ANALYST COVERAGE AND STOCK PRICE CRASH RISK

by

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Abstract

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In this study, I investigate the impact of analyst coverage changes on firms' subsequent firm-specific crash risk. Using a sample of 24,228 firm-year observations from 2000 to 2013, I show that changes in analyst coverage are negatively associated with changes in one-year-ahead crash risk. This result is consistent with analysts' information gathering activities and analyses limiting bad news hoarding behavior, and is generally inconsistent with analyst pressure leading to more bad news hoarding by managers. Moreover, I find the negative association between coverage changes and changes in subsequent crash risk to be more pronounced when the coverage change is attributable to Institutional Investor All-Star analysts. This supports my conjecture that a combination of skills, information acquisition advantages, and reputation allows star analysts to more efficiently disseminate information to the market and reduce the likelihood of future crashes for the firms they cover than their non-star counterparts. My findings are robust to the use of alternative measures of crash risk and after controlling for potential endogeneity. Finally, consistent with the argument that both the investors' demands for analyst coverage and the value analysts can provide through their information acquisition should increase with firm-

specific risk, I document a positive association between prior firm-specific crash risk and analyst coverage for the firms. My findings also suggest that star and non-star analysts have distinct decision models and choose what firms to cover based on different factors.

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1. Introduction

This study investigates the role of financial analysts as information intermediaries in mitigating stock price crash risk, defined as the likelihood of firms experiencing extremely negative abnormal returns. Specifically, I examine 1) the impact of analyst coverage changes on covered firms' subsequent changes in firm-specific stock price crash risk and 2) the extent to which analysts take into account prior firm-specific crash risk in making their coverage decisions. Frequent stock price crashes in recent years have generated extensive interest in understanding such crashes and investigating mechanisms that could promote or mitigate crashes. This is not surprising given the effect that stock price crashes have on the portfolios held by investors. In particular, retail investors tend to concentrate investments in a small number of firms (Goetzmann and Kumar, 2008; Barber and Odean, 2013), and stock price crashes of firms in their portfolios can be highly detrimental to their personal wealth.

When a firm is overvalued and the manager has an incentive to sustain such overvaluation, he is incentivized to selectively withhold bad news. Further, when the firm is opaque and is characterized by higher information asymmetry between the manager and outside shareholders, the manager has greater ability and opportunity to be selective in disclosures. On the other hand, if the firm is transparent, even if it is overvalued, the manager's ability to withhold news is limited and the constant flow of information into the market leads to a "soft landing" averting a precipitous stock crash. In opaque firms, managers selectively withhold bad news from investors until the accumulated bad news can no longer be hidden, leading to extreme declines in stock price (Jin and Myers, 2006; Hutton et al., 2009). Consistent with this view, prior studies provide evidence that firm-specific crash risk increases with the opacity of financial reporting, when monitoring is weak, and when managers have stronger incentives or opportunities to hoard unfavorable news (Hutton et al., 2009; DeFond et al., 2015; Callen and Fang, 2013; Kim et al., 2011; Kim and Zhang, 2015).

Analyst coverage could affect firm-specific crash risk in two opposing ways. On the one hand, in their role as important information intermediaries in the capital market, financial analysts are expected to mitigate information asymmetry between investors and managers (Healy and Palepu, 2001; Barth and Hutton, 2004). They collect and analyze information from both public and private sources and thereby limit the amount of bad news managers can withhold from outside investors. Financial analysts have the knowledge, skills, and resources to evaluate firms' underlying performance and future prospects, and reveal their findings to the markets through forecasts, recommendations, and research reports. As analyst coverage increases, more effort and resources are devoted to uncovering firm-specific private information that has not been revealed by existing analysts covering the firm (Crawford et al., 2012; Shroff et al., 2014). This private information acquisition and reporting process likely reduces information asymmetry to a greater extent when firms have bad news than good news, because managers tend to delay the release of bad news (Kothari et al., 2009), and the market may also perceive analysts' unfavorable information to be more credible than favorable information because of analysts' incentives to be optimistic.[1] Consistent with this argument, prior studies show that market reactions are consistent with analyst forecasts and reports being more informative when they convey negative news than when they convey positive news (e.g., Frankel et al., 2006). Taken together, the information perspective suggests that having greater analyst coverage reduces information asymmetry, especially when a firm has bad news. This limits the accumulation of bad news within the firm and reduces firm-specific crash risk. This view suggests a negative

[1] Prior studies suggest that analysts are optimistic due to incentives such as obtaining underwriting business, maintaining access to management, and generating trading commissions (e.g., Lin and McNichols, 1998; Lim, 2001).

association between changes in analyst coverage and subsequent changes in firm-specific crash risk. I refer to this chain of logic as the Information Hypothesis.

On the other hand, the pressure to meet or beat analysts' forecasts on a quarterly basis could lead managers to withhold bad news. Prior studies show that analysts provide optimistic forecasts that are likely to result in overvaluation of a firm's equity (Graham et al., 2005; Bradshaw et al., 2006). Jensen (2004, 2005) argues that overvalued equity is beneficial to managers in the short run and incentivizes them to try to sustain the overvaluation by hoarding bad news. Higher analyst coverage draws more investor attention and makes analyst forecasts more salient as benchmarks for managers. Increased analyst coverage could thus increase the pressure on managers to focus overly on short-term results (e.g., Fuller and Jensen, 2002; He and Tian, 2013; Irani and Oesch, 2016), potentially leading to bad-news hoarding behavior. Regulators are also concerned that investors may be unaware of analysts' conflicts of interest and be misled by analyst reports into making suboptimal investment decisions (Regulation AC, SEC 2003), exacerbating the crash risk. These arguments suggest a positive association between changes in analyst coverage and changes in future firm-specific crash risk. I refer to this chain of logic as the Pressure Hypothesis.

In this study, I empirically study the effect of analyst coverage changes on crash risk. It is important to understand how analyst coverage affects firm-specific crashes because both small (unsophisticated) and large (sophisticated) investors in the equity market rely on analyst recommendations and reports in making their investment decisions (Mikhail et al., 2007). The purpose of this study is to examine whether financial analysts mitigate information asymmetry and reduce firm-specific crash risk for firms that they cover, or alternatively exacerbate bad news hoarding by providing managers with strongerincentives to hide bad news. Taken together, the impact of analyst coverage on stock price crash risk becomes an empirical question.

Using a sample of 24,228 firm-year observations from 2000 to 2013, I document a negative association between changes in analyst coverage and changes in one-year-ahead firm-specific crash risk. The result is consistent with the information perspective, i.e., increases in analyst coverage reduce information asymmetry and restrict managers' bad news hoarding behavior for the covered firms, leading to a lower likelihood of firm-specific crashes in the subsequent year.

Information perspective also implies that coverage by better analysts should have a more negative effect on crash risk. In order to examine this proposition, I identify better analysts as those with star status based on the *All-Star Analyst* ranking published annually by *Institutional Investor* and examine whether the negative association between analyst coverage changes and changes in future firm-specific crash risk increases with the *All-Star* status of analysts changing their coverage of the firm. Star analysts possess superior ability and their reputations affect investors' perception of their credibility, leading to greater and faster market responses to their forecast revisions (Stickel, 1992; Gleason and Lee, 2003). In addition to their superior skills and resources, star analysts' reputations can also give them an informational advantage over other analysts. Managers discriminate among analysts based on their star status and reputations, and star analysts tend to have better access to mangers through both public and private interactions (Mayew, 2008; Soltes, 2014). The privileges of prompting management for specific public signals that facilitate their own private information generation and acquiring unique information during private meetings with management should allow star analysts to produce more informative research reports, which in turn should reduce information asymmetry to a greater extent than non-star analysts do. Moreover, compared to non-star analysts, star analysts' high prestige gives them more independence, making them less likely to ignore their private negative information, if any, about a firm and sacrifice informativeness in order to curry favor with management. Therefore, star analysts are better information intermediaries than average analysts and are more likely to disseminate unfavorable information that managers intend to hide from outside investors.

In contrast, pressure hypothesis predicts that star analysts impose greater pressure on managers to meet or beat their forecasts than non-star analysts do, because the investor expectation becomes stronger when a star analyst makes the forecast. In turn, as per the pressure hypothesis, an increase in star analyst coverage results in a greater incentive for managers to hide bad news and increase the crash risk, more than a similar increase in non-star analyst coverage.

Consistent with the information hypothesis and inconsistent with the pressure hypothesis, I find the negative association between analyst coverage changes and changes in future firm-specific crash risk to be more pronounced when the coverage change is attributable to star analysts. These findings are robust to alternative measures of crash risk that consider only the downside risk and the left tail of the returns distribution.

However, the above analyses do not conclusively establish the directionality of the result. The negative association between coverage and crash risk could also result if analysts selectively choose to cover firms with low crash risk, (with star analysts being better able to identify firms with low crash risk). In order to address this issue, I study analyst coverage decisions and examine whether the negative impact of analyst coverage changes on changes in future crash risk is merely a result of analysts systematically choosing to follow firms with low crash risk. If analysts are effective in mitigating information asymmetry and providing valuable information for high crash risk firms, investors' demands for analyst coverage should increase with firm-specific crash risk, leading to higher analyst coverage. Nevertheless, analysts may be reluctant to cover high crash risk firms because making accurate forecasts for such firms is more challenging and requires greater effort. In addition, the higher variation in accuracy for forecasts of high crash risk firms could pose a greater risk to their reputation. I investigate whether firm-specific crash risk is a determinant of analysts' coverage decisions, and document a positive association between firm-specific crash risk and analyst coverage for the firms in the subsequent year, for both star and non-star analysts. This positive association suggests that analysts tend to follow firms with high crash risk and rules out the possibility that the reduction in crash risk for firms with increased analyst coverage is due to analysts choosing to cover firms with reduced crash risk. The finding suggests that analysts are more likely to cover firms with higher crash risk, in which their informational role would be more valuable, and their research outputs and reports are likely to provide more incremental information to investors in equity markets.

A different endogeneity issue could arise if an analyst's decision to cover a firm is determined by firm characteristics that can also explain the firm's likelihood of experiencing changes in crash risk. I utilize a propensity score matching technique to address this potential endogeneity problem. My findings from the propensity score matched samples suggest that the coverage decision is made differently by star analysts than by non-star analysts, and that increases in coverage by star analysts significantly reduce firm-specific crash risk after controlling for firm characteristics that affect their coverage decisions.

To further ensure that the positive association between prior crash risk and analyst coverage is not due to misspecification of the analysts' coverage decision model, I conduct an exploratory analysis to investigate whether the positive association is in fact a result of analysts choosing to follow firms based on other factors that are correlated with crash risk. The additional data requirements reduce the sample to 15,021 firm-year observations for my exploratory analysis. I find that non-star analysts appear to follow high crash risk firms for several reasons including divergence of opinion, short sale activities, and overvaluation. After controlling for these factors, crash risk continues to be a significant determinant of star analysts' coverage decision. Moreover, my findings suggest that there are heterogeneities in analysts' coverage decisions. Particularly, star analysts seem to see more value in covering high crash risk firms than their non-star counterparts.

My study contributes to the literature in several ways. First, I contribute to the literature on crash risk by showing that coverage by financial analysts is an effective external monitoring mechanism that mitigates information asymmetry and significantly reduces firm-specific crash risk in the subsequent year. Earlier literature focuses mostly on the effect of a firm's internal factors, such as firm characteristics, reporting choices, and contracting decisions, on crash risk. Relatively few studies (e.g., Callen and Fang, 2013) examine the impact of factors and parties external to the firm on crash risk.[2] My study adds to our understanding of how external institutions and mechanisms mitigate information asymmetry and reduce crash risk. My results suggest that analyst coverage is an important factor that investors should consider when making their investment decisions. My study also suggests that managers should consider the impact of analyst coverage in their disclosure and bad news hoarding behaviors.

[2] Callen and Fang (2013) examine the association between institutional ownership and crash risk. However, unlike financial analysts, institutional investors have significant ownership in the firm and can influence managers' behavior through their direct involvements and their seats on the board of directors. In addition, their incentives as shareholders are very different from financial analysts.

Second, my study contributes to the financial analyst literature by identifying a material benefit that analysts bring to equity markets and investors. Firm-specific crashes impose significant costs on market participants investing in the firms because the declines in price are extreme and the losses from crashes destroy a considerable portion of investor wealth, particularly when they are not fully diversified. By showing that analysts help to mitigate the extreme downside risks in capital markets, my study provides empirical support for the analysts' informational roles. My study provides evidence that the informational role of analysts is, on average, more valuable to investors than the potential cost of analysts imposing short term pressure on managers. My results support the notion that the benefits of having analyst coverage outweigh the costs in high information asymmetry environments.

Third, my findings contribute to the literature on star analysts by providing empirical evidence that star analysts are more effective in mitigating crash risk than non-star analysts. This suggests that their coverage increases result in more timely revelation of firm-specific bad news. In addition, my findings suggest that star analysts' informational advantage and superior performance persist in the post-Regulation Fair Disclosure environment.

Finally, my analysis extends our understanding of analyst coverage decision by documenting additional factors that explain analysts' choice to follow a firm. More importantly, the differential results for star and non-star analysts suggest that individual analysts have different decision models, and choose what firms to cover, for diverse reasons. While my results show that analysts generally have a proclivity to cover firms with higher information asymmetry and investor demand for information, star analysts see more value in covering high crash risk firms than non-star analysts.

The remainder of the paper is organized as follows. Section 2 reviews related literature and develops the hypotheses. Section 3 describes the data and discusses the empirical design. Section 4 discusses primary results, and Section 5 presents additional analyses. Section 6 concludes.

2. Related literature and hypotheses development

2.1. Crash risk

Recent studies suggest that stock prices experience extremely large downward movements more frequently than upward ones due, at least in part, to managers withholding bad news from outside investors. Jensen (2004, 2005) argues that managers' incentives to withhold bad news could arise from the benefits of sustaining the overvaluation of the firm's equity (the overvaluation of the firm's equity is better known to the privately informed manager than to the investor). Jin and Myers (2006) argue that managers hide bad news from investors as long as they have the opportunity and experience incremental net benefits in doing so. As a result, bad news will accumulate within the firm until the amount of hidden news exceeds what the managers are willing or able to withhold (bad news hoarding). In their model, the amount of bad news a manager is able to withhold and accumulate increases with the opacity of the firm. Supporting this argument, Jin and Myers (2006) document that firms in countries with greater opacity are more likely to experience crashes in firm-specific returns. Consistent with this argument, several studies document evidence of managers' bad news hoarding behavior. Kothari et al. (2009) examine market reactions to dividend changes and voluntary management forecasts and find that managers strategically delay the release of bad news relative to good news, and this asymmetric disclosure behavior varies across firms. Hutton et al. (2009) investigate opacity at the firm level and find that firms with more opaque financial reporting, captured by larger unsigned discretionary accruals, have higher firm-specific crash risk. This positive relationship between reporting opacity and crash risk disappears in the post-Sarbanes-Oxley Act (SOX) period, consistent with the argument that increased scrutiny post-SOX has reduced reporting opacity associated with accrual-based earnings management. Kothari et al. (2009) show that managers' tendency to delay bad news becomes stronger when there is greater information asymmetry. Kim et al. (2011) investigate firms' corporate tax avoidance activities and argue that the complexity of tax transactions furnishes managers with opportunities and justification to be vague about firm performance, which in turn facilitates bad news hoarding and leads to crashes. Together, these studies suggest that higher information asymmetry is associated with greater crash risk.

