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Investor sentiment and stock price crash risk: The mediating role of analyst herding

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ABSTRACT

This study analyzes the impact of investor sentiment on firm's stock price crash risk by using Chinese A-Share firms data this study assesses the potency and existence of a relationship between crash risk and investor sentiment in the Chinese stock market and introduces analyst herding as a mediating variable for explaining the relationship between crash risk and investor sentiment. By utilizing a large data set of A-share listed firms on Chinese stock exchanges, comprising of 19,371 firm-year observations for the period of 2004–2019, an investor sentiment index is constructed. Results point towards a positive significant relation between stock price crash risk and investor sentiment. Furthermore, stock price crash is positively correlated with analyst herding i.e. it significantly mediates between stock price crash risk and investor sentiment. By measuring the relationship between crash risk, investor sentiment, and analyst herding this study provides systematic support on the mediating role of analyst herding in deepening the market sentiment which results in crash risk. These findings are robust by utilizing alternate proxies and controlling for firm specific variables, economy-wide shocks, and time trends year fixed effects.

1. Introduction

There has been a substantial amount of discussion and a series of scholarly literature that documents stock price crash risk (hereafter referred to as crash risk) in a variety of different contexts. Researchers and policymakers have repeatedly emphasized the significance of understanding why crash risk occurs and how it can be mitigated. The principal-agent framework, in which the agent's incentives cause them to withhold negative information from the principal, is the basis for this statement. A stock price crash is the result of releasing all of the bad news to the market at once (Jin & Myers, 2006; Hutton, Marcus, & Tehranian, 2009). This occurs when the bad news has accumulated to a particularly critical level and further hoarding is not possible. Most of the empirical research has recognized various firm-specific characteristics as determinants of crash risk such as tax evasion, stock liquidity, opaque financial reporting, corporate social responsibility, manager overconfidence, and informal institutions, for example, see (Callen & Fang, 2015; Chang, Chen, & Zolotoy, 2017; DeFond, Hung, Li, & Li, 2014; Hutton et al., 2009; Kim & Zhang, 2014; Li, Wang, & Wang, 2017; Luo, Gong, Lin, & Fang, 2016; Piotroski, Wong, & Zhang, 2015). As was mentioned earlier, the majority of studies are restricted to the internal characteristics of companies that influence the risk of crashes. Despite this, a number of studies have demonstrated that the involvement of external investors is a significant factor in the risk of a crash.

Earlier research has provided support for the hypothesis that there is a connection between investor sentiment and stock market crashes. Several pieces of research argue that a sudden shift in investor sentiment could have a catastrophic impact on the stock market, which would ultimately result in a crash. This is demonstrated by the October crash that occurred in 1987, which occurred during a period of time when market returns were highly correlated with market sentiment (for more information, see the works of Shiller, 1989; Siegel, 1992). According to

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Baker and Wurgler (2006, 2007), the bubble in technology stocks that occurred in the 1990s was characterized by a generally positive sentiment among investors prior to its bursting in the year 2000. According to Chen et al. (2001), there is empirical evidence that demonstrates that differences in opinion among stockholders are positively associated with the risk of a crash. It was argued by Yin and Tian (2017) in their findings that market sentiment has a tendency to be positively linked with future crash risk, and that poor quality financial reports will intensify this link. I believe that the market sentiment will have a positive effect on the crash risk of firms, and this conclusion is based on the studies that were presented earlier. An important factor of analyst herding, which causes a shift in market sentiment, is neglected in earlier studies, as was mentioned above. These studies focus on market-wide sentiment alone as the sole factor that causes crash risk. Market analysts are more knowledgeable and advanced than ordinary investors when it comes to predicting the value of assets and they are able to make more accurate predictions. Nevertheless, when compared to noise traders, market analysts are not immune to the effects of factors that are not related to the economy. The sentiment of investors is one of the most important noneconomic factors that is linked with the earnings forecasts and stock recommendations of professionals in the industry. Block (1999), Clement, Hales, and Xue (2011), De Long, Shleifer, Summers, and Waldmann (1990), Hribar and McInnis (2012), Lee, Shleifer, and Thaler (1991), Kaplanski and Levy (2017), and Walther and Willis (2013) are some of the studies that have been conducted on this topic. I introduce analyst herding as a mediating variable for the purpose of explaining the relationship between crash risk and investor sentiment in the Chinese stock market. The data from Chinese A-Share firms are used in this paper to evaluate the potential and existence of a relationship between crash risk and investor sentiment in the Chinese stock market. In order to put the hypothesis that was proposed to the test, I will first propose two hypotheses and then attempt to establish a connection between crash risk and investor sentiment.

