Analyst coverage and future stock price crash risk

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Abstract:

Purpose – Whether financial analysts play an effective role as information intermediaries and monitors has triggered a wide spread of debate among academics and practitioners to date. This study complements this debate by investigating the association between analyst coverage and firm-specific future stock price crash risk.

Design/methodology/approach – Regression analysis is based on a large sample of U.S. public firms and the crash risk measure of Hutton *et al.* (2009). Potential endogeneity concerns are alleviated by (i) restricting the sample period to the post-Regulation-FD period and (ii) conducting an analysis of the impact threshold for a confounding variable method per Larcker and Rusticus (2010).

Findings – Evidence reveals that a high level of analyst coverage is associated with lower future stock price crash risk. Further, the negative association between analyst coverage and stock price crash risk is stronger for firms that have high financial opacity. Additionally, analyst forecast pessimism is negatively associated with future crash risk.

Originality/value – The findings of this study offer support for the view that analysts serve positive roles as information intermediaries and monitors in the US stock market.

Practical implications – This study is of interest to investors who seek analyst reports for their investment decision-making and for information providers who demand external financing. The findings of this study also have some other important implications for practitioners, given the economic and welfare consequences of stock price crashes.

Keywords Analyst following, Stock price crashes, Information intermediary, Monitoring, Financial opacity

Paper type Research paper

JEL Classification – G14, G29

1. Introduction

Financial analysts play two important roles in the financial marketplace. First, they act as information intermediaries between firm management and market participants. To this end, analysts acquire and process various value-relevant information, synthesize it in an understandable form, and disseminate it to the market; this improves information quality and increases the informational efficiency of stock markets. Second, analysts may also play a role as a monitor for a firm. By analyzing corporate information on a regular basis, analysts can scrutinize and interfere with management in a way that prevents it from pursuing suboptimal or value-destroying business activities. In uncovering and disseminating information to the public, analysts help investors detect and curb managerial misbehaviors.

Whether and to what degree analysts in the U.S.'s capital markets fulfill their roles as information intermediaries and monitors is still inconclusive in the literature and warrants further research (Leuz, 2003; Frankel *et al.*, 2006; Hansen, 2015). In respect of the information intermediary role, a large body of literature shows that financial analysts help boost stock price efficiencies (e.g., Barth and Hutton, 2004), reduce mispricing (e.g., Hong *et al.*, 2000; Elgers *et al.*, 2001; Griffin and Lemmon, 2002), increase stock liquidity (e.g., Roulstone, 2003; Balakrishnan *et al.*, 2014), decrease information asymmetry among investors (Brennan and Subrahmanyam, 1995), and lower cost of capital (e.g., Gebhardt *et al.*, 2001; Gode and Mohanram, 2003; Bowen *et al.*, 2008).

However, some research scholars (e.g., Elton and Gruber, 1972; Guerard and Beidleman, 1986) question the effective role analysts act as information intermediaries. Empirical evidence reveals that analyst earnings forecasts fail to reflect the effects of conservative accounting (Mensah *et al.*, 2004; Sohn, 2012) and of the transitory nature of current accruals (Elgers *et al.*, 2003). Kothari *et al.* (2009) show that analyst reports contain little information about risk and uncertainty. Furthermore, analysts with an incentive to generate trading commissions tend to compromise their independence and objectivity and to bias their forecasts and stock recommendations (e.g., Michaely and Womack, 1999; Dechow *et al.*, 2000; Richardson *et al.*, 2004), especially when the investment bank with which analysts are affiliated has an underwriting relationship with the covered firm. Also, prior studies (e.g., Chan *et al.*, 1996; Gleason and Lee, 2003) find evidence on market inefficiency with respect to analyst reports (i.e., the market's under- or over-reactions to analyst reports); this lends further support to the notion that analysts do not unambiguously act an effective information intermediary role that promotes the informational efficiency of stock markets.

Regarding analysts' role as monitors, on one hand, a number of studies document that analysts play an effective governance role in constraining management malpractices, including accrual-based and real earnings management, excessive executive compensations, value-destroying investments, and asset mismanagement (e.g., Yu, 2008; Jung *et al.*, 2012; Irani and Oesch, 2013; Chen *et al.*, 2015; Irani and Oesch, 2016), and as a result, future firm performance improves (e.g., Demiroglu and Ryngaert, 2010; Jung *et al.*, 2012). On the other hand, evidence shows that analysts tend to issue biased forecasts and recommendations in the hope of currying favor with management for access to private information (e.g., Ke and Yu, 2006). As such, analysts may not have sufficient motivations to monitor managers in an effective manner, and therefore, the effectiveness of their role as monitors is questionable.

To contribute to the inconclusive debate regarding whether analysts serve effective roles as information intermediaries and monitors for firms, we set out to investigate whether analyst coverage affects firm-specific future stock price crash risk (hereafters, crash risk). Crash risk refers to the likelihood of a sudden, drastic decline in stock price (Chen *et al.*, 2001; Jin and Myers, 2006; Hutton *et al.*, 2009). With separation of ownership and control, managers have incentives to withhold bad news within a firm in order to secure private benefits (Jensen and Meckling, 1976). As bad news accumulates, the extent to which stock price is overvalued increases, thus creating a stock price bubble. There exists a critical threshold at which it is too costly for management to withhold the accumulated bad news any longer. At such threshold point, all the bad news comes out at once, resulting in a stock price crash (Jin and Myer, 2006; Hutton *et al.*, 2009). Hence, crash risk is closely bound up with both information opacity and agency conflicts. By examining the effect of analyst coverage on future crash risk, we can shed light on the effectiveness of analysts' roles as information intermediaries and monitors.