From the above rationale, it follows that mechanisms that limit managers' ability to withhold negative information should reduce crash risk. Consistent with this argument, Kim et al. (2015) argue that the higher degree of verification required by the accounting system to recognize good news over bad news (conditional conservatism) limits managers' tendency to hoard bad news. They find that the likelihood of a firm experiencing future stock price crashes decreases with the degree of conditional conservatism, and the negative association is stronger in environments with higher information asymmetry. DeFond et al. (2015) analyze the impact of IFRS adoption on non-financial firms and document a decrease in crash risk after the adoption, suggesting that the increased transparency from IFRS adoption restricts managers' ability to hoard bad news. They also find more pronounced reductions among firms in poor information environments, i.e., those that are likely to experience greater improvements in transparency after IFRS adoption. Callen and Fang (2013) suggest that monitoring by more stable institutional investors curbs managers' opportunities to withhold bad news and decreases firm-specific crash risk. The above findings, taken together, suggest that implementing superior financial reporting systems or monitoring mechanisms that reduce information asymmetry and limit managers' ability to conceal bad news could decrease firm-specific crash risk.

Although most prior studies on crash risk focus on the impact of firms' reporting and internal monitoring mechanisms on crash risk, external monitoring mechanisms could also mitigate information asymmetry between managers and investors and reduce the likelihood of a firm experiencing extreme negative returns. Expanding on this stream of literature, I investigate the impact of analyst coverage changes on firm-specific crash risk.

2.2. The impact of analyst coverage

Financial analysts are arguably among the most important information intermediaries in the capital markets. Analysts acquire and process information from public and private sources, evaluate the performance and future prospects of the firms that they cover, and disseminate information to investors through their forecasts, recommendations, and reports. This process reduces information asymmetry between corporate insiders and outside investors. Higher analyst coverage indicates that more analysts devote their time, effort, and resources into gathering and analyzing information for the covered firm.[3] Consistent with this informational role of financial analysts, Hong et al. (2000) document that momentum-based strategies are more profitable among firms with low analyst coverage, suggesting higher information asymmetry in those firms. Elgers et al. (2001) show that analyst following increases the speed with which stock prices reflect information in analysts' forecasts about future earnings. Frankel and Li (2004) find that

[3] However, it is also possible that, because of the free rider problem, each individual analyst might devote less time and resources with increased coverage.

insiders' information advantage and the profitability of insider trades declines as the number of analysts following the firm increases. Crawford et al. (2012) find that coverage initiations of firms with no prior analyst coverage provide more market- and industry-wide information, while subsequent analysts produce more firm-specific information. Shroff et al. (2014) show that analysts who provide their forecasts late incorporate in their forecast revisions both the information revealed by preceding analysts and new information from their private sources and that even the least timely analyst brings new information to the market. These findings suggest that analysts complement the coverage by other analysts in deciding on the type of information to provide, and that having one more analyst following the firm likely generates incremental firm-specific information. The above studies suggest that, as analyst coverage increases, more resources are devoted to the collection and dissemination of firm-specific information, leading to an incremental reduction in information asymmetry between managers and investors.

In addition, the reduction in information asymmetry due to coverage increase is likely to be greater when analysts reveal bad news compared to when analysts reveal good news about the firm. First, managers are more forthcoming with good news than bad news in their disclosures (e.g., Kothari et al., 2009). Given this asymmetry, the market is likely to better anticipate the favorable information analysts deliver, compared to unfavorable information. Therefore, analysts' unfavorable disclosures contain more information than their favorable disclosures. Second, analysts' conflicts of interest can lead to optimism about firm prospects (e.g., Lin and McNichols, 1998; Jackson, 2005). If the market recognizes analysts' incentives and expects them to be optimistic, investors may consider analysts' unfavorable information releases to be more reliable and credible than favorable ones. Based on these arguments, I expect analysts to be more informative in disseminating bad news compared to when disseminating good news. Consistent with this argument, Hong et al. (2000) find that momentum profits are driven by losers, as opposed to winners, suggesting that stock prices are more prone to under-react to bad news than to good news. They also show that the under-reaction to bad news is more severe for firms with low coverage than those with high coverage, and the effect of coverage on momentum profits is entirely driven by bad news firms. Frankel et al (2006) suggest that analyst forecasts that convey bad news have a greater price impact than good news forecast revisions. Huang et al. (2014) analyze textual opinions in analyst reports and document that investors place more than twice as much weight on negative report text than on positive text. These studies provide empirical support for the argument that the informational role of analysts is particularly important in distributing bad news, implying that investors react more strongly to negative than to positive information conveyed by analysts. In turn, having higher analyst coverage reduces information asymmetry most when firms have bad news.

Collectively, the information perspective suggests that increases in the number of analysts covering the firms reduce information asymmetry and make it more difficult for managers to conceal negative news. As analyst coverage increases, managers' ability to delay the release of bad news is more constrained, which lowers the threshold beyond which managers start releasing their private negative information to the market. Thus, with greater coverage, bad news is released more gradually to the market in relatively smaller chunks, reducing the likelihood of crashes that happen when a significant amount of withheld bad news comes out to the market all at once. This reasoning suggests that future firm-specific crash risk is likely to decrease (increase) as the number of analysts covering the firm increases (decreases).

Analyst coverage can also affect the delay in the release of bad news to investors through analysts' optimism. Prior studies suggest that analysts are optimistic due to incentives such as obtaining underwriting business, maintaining access to management, and generating trading commissions.[4] Such optimism can delay the distribution of firm-specific bad news to the market (O'Brien et al, 2005) and increase the probability of future crashes for the firms they cover. However, Hong and Kacperczyk (2010) find that optimism in analyst earnings forecasts increases after covered firms experience a reduction in analyst coverage, suggesting that competition among analysts reduces analyst optimism. Thus, the delayed release of bad news due to analyst optimism should decrease with the number of analysts following the firm, leading to a negative association between changes in coverage and changes in future crash risk.[5]

Alternatively, analyst coverage could increase the pressure on managers to meet or beat analyst forecasts to avoid negative consequences of missing analyst forecasts, such as significant declines in stock prices (Bartov et al., 2002), reduced CEO bonuses (Matsunaga and Park, 2001), and increased probability of management turnover (Mergenthaler et al., 2011). In their responses to surveys by Graham et al. (2005), CEOs recognize the importance of analysts in affecting their companies' stock prices, and indicate that they are willing to sacrifice firm value to meet earnings targets, due to their own wealth, career, and external reputation concerns. When analysts are pessimistic and the firm is undervalued, managers are likely to be more forthcoming with private positive information, leading to a more timely correction of the pessimism or undervaluation. When analysts are optimistic and the firm is overvalued, managers are likely to withhold bad news and sustain the overvaluation, leading to higher crash risk in the future. This pressure to hide negative information could increase with analyst coverage, because higher

[4] Lin and McNichols (1998) show that affiliated analysts issue forecasts and recommendations that are more favorable than the ones prepared by unaffiliated analysts to promote investment banking business. Lim (2001) proposes that rational analysts trade off optimistic forecast bias against access to management in order to improve their forecast accuracy. Jackson (2005) provides support that analysts use optimistic forecasts to boost short-term trading commissions.

[5] However, to the extent that investors anticipate analyst optimism and deflate analysts' optimistic reports, the impact of analyst optimism will be attenuated.

coverage attracts more investor attention and potentially leads to a greater penalty in the capital markets. Consistent with this view, prior studies document evidence that, in response to pressure from greater analyst coverage, managers invest less in innovative long-term projects and engage in more real activities manipulation to achieve short-term goals (e.g., He and Tian, 2013; Irani and Oesch, 2016). Thus, higher analyst following can promote bad news hoarding by the managers to avoid missing analyst forecasts, leading to higher firm-specific crash risk.

Altogether, while analysts' informational and monitoring roles and the competition among analysts suggest a negative association between changes in analyst coverage and changes in crash risk, the pressure to meet or beat analyst expectations suggests a positive association. Therefore, the effect of coverage changes on crash risk is ultimately an empirical question. I investigate the following hypothesis, stated in null form:

H1: There is no association between changes in analyst coverage and changes in firm-specific crash risk in the subsequent year.

2.3. Star analysts coverage

Prior literature documents persistent differences between star analysts and non-stars in both the information content of their reports and the impact they have on market participants (e.g., Stickel, 1992; Gleason and Lee, 2003). If the informational role of analysts is effective in reducing crash risk, and star analysts are better information intermediaries than non-star analysts, star analysts should be more effective in reducing firm-specific crash risk than other analysts. I investigate whether increases (decreases) in coverage by analysts who are identified as *All-Stars* (*All-American Research Team*) by *Institutional Investor* magazine lead to greater decreases (increases) in the covered firms' crash risk.

Stickel (1992) shows that *All-Stars* produce more accurate earnings forecasts than other analysts following the same firm. Desai et al. (2000) implement a buy-and-hold strategy and find that the stocks recommended by all-stars outperform those in the same industry and of similar size, suggesting that star analysts have superior stock-picking ability. Leone and Wu (2007) document superior performance by star analysts than non-stars in terms of earnings forecast accuracy and stock recommendation returns. They also find that, for analysts who are ranked consecutively as stars, their superior performance persists over the years after an analyst is first ranked, suggesting that their performance is likely due to superior ability. These studies indicate that star analysts tend to have more accurate assessments about firms' underlying value and future prospects.

Prior literature provides several potential explanations for star analysts' superior performance, including their superior research ability/skills and better access to additional resources. To the extent that there exists some skill difference between star and non-star analysts (e.g., Leone and Wu, 2007; Fang and Yasuda, 2014), star analysts are likely better able to extract private information and/or process and analyze information for investors. Therefore, an increase in analyst coverage by a star analyst should reduce information asymmetry to a greater extent than coverage increase by a non-star analyst.

Star analysts' prestige can give them an advantage over other analysts in information acquisition, which in turn allows them to produce more informative analyst reports. Mayew (2008) examines conference call transcripts and documents how managers discriminate among analysts based on their star status. He finds that, among analysts giving favorable recommendations, star analysts are more likely to be allowed to ask questions during conference calls. Soltes (2014) finds that the probability of having private interactions with management in a given month is significantly higher for all-star analysts than for others. The participation during conference calls gives star analysts the opportunities to prompt managers for public information that complements their existing private information, while their private conversations with management allow them to obtain additional private information that is not available to other analysts or investors.[6,7] The better access to management through both public and private channels can provide star analysts distinct informational advantage over non-star analysts, enhancing their ability to mitigate information asymmetry.

Furthermore, star analysts are less likely to ignore their private information and be optimistic in order to obtain underwriting business or gain access to management. Ljungqvist et al. (2006) show that, while analysts in general tend to be more optimistic in their recommendations when more fee income can be earned from an underwriting mandate, star analysts are associated with less aggressive recommendation upgrades compared to non-star analysts. This is consistent with the career concern /reputational damage argument that analysts trade off the cost of jeopardizing reputation against the benefit of being optimistic. Mayew (2008) documents that, when analysts downgrade their recommendations, managers punish only non-star analysts by decreasing their access to management during conference calls, but not star analysts. Thus, the above studies suggest that, compared to non-star analysts, star analysts are more likely to truthfully communicate negative information about the firms they cover, which should more effectively alleviate information asymmetry between managers and investors and reduce firm-specific crash risk.

[6] Regulation FD does not prohibit analysts from obtaining non-material information from management during private meetings, "*even if, unbeknownst to the issuer, that piece helps the analyst complete a 'mosaic' of information that, taken together, is material*." (Security and Exchange Commission Release Number 33-7881).
[7] Mayew and Venkatachalam (2012) find that analysts are able to generate insights from managers' vocal cues and incorporate the information into their recommendations.

Prior studies show that the market differentiates star analysts from their non-star counterparts. Star analysts have reputations that elicit stronger immediate market reactions to their forecast revisions (e.g., Stickel, 1992). Loh and Stulz (2011) document that, while only about 12% of the recommendation changes in their sample are influential in stock-level abnormal returns, recommendation changes are more likely to be influential if they are issued by star analysts. Gleason and Lee (2003) find that the post-revision price drift associated with analyst forecast revisions is less pronounced when the revisions are made by all-stars than by other analysts with comparable forecasting ability, suggesting that market responses to analyst forecasts are affected by analysts' reputations, not merely their abilities.

In sum, I conjecture that star analysts' superior abilities, information advantages, and reputations allow them to more effectively mitigate information asymmetry and reduce firm-specific crash risk. Therefore, I expect that increases (decreases) in coverage by star analysts should lead to greater decreases (increases) in firm-specific crash risk than those by non-stars. Stated formally:

H2: The association between changes in analyst coverage and changes in firm-specific crash risk in the subsequent year is more negative when the coverage changes come from star analysts.

2.4. Analyst coverage decision

Analysts' coverage decisions should depend on the potential benefits and costs of following a firm. When the information asymmetry between managers and investors is high, investors will, *ceteris paribus*, have higher demand for information. Consistent with this investor demand argument, Barth et al. (2001) find that firms with higher research and development and advertising expenses relative to their industry peers tend to have greater analyst coverage. Lehavy et al. (2011) show that firms with less readable annual reports have higher analyst coverage, supporting the argument that the complexity of language used in firms' 10-Ks can negatively affect investors' ability to interpret financial results and thus create higher demand for analyst coverage. Lobo et al. (2012) document a negative association between accruals quality and the number of analysts following a firm. Moreover, analyst forecasts contain more private information when covered firms' accruals quality is low, which is consistent with the view that greater information asymmetry leads to greater demand for private information. To the extent that analysts have an information advantage over average investors and have more accurate assessments about firms' future prospects, firms with high crash risk provide more opportunities for analysts to profit from their private information acquisition and analysis of the firm. I conjecture that the information provided by analysts is more valuable to investors when firms have high crash risk, leading to higher investor demand and thus higher analyst coverage for such firms.

Alternatively, analysts likely exert greater effort and incur greater costs to process and obtain information for high crash-risk firms given the potential reputation loss, the risk associated with following high crash risk firms and the difficulty of analyzing such firms. The high information asymmetry surrounding high crash risk firms could lead to inaccurate forecasts and recommendations that adversely affect analysts' reputations and careers (e.g., Lang and Lundholm, 1996; Hong and Kubik, 2003). The higher cost of information acquisition for analysts in covering firms with high information asymmetry can also lead to lower supply of coverage (e.g., Lang and Lundholm, 1993). Therefore, analysts may be reluctant to cover high crash risk firms.