H1. Investor sentiment is positively related to crash risk.

H2. The relationship between investor sentiment and crash risk is mediated by analyst herding.

In the following ways, this research contributes to the existing body of literature. To begin, this research adds to the existing body of literature concerning the conventional agency theory framework. This framework places an emphasis on a variety of firm-specific characteristics that are associated with the crash risk. In terms of explaining individual crash risk, the findings of this study broaden our understanding of the explanatory capacity of both investor behavioral biases and the theory of hoarding bad news. Secondly, in order to measure investor sentiment, an index is developed that takes into account both the general market sentiment and the sentiment of investors to a particular company. In the third place, I provide systematic support on the mediating role that analyst herding plays in deepening the market sentiment, which ultimately results in crash risk. This is accomplished by measuring the relationship between crash risk, investor sentiment, and analyst herding. The remaining parts of the paper are broken up into the sections that are listed below. The second section provides an explanation of the data and methods, as well as the techniques for identifying the model specifically. All of the empirical estimations and findings are presented in Section 3. A conclusion regarding the study is presented in Section 4.

2. Data, methods & model specifications

The Chinese A-Share companies that were listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange between the years 2004 and 2019 are included in this study. The information was obtained from the China Securities market and Accounting Research (CSMAR) database as well as the WIND financial terminal. A small number of filters have been applied to clean data in order to ensure the reliability of our empirical findings. To begin, all of the financial companies were eliminated because of differences in their capital structures. After that, the companies that were included in the sample were those that had data for at least thirty weeks of trading during a fiscal year. Finally, the companies that were missing data on a variety of control variables were also removed from the sample. We were able to eliminate any outliers from the data that was available in our final sample, which consisted of 19,371 firm-year observations after winsorization at 99%.

2.1. Crash risk (CR)

CR is measured by using two proxies, based on the work of Jin & Myers (2006) and Hutton et al. (2009). NSKEW is one of the measure to proxy for CR. It is the negative coefficient of skewness of firm-specific weekly returns and is calculated in two steps. Initially, firms specific weekly returns for each firm and year are calculated as the natural logarithm of one plus the residual return from the expanded market model regression, the first step is given in Equation (1) as follows,

$$R_{j,t} = \alpha_j + \beta_{1,j}R_{m,t-1} + \beta_{2,j}R_{i,t-1} + \beta_{3,j}R_{m,t} + \beta_{4,j}R_{i,t} + \beta_{5,j}R_{m,t+1} + \beta_{6,j}R_{i,t+1} + \mu_{j,t} \tag{1}$$

In the second step $NCSKEW_{j,t}$ is calculated in the following Equation (2) given below, here trading weeks are represented as n given for each firm *j* in year *t*. The minus sign in front of the third standardized moment gives a simpler interpretation of the measure, it represents an increase in $NCSKEW_{j,t}$ which implies additional left skewness in the distribution of firms' excess returns representing a greater probability for that firm to crash.

$$NCSKEW_{j,t} = -\left[n(n-1)^{3/2}\sum w_{j,t}^3\right] \Big/ \left[(n-1)(n-2)\times\left(\sum w_{j,t}^2\right)^{3/2}\right] \tag{2}$$