Our empirical analysis is conducted based on a sample of 29,419 firm-year observations for U.S. listed firms over the sample period of 1998-2013. Because stock price crash risk results from bad news being withheld and accumulated over extended periods (Jin and Myers, 2006; Hutton *et al.*, 2009), one-year analyst coverage does not warrant a curb on future crash risk. Thus, we use the prior three years' analyst coverage; this is in spirit of Hutton *et al.* (2009), who use the past three years' moving sum of abnormal accruals as the measure of financial opacity when investigating its association with crash risk. We follow Hutton *et al.* (2009) to develop crash risk measures, which are based on the incidence, as well as frequency, of negative, extreme firm-specific weekly returns over a fiscal year. After controlling for a range of determinants of crash risk, we find that analyst coverage is significantly, negatively associated with future crash risk and that such association is more evident for firms with high financial opacity. These results support the view that analysts serve effective roles as information intermediaries and monitors for firms, and indicate that such roles played by analysts are more salient when firms have high financial opacity.

We also examine whether conditional on analysts' decision to cover a firm, analyst pessimism is related to future crash risk. If analysts are pessimistic in their earnings forecasts for a firm, then the firm does not need to, and thus has less incentive to, withhold bad news, if any, to meet or beat the pessimistic analyst forecasts that are relatively easier to meet or beat. What's more, analysts' pessimistic forecasts *per se* could accelerate the speed with which corporate bad news is revealed to the public, hence decreasing future crash risk. Consistent with this reasoning, we find that analyst pessimism is negatively related to future crash risk.

Our tests are subject to a concern that future crash risk is endogenously determined with analyst coverage and forecasts. To alleviate such a concern, we use lead-lag design and control for an extensive list of crash risk determinants and for industry-fixed and year-fixed effects in all the multivariate tests. On top of this, we adopt two approaches to alleviate further the endogeneity problem. First, we restrict our sample period to the post-Regulation-FD period, in which analysts are prohibited from accessing private information and thus are highly unlikely to self-select towards firms with lower anticipated crash risk. Second, following Larcker and Rusticus (2010), we conduct the impact threshold for a confounding variable method, whereby ensuring that our regression estimation is not driven by unobservable omitted variable(s). Our results are reasonably robust to using both approaches for controls of potential endogeneity.[1]

Our study makes two main contributions. First, we complement a vast literature that debates the effectiveness of financial analysts in serving information intermediary role in the financial marketplace. We provide evidence in support of the view (i) that financial analysts play an active information intermediary role in a way that increases information transparency of a firm and reduces its crash risk, and (ii) that analysts perform an effective monitoring role in a way that constrains firm management's bad news hoarding activities and reduces future crash risk. By further showing supportive evidence that the informational and oversight roles played by analysts are more pronounced for more financially opaque firms, our study gives implications for investors who seek analyst reports for their investment decision-making.

[1] The exogenous events as to brokerage mergers and closures might be used in a natural experiment to address the potential endogeneity concerns. However, such events cause an exogenous decrease in analyst coverage only in the year in which the brokerage houses are merged or closed, whereas our analyst coverage measure, which is constructed in spirit of Hutton *et al.* (2009), pertains to a three-year measure. As such, using broker mergers and closures to identify one-year exogenous variation in analyst coverage does not work effectively in solving the endogeneity issues in our research context. Therefore, we rely mainly on the two identification strategies as described in the main body text.

Second, our study contributes to a growing body of research on the determinants of crash risk. Building upon the bad-news-hoarding hypothesis, a large body of studies (e.g., Hutton *et al.*, 2009; Kim *et al.*, 2011a, b; Callan and Fang, 2013; He, 2015; Andreou *et al.*, 2017; Chang *et al.*, 2017; He and Ren, 2018) have identified a variety of firm characteristics that determine stock price crash risk. Our research adds to this literature by documenting yet another important determinant of crash risk, which is analyst coverage.[2]

2. Hypothesis development

The fundamental cause of crash risk is bad news hoarding, which is driven by the extent of information opacity and agency conflicts (Jin and Myers, 2006; Hutton *et al.*, 2009). Low corporate information transparency makes it difficult for outside investors to detect firm management's misbehavior. Thus, managers in such firms are likely inclined to withhold bad news, leading to high crash risk for the firms. On the contrary, high information transparency restrains managerial bad news hoarding and thereby reduces the likelihood of future stock price crashes. Consistent with this notion, Hutton *et al.* (2009) find that firms with high financial opacity are more likely to experience stock price crashes. Building on Hutton *et al.* (2009), we posit that financial analysts, by means of their role as information intermediaries, can mitigate bad news hoarding within firms and reduce stock price crash risk. This is because financial

[2] Using a unique Chinese database, Xu *et al.* (2013) examine the association between analyst coverage and crash risk. Our research is different from Xu *et al.* (2013) in various aspects, including institutional setting, research motivation, story, and empirical findings. First, Xu *et al.* look at China's emerging stock markets where analyst profession is still under-developed relative to that in the U.S.'s stock markets we look at in this paper. Second, unlike Xu *et al.*, we motivate our research with the academic debate regarding whether analysts serve effective roles as information intermediaries and monitors, and aim at adding to this debate by virtue of our arguments and empirical analyses. Third, Xu *et al.* predict a positive association between analyst coverage and crash risk under a premise that analyst forecasts tend to be overly optimistic. They find results consistent with their prediction. However, we argue that analyst forecasts are highly unlikely to be generally optimistic, as optimistic analyst forecasts are more difficult for a firm to meet and beat. In U.S., analyst forecasts are in general pessimistic especially during the period leading up to earnings announcements (e.g., Ke and Yu, 2006). We show that analyst coverage is negatively associated with future crash risk through the effective role analysts serve as information intermediaries and monitors.

analysts, by virtue of their sophistication in acquiring and processing information, are likely to uncover bad news in a timely manner, and communicate this with investors through analyst research reports or media outlets. When bad news is impounded into stock prices timely, stock price crash risk will be reduced.

