthly stock turnover over the previous period. The monthly stock turnover is computed as the ratio of monthly trading volume to the month's total number of shares outstanding. It has been established that a higher opinion disagreement among shareholders contributes positively to the firm's stock price crash risk (Kim et al. 2019; Chen et al. 2001). If peer information supplements the existing information possessed by shareholders to a focal firm, one can expect the strength of the positive relationship between the level of disagreement in opinion and stock price crash risk to be attenuated. Therefore, the coefficient signs for this interaction term, $ANALYST\_3PEER \times DTURN$, are expected to be negative. Table 8 provides the results. The estimated coefficient signs are negative as expected, but are statistically insignificant. Therefore, I find no evidence that peer information tends to reduce the opinion disagreements among shareholders of a firm, thereby reducing the firm's stock price crash risk.

Table 8. Detrended monthly stock turnover and stock price crash risk: The role of peer information.

This table presents the OLS results of the effect of the peer information on the association between the detrended monthly stock turnover, a proxy for disagreement in opinions among shareholders, and stock price crash risk. The dependent variables are $NCSKEW$ in Columns (1), $DUVOL$ in Columns (2); and $COUNT$ in Columns (3). The peer information environment is measured by $ANALYST\_3PEER$, which is defined as the average analyst coverage of the top three highest-ranked TNIC peer firms. Other variables are given in Appendix A**.** All regressions control for the industry and year fixed effects. The sample covers firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_3PEER_{i,t-1} \times DTURN_{i,t-1}$	-0.148	-0.062	-0.051
	(-1.574)	(-1.511)	(-0.714)
$ANALYST\_3PEER_{i,t-1}$	-0.036***	-0.013***	-0.016**
	(-3.026)	(-2.834)	(-2.115)
$DTURN_{i,t-1}$	0.584***	0.250***	0.261*
	(3.025)	(2.990)	(1.772)
$NCSKEW_{i,t-1}$	-0.001	-0.001	-0.005
	(-0.201)	(-0.305)	(-1.299)
$SIGMA_{i,t-1}$	0.891	0.812**	1.725***
	(0.990)	(2.223)	(3.012)
$RET_{i,t-1}$	0.277**	0.168***	0.208***
	(2.479)	(3.595)	(2.818)
$SIZE_{i,t-1}$	0.085***	0.037***	0.036***
	(13.372)	(14.415)	(8.692)
$MB_{i,t-1}$	0.004***	0.002***	0.002**
	(3.637)	(3.389)	(2.437)
$LEV_{i,t-1}$	-0.218***	-0.086***	-0.113***
	(-6.165)	(-5.843)	(-4.678)
$ROA_{i,t-1}$	-0.141***	-0.090***	-0.144***
	(-3.879)	(-5.830)	(-5.134)
$ACCM_{i,t-1}$	0.022***	0.009***	0.013***
	(3.470)	(3.510)	(3.108)
$ANALYST\_FOCAL_{i,t-1}$	-0.015	-0.004	0.005
	(-1.222)	(-0.722)	(0.573)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	34,454	34,454	34,454
Adjusted R^2	0.027	0.031	0.013

8. Additional Tests and Robustness Checks

Before concluding, this section considers several additional tests and robustness checks about the effects of the peer information environment on the investment efficiency of focal firms.

8.1 Peer characteristics and the impact of peer information on crash risk

As an additional test, I am interested in exploring how the negative relationship between peer information and focal firms' stock price crash risk varies by peer characteristics. Wang et al. (2016) find that behaviour is influenced, not only by comparison with peers, but also by the size of the comparison group. A larger firm attracts a higher level of analyst coverage, resulting in higher volume and potentially higher quality of information available to investors and the public (Bhushan 1989). Therefore, larger peer firms are expected to contribute to a higher level of information transmission in influencing the focal firm. Besides, it is also expected that the more relevant peer firms will transfer more effective information to influence the focal firms. A higher TNIC similarity score between two firms indicates that the firms are closer rivals, and are more relevant than others (Hoberg & Phillips 2010). As such, I expect that a larger peer firm and a higher similarity score between the focal firm and its peer tends to magnify the relationship between peer information and its stock price crash risk.

I first establish this size effect by including an interaction term of $ANALYST\_3PEER \times SIZE\_PEER$, and controlling for $SIZE\_PEER$, lagged one year, into the baseline regression model specified in Eq. (4). The regression model is as follow:

$$FIRM\_CRASH_{i,t} = \alpha_0 + \alpha_1 ANALYST\_3PEER_{i,t-1} \times SIZE\_PEER_{i,t-1} + \alpha_2 ANALYST\_3PEER_{i,t-1} + \alpha_3 SIZE\_PEER_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (12)$$

where $SIZE\_PEER$ represents the equal-weighted average size of the top three highest-ranked TNIC peer firms identified in year $t-1$. The size is computed as the natural logarithm market value of equity. The definitions of other variables in Eq. (4) remain the same. As I expect that a larger peer firm tends to strengthen the relationship between the peer information and a focal firm's stock price crash risk, the coefficient for $ANALYST\_3PEER \times SIZE\_PEER$ is predicted to be negative.

In the same spirit, the effect of peer information on the focal firm's stock price crash risk may vary depending on the similarity score of the pair firm. In a separate analysis, I interact the peer information with the average TNIC similarity score. The regression model then becomes:

$$FIRM\_CRASH_{i,t} = \alpha_0 + \alpha_1 ANALYST\_3PEER_{i,t-1} \times SCORE_{i,t-1} + \alpha_2 ANALYST\_3PEER_{i,t-1} + \alpha_3 SCORE_{i,t-1} + \gamma Controls_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t} \quad (13)$$

where $SCORE$ represents the equal-weighted average similarity score of the top three highest-ranked TNIC peer firms. Again, according to my conjecture, I expect that the estimated coefficient for $ANALYST\_3PEER \times SCORE$ to be negative and statistically significant.