Whether the benefits of following a high crash risk firm outweigh the costs of doing so is unclear *ex ante*. As such, I state the following hypothesis in null form:

H3: The number of analysts following a firm is not associated with firm-specific crash risk.

3. Data and research design

3.1. Data

I identify analysts' star status based on the All-America Research Team (*All-Star*) ranking published annually in *Institutional Investor* from 2000 to 2013.[8] I manually collect information and check the identity of individual *All-Star* analysts, then match them with the I/B/E/S database based on their employment history, the industries and firms they follow.[9] I also manually reconcile errors and inconsistencies in analyst names over time due to reasons such as changes in marital status, name changes, and errors in *Institutional Investor* or the I/B/E/S database. I obtain analyst coverage data on U.S. securities from the I/B/E/S detail recommendation file. For each firm-year, I require sufficient returns data from the Center for Research on Security Prices (CRSP) database to calculate crash risk measures and return-related control variables, as well as sufficient company financials from COMPUSTAT to construct the other control variables. My final sample consists of 24,228 firm-year observations.

[8] *Institutional Investor* magazine surveys around 3,000 buy-side managers, research directors, portfolio managers, and other investment professionals every year. Sell-side analysts are evaluated based on many dimensions, including the insight of their written reports, the overall service they provide, their stock picking ability, the quality of their recommendations, and the accuracy of their forecasts.

[9] I collect the information through searches for media mentions as well as from professional networking services, such as LinkedIn.

3.2. Measures of firm-specific crash risk

Following prior literature (e.g., Chen et al., 2001; Hutton et al., 2009; Callen and Fang, 2013), I construct three firm-specific crash risk measures to ensure robustness. To calculate measures of stock price crash risk, I first run the expanded market and industry index model regression for each firm and year to estimate firm-specific daily returns:

$$r_{j,t} = \alpha_j + \beta_{1,j}\, r_{m,t-1} + \beta_{2,j}\, r_{i,t-1} + \beta_{3,j}\, r_{m,t} + \beta_{4,j}\, r_{i,t} + \beta_{5,j}\, r_{m,t+1} + \beta_{6,j}\, r_{i,t+1} + \varepsilon_{j,t}\ , \quad (1)$$

where $r_{j,t}$ is the return of stock j on day t, $r_{m,t}$ is the return of value-weighted market index on day t, $and\ r_{i,t}$ is the return of value-weighted industry index on day t based on two-digit SIC codes. The model includes the lag and the lead terms, t-1 and t+1, to account for nonsynchronous trading (Dimson, 1979). The firm-specific daily return, $R_{j,t}$, is calculated by taking the natural log of one plus the residual return from Eq. (1). I use residual returns, which capture the portion of returns not explained by the market or the industry, because my focus is on firm-level crash risk caused by idiosyncratic factors. The log transformation reduces the positive skew in the distribution of returns and makes the distribution more symmetric (Chen et al, 2001).

The first measure of stock price crash risk, NCSKEW, is the negative coefficient of the skewness of firm-specific daily returns. NCSKEW is calculated by taking the negative of the third moment of firm-specific daily returns for each sample year and dividing it by the standard deviation of firm-specific daily returns raised to the third power.

$$NCSKEW_{j,t} = -\,[n(n-1)^{3/2} \sum R_{j,t}^3] \,/\, [(n-1)(n-2)(R_{j,t}^2)^{3/2}] \quad (2)$$

Negative values for the skewness corresponds to left-skewed stock return distribution, indicating that the firm has a disproportionate likelihood of experiencing extreme negative stock returns. A higher magnitude in the value of NCSKEW translates to greater left tail risk.

The second measure of crash risk is the down-to-up volatility (DUVOL) and is computed as:

$$DUVOL_{j,t} = log\ \{(n_u - 1) \sum Down\ R_{j,t}^2 \ / \ (n_d - 1) \sum Up\ R_{j,t}^2\ \} \qquad (3)$$

where n_u and n_d stand for the number of up and down days over the year respectively. First, I separate all the days with returns below the mean return of the year from the days with returns above the annual mean return. Then I calculate the standard deviations for "down" and "up" samples and take the natural log of the ratio of standard deviations of down-day to up-day returns during the fiscal year. This DUVOL measure does not involve third moment and thus is less likely to be overly influenced by a small number of extreme returns. A higher value of DUVOL means that a stock is more crash-prone.

The last measure COUNT is defined as the number of days a firm's stock daily return is 3.09 standard deviations below the annual mean minus the number of days when its daily return is 3.09 standard deviations above the annual mean. The higher the value of COUNT, the more likely a firm will suffer from a stock price crash. The two areas that are 3.09 standard deviations away from the mean represent 0.1% of the normal distribution respectively, and I follow prior literature in using the 0.1% cutoff as the benchmark for an "extreme" stock return.

3.3. Main regression models

To test my hypothesis concerning the effect of analyst coverage changes on firm-specific crash risk (H1), I regress changes in crash risk on changes in analyst coverage along with a set of control variables described in section 3.4.

$$\Delta\ Crash\ Risk_{(t+1)} = \beta_0 + \beta_1 * \Delta Analyst\_Following_t + \beta_2 * \sum Control\ Variables_t$$
$$+ (Industry\ Dummies) + \mathcal{E},$$

where *Crash Risk* is proxied by one of the three measures described in section 3.2. The variable of interest is ***Δ****Analyst_Following*, changes in the number of analysts following the firm. A negative (positive) coefficient estimate on the variable (β_1) is consistent with the viewpoint that an increase (decrease) in analyst following decreases (increases) future crash risk.

To test whether star analysts are better information intermediaries and can more effectively reduce firm-specific crash risk than non-star analysts (H2), I regress changes in crash risk on ***Δ****Star_Analyst* and ***Δ****NonStar_Analyst*, changes in the number of star and non-star analysts covering the firm, respectively.

$$\Delta\ Crash\ Risk_{(t+1)} = \beta_0 + \beta_1 * \Delta Star\_Analyst_t + \beta_2 * \sum Control\ Variables_t$$
$$+ (Industry\ Dummies) + \mathcal{E}$$

$$\Delta\ Crash\ Risk_{(t+1)} = \beta_0 + \beta_1 * \Delta NonStar\_Analyst_t + \beta_2 * \sum Control\ Variables_t$$
$$+ (Industry\ Dummies) + \mathcal{E}$$

$$\Delta\ Crash\ Risk_{(t+1)} = \beta_0 + \beta_1 * \Delta Star\_Analyst_t + \beta_2 * \Delta NonStar\_Analyst_t$$
$$+ \beta_3 * \sum Control\ Variables_t + (Industry\ Dummies) + \mathcal{E}$$

I expect the coefficient estimate on *ΔStar_Analyst* to be more negative (less positive) than that on *ΔNonStar_Analyst*, indicating that coverage by star analysts more effectively reduces future firm-specific crash risk than coverage by non-star analysts.

3.4. Control variables for crash risk models

Following prior literature, I control for the following variables: $KURT_t$ is the kurtosis of firm-specific daily returns in fiscal year t and measures the heaviness of the distribution's tail. Higher value of $KURT_t$ means that more of the variance is attributable to infrequent extreme deviation, rather than frequent modest deviation. $SIGMA_t$ is the standard deviation of firm-specific daily returns. More volatile stocks are expected to have higher risk of crashes. $DTURN_t$ is the average monthly share turnover over year t minus the average monthly share turnover over year t-1, where monthly share turnover is calculated by dividing trading volume by number of shares outstanding over the month. $DTURN_t$ is a measure of the disagreement among investors. Firms with higher share turnovers are predicted to be more crash-prone. RET_t is defined as the cumulative firm-specific daily returns in year t. The stocks with high past returns are more likely to crash in the future. MB_t is the market value of equity divided by the book value of equity in year t. Growth stocks have been shown in the past to be more likely to experience stock price crashes. LEV_t is defined as the total liabilities divided by the total assets at the end of year t. ROE_t is defined as income before extraordinary items divided by the lagged book value of equity. Both financial leverage and operating performance are found to be negatively associated with future crash risk in the prior literature. $SIZE_t$ is the log of market capitalization at the end of year t. $OPAQUE_t$ is the 3-year moving sum of the absolute value of annual discretionary accruals and measures the firm's underlying policy regarding earnings management. Hutton et al. (2009) show that firms with larger discretionary accruals exhibit higher stock price crash risk.

3.5. Regression models for analyst coverage decisions

To examine my hypothesis about whether firms-specific crash risk affects the demand and/or supply of analyst coverage (H3), I estimate the following regression using a negative binomial count-data model: [10]

$$\begin{aligned} Analyst\ Coverage_t = {} & \beta_0 + \beta_1 * Crash\ Risk_{t-1} + \beta_2 * RetSTD_{t-1} + \beta_3 * RSQ_{t-1} \\ & + \beta_4 * AvgEFF_{t-1} + \beta_5 * AvgBROKER_{t-1} + \beta_6 * AvgEXP_{t-1} + \beta_7 * SIZE_{t-1} \\ & + \beta_8 * SalesGrowth_{t-1} + \beta_9 * Momentum_{t-1} + (Industry\ Dummies) + \mathcal{E}, \end{aligned}$$

where *Analyst Coverage* is one of *N_FOLLOW, N_STAR,* or *N_NonSTAR*, the number of all analysts, star analysts, or non-star analysts following the firm, respectively. A positive (negative) estimate of the coefficient on *Crash Risk*, β_1 , is consistent with the argument that the benefits of covering a high crash risk firm are greater (less) than the costs, leading to higher (lower) analyst coverage. Following previous research, I include a set of control variables that are believed to be likely predictors of analyst coverage. These control variables are measured with a one-year lag relative to the dependent variables. The variable *RetSTD* is the standard deviation of returns. Bhushan (1989) argues that the potential trading profits based on private information are expected to be higher for firms with high return variability. Consequently, the private information provided by analysts is more valuable to investors and demand for analyst coverage is stronger for firms with higher return volatility. The variable RSQ is the synchronicity of the

[10] Rock et al. (2001) show that when analyzing count data (i.e. nonnegative integers) dependent variables like analyst coverage, the negative binomial model is more appropriate than the OLS or Poisson model and better captures the true underlying data generating process. It also addresses the econometric issues associated with truncation (zero value) and over-dispersion (lower standard error) in the data.

firm and market returns, defined as the R^2 from the regression of the firm's returns on market returns. The higher the degree of co-movement of firm and market returns, the less costly it is for analysts to acquire firm-specific information. However, such firm-specific information would be less valuable as well. The lower private benefits of covering the firm can discourage analyst coverage. Therefore, the effect of R^2 on analyst coverage is unclear. Following Barth, Kasznik, and McNichols (2001), I control for analyst effort (*AvgEFF*) and brokerage size (*AvgBROKER)*. I expect fewer analysts to follow firms that require greater effort and thus a negative relation between analyst effort and coverage. *AvgEFF* is defined as the negative of the average number of firms followed by the firm's analysts. Analysts have limited capacity, and the more firms they cover, the less time and resources they can invest in each firm. The average number of firms covered is multiplied by -1 so that higher *AvgEFF* indicates greater effort. *AvgBROKER* is defined as the average number of analysts employed by the brokerage houses that employ a firm's analysts. On one hand, there may be a mechanical negative relation between coverage and sizes of covering analysts' brokerage house because firms with lower coverage are usually only covered by large brokerage houses, while firms with higher coverage are covered by both large and small brokerage houses. On the other hand, Barth et al. (2001) argue that brokerage house size also plays a crucial role in dictating analyst effort because larger brokerage houses have more resources and manpower in addition to their analysts (e.g., assistants that do not appear on analyst reports) and thus their analysts may be able to follow more firms without compromising the amount of effort they put into each firm. *AvgEXP* is defined as the average number of years of experience the analysts covering the firm have, and is measured by the average number of years since the firm's analysts first appeared in the I/B/E/S database. The variable *SIZE* is controlled for since both the aggregate demand for and supply of analyst coverage are likely to increase with firm size. Investors are likely more interested in investing in large firms' stocks because of the liquidity advantage, while analysts are more inclined to cover large firms due to more potential transaction businesses. *SalesGrowth* is included because firms with higher growth prospects have greater earnings uncertainty. As a result, both benefits and costs associated with collecting private information for analysts are higher, and thus the effect of growth on coverage is not obvious. *Momentum* is defined as the stock return in the previous year. Firms that performed well in the past are likely to attract investor attention and analyst coverage.

4. Empirical results

4.1. Descriptive statistics

Table 1 Panel A provides the descriptive statistics for the variables used in the main regression analyses for my final sample of 24,228 firm-years from 2000 to 2013. The mean (median) coverage by all analysts is 6.23 (5) for firms in my sample, while the mean (median) coverage by star analysts is 0.72 (0). The distributions of the crash risk measures and the control variables are generally in line with prior studies. Panel B compares the subsamples of firms covered by at least one star analyst and firms without star analyst coverage and suggests that firms in the two subsamples are significantly different from each other in many characteristics. Most importantly, firms covered by at least one star analyst on average experience greater reductions in crash risk in the subsequent year than firms covered by only non-star analysts.

Table 2 presents the correlation matrix with Pearson correlations above the diagonal and Spearman correlations below. Panel A presents the variables in my analysis of the impact of changes in analyst following. As expected, the three measures of change in crash risk (i.e., $\Delta NCSKEW_{t+1}$, $\Delta DUVOL_{t+1}$, *and* $\Delta COUNT_{t+1}$) are significantly and positively correlated with each other, indicating that they capture different aspects of the same construct. Consistent with prior literature, I observe positive correlations between measures of change in future crash risk and $DTURN_t$, RET_t, MB_t, and $SIZE_t$. More importantly, all three measures of change in future crash risk are negatively correlated with ΔN_FOLLOW_t, ΔN_STAR_t, *and* $\Delta N\_NonSTAR_t$, consistent with the argument that an increase in analyst following constrains managers' bad news hoarding behavior, and in turn lessens future crash risk. Moreover, the negative correlations between crash risk measures and ΔN_STAR_t are stronger than those between crash risk measures and $\Delta N\_NonSTAR_t$, suggesting that star analysts are more effective in reducing information asymmetry and future crash risk than their non-star peers. Table 2 Panel B presents the variables included in my analysis of analyst coverage decision. The positive associations between the analyst coverage variables and the crash risk measures in the previous year suggest that analysts, regardless of whether they are star or non-star, tend to follow firms with higher crash risk. The positive associations are significant and consistent across different coverage and crash risk measures.