Analysts' monitoring role is another channel through which analyst coverage affects crash risk. If analysts can discipline management by actively monitoring and publicizing managerial actions, they act as monitors that decrease agency risk, reduce managerial malfeasances, and improve investment and operation decisions for a firm. As such, analysts, through their monitoring role, could reduce corporate bad news, deter managers from hoarding bad news, and thereby reduce crash risk for a firm.

Taken together, provided that analysts fulfill their roles as information intermediaries and monitors, analyst coverage should lead to a more transparent information environment and a stronger monitoring mechanism for a firm, which limit management's ability of concealing bad news, and ultimately, reduce the firm's future crash risk. Nonetheless, if analysts fail to perform such effective informational and monitoring roles, we would not observe a negative association between analyst coverage and future crash risk. Based on the above discussion, we present our main hypothesis in a null form as follows:

H1: Analyst coverage is unrelated to future stock price crash risk.

3. Data and sample

Our tests are based on data collected primarily from I/B/E/S, CRSP, Compustat, and FactSet. Our sample period covers the years 1998-2013. We require that firms have necessary data from these databases to construct the variables of interest for our tests. To mitigate the effect of potential outliers, we winsorize all the continuous variables at both the 1st and 99th percentiles.[3] The final sample for testing the association between analyst coverage (analyst forecast pessimism) and future stock price crash risk is composed of 29,419 (11,685) firm-year observations for 7,488 (4,133) unique U.S. listed firms. Table 1 reports summary statistics of the variables used in the tests.

We carry out a test of Spearman correlations for the independent variables used in the regression of future crash risk on analyst coverage (analyst forecast pessimism). In the results (not tabulated for brevity), the magnitudes of the correlations all fall short of 75%, indicating no multicollinearity arising should all these variables be included in the same regression. In un-tabulated analysis, we also run the variance inflation factors (VIF) test, and find that none of the variables have a VIF value higher than 5, which indicates that multi-collinearity is not an issue in our regression analyses (O'Brien, 2007).[4]

4. Research design and results

4.1 Test of H1: The association between analyst coverage and future stock price crash risk

The following regression model is specified to test the relation between analyst coverage and future crash risk:

$$crashrisk_t(ncrash_t) = a_0 + a_1 anacov_{t-1} + a_2 controls_{t-1} + e \tag{1}$$

Two crash risk measures are used. The first, $crashrisk_t$, is measured based on Hutton *et al.* (2009), and equals 1 if a firm experiences one or more firm-specific weekly returns falling 3.2 standard deviations below the mean firm-specific weekly return over the fiscal year t, and 0

[3] We also delete the observations that have the three-year analyst coverage higher than 1,500. Noticeably, one drawback of such winsorization or trimming is that it might undermine the economic meaning inherent in, and conveyed by, the variables (assuming no data-reporting error existing for the databases we use). Regarding this, we also re-do our empirical tests using samples that are not winsorized nor trimmed, and obtain qualitatively identical results.

[4] The largest VIF amounts to 3.05. Our results for the VIF test are not reported for parsimony and are available upon request.

otherwise.[5] The second crash risk measure (*ncrash*$_t$) equals the natural logarithm of 1 plus the frequency of negative, extreme firm-specific weekly returns over the fiscal year t. The measurement of the firm-specific weekly returns follows Kim *et al.* (2011a), with the returns all adjusted for market-wide factors.[6] When crash risk is proxied by *crashrisk*$_t$ (*ncrash*$_t$), a logit (ordinary least squares (OLS)) regression is applied. The treatment variable, *anacov*$_{t-1}$, equals the number of analysts that make at least one annual EPS forecast for a firm over a three-year period that ends at the end of the fiscal year t-1, and equals 0 if there is no analyst forecasting annual EPS for the firm. To cause a stock price crash, bad news should be not only withheld but also accumulated for extended periods until the amount of it reaches a critical threshold level. Therefore, one-year analyst coverage does not warrant a curb on crash risk, and thus we use the three-year measure for analyst coverage; this is in spirit to Hutton *et al.* (2009), who measure financial opacity by the three-year moving sum of absolute abnormal accruals when examining its relationship with crash risk. One red flag for earnings management is an abnormal level of positive accruals followed by a subsequent accruals reversal which takes negative. In this sense, both positive and negative abnormal accruals in the three-year period capture the extent of financial opacity for a firm. Hence, in calculating the *opacity* measure as the control for crash risk, we follow Hutton *et al.* to use the absolute value, rather than the signed value, of abnormal accruals for the three-year period.

Based on prior research on crash risk (e.g., Chen *et al.*, 2001; Hutton *et al.*, 2009; Kim *et al.*, 2011a, b; Callan and Fang, 2013; He, 2015; Andreou *et al.*, 2017; Chang *et al.*, 2017; He and Ren, 2018), we control for firm size (*size*), return volatility (*stdret*), negative return skewness (*ncskew*), abnormal stock returns (*meanret*), return on assets (*roa*), abnormal trading

5 All our statistically inferences remain unchanged if we re-define the negative, extreme firm-specific weekly returns as being lower than the mean firm-specific weekly return by 3, or 3.4, standard deviation.