Table 9 presents the results. Columns (1) to (3) report the effect of peer firm size on the association between peer information and stock price crash risk of focal firms. Across all models, the coefficients of the interaction term $ANALYST\_3PEER \times SIZE\_PEER$ are negative and statistically significant (t-statistics of -3.422, -3.055, and -2.642). On average, an increase of one unit in $SIZE\_PEER$ above its average (i.e., from 6.973 to 7.973) results in $ANALYST\_3PEER$ contributing to a further decline in crash risk measure by 0.023 unit in $NCSKEW$, 0.008 in $DUVOL$, and 0.012 in $COUNT$.[25] From the reported adjusted R^2, these models with the interaction term results in a better fit. This supports my conjecture that the size of peer firms strengthens the relationship between peer information and a focal firm's stock price crash risk. These results indicate that larger peer firms, on average, tend to contribute a higher level of information transmission to further reduce the asymmetries in information.

Columns (4) to (6) of Table 9 document the impact of the TNIC similarity score on the association between peer information and the stock price crash risk of focal firms. Across all models, the coefficient signs of the interaction term are consistently negative, in line with the expectation. However, only the result in Column (6) is statistically significant at the 5% level (t-statistic of -2.198), suggesting weaker evidence of the effect of the TNIC similarity score.

[25] Interpreting the coefficient of interaction term requires consideration of the joint effect. $SIZE\_PEER$ has a mean of 6.973. Using model in Column (1) of Table 5 as an example, at the mean level (i.e., when $SIZE\_PEER$ = 6.973), the new coefficient of $ANALYST\_3PEER$ becomes $\alpha_1 \times 6.973 + \alpha_2$, which is -0.016379. An additional unit increase in $SIZE\_PEER$ to 7.973 will further reduce the coefficient of $ANALYST\_3PEER$ from -0.01639 to -0.039379, a decrease of 0.023 unit in crash risk measure of $NCSKEW$.

Table 9. The impact of peer information environment on stock price crash risk: The effect of peer characteristics.

This table presents the OLS results of the effect of peer firm size and TNIC similarity score on the association between peer information environment and stock price crash risk. The dependent variables are $NCSKEW$ in Columns (1) and (4), $DUVOL$ in Columns (2) and (5); and $COUNT$ in Columns (3) and (6). The peer information environment is measured by $ANALYST\_3PEER$, which is defined as the average analyst coverage of the top three highest-ranked TNIC peer firms. Other variables are given in Appendix A**.** All regressions control for the industry and year fixed effects. The sample covers 34,454 firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_3PEER_{i,t-1} \times SIZE\_PEER_{i,t-1}$	-0.023***	-0.008***	-0.012***			
	(-3.422)	(-3.055)	(-2.642)			
$ANALYST\_3PEER_{i,t-1} \times SCORE_{i,t-1}$				-0.155	-0.067	-0.225**
				(-0.773)	(-0.904)	(-2.198)
$ANALYST\_3PEER_{i,t-1}$	0.144***	0.051***	0.076**	-0.024	-0.008	0.001
	(2.940)	(2.628)	(2.341)	(-1.263)	(-1.115)	(0.113)
$SIZE\_PEER_{i,t-1}$	0.033**	0.011*	0.017*			
	(2.293)	(1.932)	(1.779)			
$SCORE_{i,t-1}$				0.396	0.182	0.523**
				(1.002)	(1.206)	(2.409)
$DTURN_{i,t-1}$	0.271***	0.118***	0.158***	0.294***	0.129***	0.163***
	(4.782)	(5.027)	(3.873)	(5.423)	(5.691)	(4.119)
$NCSKEW_{i,t-1}$	-0.002	-0.001	-0.005	-0.001	-0.001	-0.005
	(-0.316)	(-0.433)	(-1.156)	(-0.179)	(-0.271)	(-1.272)
$SIGMA_{i,t-1}$	0.684	0.725*	1.679***	0.805	0.768**	1.667***
	(0.721)	(1.892)	(2.820)	(0.892)	(2.096)	(2.902)

	(1)	(2)	(3)	(4)	(5)	(6)
$RET_{i,t-1}$	0.244**	0.154***	0.211***	0.268**	0.163***	0.205***
	(2.063)	(3.147)	(2.739)	(2.399)	(3.497)	(2.764)
$SIZE_{i,t-1}$	0.090***	0.039***	0.037***	0.085***	0.037***	0.035***
	(13.209)	(14.231)	(8.487)	(13.324)	(14.369)	(8.582)
$MB_{i,t-1}$	0.005***	0.002***	0.002***	0.004***	0.002***	0.002**
	(3.724)	(3.456)	(2.684)	(3.638)	(3.385)	(2.446)
$LEV_{i,t-1}$	-0.206***	-0.081***	-0.107***	-0.220***	-0.087***	-0.115***
	(-5.595)	(-5.287)	(-4.235)	(-6.242)	(-5.944)	(-4.776)
$ROA_{i,t-1}$	-0.145***	-0.095***	-0.153***	-0.135***	-0.087***	-0.138***
	(-3.812)	(-5.859)	(-5.123)	(-3.691)	(-5.602)	(-4.889)
$ACCM_{i,t-1}$	0.021***	0.009***	0.012***	0.022***	0.009***	0.013***
	(3.014)	(3.203)	(2.703)	(3.451)	(3.480)	(3.086)
$ANALYST\_FOCAL_{i,t-1}$	-0.023*	-0.007	0.001	-0.016	-0.004	0.004
	(-1.756)	(-1.320)	(0.164)	(-1.263)	(-0.797)	(0.553)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34,454	34,454	34,454	34,454	34,454	34,454
Adjusted R^2	0.028	0.032	0.013	0.027	0.031	0.013

8.2 Alternative model specifications

It is possible that there are some unobservable variables that determine crash risk, at the same time, correlated with other included variables, are omitted in the baseline regression, leading to biased results being presented. To mitigate this problem, the models in Table 4 are re-estimated by including firm-fixed effects, and the results are tabulated in Table 10. In the table, the relation between peer information environment and crash risk remains significant with negative coefficient estimates. Although the results are only marginally statistically significant at the 10% level, they are economically meaningful. A one-unit increase in the average number of analysts following the top three highest-ranked TNIC peers is associated with a 2.7% decrease in $NCSKEW$, a 1.0% decrease in $DUVOL$ of 1.0%, and a 1.5% decrease in $COUNT$. These magnitudes are similar to the baseline results reported in Table 4, suggesting that, holding all else constant, more informative peer firms contribute to a reduction in a firm's stock price crash risk. These results also suggest that our baseline results reported in Table 4 are unlikely to be driven by the omitted correlated time-invariant variables.