In addition, *NCSKEW* used for crash risk is Down-to-Up Volatility, $DUVOL_{j,t}$ measured as in Equation (3) encapsulates the "down-to-up volatility" for individual stocks. $DUVOL_{j,t}$ is calculated as the log of the ratio of the standard deviation of residual returns on "down" weeks to the log of the standard deviation of residual returns on "up" weeks, it is given as Equation (3) as follows,

$$DUVOL_{j,t} = log\left[\left((n_u-1)\sum_{Down} w_{j,t}^2\right) \Big/ \left((n_d-1)\sum_{Up} w_{j,t}^2\right)\right] \tag{3}$$

Higher level of $DUVOL_{j,t}$ for firms are prone to a higher probability of suffering crash risk, this is where n_u *and* n_d represents the amount of weeks that firm *j* specific weekly residual returns are higher (lower) than the mean firm-specific weekly returns over year *t*.

2.2. Investor sentiment

To measure investor sentiment this research follows the study of Baker and Wurgler (2006) and Fan, Zhou, An, and Yang (2021). To construct the Sentiment Index (SI) for the Chinese market several proxies have been used which are closed-end fund discount (CEFD), A-Share Turnover (TURN), price to earnings ratio (PE), investors opening account (OP), and consumer confidence index (CCI). Based on these proxies a composite index is formed, this is estimated by the first principal components of these proxies and their lags. Based on the loading and lagged proxies from the first stage the correlation is calculated among the first stage index and the lagged proxies. This procedure results in the SI,

$$SI_t = -0.091CEFD_t + 0.721\,TURN_t + 0.612\,PE_t + 0.013\,OP_t + 0.311\,CCI_t \quad (4)$$

2.3. Analyst herding

This study measures analyst herding following the method of Olsen (1996) and Wylie (2005) using the Degree of Herding Index approach (DHI),[1] this method of measuring analyst forecast of firms' earnings is based on the notion of being normally distributed. Therefore, compared with expectations based on a normal distribution, the proportion of a forecast of a given company that falls within the 95% confidence interval is deemed a measure of the degree of herding. Given as follows DHI assesses the degree of herding forecasts, higher DHI would suggest more aggressive herding amongst analysts and lower value would depict the contrary.

$$DHI_{i,t} = \frac{[L_{95\%} < \#\,Forecasts_{i,t} < U_{95\%}]}{[\#\,Forecasts_{i,t}]} \quad (5)$$

The general econometric specification can be written as follows in Eq (6),

$$CR_{i,t} = \alpha + \beta\,INSENT_t + \gamma\,ANAHERD_{i,t} + \sum_{n=1}^{p}\theta \times Controls_{it} + \varepsilon_{it} \quad (6)$$

$CR_{i,t}$ denotes the crash risk (NSKEW, DUVOL), $INSENT_t$ and $ANAHERD_{i,t}$ are the main variables of interest as discussed above. $\sum_{n=1}^{p}\theta \times Controls_{it}$ signifies several factors which are controlled which have been highlighted in earlier literature to have an influence on crash risk. The following controls are included in this investigation: past return (RET), which is calculated in the same manner as the average of firm-specific weekly returns for a specific year; financial leverage (LEV); firm size (SIZE); profitability as measured by return on assets (ROA); and market-to-book ratio (MB). Furthermore, controls also included stock volatility (SIGMA), which is measured as the standard deviation for the firm-specific weekly returns and for the absolute value of abnormal accruals (ABAC). Both of these metrics are used to determine the level of market volatility. The Board of Directors (BOARD) is a proxy for the total number of directors that are serving on a board during that particular year. This is done for the purpose of controlling governance effects.