6 Considering the possibility that the financial crisis may still have some confounding effects on our crash risk measures, we exclude the crisis period (i.e., 2007-2008) from our sample period, and obtain qualitatively the same results for the hypothesis tests.

volume (*tradevol*), institutional ownership (*insti*), sales growth (*salesgrowth*), book-to-market ratio (*btm*), financial leverage (*debt*), stock market liquidity (*liq*), and financial opacity (*opacity*), and additionally, include industry-fixed and year-fixed effects in model (1).[7] As with the treatment variable (*anacov*), all the control variables, which are defined in the appendix, have the measurement windows ending at the end of the fiscal year t-1; this lead-lag design, together with the inclusion of industry-fixed and year-fixed effects, helps mitigate potential endogeneity issues. In addition, we cluster the standard errors of the coefficients by firm to control for potential time-series correlations of residuals within firms (Petersen, 2009).[8]

Table 2 reports the regression results. Column (1) ((3)) presents the result of the logit (OLS) regression, in which *crashrisk* (*ncrash*) is used as the dependent variable for the full sample period. In both columns, the coefficients on *anacov* are negative and statistically significant at the 5% level. Such results reject the null hypothesis, H1, suggesting that analyst coverage curbs bad news hoarding and mitigates crash risk.

Analyst coverage and future crash risk might be endogenously determined by factors related to private corporate information. To cope with this concern, we restrict our sample to the post-Regulation-FD period in which insiders are not allowed to provide private information to analysts, and re-run regressions for model (1). Columns (2) and (4) of Table 2 report the results. The coefficients for *anacov* remain negative and highly significant, when crash risk is proxied by *crashrisk* and *ncrash*, respectively. A one-standard-deviation increase in *anacov* is associated with a decrease of 1.07% in the predicted likelihood of *crashrisk*. A one-standard-deviation increase in *anacov* is associated with a decrease of 0.00779 in *ncrash*, which accounts

[7] As with prior research that investigates the effects of analyst coverage (e.g., Irani and Oesch, 2013; Chen et al., 2015), we include firm size (*size*) as a key control in our multivariate tests. Though firm size (*size*) and analyst coverage (*anacov*) are strongly correlated, our variance inflation factor (VIF) statistics show that the VIF value for *size* is only 3.05, which is below 5. This suggests no multicollinearity associated with *size* that would pose a threat to our empirical analysis (O'Brien, 2007).

[8] Our results remain qualitatively the same if we cluster the standard errors by industry for all our regression analyses.

for 5.72% of its sample mean. The results for the coefficients on the control variables are in general consistent with the prior literature.

A plausible endogenous selectivity issue with our analysis is that analysts' anticipation of future crash risk drives their current firm coverage decision. Nevertheless, crash risk is attributed to managers' bad news hoarding which is unobservable to analysts who are restricted from accessing private information in the post-Regulation-FD era. As such, analysts' ability to anticipate future crash risk is largely limited, thus substantially lowering the possibility that such analysts' anticipation drives their current coverage decisions. Therefore, our results for the post-Regulation-FD sample period, as reported in Columns (2) and (4) of Table 2, also mitigate the endogenous selectivity concern.

4.2 The impact threshold for a confounding variable in the multivariate test of H1

To further check whether our results, as shown in Columns (2) and (4) of Table 2, are still subject to correlated-omitted-variables bias, we follow Larcker and Rusticus (2010) to conduct a test as to the impact threshold for a confounding variable (ITCV). The larger the value of ITCV, the less susceptible our regression results are to potential omitted-variables bias. Panel A (B) of Table 3 reports the results of the ITCV test for the regression, in which the dependent variable is *crashrisk* (*ncrash*) and that is run for the post-Regulation-FD period. We take the results in Panel A to illustrate how our regression results are not driven by the omitted-variables concern. None of the control varilables we include in our regression model has an *impact* with its absolute value higher than the absolute value of ITCV which is 0.0238. On this basis, it is very unlikely that an omitted variable has a higher correlation with *crashrisk* and *anacov* than do any of our control variables to overturn our result for *anacov*; this could be taken as strong evidence that our regression result of interest is immune from potential endogeneity concerns. The same conclusion could be drawn from the ITCV results in Panel B.[9]

4.3 A cross-sectional analysis of H1: The moderating effect of financial opacity on the association between analyst coverage and future crash risk

To further test whether analyst coverage is more strongly, negatively associated with future crash risk for firms with high financial opacity, we split our full sample into two subsamples based on the sample median of the measure of financial opacity (i.e., *opacity* as per Hutton *et al.* (2009)), and then estimate model (1) separately for the two subsamples. Table 4 reports the results. For both the *crashrisk* and *ncrash* regressions, the coefficients for *anacov* are positive and highly significant for the high-financial-opacity subsample but are statistically insignificant for the low-financial-opacity subsample. This result indicates that the negative link between analyst coverage and future crash risk is more evident for firms with high financial opacity.