Working with sampled data to infer a relationship requires the standard errors to be clustered for the regression. The baseline regression analysis reported in Table 4 is based on standard errors clustering at the firm level. As a robustness check, all models in Table 4 are re-estimated, not only based on standard errors clustered at the firm, but also at year levels, and the results are reported in Table 11. As shown in Table 11, the coefficient estimates for $ANALYST\_3PEER$ are still negative and statistically significant at least at the 5% level.

Table 10. Alternative model specifications: Firm and year fixed effects.

This table reports the OLS results of the impact of the peer information environment on stock price crash risk of the focal firm. The dependent variables are $NCSKEW$ in Column (1), $DUVOL$ in Column (2); and $COUNT$ in Column (3). The peer information environment is measured by $ANALYST\_3PEER$, which is defined as the average analyst coverage of the top three highest-ranked TNIC peer firms. Other variables are given in Appendix A**.** All regressions control for firm and year fixed effects. The sample covers 33,575 firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for firm clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_3PEER_{i,t-1}$	-0.027*	-0.010*	-0.015*
	(-1.710)	(-1.665)	(-1.651)
$DTURN_{i,t-1}$	0.221***	0.084***	0.115***
	(3.742)	(3.477)	(2.689)
$NCSKEW_{i,t-1}$	-0.096***	-0.039***	-0.051***
	(-13.564)	(-13.903)	(-11.462)
$SIGMA_{i,t-1}$	-0.216	0.572	1.573**
	(-0.191)	(1.246)	(2.180)
$RET_{i,t-1}$	0.075	0.090	0.170*
	(0.534)	(1.563)	(1.861)
$SIZE_{i,t-1}$	0.253***	0.123***	0.144***
	(20.763)	(24.385)	(18.021)
$MB_{i,t-1}$	0.004**	0.001*	0.001
	(2.088)	(1.880)	(0.985)
$LEV_{i,t-1}$	-0.178***	-0.056**	-0.087*
	(-2.625)	(-2.040)	(-1.924)
$ROA_{i,t-1}$	-0.500***	-0.269***	-0.348***
	(-9.600)	(-11.754)	(-8.479)
$ACCM_{i,t-1}$	0.015*	0.006*	0.008
	(1.868)	(1.848)	(1.634)
$ANALYST\_FOCAL_{i,t-1}$	-0.062***	-0.023***	-0.024*
	(3.301)	(-3.041)	(-1.950)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	33,575	33,575	33,575
Adjusted R^2	0.038	0.051	0.032

Table 11. Alternative model specification: Cluster standard errors at the firm and year level.

This table shows the OLS regression results of the impact of the peer information environment on stock price crash risk. The dependent variables are $NCSKEW$ in Column (1) $DUVOL$ in Column (2); and $COUNT$ in Column (3). The peer information environment is measured by $ANALYST\_3PEER$, which is defined as the average analyst coverage of the top three highest-ranked TNIC peer firms. Other variables are given in Appendix A**.** All regressions control for the industry and year fixed effects. The sample covers 34,454 firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm and year clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_3PEER_{i,t-1}$	-0.036***	-0.013***	-0.016**
	(-3.338)	(-2.892)	(-2.090)
$DTURN_{i,t-1}$	0.293***	0.129***	0.161***
	(5.078)	(5.526)	(3.791)
$NCSKEW_{i,t-1}$	-0.001	-0.001	-0.005
	(-0.184)	(-0.271)	(-1.217)
$SIGMA_{i,t-1}$	0.867	0.802	1.717**
	(0.614)	(1.556)	(2.458)
$RET_{i,t-1}$	0.272	0.165**	0.207**
	(1.583)	(2.498)	(2.440)
$SIZE_{i,t-1}$	0.085***	0.037***	0.036***
	(9.828)	(10.648)	(8.178)
$MB_{i,t-1}$	0.004***	0.002**	0.002**
	(2.839)	(2.659)	(2.174)
$LEV_{i,t-1}$	-0.218***	-0.086***	-0.113***
	(-4.554)	(-4.443)	(-4.156)
$ROA_{i,t-1}$	-0.141*	-0.090***	-0.143***
	(-1.959)	(-3.122)	(-3.131)
$ACCM_{i,t-1}$	0.022***	0.009***	0.013***
	(3.327)	(3.214)	(3.745)
$ANALYST\_FOCAL_{i,t-1}$	-0.015	-0.004	0.005
	(-1.169)	(-0.598)	(0.591)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	34,454	34,454	34,454
Adjusted R^2	0.027	0.031	0.013

8.3 Alternative measures of peer information

This section examines the baseline regression using an alternative definition of peer information environment. The baseline results reported in Table 4 are based on the main variable of interest, $ANALYST\_3PEER$, which are defined as the equal-weighted average analyst coverage of the top three highest-ranked TNIC peer firms. As robustness checks, this section re-defines the peer information measure by considering the average analyst coverage of the top one, the top five, the top ten, and the top 20, highest-ranked TNIC peer firms.

Panel A of Table 12 reports the regression results using analyst coverage of the top highest-ranked TNIC peer, $ANALYST\_1PEER$, as a proxy for peer information. Panels B, C, and D of Table 12 document the regression results using the average analyst coverage of the top five ($ANALYST\_5PEER$), top ten ($ANALYST\_10PEER$), and top 20 ($ANALYST\_20PEER$), highest-ranked TNIC peer firms, respectively, identified in year $t-1$, as proxies for peer information. All regression specifications control for the industry- and year-fixed effects, with standard errors corrected for firm clustering. Results across all panels show that the coefficient estimates for these peer information measures are negative and statistically significant, confirming the baseline results.

Further, the results also show that the t-statistics become less robust when the number of peer firms included in the analysis increases. For instance, when regress $NCSKEW$ with $ANALYST\_1PEER$, the coefficient estimates reported are negative and statistically significant at 1% level (t-statistic of -3.157 in Panel A). The t-statistics reduce monotonically to -2.702 (in Panel B), -2.473 (in Panel C), and -1.922 (in Panel D), when $ANALYST\_5PEER$, $ANALYST\_10PEER$, and $ANALYST\_20PEER$, respectively, are used as the main independent variable, replacing $ANALYST\_3PEER$ in the baseline model. These results suggest that highly related peer firms contribute more information than less related peer firms in reducing the crash risk of the focal firm. These findings also complement the results found in Table 9.