To test the hypothesis (H1 & H2) mentioned in this study I adopt a three-step process as explained by Muller and Judd (2005). Step One, I estimate CR as a function of INSENT. Second step, I estimate ANAHERD as a function of INSENT, and check if H1 is valid. In third step, I estimated a regression where both ANAHERD and INSENT are a function of CR. After estimating 3 models I evaluate the mediating role of ANAHERD in the association among INSENT and CR by assessing the significance and magnitude of the coefficients of INSENT this is verified in all of the above mentioned three steps (Baron & Kenny, 1986). In order to accept H2, INSENT should significantly explain CR in first step and ANAHERD in the second step. Furthermore, the inclusion of ANAHERD in third step should lead to INSENT losing its significance in explaining CR. In order to achieve full mediation INSENT should lose its significance in third step, in case INSENT is significant partial mediation is concluded. Another concern for regression analysis is the endogeneity issue. To deal with the endogeneity issue, I include industry-fixed effects to tackle the concern that omitted time-invariant firm attributes may be influencing the results. In the process of analyzing the impact of investor sentiment on crash risk, endogeneity problems may arise as a result of omission or characteristics of the firm that are not immediately noticeable. There is a possibility that spurious correlations between investor sentiment and crash risk could be the result of omitted variables that interact with investor sentiment and crash risk. The results of this study remain consistent even when firm fixed effects are taken into account. Furthermore, in order to prevent shocks that affect the entire economy in addition to trends that occur over time, year-fixed effects are incorporated into each estimation.

Table 1A
Regression estimates for Investor sentiment, analyst herding, and NSKEW as proxy of crash risk.

	Dependent Variables: CR proxy NSKEW		
	CR	ANAHERD	CR
	Column 1	Column 2	Column 3
INSENT	0.099 (0.05)***	0.053 (0.05) ***	0.083 (0.04) *
ANAHERD			0.638 (0.11) ***
SIZE	−0.048 (0.11)	−0.151 (0.31)	−0.05 (0.11)
ROA	−0.015 (0.02)	−0.015 (0.02)	−0.015 (0.02)
BM	−0.168 (0.01) *	−0.164 (0.01) *	−0.164 (0.01) *
LEV	0.282 (0.04)	0.165 (0.04)	0.020 (0.04)
ABAC	0.216 (0.13)	0.214 (0.13)	0.214 (0.13)
SIGMA	2.802 (0.60) **	3.990 (1.003)***	1.659 (0.72) **
RET	−0.019 (0.061)	0.016 (0.862)	0.015 (0.060)
BOARD	−0.988 (1.407)	−0.189 (1.437)	−0.757 (1.444)
CONSTANT	−0.112 (0.25)	−0.625 (0.78)	0.130 (0.21)
Year fixed effects	YES	YES	YES
Ind fixed effects	YES	YES	YES
No. of obs	19,371	19,371	19,371
Adj-R^2	0.113	0.111	0.114
Sobel Test P-Value			0.0001
Indirect Effect			0.016
Direct Effect			0.083
Total Effect			0.099
Mediation (%)			16%

Robust Standard Errors are given in parentheses. Estimations consist of year and industry fixed effects and lagged dependent variables (coefficients are not stated). The superscripts ***, **, and * imply the estimated coefficients are significant at 1%, 5%, and 10% levels.

3. Empirical findings

The results for estimation Eq (1) are given in Tables 1A and 1B, where crash risk is measured as NSKEW and DUVOL. All the estimated regressions include industry and year fixed effects. To avoid any serial correlation issue lagged dependent variable[2] is also introduced on the right-hand side of the equation. Findings of this study are robust by reporting White standard errors corrected from clustering for industry as well as year. Empirical results for crash risk proxy NSKEW are presented in Table 1A in columns 1–3 by testing the mediating role of ANAHERD in the relationship between INSENT and CR. To achieve this purpose, I perform hierarchical regression estimation in three stages in column 1 to

[1] For detailed explanation for the construction for DHI see the work of Olsen (1996), Wylie (2005).

[2] The coefficients for the lagged NSKEW and DUVOL are not reported due to case of brevity.

Table 1B
Regression estimates for Investor sentiment, analyst herding, and DUVOL as proxy of crash risk.