4.4 Additional analysis: The association between analyst forecast pessimism and future stock price crash risk

To test the relationship between analyst forecast pessimism and future crash risk, we replace *anacov* with *pessimism* in model (1), and derive the following model.

$$crashrisk_t(ncrash_t) = \alpha_0 + \alpha_1 pessimism_{t-1} + \alpha_2 controls_{t-1} + \varepsilon \qquad (2)$$

We measure analyst forecast pessimism by the average of analysts' annual EPS forecasts for a firm over a three-year period ending at the fiscal year t-1 (*avgEPS*). $pessimism_{t-1}$ equals 1 if the average figure, *avgEPS,* is below the lower sample quartile point, and 0 if *avgEPS* is

9 We repeat the ITCV evaluation procedure for model (1) (as well as model (2) as described in Section 4.4) that is run for the whole sample period, and obtain the same conclusion that our results reported in Columns (1) and (3) of Table 2 (Table 5) are insensitive to potential correlated-omitted-variables bias.

above the upper sample quartile point. *crashrisk*$_t$ and *ncrash*$_t$ are as defined previously. We include the same control variables as we do in model (1). Column (1) ((3)) of Table 5 reports the logit (OLS) regression results for the full sample period of 1998-2013; Column (2) ((4)) presents the logit (OLS) regression results run for the post-Regulation-FD period only. In all sets of results, we find significantly negative coefficients on *pessimism*, thus supporting the notion that high analyst forecast pessimism is associated with lower future crash risk. For the post-Regulation-FD sample, a one-standard-deviation increase in *pessimism* is associated with a decrease of 1.32% in the predicted probability of *crashrisk*; a one-standard-deviation increase in *pessimism* is associated with a decrease of 0.0116 in *ncrash*, which is equivalent to 8.29% of the sample mean of *ncrash*.

To assess the robustness of the results to potential correlated omitted variables, we repeat the ITCV evaluation procedure as we do in Section 4.2. In results not tabulated, we find an ITCV of -0.0226 (-0.0244) with its absolute value higher than all the absolute value of *impact* for the *crashrisk* (*ncrash*) regression. Hence, our regression results reported in Table 5 are reasonably robust to potential correlated-omitted-variables bias.

5. Conclusion

Whether the informational and monitoring roles played by financial analysts are effective has sparked widespread debate among academics and practitioners to date. We add to this debate by examining the association between analyst coverage and future stock price crash risk. Our results reveal that a high level of analyst coverage is associated with lower future crash risk, which lends support to the view that analysts serve positive roles as information intermediaries and monitors in the stock markets. Our results also show that the negative association between analyst coverage and future crash risk is stronger for firms with high financial opacity, suggesting that the roles played by analysts become more salient when firms are subject to high financial opacity. Our study is thus relevant to investors who seek analyst reports to aid in their investment decision-making. Given analysts' effective information intermediary role as well as monitoring role in stock markets, information providers (particularly, accountants) may increase public disclosures of value-relevant information so as to enhance the quality and transparency of corporate information to its users and thereby facilitate external financing. Our findings also have some other important practical implications. Specifically, market participants can use analyst coverage to aid themselves in *ex ante* assessing future stock price crash risk, and therein assessing the likelihood and degree of insiders' bad news hoarding which results in crash risk. This is of particular interest to investors for their portfolio investment decisions, and to suppliers and creditors who monitor the creditworthiness of their clients.

Analyst coverage reduces crash risk via analysts' role as information intermediaries and monitors. It is interesting to further test (i) whether and to what degree analyst coverage reduces crash risk via the information intermediary role, and (ii) whether and to what extent analyst coverage reduce crash risk via the monitoring role. However, the information intermediary role and monitoring role financial analysts play are interrelated and mutually reinforcing; specifically, by playing an active part in monitoring firm management, analysts may serve better as information intermediaries, and analysts' serving an effective role as information intermediaries would in turn facilitate effective monitoring. It is difficult for an archival study to effectively disentangle the effects of the two distinct roles played by analysts. We thus leave this issue for future research in an experimental setting.

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Appendix

Variables	Definitions
crashrisk	1 if a firm experiences one or more firm-specific weekly returns falling 3.2 standard deviations below the mean firm-specific weekly return over the fiscal year, and 0 otherwise. The firm-specific weekly returns measure follows Kim *et al.* (2011a).
ncrash	The natural logarithm of 1 plus the number of firm-specific weekly returns that fall 3.2 standard deviations below the mean firm-specific weekly return over the fiscal year. The firm-specific weekly returns measure follows Kim *et al.* (2011a).
anacov	The number of analysts that make at least one annual EPS forecast for a firm over the recent three fiscal years, and 0 if there is no analyst forecasting annual EPS for the firm.
pessimism	1(0) if the mean analyst EPS forecast (namely, *avgEPS*) is below (above) its lower (upper) sample quartile point. *avgEPS* is defined as the average of analysts' annual EPS forecasts for a firm over the recent three fiscal years.
ncskew	The negative skewness of firm-specific weekly stock returns over a 12-month period ending at the end of the fiscal year.
debt	Long-term debt plus short-term debt, divided by total assets for the fiscal year.
roa	Return on assets at the end of the fiscal year.
stdret	The standard deviation of firm-specific weekly returns over a 12-month period ending at the end of the fiscal year.
insti	Institutional investors' stock ownership as a percentage of the outstanding shares for a firm at the end of the fiscal year.
salesgrowth	Sales revenues for the current fiscal year minus sales revenues for the previous fiscal year, scaled by sales revenues for the previous fiscal year.
meanret	The mean of firm-specific weekly return over a 12-month period ending at the end of the fiscal year.
size	The natural logarithm of the market value of a firm's equity at the end of the fiscal year.
btm	The book value of firm equity divided by the market value of firm equity at the end of the fiscal year.
tradevol	The monthly trading volume, divided by the number of outstanding shares at the end of the month, and averaged over the fiscal year for a firm.
liq	A liquidity measure constructed as per Fang *et al.* (2009). It is calculated as the average of daily relative effective spread for the PBE announcement quarter. The daily relative effective spread is calculated as the absolute value of the difference between the transaction price and the midpoint of the prevailing bid-ask quote, divided by the midpoint of the prevailing bid-ask quote.
opacity	The three-year moving sum of the absolute value of abnormal accruals for the current and previous two fiscal years, a measure of financial opacity developed by Hutton *et al.* (2009).