Table 12. Alternative peer information measures.

This table shows the OLS results of the impact of the peer information environment on stock price crash risk. The dependent variables are $NCSKEW$ in Columns (1) and (4), $DUVOL$ in Columns (2) and (5); and $COUNT$ in Columns (3) and (6). In Panel A, the peer information environment is measured by $ANALYST\_1PEER$, which is defined as the analyst coverage of the top one highest-ranked TNIC peer firm. Panel B analyses the regression using $ANALYST\_5PEER$ as a measure for peer information environment, which is defined as the average analyst coverage of the top five highest-ranked TNIC peer firms. Panel C and Panel D measure the peer information environment using $ANALYST\_10PEER$, and $ANALYST\_20PEER$, respectively, which are defined as the average analyst coverage of the top ten, and top 20 highest-ranked TNIC peer firms, respectively. Other variables are given in Appendix **A.** Columns (2), (4) and (6) includes the industry and year fixed effects, whereas columns (1), (3), and (5) do not. The sample covers firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$	$NCSKEW$	$DUVOL$	$COUNT$
	Panel A: Top one highest-ranked TNIC peer			**Panel B: Top five highest-ranked TNIC peers**		
$ANALYST\_1PEER_{i,t-1}$	-0.025***	-0.009***	-0.009*			
	(-3.157)	(-2.825)	(-1.682)			
$ANALYST\_5PEER_{i,t-1}$				-0.037***	-0.015***	-0.016*
				(-2.702)	(-2.711)	(-1.840)
$DTURN_{i,t-1}$	0.293***	0.129***	0.161***	0.293***	0.129***	0.161***
	(5.404)	(5.671)	(4.088)	(5.401)	(5.566)	(4.084)
$NCSKEW_{i,t-1}$	-0.001	-0.001	-0.005	-0.001	-0.001	-0.005
	(-0.224)	(-0.327)	(-1.312)	(-0.191)	(-0.295)	(-1.292)
$SIGMA_{i,t-1}$	0.924	0.824**	1.747***	0.869	0.801**	1.719***
	(1.025)	(2.252)	(3.051)	(0.966)	(2.191)	(3.004)
$RET_{i,t-1}$	0.279**	0.168***	0.210***	0.272**	0.165***	0.207***
	(2.493)	(3.599)	(2.844)	(2.433)	(3.539)	(2.797)
$SIZE_{i,t-1}$	0.085***	0.037***	0.036***	0.085***	0.037***	0.036***
	(13.371)	(14.425)	(8.666)	(13.382)	(14.440)	(8.686)
$MB_{i,t-1}$	0.004***	0.002***	0.002**	0.004***	0.002***	0.002**
	(3.636)	(3.388)	(2.433)	(3.619)	(3.374)	(2.425)
$LEV_{i,t-1}$	-0.217***	-0.085***	-0.113***	-0.218***	-0.086***	-0.113***
	(-6.148)	(-5.828)	(-4.661)	(-6.173)	(-5.854)	(-4.681)
$ROA_{i,t-1}$	-0.140***	-0.090***	-0.143***	-0.140***	-0.090***	-0.143***
	(-3.858)	(-5.811)	(-5.113)	(-3.849)	(-5.806)	(-5.115)
$ACCM_{i,t-1}$	0.022***	0.009***	0.013***	0.022***	0.009***	0.013***
	(3.450)	(3.492)	(3.098)	(3.461)	(3.501)	(3.102)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_FOCAL_{i,t-1}$	-0.016	-0.004	0.004	-0.016	-0.004	0.004
	(-1.293)	(-0.797)	(0.473)	(-1.273)	(-0.746)	(0.532)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34,454	34,454	34,454	34,454	34,454	34,454
Adjusted R^2	0.027	0.031	0.013	0.027	0.031	0.013
	Panel C: Top ten highest-ranked TNIC peers			**Panel D: Top 20 highest-ranked TNIC peers**		
$ANALYST\_10PEER_{i,t-1}$	-0.039*	-0.016*	-0.017*			
	(-2.473)	(-2.587)	(-1.702)			
$ANALYST\_20PEER_{i,t-1}$				-0.033*	-0.013*	-0.012
				(-1.922)	(-1.915)	(-1.107)
$DTURN_{i,t-1}$	0.293***	0.129***	0.161***	0.293***	0.129***	0.161***
	(5.404)	(5.668)	(4.087)	(5.399)	(5.664)	(4.085)
$NCSKEW_{i,t-1}$	-0.001	-0.001	-0.005	-0.001	-0.001	-0.005
	(-0.182)	(-0.284)	(-1.285)	(-0.178)	(-0.282)	(-1.287)
$SIGMA_{i,t-1}$	0.868	0.798**	1.718***	0.889	0.809**	1.734***
	(0.964)	(2.184)	(3.001)	(0.988)	(2.213)	(3.031)
$RET_{i,t-1}$	0.272**	0.165***	0.207***	0.275**	0.166***	0.209***
	(2.433)	(3.534)	(2.796)	(2.461)	(3.566)	(2.825)
$SIZE_{i,t-1}$	0.085***	0.037***	0.036***	0.085***	0.037***	0.036***
	(13.374)	(14.438)	(8.675)	(13.328)	(14.385)	(8.632)
$MB_{i,t-1}$	0.004***	0.002***	0.002**	0.004***	0.002***	0.002**
	(3.623)	(3.378)	(2.429)	(3.619)	(3.374)	(2.426)
$LEV_{i,t-1}$	-0.218***	-0.086***	-0.113***	-0.218***	-0.086***	-0.113***
	(-6.175)	(-5.857)	(-4.683)	(-6.163)	(-5.844)	(-4.670)
$ROA_{i,t-1}$	-0.139***	-0.090***	-0.143***	-0.139***	-0.090***	-0.143***
	(-3.825)	(-5.784)	(-5.100)	(-3.814)	(-5.771)	(-5.088)
$ACCM_{i,t-1}$	0.022***	0.009***	0.013***	0.022***	0.009***	0.013***
	(3.463)	(3.502)	(3.104)	(3.460)	(3.500)	(3.103)
$ANALYST\_FOCAL_{i,t-1}$	-0.017	-0.004	0.004	-0.018	-0.004	0.003
	(-1.332)	(-0.792)	(0.491)	(-1.428)	(-0.902)	(0.399)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34,454	34,454	34,454	34,454	34,454	34,454
Adjusted R^2	0.027	0.031	0.013	0.027	0.031	0.013