	Dependent Variables: CR proxy DUVOL		
	CR	ANAHERD	CR
	Column 1	Column 2	Column 3
INSENT	0.143 (0.06) ***	0.157 (0.07) ***	0.127 (0.07)*
ANAHERD			0.761 (0.13) ***
SIZE	−0.027 (0.11)	−0.128 (0.32)	−0.029 (0.11)
ROA	−0.016 (0.02)	−0.016 (0.02)	−0.016 (0.02)
BM	−0.164 (0.01) *	−0.158 (0.01) *	−0.158 (0.01) *
LEV	0.292 (0.04)	0.388 (0.04)	0.107 (0.04)
ABAC	0.181 (0.12)	0.177 (0.11)	0.176 (0.13)
SIGMA	1.661 (0.72) **	5.119 (1.146)***	1.899 (0.69) **
RET	0.031 (0.070)	0.038 (0.070)	0.004 (0.061)
BOARD	−0.641 (1.511)	−0.299 (1.517)	−0.764 (1.612)
CONSTANT	0.856 (0.15)	−0.953 (0.35)	0.726 (0.25)
Year fixed effects	YES	YES	YES
Ind fixed effects	YES	YES	YES
No. of obs	19,371	19,371	19,371
Adj-R^2	0.117	0.116	0.117
Sobel Test P-Value			0.0001
Indirect Effect			0.016
Direct Effect			0.127
Total Effect			0.143
Mediation (%)			11%

Robust Standard Errors are given in parentheses. Estimations consist of year and industry fixed effects and lagged dependent variables (coefficients are not stated). The superscripts ***, **, and * imply the estimated coefficients are significant at 1%, 5%, and 10% levels.

3. Column 1 reports the relation between CR and INSENT, by controlling for battery of variables. The coefficient sign for INSENT is positive and significant for INSENT at less than 1%. Column 2, I check for any significance in the relationship between INSENT as a determinant for ANAHERD. The results point towards a positive significant relationship between INSENT and ANAHERD at less than 1%. As per literature Muller and Judd (2005), to corroborate the mediating function of ANAHERD, the treatment influence of INSENT on the outcome (i.e., CR) and mediator (i.e., ANAHERD) should be significant. While controlling for INSENT, ANAHERD ought to have a significant outcome on CR, meanwhile, the key impact of INSENT must decline noticeably. In column 3, ANAHERD has a significantly positive coefficient at less than 1%, and both the statistical significance is less than 1% and magnitude (b = 0.083) drop considerably. I conduct a Sobel test (Sobel, 1982, 1986; Preacher and Hayes 2004) to evaluate the magnitude of the mediation effect, the findings show a significant weakening of the main effect (16 %, at less than 1% significance). Thus the data supports hypotheses 1 and 2. I repeat the same analysis conducted in Table 1B columns 1–3 using the second proxy of crash risk DUVOL. Mediation analysis shows a significant direct effect of INSENT on ANAHERD significant at less than 1% and a significant mediated main effect of INSENT (11.7 %, at less than 1% significance).

Furthermore, to check for robustness in our investor sentiment we create firm-specific measure of investor sentiment this is motivated by the fact that sentiment measure in Eq (4) captures the market wide sentiment for investors. To account for any cross-sectional variation for investor's sentiment I follow the work of Baker and Wurgler (2007) to use sentiment beta. The process accounts for using Fama and French (1992) three-factor model and using the composite sentiment index to obtain sentiment beta.[3] I use $ROBSENT_{it}$ which is obtained by multiplying the INSENT with the sentiment beta to obtain a measure to accommodate individual firm investor sentiment. Tables 2A and 2B the data supports hypotheses 1 and 2. I repeat the same analysis conducted in Tables 2A and 2B for CR proxy measures of NSKEW and DUVOL. Mediation analysis reveals a significant direct effect of INSENT on ANAHERD significant at less than 1% and a significant mediated main effect of INSENT (24 %, at less than 1% significance & 16% at less than 1% significance) for NSKEW and DUVOL respectively. Tables 2A and 2B presents these results which are in accordance with the findings in Tables 1A and 1B, pointing towards the evidence of being robust.[4]

Table 2A
Regression estimates for Investor sentiment, analyst herding, and NSKEW as proxy of crash risk.