4.2. Impact of analyst coverage

Table 3 presents the multivariate regression analyses for the impact of analyst coverage changes on firms' subsequent firm-specific crsh risk. Panel A displays the coefficient estimates using OLS regressions with $\Delta NCSKEW_{t+1}$ (change in *NCSKEW* from year t to year t+1) as the dependent variable. In column (1), the significantly negative relation (-0.013, t= -3.03) between the change in the number of analysts following the firm (ΔN_FOLLOW_t) and the change in future crash risk ($\Delta NCSKEW_{t+1}$) indicates that, on average, firms experience a reduction in crash risk following an increase in analyst coverage. This is consistent with the information perspective, which suggests that analysts curb managers' bad news hoarding behavior and play a crucial role in lowering future crash risk. Columns (2) to (4) provide evidence on the differential impact of coverage by star and non-star analysts. The coefficient on change in star analyst coverage (ΔN_STAR_t = -0.034, t = -2.81) is more negative and significant than that on non-star analyst coverage ($\Delta N\_NonSTAR_t$ = -0.010, t= -2.13), indicating that having one more star analyst following the firm reduces future crash risk to a greater degree than when the coverage increase is attributable to a non-star analyst. Panels B and C report the results of OLS regressions with $\Delta DUVOL_{t+1}$ and $\Delta COUNT_{t+1}$ as the measure of change in crash risk, respectively. The results are robust to the use of alternative measures of crash risk and are similar to those presented in Panel A. Consistent with my prediction, the findings suggest that star analysts are likely better information intermediaries than non-star analysts due to their superior research skills, information acquisition advantages, independence, and/or reputations. The combination of these characteristics allow star analysts to more efficiently disseminate bad news to the market and reduce the likelihood of future crashes for the firms they cover.

4.3. Analyst coverage decision

Table 4 reports the negative binomial regression analyses for analyst coverage decision. Panel A presents the results for the overall analyst coverage decision, with N_FOLLOW_t being the dependent variable and the three *Crash Risk* measures $NCSKEW_{t-1}$, $DUVOL_{t-1}$, and $COUNT_{t-1}$ reported in each of the three columns. The positive associations between $Crash\ Risk_{t-1}$ and N_FOLLOW_t are significant across all three measures of crash risk, $NCSKEW_{t-1}$ (0.030, t= 11.72), $DUVOL_{t-1}$ (0.122, t= 13.92), and $COUNT_{t-1}$ (0.025, t= 11.74), indicating that analysts tend to follow high crash risk firms, probably because the benefits of satisfying investors demand for private firm-specific information outweighs the higher costs of information gathering for crash-prone firms. Consistent with previous studies (e.g., Barth et al, 2001, Bhushan, 1989), I also find that analyst coverage increases with firm size (*Size*), return variability (*RetSTD*), the synchronicity of the firm and market returns (*RSQ*), and growth (*SalesGrowth*), and firms that command more analyst effort tend to be followed by fewer analysts.

Panel B and Panel C of Table 4 present the regression results for star and non-star analyst coverage, *N_STAR* and *N_NonSTAR*, respectively. The estimated coefficients on crash risk measures, β_1, are significantly positive at less than 1% significance level across all three crash risk measures ($NCSKEW_{t-1}$, $DUVOL_{t-1}$, and $COUNT_{t-1}$), indicating that coverage by both star and non-star analysts increases with crash risk. The negative and significant coefficient on *RSQ* in Panel B indicates that star analysts have a preference for firms with lower degree of return co-movement with market returns, which is consistent with the notion that the potential benefits from acquiring private information about these firms are higher, and star analysts, who have superior ability to gather and process firm-specific information at a lower cost, are more likely to cover such firms. The positive associations between prior crash risk and analyst coverage documented across all three panels indicate that both star and non-star analysts tend to follow firms with high crash risk, likely because the higher information asymmetry in these firms makes their role as information intermediaries more valuable to investors. More importantly, the positive association also rules out the alternative argument that the reduction in crash risk for firms with increased analyst coverage is due to analysts systematically choosing to cover firms with reduced crash risk. The results are consistent with analysts choosing to satisfy investors' greater demand for firm-specific information when crash risk is high. More skilled analysts who are able to provide firm-specific information about high crash risk firms at a relatively low cost choose to follow those firms, which allows them to profit from generating private information.

5. Additional analyses

5.1. Propensity score matched (PSM) samples

Analyst coverage decision is likely endogenous with respect to a firm's crash risk in that firm characteristics could determine both analysts' decision to cover a firm and the firm's tendency to experience crashes. Firms that are prone to crashes may have characteristics that are very distinct from other firms and are less attractive to some analysts. To address this potential endogeneity issue, I use a propensity score matching technique to construct the control samples and account for observable variables that affect analysts' decisions to increase coverage. I first model the propensity of analyst coverage increase with a logit regression based on the determinants of analyst coverage discussed in Section 3.5. A propensity score is estimated for each firm-year in my sample based on the predicted probability of the firm experiencing analyst coverage increase from the logit model. I then match, without replacement, firms that experience an analyst coverage increase (the treatment group) and those that do not experience an increase in coverage (the control group) by selecting the closest control firm available.[11] I require that the matching control firm selected to be within a caliper of 0.01 of the treatment firm to ensure the similarity of the observable determinants of analyst coverage between the treatment and control groups. The propensity score matching procedure generates a sample of 9,455 pairs in my sample. Alternatively, I also construct separately the matching control groups among firms that experience no coverage changes and those that suffer from a decrease in analyst coverage for the robustness of the results. The alternative samples contain 4,250 and 8,096 firm-pairs, respectively. The mean values of the determinants of analyst coverage for the respective

[11] The closest control firm available is the one that minimizes the absolute difference between the propensity scores of the treatment firm and the control firm.

treatment and control groups are reported in Table 5 Panel A. The differences between the treatment and control groups are statistically insignificant for all of the variables, indicating that the propensity score matching processes generate matched samples that are similar in all dimensions of the coverage decision determinants. Results from the regression analyses using the matched samples, shown in Panel B to Panel D, suggest that coverage increases by star analysts are more effective in reducing firm-specific crash risk than those by non-star analysts, and that the reductions in crash risk following analyst coverage increases are driven mainly by star analysts.

5.2. Alternative measures of crash risk

To further examine whether increases in analyst coverage actually reduce the downside risk and the likelihood of firms experiencing extremely negative stock returns, I focus on the left-hand side of the returns distribution using two alternative measures of firm-specific stock price crash risk. The first alternative measure of crash risk is the downside volatility (*DOWNVOL*), which is the standard deviation of firm-specific daily returns on the days with returns below the mean of the fiscal year. The results, reported in Panel A of Table 6, are consistent with the findings from the main analyses in Table 3. The second alternative crash risk measure is the number of days with extremely negative daily returns (EXTREMELOW) that are 3.2 standard deviations below the mean firm-specific daily returns during the fiscal year. Table 6 Panel B presents the results for this measure. Findings from both of the alternative measures suggest that greater coverage by analysts significantly reduces the likelihood of stock price crashes, supporting my conjecture that increases in analyst coverage, especially those made by star analysts, mitigate managers' bad news hoarding behavior and facilitate the dissemination of bad news to the market.

5.3. Analyst coverage decision

While the positive associations between prior crash risk and analyst coverage in Table 4 suggest that analysts tend to follow high crash risk firms, likely because of the higher demand for information from investors, an alternative explanation for this positive association is that analysts make their coverage decisions based on other factors that are correlated with crash risk. Thus, the greater analyst coverage observed for high crash risk firms could be an indirect result of other variables in analysts' decision model, rather than a response to investor demand or an attempt to signal their ability by following high crash risk firms. To address this issue, I conduct an exploratory analysis on factors that could affect analysts' decision to cover a firm. First, I conjecture that information asymmetry and divergence of investors' opinion lead to greater demand for private information as investors seek to reconcile their disagreement, which in turn leads to higher analyst coverage. I include bid-ask spread (*BidAskSpread*) and trading volume (*TradingVolume*) as proxies for divergent opinions among investors and expect analyst coverage to increase with both bid-ask spread and trading volume. Second, I expect information provided by analysts to be more valuable to investors when there is greater information asymmetry between informed and uninformed traders. Short sellers are generally considered informed traders and short sale activities represent their profitable trading opportunities. I use short interest ratio (*ShortInt*), measured as the number of shares sold short divided by total shares outstanding from the last month of the fiscal year, to capture the trading opportunities and investors' demand for private information. Thus, I expect analyst coverage to increase with short interest. Finally, I consider the impact of market valuation of stocks on analyst coverage. Glamour stocks are popular among investors and receive higher valuation because the market views such stocks as having strong future prospects and growth potential. However, the greater investor attention and stronger demand for glamour stocks often lead to overvaluation of the stocks. Consistent with Desai et al. (2004), I use price-to-earnings (P/E) ratio as a proxy for glamour stocks. While high uncertainty and growth potential would create investor demand for information, analysts could still shy away from a glamour stock if their own analyses suggest extreme overvaluation. I sort stocks into deciles based on P/E ratios and identify stocks in the top P/E ratio decile as suspects for extreme overvaluation (*Overvaluation*).

The results of my exploratory analysis on the determinants of analyst coverage decisions are presented in Table 7 Panel A to Panel C. Interestingly, the impact of crash risk on analyst coverage decision differs depending on whether the coverage is by star or non-star analysts. After including the above variables in the coverage decision model, crash risk is still incrementally significant for star analysts, but not for non-star analysts. The insignificant coefficient estimates on *N_NonSTAR* across columns (1) to (3) in Table 7 Panel C indicate that non-star analysts seemingly cover high crash risk firms but in fact choose those firms for other reasons. In contrast, after controlling for the above variables, crash risk continues to be a significant factor that star analysts take into account when choosing what firms to cover. The results are consistent with the argument that star analysts are more likely to follow high crash risk firms than non-star analysts, probably because star analysts are better able to provide firm-specific information at a lower cost for high crash risk firms, which are more difficult to follow and require more effort. In addition, consistent with my conjectures, both star and non-star analysts are more likely to cover firms with greater information asymmetry and greater divergence of opinion among investors. The intensity of short sales and overvaluation of the firm appear to have differential impact on the star and non-star analysts' coverage decisions. Even though analysts, on average, tend to follow firms with more short sales, the positive association is driven by the coverage by non-star analysts. While non-star analysts are more likely to follow firms that are potentially overvalued, star analysts do not seem to do so. Together, I find that analysts make their coverage decisions based on factors that are different for analysts with differential skills and resources.

6. Conclusion

In this study, I examine the impact of analyst coverage changes on firms' future firm-specific crash risk. I document that covered firms' one-year-ahead changes in firm-specific crash risk decrease with changes in analyst coverage. My findings suggest that, on average, analyst coverage has a negative effect on crash risk, suggesting that the analysts' role as information intermediaries in mitigating crash risk outweighs any potential increase in crash risk due to pressure imposed on managers by their coverage. To elaborate, an increase in the number of analysts covering the firm reduces information asymmetry, making it more difficult for managers to withhold bad news. Consequently, bad news flows into the market more promptly, reducing the possibility of a bad-news build-up and subsequent firm-specific crash risk. Moreover, I find the negative association between coverage changes and changes in future crash risk to be more pronounced when the coverage change is caused by star analysts, supporting my conjecture that star analysts are better information intermediaries than regular analysts and therefore should more effectively alleviate information asymmetry between managers and investors and reduce firm-specific crash risk. Finally, consistent with the argument that both investors' demands for analyst coverage and the value analysts can provide through their information acquisition should increase with firm-specific risk, I document a positive association between firm-specific crash risk and analyst coverage for the firms in the subsequent year. This positive association also alleviates the concern that analysts systematically choose to cover firms with reduced crash risk.

Instead, analysts, especially star analysts, tend to follow firms with high crash risk, in which investors' demand for information is greater, and analyst coverage can be more valuable. Collectively, my findings provide empirical support for analysts' informational role and suggest that financial analysts bring significant benefits to equity markets and investors by reducing the likelihood of firms experiencing extremely negative abnormal stock returns. Moreover, my findings on analyst coverage decisions suggest that star and non-star analysts have distinct decision models, and analysts with differential skills and resources make coverage choices based on different factors.

REFERENCES

Barber, B.M. and T. Odean. 2013. The Behavior of individual investors. *Handbook of the Economics of Finance*, 1533-1570.

Barth, M. E., R. Kasznik, and M.F. McNichols. 2001. Analyst coverage and intangible assets. *Journal of accounting research*, 1-34.

Barth. M.E. and A.P. Hutton. 2004. Analyst earnings forecast revisions and the pricing of accruals. *Review of Accounting Studies 9(1)*, 59-96.

Bartov, E., D. Givoly, and C. Hayn. 2002. The rewards to meeting or beating earnings expectations. *Journal of Accounting and Economics 33*(2), 173-204.

Bhushan, R. 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics 11*(2), 255-274.

Bradshaw, M. T., S.A. Richardson, and R.G. Sloan. (2006). The relation between corporate financing activities, analysts' forecasts and stock returns. *Journal of Accounting and Economics 42*(1), 53-85.

Callen, J.L. and X. Fang. 2013. Institutional investor stability and crash risk: monitoring versus short-termism?. *Journal of Banking & Finance 37(8)*, 3047–3063.

Chen, J., H. Hong, and J.C. Stein. 2001. Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics 61*(3), 345-381.

Crawford, S. S., D.T. Roulstone, and E.C. So. 2012. Analyst initiations of coverage and stock return synchronicity. *The Accounting Review 87*(5), 1527-1553.

DeFond, M.L., M. Hung, S. Li, and Y. Li. 2015. Does mandatory IFRS adoption affect crash risk?. *The Accounting Review 90(1)*, 265-299.

Desai, H., B. Liang, and A.K. Singh. 2000. Do all-stars shine? Evaluation of analyst recommendations. *Financial Analysts Journal 56*(3), 20-29.

Desai, H., S. Rajgopal, and M. Venkatachalam. 2004. Value-glamour and accruals mispricing: One anomaly or two?. *The Accounting Review* 79(2): 355-385.

Dimson, E. 1979. Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics 7*(2), 197-226.

Elgers, P. T., M.H. Lo, and R.J. Pfeiffer Jr. 2001. Delayed security price adjustments to financial analysts' forecasts of annual earnings. *The Accounting Review 76*(4), 613-632.

Fang, L. H. and A. Yasuda. 2014. Are stars' opinions worth more? The relation between analyst reputation and recommendation values. *Journal of Financial Services Research 46*(3), 235-269.

Frankel, R., S.P. Kothari, and J. Weber. 2006. Determinants of the informativeness of analyst research. *Journal of Accounting and Economics 41(1)*, 29-54.

Frankel, R., and X. Li. 2004. Characteristics of a firm's information environment and the information asymmetry between insiders and outsiders. *Journal of Accounting and Economics 37*(2), 229-259.