8.4 Alternative industry classification

A handful of relevant research classifies peers by a fixed industry classification, such as the three-digit SIC code industries (Adhikari & Agrawal 2018). As a robustness check, this section adopts an alternative peer definition using the three-digit SIC codes instead of the TNIC to identify peer firms. The peer information environment measure, $ANALYST\_PEER$, is then calculated as the average analyst coverage of all peer firms with the same three-digit SIC code. Table 13 presents the regression results. Across Columns (1) to (3), the coefficient estimates of $ANALYST\_PEER$ remain negative and statistically significant (t-statistics are -2.558, -2.154, and -1.651). These results continue to support the baseline results, that a firm's stock price crash risk is negatively associated with the peer information environment, holding all else constant.

Table 13. Alternative industry classification based on three-digit SIC.

This table shows the OLS results of the impact of the peer information environment on stock price crash risk. The dependent variables are $NCSKEW$ in Column (1), $DUVOL$ in Column (2); and $COUNT$ in Column (3). The peer information environment is measured by $ANALYST\_PEER$, which is defined as the average analyst coverage of all peer firms with the same three-digit SIC industry code. Other variables are given in Appendix A**.** All regressions control for the industry and year fixed effects. The sample covers 39,780 firm-year observations with non-missing values for all variables from 1996 to 2018. The t-statistics reported in the parentheses are based on standard errors corrected for the firm clustering. Each of the ***, ** and * represents a 1%, 5% and 10% level of significance, respectively.

	(1)	(2)	(3)
Dependent variable	$NCSKEW$	$DUVOL$	$COUNT$
$ANALYST\_PEER_{i,t-1}$	-0.050**	-0.017**	-0.008*
	(-2.558)	(-2.154)	(-1.651)
$DTURN_{i,t-1}$	0.296***	0.133***	0.150***
	(5.752)	(6.182)	(3.975)
$NCSKEW_{i,t-1}$	0.001	0.000	-0.003
	(0.207)	(0.178)	(-0.809)
$SIGMA_{i,t-1}$	0.566	0.756**	1.944***
	(0.658)	(2.170)	(3.635)
$RET_{i,t-1}$	0.243**	0.162***	0.242***
	(2.248)	(3.650)	(3.458)
$SIZE_{i,t-1}$	0.088***	0.038***	0.037***
	(14.463)	(15.452)	(9.728)
$MB_{i,t-1}$	0.005***	0.002***	0.002***
	(4.151)	(3.969)	(2.851)
$LEV_{i,t-1}$	-0.219***	-0.088***	-0.100***
	(-6.417)	(-6.246)	(-4.368)
$ROA_{i,t-1}$	-0.086**	-0.069***	-0.117***
	(-2.468)	(-4.608)	(-4.352)
$ACCM_{i,t-1}$	0.019***	0.008***	0.011***
	(3.118)	(3.149)	(2.836)
$ANALYST\_FOCAL_{i,t-1}$	-0.018	-0.004	0.004
	(-1.548)	(-0.828)	(0.498)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	39,780	39,780	39,780
Adjusted R^2	0.029	0.032	0.013

9. Conclusion

Utilising the TNIC database in identifying peer firms, this study finds evidence that the peer information environment, measured by peer analyst coverage, is negatively associated with the focal firms' stock price crash risk. Using two natural experiments, broker house closures and mergers, as the sources of exogenous shocks to analyst coverage reduction experienced by the peer firms, the negative relation between the peer information environment and the focal firms' stock price crash risk remains robust. These findings are consistent with the conjecture that information about peer firms released by their analysts is transmitted to focal firms, alleviating information asymmetry between shareholders and managers, to curb the bad-news hoarding activities. These findings are robust to alternative model specifications, alternative peer information measurements, and alternative industry classification based on three-digit SIC industry codes.

The negative relation between the peer information environment and the focal firms' stock price crash risk varies by the peer reference group. Cross-sectional analyses reveal that larger peer firms tend to strengthen the relationship between peer information and the focal firms' stock price crash risk. Peer firms with higher TNIC similarity scores also tend to intensify the negative association between peer information and the focal firms' exposures to stock price crashes. Moreover, this study also uncovers the importance of peer information as information supplementing the existing information possessed by focal firms in enhancing the overall focal firms' information environment and reducing the managers' bad news hoarding activities. These findings enrich the understanding of the influence of peer information on future stock price crash risk and shed light on the vital role of peer firms in information dissemination to influence the focal firms.

The findings of this study are consistent with the theory of managerial learning motives (Leary & Roberts 2014), as well as the bad news hoarding theory of stock price crash risk (Jin & Myers 2006). In the last decades, an increasing amount of attention has been paid by academic researchers, regulators, and share market participants to the determinants of the stock market extreme events such as price crashes. Besides, there is also a significant academic effort on corporate research related to peer firms. This study links both phenomena with the view that peer information conveys incremental information in reducing the principle-agent issues due to information asymmetry, thereby reducing bad news hoarding activities.

This study contributes to the literature on peer effects in corporate research by providing an additional peer-driven angle on corporate issues. It also contributes to the literature on crash risk by providing a different angle of stock price crash risk determinants relating to peer firms. To my best knowledge, this study is the first to explore the determinants of stock price crash risk in relation to the peer information environment. From a practical perspective, this study has implications for various stakeholders who are interested in the changes in corporate policies and decisions due to the information, characteristics, and actions of peer firms. For investors, the findings raise their awareness of the importance of peer information during their investment period. In terms of information disclosure, the findings demonstrate whether the reactions of share market participants could also be affected by peer information. This study also brings policy implications for regulators from the perspective of corporate transparency. Changes in corporate decisions and policies characterised by peers' environment can also contribute to better transparency in financial reporting and decision-making due to peer pressure, which will ultimately enhance market efficiency.