Table 1 Summary statistics

Variables	N	Mean	Std	Min.	25%	Median	75%	Max.
Key variables								
crashrisk	29,419	0.1745	0.3795	0	0	0	0	1
ncrash	29,419	0.1292	0.3058	0	0	0	0	3.8918
anacov	29,419	100.3452	139.5935	0	9	49	136	1343
avgEPS	23,371	0.9939	1.7809	-5.8622	0.2858	0.7533	1.4492	11.0456
pessimism	11,685	0.5000	0.5000	0	0	1	1	1
Control variables								
roa	29,419	-0.0201	0.2271	-1.5979	-0.0166	0.0319	0.0708	0.2722
size	29,419	5.9701	2.0704	1.2671	4.5262	6.0617	7.3719	10.9121
stdret	29,419	0.0737	0.0470	0.0106	0.0424	0.0609	0.0901	0.2883
btm	29,419	2.5787	8.5759	0.0411	0.3293	0.5950	1.0982	59.7229
ncskew	29,419	4.2554	14.6503	-70.5999	-2.7759	4.1476	11.0478	58.4554
meanret	29,419	0.2665	1.2629	-5.1931	-0.2809	0.2904	0.8492	4.9159
opacity	29,419	10.8456	49.3328	0	0.0331	0.1389	0.7882	356.6239
salesgrowth	29,419	0.1734	0.6632	-0.9141	-0.0528	0.0723	0.2249	5.3975
tradevol	29,419	1.5651	1.6071	0.0367	0.5038	1.0542	2.0381	9.2068
debt	29,419	0.1963	0.1974	0	0.0008	0.1558	0.3323	0.9104
insti	29,419	0.9996	1.3504	0	0	0.2051	1.7920	4.4662
liq	29,419	0.0184	0.0293	0.0003	0.0016	0.0072	0.0215	0.1657

Notes: This table tabulates descriptive statistics of all the variables used for the multivariate tests. The sample period for the crash risk measures spans the years 1998-2013. All the variables are defined in the appendix.

Table 2 Multivariate test of the association between analyst coverage and future stock price crash risk

Variables	*crashrisk*		*ncrash*	
	Full sample period	Post Regulation FD period	Full sample period	Post Regulation FD period
	(1)	(2)	(3)	(4)
anacov	**-0.0004****	**-0.0005*****	**-0.00004****	**-0.0001*****
	(-2.572)	**(-2.700)**	**(-2.150)**	**(-2.705)**
roa	0.7461***	0.7302***	0.0467***	0.0593***
	(7.461)	(6.688)	(3.332)	(4.059)
size	0.0918***	0.0920***	0.0083***	0.0093***
	(6.159)	(5.268)	(5.271)	(5.064)
stdret	5.9554***	7.4409***	0.9511***	1.1377***
	(11.311)	(11.044)	(12.776)	(11.597)
btm	-0.0027	-0.0022	-0.0001	0.00003
	(-1.023)	(-0.735)	(-0.516)	(0.139)
ncskew	-0.0017	-0.0017	-0.0002	-0.0002
	(-1.453)	(-1.253)	(-1.414)	(-1.345)
meanret	-0.4173***	-0.4393***	-0.0459***	-0.0507***
	(-27.376)	(-22.868)	(-20.732)	(-17.698)
opacity	0.0005	0.0004	0.0001	0.0001
	(1.628)	(1.236)	(1.434)	(1.229)
salesgrowth	-0.0347	-0.0105	-0.0061**	-0.0018
	(-1.324)	(-0.339)	(-1.990)	(-0.464)
tradevol	-0.0163	0.00005	-0.0021	-0.0007
	(-1.318)	(0.004)	(-1.530)	(-0.445)
debt	-0.0780	-0.2692**	-0.0060	-0.0230*
	(-0.792)	(-2.289)	(-0.546)	(-1.784)
Insti	0.0843***	0.0834***	0.0112***	0.0105***
	(4.733)	(4.505)	(5.540)	(5.000)
liq	-1.8731*	-6.4535***	0.0472	-0.3577**
	(-1.912)	(-3.870)	(0.421)	(-2.218)
Intercept	-2.4415***	-2.7724***	-0.0181	-0.1267***
	(-9.846)	(-9.571)	(-0.118)	(-7.671)
Pseudo R_2/adj. R_2	0.0687	0.0714	0.0543	0.0603
Observations	29,419	21,270	29,419	21,270