Fuller, J. and M.C. Jensen. 2002. Just say no to Wall Street: Putting a stop to the earnings game. *Journal of Applied Corporate Finance*, *14*(4), 41-46.

Gleason, C.A. and C.M.C. Lee. 2003. Analyst Forecast Revisions and Market Price Discovery. *The Accounting Review 78(1)*, 193-225.

Goetzmann, W. N. and A. Kumar. 2008. Equity portfolio diversification. *Review of Finance 12(3)*, 433-463.

Graham, J. R., C.R. Harvey, and S. Rajgopal. 2005. The economic implications of corporate financial reporting. *Journal of accounting and economics*, *40*(1), 3-73.

He, J. and X. Tian. 2013. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, *109*(3), 856-878.

Healy, P.M. and K.G. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics 31(1-3)*, 405-440.

Hong, H. and M. Kacperczyk. 2010. Competition and bias. *The Quarterly Journal of Economics 125*(4), 1683-1725.

Hong, H. and J.D. Kubik. 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance*, 313-351.

Hong, H., T. Lim, and J.C. Stein. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance 55*(1), 265-295.

Huang, A. H., A.Y. Zang, and R. Zheng. 2014. Evidence on the information content of text in analyst reports. *The Accounting Review 89*(6), 2151-2180.

Hutton, A.P., A.J. Marcus, and H. Tehranian. 2009. Opaque financial reports, R2, and crash risk. *Journal of Financial Economics 94(1)*, 67–86.

Irani, R.M. and D. Oesch. 2016. Analyst Coverage and Real Earnings Management: Quasi-Experimental Evidence. *Journal of Financial and Quantitative Analysis*, *51*(02), 589-627.

Jackson, A.R. 2005. Trade generation, reputation, and sell-side analysts. *Journal of Finance 60*, 673-717.

Jensen, M. C. 2004. The agency cost of overvalued equity and the current state of corporate finance. *European Financial Management 10*(4), 549-565.

Jensen, M. C. 2005. Agency costs of overvalued equity. *Financial management*, 5-19.

Jin, L. and S.C. Myers. 2006. R2 around the world: new theory and new tests. *Journal of Financial Economics 79(2)*, 257–292.

Kim, J. B., Y. Li, and L. Zhang. 2011. Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics 100*(3), 639-662.

Kim, J.B. and L. Zhang. 2015. Accounting conservatism and stock price crash risk: Firm-level evidence. *Contemporary Accounting Research, Forthcoming.*

Kothari, S. P., Shu, S., and P.D. Wysocki. 2009. Do managers withhold bad news?. *Journal of Accounting Research 47*(1), 241-276.

Lang, M. and R. Lundholm. 1993. Cross-sectional determinants of analyst ratings of corporate disclosures. *Journal of Accounting research*, 246-271.

Lang, M. and R.J. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review 71(4)*, 467-492.

Lehavy, R., F. Li, and K. Merkley. 2011. The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review 86*(3), 1087-1115.

Lim, T. 2001. Rationality and analysts' forecast bias. *The Journal of Finance 56(1)*, 369–385.

Lin, H. W., & McNichols, M. F. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics 25*(1), 101-127.

Leone, A. and J.S. Wu. 2007. What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts. *Working Paper.*

Ljungqvist, A., F. Marston, and W.J. Wilhelm. 2006. Competing for securities underwriting mandates: Banking relationships and analyst recommendations. *The Journal of Finance 61*(1), 301-340.

Lobo, G. J., M. Song, and M. Stanford. 2012. Accruals quality and analyst coverage. *Journal of Banking & Finance 36*(2), 497-508.

Loh, R. K. and R.M. Stulz. 2011. When are analyst recommendation changes influential?. *Review of Financial Studies 24*(2), 593-627.

Matsunaga, S. R. and C.W. Park. 2001. The effect of missing a quarterly earnings benchmark on the CEO's annual bonus. *The Accounting Review 76*(3), 313-332.

Mayew, W. J. 2008. Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research 46*(3), 627-659.

Mayew, W. J. and M. Venkatachalam. 2012. The power of voice: Managerial affective states and future firm performance. *The Journal of Finance 67*(1), 1-43.

Mergenthaler, R., S. Rajgopal, and S. Srinivasan. 2012. CEO and CFO career penalties to missing quarterly analysts forecasts. *Working Paper*.

Mikhail, M. B., B.R. Walther, and R.H. Willis. 2007. When security analysts talk, who listens?. *The Accounting Review 82*(5), 1227-1253.

O' Brien, P.C., M.F. McNichols, and H.W. Lin. 2005. Analyst impartiality and investment banking relationships. *Journal of Accounting Research 43 (4)*, 623-650.

Rock, S., S. Sedo, and M. Willenborg. 2001. Analyst Following and Count-data Econometrics. *Journal of Accounting and Economics 30(3),* 351-373.

Shroff, P. K., R. Venkataraman, and B. Xin. 2014. Timeliness of Analysts' Forecasts: The Information Content of Delayed Forecasts. *Contemporary Accounting Research 31*(1), 202-229.

Soltes, E. 2014. Private Interaction Between Firm Management and Sell-Side Analysts. *Journal of Accounting Research 52*(1), 245-272.

Stickel, S. E. 1992. Reputation and performance among security analysts. *Journal of Finance*, 1811-1836.

Yu, F. F. 2008. Analyst coverage and earnings management. *Journal of Financial Economics 88*(2), 245-271.

Appendix A

Variable Definitions

Crash Risk measures	
$\Delta NCSKEW_{t+1}$	Change in the negative coefficient of the skewness of firm-specific daily returns from fiscal year *t* to fiscal year *t+1*
$\Delta DUVOL_{t+1}$	Change in the natural logarithm of the ratio of the standard deviation of firm-specific daily returns below the mean to the standard deviation of firm-specific daily returns above the mean from fiscal year t to fiscal year t+1
$\Delta COUNT_{t+1}$	Change in the number of days a firm's daily returns is 3.09 standard deviations below the annual mean minus the number of days when its daily returns is 3.09 standard deviations above the annual mean from fiscal year t to fiscal year t+1
Δ Analyst_Following	
ΔN_Follow_t	Change in the number of analysts following the firm from fiscal year *t-1* to fiscal year *t*
ΔN_Star_t	Change in the number of star analysts following the firm from fiscal year *t-1* to fiscal year *t*
$\Delta N\_NonStar_t$	Change in the number of non-star analysts following the firm from fiscal year *t-1* to fiscal year *t*
Control Variables	
$KURT_t$	The kurtosis of firm-specific daily returns in fiscal year *t*
$SIGMA_t$	The standard deviation of firm-specific daily returns in fiscal year *t*
$DTURN_t$	The average monthly share turnover over fiscal year *t* minus the average monthly share turnover over fiscal year *t-1*
RET_t	The cumulative firm-specific daily returns in fiscal year *t*
MB_t	The market value of equity divided by the book value of equity at the end of fiscal year *t*
LEV_t	The ratio of the book value of total liabilities over the book value of total assets at the end of fiscal year *t*
ROE_t	Income before extraordinary items divided by the lagged book value of equity in fiscal year *t*
$SIZE_t$	Natural logarithm of the market value of equity at the end of fiscal year *t*
$OPAQUE_t$	The 3-year moving sum of the absolute value of annual discretionary accruals
$RetSTD_{t-1}$	The standard deviation of firm-specific daily returns in fiscal year *t-1*
RSQ_{t-1}	The R^2 from the market model regression of a firm’s returns on the value-weighted market returns for fiscal year *t-1*
$AvgEXP_{t-1}$	Average experience of the analysts following a firm, measured by the average number of years since a firm's analysts first appeared in the I/B/E/S database to fiscal year t-1
$AvgEFF_{t-1}$	Average analyst effort, measured by the average number of firms followed by a firm's analysts multiplied by -1 in fiscal year *t-1*
$AvgBROKER_{t-1}$	Average brokerage house size, measured by the average number of analysts employed by the brokerage houses that employ a firm's analysts in fiscal year t-1
$SalesGrowth_{t-1}$	Sales in fiscal year *t* minus sales in fiscal year *t-1* divided by sales in fiscal year *t-1*
$Momentum_{t-1}$	The cumulative stok returns in fiscal year t-1

Table 1 Descriptive statistics

This table presents descriptive statistics on firm-specific stock price crash risk, analyst following, and control variables. The sample contains the firms in the I/B/E/S database between 2000 and 2013 with non-missing values for the crash risk measures and all control variables. The detailed definitions of the variables are provided in Appendix A.

Panel A: Entire sample

Variable	N	Mean	Std	5%	25%	Median	75%	95%
Δ Crash Risk measures								
$\Delta NCSKEW_{t+1}$	24,228	-0.038	2.188	-3.607	-0.930	-0.010	0.878	3.443
$\Delta DUVOL_{t+1}$	24,228	-0.007	0.613	-1.009	-0.357	-0.005	0.349	0.980
$\Delta COUNT_{t+1}$	24,228	-0.003	2.373	-4	-2	0	2	4
$NCSKEW_{t-1}$	24,228	0.106	1.454	-1.680	-0.548	-0.073	0.472	2.740
$DUVOL_{t-1}$	24,228	-0.034	0.420	-0.663	-0.289	-0.056	0.186	0.694
$COUNT_{t-1}$	24,228	-0.342	1.717	-3	-1	0	1	2
Analyst_Following								
N_Follow_t	24,228	6.230	5.374	1	2	5	9	17
N_Star_t	24,228	0.722	1.294	0	0	0	1	4
$N\_NonStar_t$	24,228	5.508	4.713	1	2	4	8	15
Δ Analyst_Following								
ΔN_Follow_t	24,228	0.040	3.158	-5	-2	0	2	5
ΔN_Star_t	24,228	0.059	1.090	-2	0	0	0	2
$\Delta N\_NonStar_t$	24,228	-0.018	3.000	-5	-2	0	2	5
Control Variables								
$KURT_t$	24,228	8.634	11.622	0.775	2.176	4.406	9.741	32.501
$SIGMA_t$	24,228	0.028	0.016	0.010	0.017	0.024	0.035	0.060
$DTURN_t$	24,228	0.000	0.001	-0.002	0.000	0.000	0.000	0.002
RET_t	24,228	-0.128	0.152	-0.444	-0.155	-0.073	-0.035	-0.012
MB_t	24,228	3.026	2.859	0.696	1.375	2.164	3.553	8.315
LEV_t	24,228	0.458	0.210	0.124	0.288	0.461	0.611	0.813
ROE_t	24,228	-0.029	0.465	-0.795	-0.024	0.085	0.156	0.318
$SIZE_t$	24,228	6.659	1.781	3.822	5.434	6.566	7.780	9.824
$OPAQUE_t$	24,228	0.388	0.450	0.054	0.130	0.243	0.464	1.196
$RetStd_{t-1}$	24,228	0.035	0.017	0.015	0.023	0.031	0.043	0.069
RSQ_{t-1}	24,228	0.211	0.172	0.005	0.063	0.177	0.319	0.550
$AvgEFF_{t-1}$	24,228	-12.276	10.862	-21	-12.733	-10.286	-8.222	-5
$AvgBROKER_{t-1}$	24,228	53.891	33.613	8	27.250	50.200	74.760	116
$AvgEXP_{t-1}$	24,228	5.531	2.713	1.143	3.750	5.250	7.000	10.500
$SIZE_{t-1}$	24,228	6.646	1.746	3.934	5.425	6.520	7.724	9.795
$SalesGrowth_{t-1}$	24,228	0.160	0.358	-0.261	-0.002	0.099	0.239	0.754
$Momentum_{t-1}$	24,228	-0.138	0.157	-0.470	-0.172	-0.082	-0.039	-0.014
$ShortInt_{t-1}$	19,698	0.054	0.064	0.001	0.013	0.034	0.072	0.183
$BidAskSpread_{t-1}$	24,213	0.008	0.011	0.000	0.001	0.003	0.010	0.031
$TradingVolume_{t-1}$	24,228	15.479	2.127	11.806	14.033	15.549	16.978	18.950
$Overvaluation_{t-1}$	17,677	0.100	0.300	0	0	0	0	1

Panel B: Subsamples of firms with and without star analyst coverage

	Without Star Analyst at $Year_t$			With Star Analyst at $Year_t$			Difference in Mean	
Variable	N	Mean	Median	N	Mean	Median	t-value	Pr > |t|
$\Delta NCSKEW_{t+1}$	15,821	-0.005	-0.004	8,407	-0.099	-0.023	3.16	0.002
$\Delta DUVOL_{t+1}$	15,821	0.005	0.000	8,407	-0.030	-0.014	4.18	<.0001
$\Delta COUNT_{t+1}$	15,821	0.042	0	8,407	-0.087	0	4.00	<.0001
$NCSKEW_{t-1}$	15,821	0.061	-0.118	8,407	0.193	0.000	-6.74	<.0001
$DUVOL_{t-1}$	15,821	-0.055	-0.079	8,407	0.006	-0.018	-10.74	<.0001
$COUNT_{t-1}$	15,821	-0.436	0	8,407	-0.167	0	-11.63	<.0001
N_Follow_t	15,821	4.154	3	8,407	10.136	9	-97.26	<.0001
$KURT_t$	15,821	8.819	4.533	8,407	8.287	4.191	3.39	0.001
$SIGMA_t$	15,821	0.031	0.027	8,407	0.023	0.019	40.11	<.0001
$DTURN_t$	15,821	0.000	0.000	8,407	0.000	0.000	-8.91	<.0001
RET_t	15,821	-0.150	-0.091	8,407	-0.086	-0.046	-31.75	<.0001
MB_t	15,821	2.893	2.040	8,407	3.278	2.419	-10.02	<.0001
LEV_t	15,821	0.426	0.420	8,407	0.519	0.532	-33.58	<.0001
ROE_t	15,821	-0.069	0.070	8,407	0.046	0.113	-18.37	<.0001
$SIZE_t$	15,821	5.976	5.960	8,407	7.943	7.872	-96.18	<.0001
$OPAQUE_t$	15,821	0.414	0.267	8,407	0.338	0.199	12.67	<.0001
$RetStd_{t-1}$	15,821	0.037	0.033	8,407	0.030	0.026	33.18	<.0001
RSQ_{t-1}	15,821	0.188	0.145	8,407	0.252	0.228	-27.86	<.0001
$AvgEFF_{t-1}$	15,821	-11.275	-9.800	8,407	-14.159	-11.083	19.83	<.0001
$AvgBROKER_{t-1}$	15,821	40.685	34.500	8,407	78.745	74.000	-99.60	<.0001
$AvgEXP_{t-1}$	15,821	5.331	5.000	8,407	5.908	5.621	-15.82	<.0001
$SIZE_{t-1}$	15,821	5.950	5.917	8,407	7.957	7.842	-101.73	<.0001
$SalesGrowth_{t-1}$	15,821	0.162	0.098	8,407	0.157	0.101	1.22	0.223
$Momentum_{t-1}$	15,821	-0.163	-0.103	8,407	-0.091	-0.050	-34.90	<.0001
$ShortInt_{t-1}$	12,575	0.054	0.034	7,123	0.055	0.034	-0.85	0.393
$BidAskSpread_{t-1}$	15,817	0.009	0.004	8,396	0.005	0.002	25.92	<.0001
$TradingVolume_{t-1}$	15,821	14.692	14.770	8,407	16.960	17.060	-91.69	<.0001
$Overvaluation_{t-1}$	10,799	0.107	0.000	6,878	0.089	0.000	3.89	0.000

Table 2 Correlation matrix

This table reports the correlations among the major variables employed in my empirical tests. Pearson correlations are above the diagonal; Spearman correlations are below the diagonal. P-values appear correlations.