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Appendix

Appendix A: Variable Definitions

Variables	Acronym	Definition	Source
Variable of interest: Peer Information Environment Variables			
Peer Analyst Coverage	$ANALYST\_3PEER$	The average analyst coverage of the top three highest-ranked TNIC peer firms. Analyst coverage is calculated as the natural logarithm of one plus the number of analysts following.	IBES
	$ANALYST\_1PEER$	The analyst coverage of the top highest-ranked TNIC peer firm. Analyst coverage is calculated as the natural logarithm of one plus the number of analysts following.	IBES
	$ANALYST\_5PEER$	The average analyst coverage of the top five highest-ranked TNIC peer firms. Analyst coverage is calculated as the natural logarithm of one plus the number of analysts following.	IBES
	$ANALYST\_10PEER$	The average analyst coverage of the top ten highest-ranked TNIC peer firms. Analyst coverage is calculated as the natural logarithm of one plus the number of analysts following.	IBES
	$ANALYST\_20PEER$	The average analyst coverage of the top 20 highest-ranked TNIC peer firms. Analyst coverage is calculated as the natural logarithm of one plus the number of analysts following.	IBES
Dependent variable: Crash Risk Variables			

Negative Skewness of Firm-Specific Weekly Returns	$NCSKEW$	The negative of the third moment of firm-specific weekly returns for each year, divided by the standard deviation of firm-specific weekly returns raised to the third power.	CRSP
Down-to-Up Volatility	$DUVOL$	The natural logarithm of the ratio of the standard deviation on the down weeks to the standard deviation on the up weeks	CRSP
Crash Weeks Minus Jump Weeks	$COUNT$	The number of crash weeks minus the number of jump weeks of the year. It is based on the number of firm-specific daily returns exceeding 3.09 standard deviations above and below the mean firm-specific daily return over the fiscal year, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution.	CRSP
Control Variables			
Detrended Turnover	$DTURN$	The detrended average monthly stock turnover, which is the difference between the average monthly stock turnover over the current fiscal year period minus the average monthly stock turnover over the previous fiscal year period; The monthly stock turnover is computed as the ratio of monthly trading volume to the month's total number of shares outstanding; This a proxy for differences of opinion among investors.	CRSP
Firm Risk	$SIGMA$	The standard deviation of firm-specific weekly returns of the year.	CRSP
Firm Return	RET	The mean of firm-specific weekly returns of the year, multiply by 100.	CRSP
Firm Size	$SIZE$	The natural logarithm of the market value of equity.	Compustat
Market-to-Book Ratio	MB	The market value of equity divided by the book value of equity.	Compustat
Leverage	LEV	Long-term debt divided by total assets.	Compustat

Return on Asset	ROA	Income before extraordinary items divided by lagged total assets.	Compustat
Financial Reporting Opacity	$ACCM$	The three-year moving sum of absolute discretionary accruals of a firm.	Compustat
Focal Analyst Coverage	$ANALYST\_FOCAL$	The natural logarithm of one plus the number of analysts following.	IBES

Appendix B: Estimation of $ACCM$

In estimating $ACCM$, I will follow the same procedure as Kim et al. (2011a) in computing discretionary accruals. This method is taken from a modified Jones model in DeChow, Sloan, and Sweeney (1996) and is applied in Hutton et al. (2009). Using Fama and French 48-industry classification, the following cross-sectional regression is estimated for each fiscal year from 1980 – 2018:

$$\frac{TACC_{i,t}}{TA_{i,t-1}} = \alpha \frac{1}{TA_{i,t-1}} + \beta_1 \frac{\Delta SALE_{i,t}}{TA_{i,t-1}} + \beta_2 \frac{PPE_{i,t}}{TA_{i,t-1}} + \varepsilon_{i,t} \qquad \mathrm{B.1}$$

where $TACC_{i,t}$ represents the total accruals from firm i during year t. This is computed as income before extraordinary items minus cash flow from operating activities adjusted for extraordinary items and discontinued operations. $TA_{i,t-1}$ is the total assets for firm i at the end of year $t - 1$; $\Delta SALE_{i,t}$ measures the change in sales for firm i in year t; $PPE_{i,t}$ is the property, plant, and equipment for firm i at the end of year t.

After obtaining the estimates for the coefficients $\hat{\alpha}$, $\hat{\beta}_1$ and $\hat{\beta}_2$ from Eq. (B.1), the discretionary accruals for firm i during year t, $DISACC_{i,t}$, can then be calculated using the following equation:

$$DISACC_{i,t} = \frac{TACC_{i,t}}{TA_{i,t-1}} - \hat{\alpha} \frac{1}{TA_{i,t-1}} - \hat{\beta}_1 \frac{\Delta SALE_{i,t} - \Delta REC_{i,t}}{TA_{i,t-1}} + \hat{\beta}_2 \frac{PPE_{i,t}}{TA_{i,t-1}} \qquad \mathrm{B.2}$$

where $\Delta REC_{i,t}$ represents the change in accounts receivable of firm i at the end of year t. All other variables are defined as previous. $ACCM\_PEER_{i,t-1}$ denotes as the average $ACCM$ of all peers of firm i at the beginning of year t; whereas $ACCM_{i,t-1}$ denotes as the $ACCM$ of firm i at the beginning of year t. These $ACCM$ variables are calculated as the moving sum of the absolute value of discretionary accruals over the last three years, which include years $t - 1$, $t - 2$, and $t - 3$.

Appendix C: List of broker exits

This table presents the list of hand-collected data of broker houses that either close or are acquired during the sample period of 2000 – 2018. The event month and year is also reported. A total of 180 broker exit events are identified. These broker exits are constructed following the methods described in Chen et al. (2015). The outcomes are cross-checked and are found to be the same, for the subsample period used, as reported in Kelly and Ljungqvist (2012), Hong and Kacperczyk (2010) and Chen et al. (2015).