Notes: This table reports the regression results for the test of the association between analyst coverage and future stock price crash risk. Column (1) reports the results for the logit regression, in which *crashrisk* is the dependent variable, and that is run for the full sample period of 1998-2013. Column (2) reports the results for the logit regression, in which *crashrisk* is the dependent variable, and that is run for the post-Regulation-FD period (i.e., 2001-2012 (2002-2013) for the *anacov* (*crashrisk*) measure). Column (3) reports the results for the OLS regression, in which *ncrash* is the dependent variable, and that is run for the full sample period of 1998-2013. Column (4) reports the results for the OLS regression, in which *ncrash* is the dependent variable, and that is run for the post-Regulation-FD period. All the variables used in the regressions are defined in the appendix. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in the regressions but are not reported for brevity. The t/z statistics in parentheses are based on robust standard errors clustered by firm. ***, **, * denote the statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3 Impact threshold for a confounding variable for the test of the association between analyst coverage and future crash risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A	ITCV	ITCV implied correlations	ρ(x, *anacov*|z)	ρ(x, *crashrisk*|z)	*Impact*	ρ(x, *anacov*)	ρ(x, *crashrisk*)	$Impact_{raw}$
anacov	-0.0238	0.1543						
roa			-0.0776	0.0335	-0.002600	0.1455	0.0133	0.001935
size			0.5309	0.0188	0.009981	0.6396	0.0490	0.031340
stdret			0.0286	0.0815	0.002331	-0.1918	0.0520	-0.009974
btm			0.0247	-0.0089	-0.000220	-0.1435	-0.0456	0.006544
ncskew			-0.0228	-0.0087	0.000198	-0.1304	-0.0195	0.002543
meanret			0.0592	-0.1809	-0.010709	0.0196	-0.1840	-0.003606
opacity			0.0044	0.0147	0.000065	-0.0347	0.0126	-0.000437
salesgrowth			-0.0629	0.0031	-0.000195	-0.0243	0.0216	-0.000525
tradevol			0.2952	-0.0143	-0.004221	0.4136	0.0357	0.014766
debt			-0.0080	-0.0321	0.000257	0.0333	-0.0411	-0.001369
insti			0.1865	0.0494	0.009213	0.4522	0.0564	0.025504
liq			0.1965	-0.0269	-0.005286	-0.3083	-0.0543	0.016741
Mean			0.0962	-0.0059	-0.000099	0.0726	-0.0087	0.006955
Max			0.5309	0.0815	0.009981	0.6396	0.0564	0.031340
Panel B	ITCV	ITCV implied correlations	ρ(x, *anacov*|z)	ρ(x, *ncrash*|z)	*Impact*	ρ(x, *anacov*)	ρ(x, *ncrash*)	$Impact_{raw}$
anacov	-0.0222	0.1490						
roa			-0.0776	0.0214	-0.001661	0.1455	-0.0110	-0.001601
size			0.5309	0.0164	0.008707	0.6396	0.0253	0.016182
stdret			0.0286	0.0921	0.002634	-0.1918	0.0778	-0.014922
btm			0.0247	-0.0077	-0.000190	-0.1435	-0.0419	0.006013
ncskew			-0.0228	-0.0084	0.000192	-0.1304	-0.0159	0.002073
meanret			0.0592	-0.1790	-0.010597	0.0196	-0.1816	-0.003559
opacity			0.0044	0.0150	0.000066	-0.0347	0.0133	-0.000462
salesgrowth			-0.0629	0.0014	-0.000088	-0.0243	0.0199	-0.000484
tradevol			0.2952	-0.0160	-0.004723	0.4136	0.0283	0.011705
debt			-0.0080	-0.0263	0.000210	0.0333	-0.0371	-0.001235
insti			0.1865	0.0473	0.008821	0.4522	0.0401	0.018133
liq			0.1965	-0.0164	-0.003223	-0.3083	-0.0288	0.008879
Mean			0.0962	-0.0050	0.000012	0.0726	-0.0093	0.003394
Max			0.5309	0.0921	0.008821	0.6396	0.0778	0.018133

Notes: This table reports the impact of possible correlated omitted variables on the results for the multivariate test of the association between analyst coverage and future crash risk for the post-Regulation-FD period. Panel A (B) shows the results of the impact threshold test for the regression in which *crashrisk* (*ncrash*) is the dependent variable. Column (1) reports the impact threshold for a confounding variable (ITCV), which is the lowest product of the partial correlation between the dependent variable (i.e., *crashrisk* for Panel A and *ncrash* for Panel B) and the confounding variable and the partial correlation between the treatment variable and the confounding variable that causes the coefficient for *anacov* to be statistically insignificant. Column (2) reports the implied minimum correlation a confounding variable must have with the dependent variable and *anacov* to make the coefficient for *anacov* statistically insignificant. Column (3) reports the partial correlations between *anacov* and each control variable in our regression model (1). Column (4) presents the partial correlations between the dependent variable and each control variable in our regression model (1). Column (5) is each control variable's partial impact, which is defined as the product of the two partial correlations that are reported in Column (3) and Column (4), respectively. Column (6) presents the raw correlations between *anacov* and each control variable in our regression model (1). Column (7) reports the raw correlations between the dependent variable and each control variable in our regression model (1). Column (8) shows each control variable's raw impact, which is defined as the product of the two raw correlations that are reported in Column (6) and Column (7), respectively.

Table 4 Multivariate test of the moderating effect of financial opacity on the association between analyst coverage and future stock price crash risk