Panel A: Correlations among variables included in the regression models testing H1 & H2

Variable	$\Delta NCSKEW_{t+1}$	$DUVOL_{t+1}$	$1COUNT_{t+1}$	ΔN_Follow_t	ΔN_Star_t	ΔN_NonSt	$KURT_t$	$SIGMA_t$	$DTURN_t$	RET_t	MB_t	LEV_t	ROE_t	$SIZE_t$
$\Delta NCSKEW_{t+1}$		0.913	0.511	-0.024	-0.021	-0.017	-0.313	-0.098	0.001	0.081	0.109	-0.010	0.053	0.067
		<.0001	<.0001	0.0002	0.001	0.0075	<.0001	<.0001	0.8741	<.0001	<.0001	0.132	<.0001	<.0001
$\Delta DUVOL_{t+1}$	0.918		0.657	-0.026	-0.028	-0.017	-0.253	-0.102	0.012	0.090	0.131	-0.013	0.080	0.085
	<.0001		<.0001	<.0001	<.0001	0.0091	<.0001	<.0001	0.058	<.0001	<.0001	0.0411	<.0001	<.0001
$\Delta COUNT_{t+1}$	0.605	0.673		-0.026	-0.029	-0.017	-0.105	-0.045	0.021	0.038	0.097	-0.012	0.066	0.060
	<.0001	<.0001		<.0001	<.0001	0.0101	<.0001	<.0001	0.0009	<.0001	<.0001	0.0558	<.0001	<.0001
ΔN_Follow_t	-0.020	-0.020	-0.021		0.314	0.939	0.045	0.014	0.234	0.007	0.034	-0.021	0.064	0.050
	0.002	0.002	0.001		<.0001	<.0001	<.0001	0.0282	<.0001	0.2792	<.0001	0.0014	<.0001	<.0001
ΔN_Star_t	-0.024	-0.028	-0.028	0.259		-0.033	0.008	0.035	0.069	-0.019	0.012	0.029	0.018	0.046
	0.0001	<.0001	<.0001	<.0001		<.0001	0.2182	<.0001	<.0001	0.0027	0.0725	<.0001	0.0053	<.0001
$\Delta N\_NonStar_t$	-0.013	-0.013	-0.014	0.931	-0.033		0.045	0.002	0.221	0.014	0.031	-0.032	0.060	0.036
	0.049	0.037	0.030	<.0001	<.0001		<.0001	0.7419	<.0001	0.0258	<.0001	<.0001	<.0001	<.0001
$KURT_t$	-0.144	-0.131	-0.079	0.032	0.008	0.045		0.153	0.093	-0.134	-0.007	-0.020	-0.029	-0.023
	<.0001	<.0001	<.0001	<.0001	0.218	<.0001		<.0001	<.0001	<.0001	0.3088	0.002	<.0001	0.0003
$SIGMA_t$	-0.077	-0.080	-0.041	0.037	0.035	0.002	0.153		0.079	-0.960	-0.040	-0.120	-0.458	-0.630
	<.0001	<.0001	<.0001	<.0001	<.0001	0.742	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
$DTURN_t$	0.012	0.023	0.018	0.238	0.069	0.221	0.093	0.079		-0.073	0.073	0.051	0.085	0.070
	0.067	0.000	0.004	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001
RET_t	0.070	0.073	0.037	-0.036	-0.019	0.014	-0.134	-0.960	-0.073		0.020	0.077	0.462	0.537
	<.0001	<.0001	<.0001	<.0001	0.003	0.026	<.0001	<.0001	<.0001		0.0014	<.0001	<.0001	<.0001
MB_t	0.148	0.172	0.125	0.065	0.012	0.031	-0.007	-0.040	0.073	0.020		0.164	-0.127	0.245
	<.0001	<.0001	<.0001	<.0001	0.073	<.0001	0.309	<.0001	<.0001	0.001		<.0001	<.0001	<.0001
LEV_t	-0.003	-0.007	-0.010	-0.017	0.029	-0.032	-0.020	-0.120	0.051	0.077	0.164		-0.126	0.182
	0.623	0.309	0.124	0.007	<.0001	<.0001	0.002	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001
ROE_t	0.091	0.102	0.081	0.063	0.030	0.055	-0.019	-0.487	0.136	0.487	0.364	0.083		0.3912
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.003	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001
$SIZE_t$	0.078	0.088	0.060	0.059	0.046	0.036	-0.023	-0.630	0.070	0.537	0.245	0.182	0.391	
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0003	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	
$OPAQUE_t$	-0.011	-0.011	0.000	0.006	0.006	0.002	0.035	0.213	-0.036	-0.205	0.071	-0.081	-0.203	-0.119
	0.101	0.089	0.954	0.316	0.312	0.754	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

Panel B: Correlations among variables included in the regression models testing H3

Variable	N_Follow_{t}	N_Star_{t}	$N\_NonStar_{t}$	$NCSKEW_{t-1}$	$DUVOL_{t-1}$	$COUNT_{t-1}$	$RetSTD_{t-1}$	RSQ_{t-1}	$AvgEFF_{t-1}$	$AvgBROKER_{t-1}$	$AvgEXP_{t-1}$	$Size_{t-1}$	$SalesGrowth_{t-1}$	$Momentum_{t-1}$	$ShortInt_{t-1}$	$BidAskSpread_{t-1}$	$TradingVolume_{t-1}$	$Overvaluation_{t-1}$
N_Follow_{t}		0.600	0.976	0.039	0.069	0.088	-0.142	0.307	-0.097	0.287	0.043	0.675	0.070	0.222	0.110	-0.300	0.701	0.048
		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
N_Star_{t}	0.586		0.409	0.035	0.068	0.077	-0.200	0.145	-0.108	0.489	0.071	0.549	-0.024	0.209	-0.035	-0.124	0.489	-0.023
	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0001	<.0001	<.0001	<.0001	<.0001	0.0021
$N\_NonStar_{t}$	0.976	0.430		0.035	0.059	0.080	-0.107	0.310	-0.081	0.193	0.029	0.619	0.087	0.196	0.136	-0.308	0.665	0.062
	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
$NCSKEW_{t-1}$	0.075	0.072	0.068		0.906	0.520	0.021	-0.020	-0.007	0.037	0.021	-0.003	-0.052	-0.040	0.043	-0.064	0.080	-0.017
	<.0001	<.0001	<.0001		<.0001	<.0001	0.0013	0.0014	0.293	<.0001	0.0013	0.6014	<.0001	<.0001	<.0001	<.0001	<.0001	0.0279
$DUVOL_{t-1}$	0.077	0.082	0.068	0.925		0.668	0.011	0.028	-0.008	0.064	0.034	0.015	-0.082	-0.008	0.043	-0.067	0.099	-0.036
	<.0001	<.0001	<.0001	<.0001		<.0001	0.0995	<.0001	0.219	<.0001	<.0001	0.0215	<.0001	0.2354	<.0001	<.0001	<.0001	<.0001
$COUNT_{t-1}$	0.089	0.081	0.080	0.703	0.710		-0.048	0.064	-0.010	0.065	0.039	0.064	-0.074	0.067	0.052	-0.092	0.122	-0.032
	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	0.1147	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
$RetStd_{t-1}$	-0.208	-0.250	-0.169	0.022	0.023	-0.025		-0.195	0.101	-0.173	-0.174	-0.476	0.095	-0.924	0.010	0.393	-0.269	0.178
	<.0001	<.0001	<.0001	0.0006	0.000	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.1717	<.0001	<.0001	<.0001
RSQ_{t-1}	0.374	0.201	0.367	0.047	0.071	0.078	-0.232		-0.034	0.108	0.308	0.482	-0.105	0.358	0.092	-0.501	0.524	-0.039
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
$AvgEFF_{t-1}$	-0.174	-0.207	-0.145	-0.035	-0.045	-0.038	0.082	-0.131		-0.058	-0.030	-0.112	0.011	-0.084	0.005	0.075	-0.091	0.004
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	0.0764	<.0001	0.5089	<.0001	<.0001	0.5583
$AvgBROKER_{t-1}$	0.438	0.582	0.338	0.063	0.077	0.069	-0.235	0.191	-0.175		0.001	0.435	-0.032	0.174	-0.008	-0.087	0.375	-0.017
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		0.9384	<.0001	<.0001	<.0001	0.2514	<.0001	<.0001	0.0275
$AvgEXP_{t-1}$	0.114	0.137	0.087	0.026	0.035	0.039	-0.201	0.316	-0.184	0.038		0.146	-0.097	0.201	0.055	-0.231	0.157	-0.044
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
$SIZE_{t-1}$	0.713	0.574	0.658	0.020	0.024	0.058	-0.521	0.531	-0.151	0.527	0.188		0.013	0.499	0.039	-0.487	0.889	-0.033
	<.0001	<.0001	<.0001	0.002	0.0002	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		0.0481	<.0001	<.0001	<.0001	<.0001	<.0001
$SalesGrowth_{t-1}$	0.126	0.013	0.141	-0.092	-0.110	-0.080	0.003	-0.083	0.034	-0.014	-0.081	0.069		-0.0987	0.0973	-0.025	0.056	0.060
	<.0001	0.046	<.0001	<.0001	<.0001	<.0001	0.670	<.0001	<.0001	0.0355	<.0001	<.0001		<.0001	<.0001	0.0001	<.0001	<.0001
$Momentum_{t-1}$	0.328	0.321	0.287	-0.029	-0.017	0.032	-0.939	0.465	-0.124	0.287	0.268	0.651	-0.022		0.051	-0.476	0.340	-0.155
	<.0001	<.0001	<.0001	<.0001	0.0065	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0005		<.0001	<.0001	<.0001	<.0001
$ShortInt_{t-1}$	0.244	0.021	0.263	0.058	0.059	0.065	0.001	0.291	-0.031	0.059	0.104	0.172	0.117	0.067		-0.255	0.240	0.037
	<.0001	0.0026	<.0001	<.0001	<.0001	<.0001	0.8597	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	<.0001	<.0001
$BidAskSpread_{t-1}$	-0.457	-0.217	-0.458	-0.033	-0.037	-0.065	0.491	-0.661	0.108	-0.181	-0.337	-0.621	-0.074	-0.609	-0.412		-0.594	0.009
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		<.0001	0.2128
$TradingVolume_{t-1}$	0.753	0.541	0.713	0.098	0.103	0.118	-0.316	0.557	-0.159	0.463	0.196	0.892	0.093	0.475	0.355	-0.687		-0.015
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		0.0466
$Overvaluation_{t-1}$	0.031	-0.029	0.043	-0.024	-0.038	-0.032	0.174	-0.031	0.014	-0.018	-0.056	-0.038	0.024	-0.170	0.043	0.049	-0.023	
	<.0001	0.0001	<.0001	0.0012	<.0001	<.0001	<.0001	<.0001	0.0727	0.0144	<.0001	<.0001	0.0016	<.0001	<.0001	<.0001	0.0025	

Table 3 Regression analyses for the impact of analyst coverage changes

This table presents the results of the impact of changes in analyst following on subsequent changes in firm-level stock price crash risk. Panels A to C present results from the regressions of changes in crash risk measures (*$\Delta NCSKEW_{t+1}$, $\Delta DUVOL_{t+1}$, and $\Delta COUNT_{t+1}$*) on changes in analyst coverage. Columns (1) to (4) use *N_Follow_t, N_Star_t, $N\_NonStar_t$, and N_Star_t and $N\_NonStar_t$* as the key variables of interest correspondingly in the analyses. Industry dummies are included in all regressions. The t-statistics are reported in parentheses below the coefficients. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Panel A: OLS regression of $\Delta NCSKEW_{t+1}$ on change in Analyst Following

	(1)	(2)	(3)	(4)
$\Delta NCSKEW_{t+1} = \beta_0 + \beta_1$ * ΔAnalyst_Following $_t$ + β_2 * ∑ Control Variables $_t$ + (Industry Dummies) + Ɛ				
Δ Analyst_Following				
ΔN_Follow_t	-0.013 ***			
	(-3.03)			
ΔN_Star_t		-0.034 ***		-0.036 ***
		(-2.81)		(-2.93)
$\Delta N\_NonStar_t$			-0.010 **	-0.010 **
			(-2.13)	(-2.29)
Control Variables				
$KURT_t$	-0.058 ***	-0.058 ***	-0.058 ***	-0.058 ***
	(-49.50)	(-49.60)	(-49.49)	(-49.54)
$SIGMA_t$	-24.906 ***	-24.795 ***	-25.478 ***	-24.292 ***
	(-6.78)	(-6.73)	(-6.95)	(-6.59)
$DTURN_t$	64.911 ***	57.964 ***	62.217 ***	64.319 ***
	(4.82)	(4.40)	(4.63)	(4.78)
RET_t	-1.939 ***	-1.944 ***	-1.984 ***	-1.897 ***
	(-5.70)	(-5.72)	(-5.85)	(-5.57)
MB_t	0.085 ***	0.085 ***	0.085 ***	0.085 ***
	(16.45)	(16.35)	(16.44)	(16.40)
LEV_t	-0.342 ***	-0.329 ***	-0.341 ***	-0.336 ***
	(-4.68)	(-4.52)	(-4.67)	(-4.61)
ROE_t	0.200 ***	0.198 ***	0.199 ***	0.201 ***
	(5.76)	(5.71)	(5.72)	(5.78)
$SIZE_t$	-0.011	-0.010	-0.012	-0.009
	(-0.98)	(-0.89)	(-1.10)	(-0.82)
$Opaque_t$	0.056 *	0.055 *	0.055 *	0.056 *
	(1.73)	(1.70)	(1.71)	(1.74)
Intercept	0.807 **	0.788 *	0.827 **	0.779 *
	(1.97)	(1.92)	(2.02)	(1.90)
No. of observations	24,228	24,228	24,228	24,228
Adj. R-squared	0.1156	0.1156	0.1155	0.1157