YEAR	MONTH	CLOSED FIRMS	EVENT	YEAR	MONTH	CLOSED FIRMS	EVENT
2000	Oct	GEORGE K. BAUM & CO.	Closure	2001	Mar	ING BARINGS	MA
2000	Jun	J. C. BRADFORD & CO.	MA	2001	Nov	HOAK BREEDLOVE WESNESKI & CO.	Closure
2000	Jun	BROWN BROTHERS HARRIMAN & CO.	Closure	2001	Nov	BNP PARIBAS EQUITIES	MA
2000	Nov	DONALDSON, LUFKIN & JENRETTE SECURITIE	MA	2002	Apr	GRUNTAL & CO., INC.	MA
2000	May	SCHRODER & COMPANY	MA	2002	Jul	ROBERTSON STEPHENS	Closure
2000	Apr	WAKO SECURITIES CO., LTD	MA	2002	Apr	ABN AMRO (LATIN AMERICA)	Closure
2000	Apr	BLACK & COMPANY, INC.	MA	2002	Jul	FROST SECURITIES	Closure
2000	Sep	GLOBAL STRATEGIES GROUP, INC.	MA	2002	Aug	VESTIGO ASSOCIATES	Closure
2000	Jan	SANDERS MORRIS MUNDY, INC.	MA	2002	May	ARAGON FONDKOMMISSION	MA
2000	Oct	BRANCH CABELL & COMPANY	MA	2002	Aug	BARITS SECURITIES	MA
2000	Sep	WIT CAPITAL	MA	2002	Sep	TOKYO-MITSUBISHI SECURITIES CO., LTD.	MA
2000	Jun	ARM SECURITIES	MA	2003	Jan	WACHOVIA SECURITIES, INC.	MA
2000	Apr	BETA CAPITAL, SV., S.A.	MA	2003	Jul	THE CHAPMAN COMPANY	Closure
2000	Sep	CHARTERHOUSE SECURITIES LTD	MA	2003	Apr	COMMERCE CAPITAL MARKETS	Closure
2000	Nov	CHICAGO INVESTMENTS	MA	2003	Jan	F J MORRISSEY & CO. INC	MA
2000	Jun	ALTIUM CAPITAL LTD	MA	2003	Sep	JBWERE LIMITED	MA
2000	Oct	SANFORD BERNSTEIN	MA	2004	Feb	SCHWAB SOUNDVIEW CAPITAL MARKETS	Closure
2000	Oct	MORGAN STOCKBROKING LTD	MA	2004	Feb	WILLIAM R. HOUGH	MA
2000	Apr	TOWA SECURITIES CO., JPN LNG	MA	2004	Dec	KIRKPATRICK PETTIS	MA
2001	Oct	CONNING & CO.	Closure	2004	Feb	MONTAUK CAPITAL MARKETS	Closure
2001	Dec	PIPER JAFFRAY	MA	2004	Oct	WALL STREET ACCESS	MA
2001	Sep	JOSEPHTHAL & COMPANY	MA	2004	Jan	SOUNDVIEW TECHNOLOGY GROUP	MA
2001	Jul	EMERALD RESEARCH	Closure	2004	Feb	CREDIT LYONNAIS SECURITIES	MA

YEAR	MONTH	CLOSED FIRMS	EVENT	YEAR	MONTH	CLOSED FIRMS	EVENT
2004	Feb	DAO HENG FUND MANAGEMENT LTD	MA	2007	Apr	COHEN & COMPANY	Closure
2004	Nov	SUTHERLANDS LIMITED	MA	2007	May	JB HANAUER & CO.	MA
2005	Dec	ADVEST INC.	MA	2007	Nov	NOLLENBERGER CAPITAL PARTNERS	Closure
2005	Nov	AMERICAN EXPRESS FINANCIAL CORP.	MA	2007	Apr	YUANTA CORE-PACIFIC	MA
2005	Dec	LEGG MASON WOOD WALKER, INC.	MA	2007	Mar	GRANGE SECURITIES	MA
2005	Aug	WELLS FARGO SECURITIES	Closure	2007	Dec	JF APEX SECURITIES BERHAD	MA
2005	May	MAXCOR FINANCIAL	MA	2007	Feb	SBB SECURITIES SDN. BHD.	MA
2005	May	TRISTONE CAPITAL INC	MA	2008	Jan	JULIUS BAER HOLDING LIMITED	MA
2005	Apr	TRADITION ASIEL SECURITIES	Closure	2008	Jun	FERRIS, BAKER WATTS, INC.	MA
2005	Jun	BEREAN CAPITAL, INC.	MA	2008	Nov	J & W SELIGMAN SECURITIES, INC.	MA
2005	Jun	IRG RESEARCH	Closure	2008	May	PUNK, ZIEGEL & CO.	MA
2005	Apr	PANMURE GORDON & CO. LIMITED	MA	2008	Jan	CIBC WORLD MARKETS USA	MA
2005	Apr	CYRIL FINANCE	MA	2008	Oct	AXIS CAPITAL LIMITED	MA
2005	Sep	GK GOH RESEARCH PTE LTD	MA	2009	Oct	FOX-PITT COCHRAN CARONIA	MA
2005	Sep	GK GOH SECURITIES HK LTD	MA	2009	Nov	EDWARD JONES	MA
2005	Mar	PARKER/HUNTER INC.	MA	2009	Feb	PACIFIC GROWTH EQUITIES	MA
2005	Apr	WOORI SECURITIES	MA	2009	Aug	SBK BROOKS	MA
2006	Aug	FIDEURAM WARGNY	MA	2009	Feb	STANFORD GROUP COMPANY	Closure
2006	Sep	MOORS & CABOT CAPITAL MARKETS	Closure	2009	May	MIZUHO SECURITIES CO., LTD.	MA
2006	Jul	HOEFER & ARNETT INC.	MA	2009	Sep	UBS PACTUAL	MA
2006	Dec	PETRIE PARKMAN & CO	MA	2010	Apr	COSMO SECURITIES CO. LTD.	MA
2006	Sep	BROADWALL CAPITAL	MA	2010	May	MORGAN STANLEY JAPAN LIMITED	MA
2007	Jun	PRUDENTIAL EQUITY GROUP, LLC	Closure	2010	Feb	FTN EQUITY CAPITAL MARKETS	Closure
2007	Aug	WIDMANN, SIFF & CO.	MA	2010	Jun	JESUP & LAMONT SECURITIES CORP	Closure
2007	Feb	RYAN BECK & CO.	MA	2010	Jul	DELTA LLOYD SECURITIES	MA
2007	Jun	PUTNAM LOVELL NBF	MA	2010	Jan	OCTAGON CAPITAL CORPORATION	MA
2007	Sep	COCHRAN CARONIA WALLER	MA	2010	Jul	THOMAS WEISEL PARTNERS (HIST)	MA
2007	Dec	WELLINGTON WEST CAPITAL MARKETS (HIST)	MA	2010	Jan	THE ROBINS GROUP	Closure