Variables	*crashrisk*		*ncrash*	
	High *opacity*	Low *opacity*	High *opacity*	Low *opacity*
	(1)	(2)	(3)	(4)
anacov	**-0.0007*****	**-0.0004**	**-0.0001****	**-0.00002**
	(-2.878)	**(-1.301)**	**(-2.471)**	**(-0.702)**
roa	0.7354***	0.8874***	0.0534***	0.0294
	(7.216)	(3.921)	(4.826)	(1.424)
size	0.1084***	0.0801***	0.0103***	0.0069***
	(5.489)	(3.783)	(4.520)	(3.304)
stdret	6.7207***	5.3349***	1.0517***	0.8520***
	(10.591)	(7.030)	(14.412)	(11.414)
btm	-0.0003	-0.0047	0.0001	-0.0002
	(-0.079)	(-1.383)	(0.220)	(-0.842)
ncskew	-0.0015	-0.0016	-0.0001	-0.0002
	(-0.954)	(-1.028)	(-0.784)	(-0.965)
meanret	-0.4039***	-0.4510***	-0.0450***	-0.0482***
	(-21.631)	(-19.818)	(-21.876)	(-22.775)
salesgrowth	-0.0506*	0.0335	-0.0082**	0.0017
	(-1.812)	(0.612)	(-2.489)	(0.313)
tradevol	-0.0194	-0.0072	-0.0020	-0.0019
	(-1.240)	(-0.369)	(-1.066)	(-0.996)
debt	-0.3075**	0.1471	-0.0320**	0.0164
	(-2.332)	(1.057)	(-2.134)	(1.189)
insti	0.1022***	0.0727***	0.0139***	0.0091***
	(4.386)	(2.973)	(4.850)	(3.559)
liq	-2.1479	-1.7888	0.0761	0.0048
	(-1.637)	(-1.364)	(0.565)	(0.040)
Intercept	-2.2884***	-3.1877***	0.2623	-0.0326
	(-8.134)	(-5.463)	(1.176)	(-0.200)
Pseudo R_2/adj.R_2	0.0748	0.0688	0.0546	0.0551
Observations	14,709	14,710	14,709	14,710

Notes: This table presents the regression results for the test of the moderating effect of financial opacity on the association between analyst coverage and future stock price crash risk. The sample period for the crash risk measures ranges from 1998-2013. Column (1) ((2)) reports the results for the logit regression, in which *crashrisk* is the dependent variable, and that is run for the subsample whose observations have the values of *opacity* higher (lower) than the full sample median. Column (3) ((4)) reports the results for the OLS regression, in which *ncrash* is the dependent variable, and that is run for the subsample whose observations have the values of *opacity* higher (lower) than the full sample median. All the variables used in the regressions are defined in the appendix. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in the regressions but not reported for brevity. The t/z statistics in parentheses are based on robust standard errors clustered by firm. *** and ** denote the statistical significance at the 1% and 5% levels (two-tailed), respectively.

Table 5 Multivariate test of the association between analyst forecast pessimism and future stock price crash risk

Variables	*crashrisk*		*ncrash*	
	Full sample period	Post Regulation FD period	Full sample period	Post Regulation FD period
	(1)	(2)	(3)	(4)
pessimism	**-0.1989***** **(-2.642)**	**-0.1882**** **(-2.096)**	**-0.0273***** **(-3.129)**	**-0.0232**** **(-2.347)**
roa	0.6193*** (4.634)	0.6144*** (4.078)	0.0504*** (3.117)	0.0653*** (4.180)
size	0.0635*** (3.009)	0.0646** (2.556)	0.0055** (2.406)	0.0059** (2.025)
stdret	6.9466*** (8.296)	8.5256*** (8.072)	1.0216*** (8.535)	1.2055*** (8.243)
btm	-0.0052 (-1.219)	-0.0003 (-0.063)	-0.0004 (-1.158)	0.0001 (0.320)
ncskew	-0.0011 (-0.566)	-0.0028 (-1.280)	-0.0001 (-0.356)	-0.0003 (-1.383)
meanret	-0.4105*** (-18.453)	-0.4416*** (-15.282)	-0.0467*** (-14.665)	-0.0519*** (-12.752)
opacity	-0.0002 (-0.406)	-0.0006 (-1.018)	-0.00005 (-0.847)	-0.0001 (-1.379)
salesgrowth	-0.0380 (-1.071)	-0.0066 (-0.159)	-0.0035 (-0.794)	0.0014 (0.232)
tradevol	-0.0241 (-1.337)	-0.0045 (-0.231)	-0.0027 (-1.331)	-0.0014 (-0.658)
debt	-0.1275 (-0.862)	-0.4279** (-2.471)	-0.0124 (-0.720)	-0.0321 (-1.563)
insti	0.0576** (2.136)	0.0649** (2.280)	0.0079*** (2.670)	0.0086*** (2.710)
liq	-3.4821 (-1.631)	-6.7939* (-1.816)	0.1453 (0.533)	-0.0500 (-0.104)
Intercept	-1.7706*** (-4.958)	-2.1916*** (-5.467)	0.0607** (2.045)	0.4131*** (9.706)
Pseudo R^2/adj. R^2	0.0799	0.0821	0.0653	0.0697
Observations	11,685	8,596	11,685	8,596

Notes: This table presents the regression results for the test of the association between analyst forecast pessimism and future stock price crash risk. Column (1) reports the results for the logit regression, in which *crashrisk* is the dependent variable, and that is run for the full sample period of 1998-2013. Column (2) reports the results for the logit regression, in which *crashrisk* is the dependent variable, and that is run for the post-Regulation-FD period (i.e., 2001-2012 (2002-2013) for the *anacov* (*crashrisk*) measure). Column (3) reports the results for the OLS regression, in which *ncrash* is the dependent variable, and that is run for the full sample period of 1998-2013. Column (4) reports the results for the OLS regression, in which *ncrash* is the dependent variable, and that is run for the post-Regulation-FD period. All the variables used in the regressions are defined in the appendix. Industry dummies (constructed based on the first two digits of SIC codes) and year dummies are included in the regressions but not reported for brevity. The t/z statistics in parentheses are based on robust standard errors clustered by firm. ***, **, * denote the statistical significance at 1%, 5%, and 10% levels (two-tailed), respectively.