Panel B: OLS regression of $\Delta DUVOL_{t+1}$ on change in Analyst Following

	(1)		(2)		(3)		(4)	
$\Delta DUVOL_{t+1} = \beta_0 + \beta_1 * \Delta$Analyst_Following $_t + \beta_2 * \sum$ Control Variables $_t$ + (Industry Dummies) + Ɛ								
Δ Analyst_Following								
ΔN_Follow $_t$	-0.006	***						
	(-4.62)							
ΔN_Star $_t$			-0.015	***			-0.016	***
			(-4.42)				(-4.60)	
ΔN_NonStar $_t$					-0.004	***	-0.004	***
					(-3.20)		(-3.45)	
Control Variables								
KURT $_t$	-0.013	***	-0.013	***	-0.013	***	-0.013	***
	(-39.20)		(-39.35)		(-39.19)		(-39.27)	
SIGMA $_t$	-4.309	***	-4.246	***	-4.559	***	-4.031	***
	(-4.13)		(-4.06)		(-4.38)		(-3.85)	
DTURN $_t$	18.776	***	15.791	***	17.571	***	18.508	***
	(4.91)		(4.22)		(4.60)		(4.84)	
RET $_t$	-0.307	***	-0.308	***	-0.327	***	-0.288	***
	(-3.18)		(-3.19)		(-3.39)		(-2.98)	
MB $_t$	0.030	***	0.030	***	0.030	***	0.030	***
	(20.42)		(20.27)		(20.40)		(20.35)	
LEV $_t$	-0.115	***	-0.110	***	-0.115	***	-0.113	***
	(-5.57)		(-5.31)		(-5.55)		(-5.46)	
ROE $_t$	0.096	***	0.095	***	0.095	***	0.096	***
	(9.70)		(9.63)		(9.64)		(9.73)	
SIZE $_t$	0.002		0.002		0.001		0.002	
	(0.48)		(0.64)		(0.30)		(0.74)	
Opaque $_t$	0.017	*	0.017	*	0.017	*	0.017	*
	(1.88)		(1.84)		(1.84)		(1.89)	
Intercept	0.083		0.075		0.092		0.071	
	(0.72)		(0.64)		(0.79)		(0.61)	
No. of observations	24,228		24,228		24,228		24,228	
Adj. R-squared	0.0912		0.0911		0.0908		0.0915	

Panel C: OLS regression of $\Delta COUNT_{t+1}$ on change in Analyst Following

	(1)	(2)	(3)	(4)
$\Delta COUNT_{t+1} = \beta_0 + \beta_1 * \Delta Analyst\_Following_t + \beta_2 * \sum Control\ Variables_t + (Industry\ Dummies) + \varepsilon$				
Δ Analyst_Following				
ΔN_Follow_t	-0.027 ***			
	(-5.48)			
ΔN_Star_t		-0.070 ***		-0.073 ***
		(-5.00)		(-5.22)
$\Delta N\_NonStar_t$			-0.020 ***	-0.022 ***
			(-3.91)	(-4.17)
Control Variables				
$KURT_t$	-0.021 ***	-0.022 ***	-0.021 ***	-0.021 ***
	(-15.96)	(-16.13)	(-15.94)	(-16.03)
$SIGMA_t$	-2.757	-2.567	-4.052	-1.526
	(-0.66)	(-0.61)	(-0.97)	(-0.36)
$DTURN_t$	55.543 ***	41.199 ***	50.220 ***	54.354 ***
	(3.63)	(2.75)	(3.28)	(3.55)
RET_t	-0.554	-0.568	-0.655 *	-0.469
	(-1.43)	(-1.47)	(-1.70)	(-1.21)
MB_t	0.090 ***	0.089 ***	0.090 ***	0.090 ***
	(15.28)	(15.11)	(15.25)	(15.21)
LEV_t	-0.346 ***	-0.321 ***	-0.343 ***	-0.336 ***
	(-4.17)	(-3.87)	(-4.13)	(-4.04)
ROE_t	0.387 ***	0.383 ***	0.384 ***	0.388 ***
	(9.80)	(9.71)	(9.73)	(9.83)
$SIZE_t$	0.026 **	0.028 **	0.023 *	0.030 **
	(2.07)	(2.23)	(1.82)	(2.35)
$Opaque_t$	0.058	0.056	0.055	0.058
	(1.57)	(1.52)	(1.49)	(1.58)
Intercept	-0.223	-0.260	-0.059	-0.279
	(-0.48)	(-0.56)	(-0.39)	(-0.60)
No. of observations	24,228	24,228	24,228	24,228
Adj. R-squared	0.0268	0.0266	0.0264	0.0273

Table 4 Negative binomial regression analyses for analyst coverage decision

This table presents the results of the effect of past firm-specific stock price crash risk on analyst coverage. Panels A to C present results from the regressions of the number of analysts following the firm (N_Follow_t, N_Star_t, and $N\_NonStar_t$) on stock price crash risk measures. Columns (1) to (3) use $NCSKEW_{t-1}$, $DUVOL_{t-1}$, and $COUNT_{t-1}$ as the key variables of interest correspondingly in the analyses. Industry dummies are included in all regressions. The t-statistics are reported in parentheses below the coefficients. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix A.

Panel A: Negative binomial regression of the number of all analysts following the firm (N_Follow_t) on firm-specific crash risk

	(1)	(2)	(3)
$N\_Follow_t = \beta_0 + \beta_1$ * Crash Risk $_{t-1}$ + β_2 * ∑ Control Variables $_{t-1}$ + (Industry Dummies) + Ɛ			
Crash Risk			
$NCSKEW_{t-1}$	0.032 ***		
	(12.84)		
$DUVOL_{t-1}$		0.116 ***	
		(13.57)	
$COUNT_{t-1}$			0.022 ***
			(10.66)
Control Variables			
$RetStd_{t-1}$	24.751 ***	24.349 ***	24.320 ***
	(39.74)	(39.11)	(38.99)
RSQ_{t-1}	-0.198 ***	-0.204 ***	-0.204 ***
	(-7.13)	(-7.35)	(-7.33)
$AvgEFF_{t-1}$	-0.003 ***	-0.003 ***	-0.003 ***
	(-9.59)	(-9.59)	(-9.65)
$AvgBROKER_{t-1}$	0.001 ***	0.001 ***	0.001 ***
	(11.59)	(11.27)	(11.58)
$AvgEXP_{t-1}$	-0.008 ***	-0.008 ***	-0.008 ***
	(-5.21)	(-5.16)	(-4.99)
$SIZE_{t-1}$	0.353 ***	0.353 ***	0.353 ***
	(122.54)	(122.54)	(122.36)
$SalesGrowth_{t-1}$	0.110 ***	0.113 ***	0.108 ***
	(10.73)	(10.99)	(10.56)
$Momentum_{t-1}$	2.116 ***	2.071 ***	2.042 ***
	(29.00)	(28.44)	(27.98)
Intercept	-1.871 ***	-1.856 ***	-1.859 ***
	(-16.45)	(-16.33)	(-16.32)
No. of observations	24,228	24,228	24,228
Log Likelihood	-57,880	-57,790	-57,825
Pseudo R-squared	0.1579	0.1581	0.1576

Panel B: Negative binomial regression of the number of star analysts following the firm (N_Star_t) on firm-specific crash risk

	(1)		(2)		(3)	
$N\_Star_t = \beta_0 + \beta_1$ * Crash Risk $_{t-1}$ + β_2 * ∑ Control Variables $_{t-1}$ + (Industry Dummies) + Ɛ						
Crash Risk						
NCSKEW $_{t-1}$	0.047	***				
	(7.17)					
DUVOL $_{t-1}$			0.192	***		
			(8.49)			
COUNT $_{t-1}$					0.032	***
					(5.90)	
Control Variables						
RetStd $_{t-1}$	20.984	***	20.216	***	20.515	***
	(13.45)		(12.95)		(13.12)	
RSQ $_{t-1}$	-0.527	***	-0.532	***	-0.541	***
	(-7.77)		(-7.85)		(-7.97)	
AvgEFF $_{t-1}$	-0.010	***	-0.010	***	-0.010	***
	(-14.25)		(-14.24)		(-14.33)	
AvgBROKER $_{t-1}$	0.021	***	0.020	***	0.021	***
	(66.80)		(66.66)		(66.76)	
AvgEXP $_{t-1}$	0.051	***	0.052	***	0.052	***
	(11.33)		(11.37)		(11.49)	
SIZE $_{t-1}$	0.490	***	0.488	***	0.489	***
	(71.86)		(71.67)		(71.76)	
SalesGrowth $_{t-1}$	-0.021		-0.015		-0.025	
	(-0.71)		(-0.49)		(-0.85)	
Momentum $_{t-1}$	1.981	***	1.902	***	1.876	***
	(9.40)		(9.05)		(8.91)	
Intercept	-6.516	***	-6.486	***	-6.512	***
	(-27.69)		(-27.56)		(-27.63)	
No. of observations	24,228		24,228		24,228	
Log Likelihood	-20,371		-20,360		-20,379	
Pseudo R-squared	0.2675		0.2679		0.2672	

Panel C: Negative binomial regression of the number of Non-Star analysts following the firm ($N\_NonStar_t$) on firm-specific crash risk

	(1)	(2)	(3)
$N\_NonStar_t = \beta_0 + \beta_1$ * Crash Risk $_{t-1}$ + β_2 * ∑ Control Variables $_{t-1}$ + (Industry Dummies) + Ɛ			
Crash Risk			
$NCSKEW_{t-1}$	0.031 ***		
	(12.13)		
$DUVOL_{t-1}$		0.110 ***	
		(12.43)	
$COUNT_{t-1}$			0.021 ***
			(9.86)
Control Variables			
$RetStd_{t-1}$	25.326 ***	24.942 ***	24.906 ***
	(39.25)	(38.66)	(38.54)
RSQ_{t-1}	-0.116 ***	-0.122 ***	-0.122 ***
	(-4.02)	(-4.23)	(-4.22)
$AvgEFF_{t-1}$	-0.002 ***	-0.002 ***	-0.002 ***
	(-7.08)	(-7.07)	(-7.13)
$AvgBROKER_{t-1}$	-0.001 ***	-0.001 ***	-0.001 ***
	(-8.53)	(-8.79)	(-8.50)
$AvgEXP_{t-1}$	-0.019 ***	-0.015 ***	-0.014 ***
	(-8.98)	(-8.92)	(-8.70)
$SIZE_{t-1}$	0.342 ***	0.342 ***	0.342 ***
	(113.71)	(113.70)	(113.55)
$SalesGrowth_{t-1}$	0.127 ***	0.130 ***	0.126 ***
	(12.09)	(12.30)	(11.91)
$Momentum_{t-1}$	2.164 ***	2.120 ***	2.092 ***
	(28.74)	(28.20)	(27.78)
Intercept	-1.798 ***	-1.785 ***	-1.786 ***
	(-14.67)	(-14.56)	(-14.55)
No. of observations	24,228	24,228	24,228
Log Likelihood	-56,253	-56,249	-56,278
Pseudo R-squared	0.1427	0.1427	0.1423

Table 5 Panel A

PSM Sample: Mean Values of the Determinants for the Treatment and Control Groups

	Control: No Increase (N = 9,455)	Treatment: Increase (N = 9,455)		Control: No Change (N = 4,250)	Treatment: Increase (N = 4,250)		Control: Decrease (N = 8,096)	Treatment: Increase (N = 8,096)	
Variable	Mean	Mean	Difference	Mean	Mean	Difference	Mean	Mean	Difference
$NCSKEW_{t-1}$	-0.008	-0.006	-0.002	-0.014	-0.015	0.000	0.086	0.074	0.012
$RetStd_{t-1}$	0.033	0.033	0.000	0.035	0.035	0.000	0.033	0.033	0.000
RSQ_{t-1}	0.226	0.222	0.004	0.189	0.188	0.000	0.227	0.226	0.001
$AvgEFF_{t-1}$	-12.504	-12.340	-0.163	-11.909	-11.878	-0.031	-12.497	-12.499	0.002
$AvgBROKER_{t-1}$	57.023	57.158	-0.135	47.941	47.901	0.040	56.625	56.759	-0.134
$AvgEXP_{t-1}$	5.494	5.486	0.008	5.367	5.425	-0.058	5.586	5.598	-0.012
$SIZE_{t-1}$	6.926	6.923	0.002	6.160	6.185	-0.025	6.926	6.919	0.007
$SalesGrowth_{t-1}$	0.179	0.184	-0.005	0.166	0.154	0.011	0.156	0.163	-0.006
BM_{t-1}	0.469	0.474	-0.004	0.542	0.559	-0.018**	0.499	0.502	-0.002
ROA_{t-1}	0.025	0.025	0.000	0.007	0.004	0.003	0.020	0.019	0.000
RET_{t-1}	-0.122	-0.123	0.001	-0.143	-0.147	0.004	-0.121	-0.124	0.002

Panel B: PSM Sample (Treatment: Coverage Increase ; Control: No Increase)

Dependent Variable:	ΔNCSKEWt+1				ΔDUVOLt+1				ΔCOUNTt+1			
	(1)		(2)		(3)		(4)		(5)		(6)	
Δ Analyst_Following												
ΔN_Follow$_t$	-0.003				-0.002	*			-0.017	***		
	(-0.60)				(-1.68)				(-3.13)			
ΔN_Star$_t$			-0.034	**			-0.015	***			-0.068	***
			(-2.56)				(-3.95)				(-4.54)	
ΔN_NonStar$_t$			0.001				-0.001				-0.011	*
			(0.17)				(-0.53)				(-1.91)	
Control Variables												
KURT$_t$	-0.062	***	-0.062	***	-0.014	***	-0.014	***	-0.021	***	-0.021	***
	(-46.56)		(-46.62)		(-36.96)		(-37.05)		(-13.87)		(-13.96)	
SIGMA$_t$	-22.817	***	-21.833	***	-4.086	***	-3.688	***	-4.199		-2.592	
	(-5.23)		(-4.98)		(-3.31)		(-2.98)		(-0.86)		(-0.53)	
DTURN$_t$	50.206	***	49.485	***	13.647	***	13.356	***	46.442	***	45.264	***
	(3.27)		(3.22)		(3.14)		(3.07)		(2.69)		(2.62)	
RET$_t$	-1.461	***	-1.393	***	-0.204	*	-0.177		-0.470		-0.359	
	(-3.48)		(-3.32)		(-1.72)		(-1.49)		(-1.00)		(-0.76)	
MB$_t$	0.081	***	0.081	***	0.029	***	0.029	***	0.087	***	0.087	***
	(14.13)		(14.07)		(17.88)		(17.79)		(13.49)		(13.40)	
LEV$_t$	-0.372	***	-0.362	***	-0.128	***	-0.124	***	-0.353	***	-0.336	***
	(-4.45)		(-4.33)		(-5.42)		(-5.25)		(-3.74)		(-3.57)	
ROE$_t$	0.151	***	0.152	***	0.085	***	0.085	***	0.345	***	0.347	***
	(3.58)		(3.61)		(7.09)		(7.13)		(7.26)		(7.30)	
SIZE$_t$	-0.010		-0.007		0.002		0.003		0.032	**	0.037	**
	(-0.80)		(-0.56)		(0.54)		(0.86)		(2.20)		(2.53)	
Opaque$_t$	0.078	**	0.079	**	0.023	**	0.024	**	0.055	*	0.080	*
	(2.12)		(2.13)		(2.23)		(2.25)		(1.71)		(1.93)	
Intercept	0.633		0.585		0.035		0.015		-0.254		-0.333	
	(1.41)		(1.30)		(0.27)		(0.12)		(-0.50)		(-0.66)	
No. of observations	18,910		18,910		18,910		18,910		18,910		18,910	
Adj. R-squared	0.1287		0.1290		0.1007		0.1013		0.0265		0.0272	