YEAR	MONTH	CLOSED FIRMS	EVENT	YEAR	MONTH	CLOSED FIRMS	EVENT
2010	Jun	KEVIN DANN & PARTNERS	Closure	2013	Aug	CROWELL, WEEDON & CO. (HIST)	MA
2010	Aug	CONCORDE CAPITAL LIMITED	MA	2013	Jan	MIZUHO INVESTORS SEC (HIST)	MA
2010	Jul	BARNARD JACOBS MELLET	MA	2013	May	ALFRED BERG DENMARK	MA
2011	Jun	GOLDMAN SACHS AUSTRALIA	MA	2013	Jul	CLSA AMERICAS LLC (HISTORICAL)	MA
2011	Mar	HOWE BARNES HOEFER & ARNETT INC.	MA	2013	Jan	CAPSTONE INVESTMENTS (HIST)	Closure
2011	Dec	EVOLUTION SECURITIES (HIST)	MA	2013	Feb	SEYMOUR PIERCE LTD.	MA
2011	May	SOLEIL SECURITIES CORP. (HIST)	MA	2013	Apr	FRASER MACKENZIE LTD.	Closure
2011	Apr	HUDSON SECURITIES (HIST)	MA	2013	Mar	NORTHERN SECURITIES	Closure
2011	Oct	MF GLOBAL (HISTORICAL)	Closure	2013	Feb	AVIAN SECURITIES, LLC (HIST)	Closure
2011	Oct	RAFFERTY CAPITAL MARKETS	Closure	2013	Apr	BGB SECURITIES, INC.	Closure
2011	Nov	TKB CAPITAL (HISTORICAL)	Closure	2013	Oct	MEREDITH WHITNEY ADV.LLC(HIST	Closure
2011	Sep	INFINITY.COM FIN SEC LTD(HIST	Closure	2013	Apr	KBC SECURITIES CEE	Closure
2011	Dec	CITADEL SECURITES LLC (HIST)	MA	2013	Jan	NCP NORTHLAND CAPITAL (HIST)	MA
2011	Oct	MF GLOBAL HK LIMITED (HIST)	Closure	2013	Mar	WESTEND BROKERS AG	Closure
2012	Sep	RODMAN & RENSHAW, INC. (HIST)	Closure	2014	Aug	JANCO PARTNERS, INC.	Closure
2012	Apr	MORGAN KEEGAN & COMPANY (HIST)	MA	2014	Apr	MCADAMS WRIGHT RAGEN (HIST)	MA
2012	Nov	THINKEQUITY LLC (HIST)	Closure	2014	Dec	JENNINGS CAPITAL INC (HIST)	MA
2012	Jan	MESIROW FINANCIAL	MA	2014	Feb	STONECAP SECURITIES INC(HIST)	MA
2012	Sep	TOKAI-TOKYO SECURITIES CO., LTD.	MA	2014	Mar	GLEACHER & CO. (HISTORICAL)	Closure
2012	Jan	KAUFMAN BROS.	Closure	2014	May	ORIEL SECURITIES (HISTORICAL)	MA
2012	Dec	CARIS & COMPANY (HIST)	MA	2014	Feb	HFP CAPITAL MARKETS LLC (HIST	Closure
2012	Dec	ROCHDALE SECURITIES LLC (HIS)	Closure	2014	Jun	EAST SHORE PARTNERS, INC.	Closure
2012	Dec	HARDMAN & CO	Closure	2014	Feb	KERN SUSLOW SECURITIES (HIST)	Closure
2012	Jul	PRITCHARD CAP PARTNERS (HIST)	Closure	2014	Jan	CASIMIR CAPITAL LTD.(HIST)	Closure
2012	Dec	DOLMEN STOCKBROKERS (HIST)	MA	2014	May	BYRON CAPITAL MARKETS (HIST)	Closure
2012	Dec	CITADEL SECURITIES	MA	2014	Oct	BURRILL SECURITIES (HIST)	Closure
2012	Jan	TICONDEROGA SECURITIES (HIST)	Closure	2014	Dec	NH INVESTMENT & SEC (HIST)	MA
2012	Aug	MERLIN SECURITIES	MA	2014	Apr	IDMSA (HISTORICAL)	Closure
2012	Jan	WJB CAPITAL GROUP, INC.	Closure	2014	May	EQUITYPANDIT FIN. SVCS (P) LT	MA

YEAR	MONTH	CLOSED FIRMS	EVENT	YEAR	MONTH	CLOSED FIRMS	EVENT
2015	Jun	STERNEAGEE CRT	MA	2016	Dec	RBC WEALTH MANAGEMENT	MA
2015	Dec	OCTAGON CAPITAL CORPORATION	Closure	2016	May	CRT CAPITAL GROUP	MA
2015	Dec	JACOB SECURITIES	Closure	2016	Dec	MIRAE ASSET SECURITIES	MA
2015	Sep	MLV & CO	MA	2016	Aug	TOPEKA CAPITAL MARKETS	Closure
2015	May	MILLENNIUM BCP	MA	2016	Jun	SNS SECURITIES	MA
2015	Aug	EDGECREST CAPITAL	Closure	2017	Sep	HARGREAVE HALE LTD	MA
2015	Jan	DOMINICK & DOMINICK LLC	MA	2017	Jul	WUNDERLICH SECURITIES, INC.	MA
2016	Oct	FIRSTENERGY CAPITAL	MA	2018	May	DENVER INVESTMENT ADVISORS	MA
2016	Feb	SIMMONS & CO. INTERNATIONAL	MA	2018	Dec	GMP SECURITIES LTD.	MA
2016	Sep	MERRIMAN CAPITAL, INC.	Closure	2018	Jul	AHORRO CORPORACION FINANCIERA SA	MA