Panel C: PSM Sample (Treatment: Coverage Increase ; Control: No Change)

Dependent Variable:	ΔNCSKEWt+1				ΔDUVOLt+1				ΔCOUNTt+1			
	(1)		(2)		(3)		(4)		(5)		(6)	
Δ Analyst_Following												
ΔN_Follow$_t$	-0.011				-0.005				-0.014			
	(-0.83)				(-1.35)				(-0.90)			
ΔN_Star$_t$			-0.081	**			-0.029	***			-0.085	***
			(-2.82)				(-3.54)				(-2.59)	
ΔN_NonStar$_t$			-0.005				-0.003				-0.007	
			(-0.34)				(-0.77)				(-0.46)	
Control Variables												
KURT$_t$	-0.063	***	-0.063	***	-0.014	***	-0.014	***	-0.023	***	-0.023	***
	(-33.01)		(-33.08)		(-25.32)		(-25.42)		(-10.54)		(-10.61)	
SIGMA$_t$	-21.490	***	-20.176	***	-4.272	**	-3.824	**	-2.907		-1.565	
	(-3.28)		(-3.07)		(-2.28)		(-2.03)		(-0.39)		(-0.21)	
DTURN$_t$	71.832	***	70.379	***	23.787	***	23.292	***	63.705	**	62.221	***
	(3.15)		(3.08)		(3.64)		(3.57)		(2.43)		(2.38)	
RET$_t$	-1.594	***	-1.507	**	-0.302	*	-0.272		-0.734		-0.645	
	(-2.62)		(-2.48)		(-1.73)		(-1.56)		(-1.05)		(-0.92)	
MB$_t$	0.097	***	0.096	***	0.035	***	0.034	***	0.091	***	0.090	***
	(10.83)		(10.73)		(13.56)		(13.45)		(8.84)		(8.75)	
LEV$_t$	-0.310	**	-0.299	**	-0.100	***	-0.096	***	-0.244	*	-0.233	*
	(-2.54)		(-2.45)		(-2.86)		(-2.75)		(-1.74)		(-1.66)	
ROE$_t$	0.195	***	0.194	***	0.107	***	0.107	***	0.451	***	0.450	***
	(3.38)		(3.37)		(6.49)		(6.48)		(6.81)		(6.80)	
SIZE$_t$	0.042	**	0.048	**	0.016	***	0.018	***	0.065	***	0.072	***
	(1.99)		(2.30)		(2.70)		(3.06)		(2.70)		(2.97)	
Opaque$_t$	0.055		0.057		0.019		0.019		0.066		0.068	
	(0.98)		(1.01)		(2.23)		(1.21)		(1.03)		(1.06)	
Intercept	0.520		0.415		0.019		0.079		0.097		-0.010	
	(0.76)		(0.60)		(1.17)		(0.40)		(0.12)		(-0.01)	
No. of observations	8,500		8,500		8,500		8,500		8,500		8,500	
Adj. R-squared	0.1425		0.1432		0.1106		0.1117		0.0303		0.0309	

Panel D: PSM Sample (Treatment: Coverage Increase ; Control: Coverage Decrease)

Dependent Variable:	ΔNCSKEWt+1		ΔDUVOLt+1		ΔCOUNTt+1	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Analyst_Following						
ΔN_Follow_t	-0.004		-0.003 *		-0.017	
	(-0.87)		(-1.83)		(-3.04)	
ΔN_Star_t		-0.023 *		-0.011 ***		-0.053 ***
		(-1.65)		(-2.85)		(-3.30)
$\Delta N\_NonStar_t$		-0.002		-0.002		-0.013 **
		(-0.40)		(-1.03)		(-2.17)
Control Variables						
$KURT_t$	-0.059 ***	-0.059 ***	-0.013 ***	-0.013 ***	-0.023 ***	-0.023 ***
	(-40.50)	(-40.53)	(-32.55)	(-32.60)	(-13.74)	(-13.80)
$SIGMA_t$	-21.173 ***	-20.546 ***	-3.153 **	-2.861 **	1.747	2.918
	(-4.44)	(-4.29)	(-2.34)	(-2.12)	(0.33)	(0.54)
$DTURN_t$	52.984 ***	52.536 ***	14.942 ***	14.734 ***	48.272 **	47.436 **
	(3.12)	(3.09)	(3.12)	(3.07)	(2.53)	(2.49)
RET_t	-1.342 ***	-1.297 ***	-0.121 *	-0.100	0.150	0.233
	(-2.91)	(-2.80)	(-0.93)	(-0.77)	(0.29)	(0.45)
MB_t	0.091 ***	0.091 ***	0.031 ***	0.031 ***	0.096 ***	0.096 ***
	(14.23)	(14.19)	(17.20)	(17.14)	(13.44)	(13.38)
LEV_t	-0.412 **	-0.407 **	-0.131 ***	-0.129 ***	-0.370 ***	-0.361 ***
	(-4.49)	(-4.44)	(-5.07)	(-4.98)	(-3.60)	(-3.51)
ROE_t	0.195 ***	0.196 ***	0.092 ***	0.092 ***	0.352 ***	0.353 ***
	(4.34)	(4.35)	(7.23)	(7.25)	(6.97)	(6.99)
$SIZE_t$	-0.020	-0.018	-0.002	-0.001	0.026	0.029 *
	(-1.39)	(-1.27)	(-0.38)	(-0.19)	(1.59)	(1.77)
$Opaque_t$	0.038	0.039	0.005	0.005	0.033	0.033
	(0.95)	(0.96)	(0.42)	(0.44)	(0.72)	(0.73)
Intercept	0.865 *	0.842 *	0.095	0.084	-0.134	-0.176
	(1.71)	(1.67)	(0.66)	(0.59)	(-0.24)	(-0.31)
No. of observations	16,192	16,192	16,192	16,192	16,192	16,192
Adj. R-squared	0.1174	0.1175	0.0939	0.0942	0.0289	0.0292

Table 6

Panel A: OLS regression of $\Delta DOWNVOL_{t+1}$ on change in Analyst Following

	(1)		(2)		(3)	
$\Delta\, DOWNVOL_{t+1} = \beta_0 + \beta_1 * \Delta \text{Analyst\_Following}_t + \beta_2 * \sum \text{Control Variables}_t + \text{(Industry Dummies)} + \varepsilon$						
Δ Analyst_Following						
ΔN_Follow_t	-0.008	***				
	(-5.25)					
ΔN_Star_t			-0.017	***	-0.018	***
			(-4.31)		(-4.56)	
$\Delta N\_NonStar_t$					-0.007	***
					(-4.20)	
Control Variables						
$KURT_t$	-0.011	***	-0.011	***	-0.011	***
	(-22.98)		(-23.09)		(-23.03)	
$SIGMA_t$	-42.990	***	-43.037	***	-42.713	***
	(-35.42)		(-35.30)		(-35.09)	
$DTURN_t$	20.071	***	15.701	***	19.798	***
	(4.11)		(3.30)		(4.05)	
RET_t	-1.892	***	-1.904	***	-1.873	***
	(-16.14)		(-16.20)		(-15.94)	
MB_t	0.023	***	0.022	***	0.023	***
	(11.27)		(11.15)		(11.24)	
LEV_t	-0.032		-0.025		-0.030	
	(-1.35)		(-1.06)		(-1.25)	
ROE_t	-0.169	***	-0.171	***	0.169	***
	(-12.00)		(-12.09)		(-11.98)	
$SIZE_t$	-0.126	***	-0.126	***	-0.125	***
	(-35.59)		(-35.45)		(-35.35)	
$Opaque_t$	0.030	***	0.029	***	0.030	***
	(2.79)		(2.73)		(2.80)	
No. of observations	24,189		24,189		24,189	
Adj. R-squared	0.1794		0.1790		0.1797	

Panel B: OLS regression of $\Delta N\_EXTREMELOW_{t+1}$ on change in Analyst Following

	(1)		(2)		(3)	
$\Delta N_EXTREMELOW_{t+1} = \beta_0 + \beta_1 * \Delta$Analyst_Following $_t$ + $\beta_2 * \sum$ Control Variables $_t$ + (Industry Dummies) + Ɛ						
Δ Analyst_Following						
ΔN_Follow_t	-0.013	***				
	(-3.79)					
ΔN_Star_t			-0.024	**	-0.026	***
			(-2.51)		(-2.68)	
$\Delta N\_NonStar_t$					-0.011	***
					(-3.18)	
Control Variables						
$KURT_t$	-0.002	***	-0.002	***	-0.002	***
	(-2.78)		(-2.91)		(-2.82)	
$SIGMA_t$	-12.889	***	-13.075	***	-12.535	***
	(-6.28)		(-6.37)		(-6.08)	
$DTURN_t$	31.013	***	23.819	**	30.664	***
	(3.12)		(2.46)		(3.08)	
RET_t	-0.838	***	-0.865	***	-0.813	***
	(-4.14)		(-4.28)		(-4.01)	
MB_t	0.051	***	0.050	***	0.051	***
	(16.13)		(16.07)		(16.12)	
LEV_t	-0.235	***	-0.224		-0.232	
	(-7.25)		(-6.95)		(-7.17)	
ROE_t	0.180	***	0.178	***	0.180	***
	(8.14)		(8.07)		(8.16)	
$SIZE_t$	-0.015	***	-0.015	***	-0.014	***
	(-2.84)		(-2.78)		(-2.63)	
$Opaque_t$	0.052	***	0.051	***	0.052	***
	(3.07)		(3.01)		(3.08)	
No. of observations	24,189		24,189		24,189	
Adj. R-squared	0.0177		0.0173		0.0178	

Table 7 Additional analyses on analyst coverage decisions

Panel A: Negative binomial regression of the number of all analysts following the firm (*N_Follow$_t$*) on firm-specific crash risk

	(1)		(2)		(3)	
$N\_Follow_t = \beta_0 + \beta_1 * \text{Crash Risk}_{t-1} + \beta_2 * \sum \text{Control Variables}_{t-1} + \text{(Industry Dummies)} + \varepsilon$						
Crash Risk						
NCSKEW$_{t-1}$	0.003					
	(1.04)					
DUVOL$_{t-1}$			0.020	**		
			(2.01)			
COUNT$_{t-1}$					0.004	*
					(1.66)	
ShortInt$_{t-1}$	0.527	***	0.530	***	0.527	***
	(7.59)		(7.63)		(7.59)	
BidAskSpread$_{t-1}$	4.089	***	4.049	***	4.067	***
	(5.29)		(5.24)		(5.26)	
TradingVolume$_{t-1}$	0.227	***	0.226	***	0.227	***
	(33.19)		(33.00)		(33.32)	
Overvaluation$_{t-1}$	0.107	***	0.108	***	0.107	***
	(7.51)		(7.56)		(7.53)	
Intercept	-3.449	***	-1.856	***	-3.447	***
	(-27.31)		(-27.21)		(-27.30)	
Other control variables	Included		Included		Included	
No. of observations	15,021		15,021		15,021	
Log Likelihood	-36,174		-36,173		-36,173	
Pseudo R-squared	0.1679		0.1679		0.1679	

Panel B: Negative binomial regression of the number of star analysts following the firm (*N_Star_t*) on firm-specific crash risk

	(1)		(2)		(3)	
$N\_Star_{t} = \beta_0 + \beta_1 * \text{Crash Risk}_{t-1} + \beta_2 * \sum \text{Control Variables}_{t-1} + (\text{Industry Dummies}) + \varepsilon$						
Crash Risk						
$NCSKEW_{t-1}$	0.023	***				
	(3.05)					
$DUVOL_{t-1}$			0.104	***		
			(4.05)			
$COUNT_{t-1}$					0.010	*
					(1.65)	
$ShortInt_{t-1}$	0.095		0.099		0.071	
	(0.48)		(0.50)		(0.36)	
$BidAskSpread_{t-1}$	18.324	***	18.206	***	18.325	***
	(9.37)		(9.31)		(9.38)	
$TradingVolume_{t-1}$	0.325	***	0.322	***	0.330	***
	(17.45)		(17.33)		(17.81)	
$Overvaluation_{t-1}$	0.051		0.054		0.049	
	(1.28)		(1.35)		(1.24)	
Intercept	-8.666	***	-8.629	***	-8.709	***
	(-31.09)		(-30.94)		(-31.27)	
Other control variables	Included		Included		Included	
No. of observations	15,021		15,021		15,021	
Log Likelihood	-14,152		-14,148		-14,155	
Pseudo R-squared	0.2602		0.2604		0.2601	

Panel C: Negative binomial regression of the number of Non-Star analysts following the firm (*N_NonStar$_t$*) on firm-specific crash risk

	(1)		(2)		(3)	
$N\_NonStar_{t} = \beta_0 + \beta_1 * \text{Crash Risk}_{t-1} + \beta_2 * \sum \text{Control Variables}_{t-1} + \text{(Industry Dummies)} + \varepsilon$						
Crash Risk						
NCSKEW$_{t-1}$	0.001					
	(0.19)					
DUVOL$_{t-1}$			0.009			
			(0.83)			
COUNT$_{t-1}$					0.003	
					(1.11)	
ShortInt$_{t-1}$	0.585	***	0.587	***	0.586	***
	(8.11)		(8.14)		(8.14)	
BidAskSpread$_{t-1}$	2.753	***	2.730	***	2.726	***
	(3.37)		(3.34)		(3.34)	
TradingVolume$_{t-1}$	0.229	***	0.228	***	0.228	***
	(31.88)		(31.73)		(31.93)	
Overvaluation$_{t-1}$	0.112	***	0.112	***	0.112	***
	(7.58)		(7.60)		(7.61)	
Intercept	-3.399	***	-3.393	***	-3.393	***
	(-24.67)		(-24.60)		(-24.64)	
Other control variables	Included		Included		Included	
No. of observations	15,021		15,021		15,021	
Log Likelihood	-35,086		-35,086		-35,085	
Pseudo R-squared	0.1535		0.1535		0.1535	