	Dependent Variables: CR proxy NSKEW		
	CR	ANAHERD	CR
	Column 1	Column 2	Column 3
ROBSENT	0.156 (0.03)***	0.121 (0.06) **	0.118 (0.04) *
ANAHERD			0.764 (0.17) ***
CONSTANT	YES	YES	YES
CONTROLS	YES	YES	YES
Year fixed effects	YES	YES	YES
Ind fixed effects	YES	YES	YES
No. of obs	19,371	19,371	19,371
Adj-R2	0.113	0.111	0.114
Sobel Test P-Value			0.0001
Indirect Effect			0.038
Direct Effect			0.118
Total Effect			0.156
Mediation (%)			24%

Robust Standard Errors are presented in parentheses. Estimations consist of year and industry fixed effects and lagged dependent variables (coefficients are not stated). The superscripts ***, **, and * imply the estimated coefficients are significant at 1%, 5%, and 10% levels.

4. Conclusion

Within the scope of this study, the influence of investor sentiment on the risk of a company's stock price crash is investigated. Based on the research conducted by Baker and Wurgler (2007) and Fama and French (1992), an investor sentiment index is developed. A large data set of A-share listed companies on the Shanghai and Shenzhen Stock Exchanges, consisting of 19,371 firm-year observations for the period of 2004–2019, was utilized, and the results indicate that there is a positive significant relation between the risk of a stock price crash and investor sentiment. Moreover, there is a positive correlation between analyst herding and stock price crashes, which means that it plays a significant role in mediating the relationship between stock price crash risk and investor sentiment. To ensure the reliability of the findings of this study, alternative proxies for crash risk and investor sentiment were utilized. As an additional measure, a battery of control variables was utilized to address endogeneity concerns. Additionally, industry-fixed effects were incorporated to address the concern that time-invariant firm characteristics that were not taken into account may be influencing the

[3] For detailed construction of investor sentiment measure for each firm and sentiment beta see Baker and Wurgler (2007), Fama and French (1992).

[4] Various methods can be utilized in understanding human behavior such as gait analysis for more details refer to work of Achanta and Karthikeyan (2019), Achanta, Karthikeyan, and Vinothkanna (2019), Achanta, Karthikeyan, and Kanna (2021) and Murthy, Karthikeyan, and Jagan (2020), Sampath Dakshina Murthy, Karthikeyan, and Vinoth Kanna (2022).

Table 2B
Regression estimates for Investor sentiment, analyst herding, and crash risk.

	Dependent Variables: CR proxy DUVOL		
	CR	ANAHERD	CR
	Column 1	Column 2	Column 3
ROBSENT	0.507 (0.11) ***	0.341 (0.04) ***	0.427 (0.20) *
ANAHERD			0.817 (0.20) ***
CONSTANT	YES	YES	YES
CONTROLS	YES	YES	YES
Year fixed effects	YES	YES	YES
Ind fixed effects	YES	YES	YES
No. of obs	19,371	19,371	19,371
Adj-R2	0.117	0.116	0.117
Sobel Test P-Value			0.0001
Indirect Effect			0.08
Direct Effect			0.427
Total Effect			0.507
Mediation (%)			16%

Robust Standard Errors are presented in parentheses. Estimations consist of year and industry fixed effects and lagged dependent variables (coefficients are not stated). The superscripts ***, **, and * imply the estimated coefficients are significant at 1%, 5%, and 10% levels.

outcomes. The purpose of this study is to provide investors with a preliminary evaluation of the ways in which sentiments and analyst herding in business settings influence the behavior of corporate entities. It is possible that the empirical findings of this study will be useful to businesses that are making decisions regarding portfolio investments in order to prevent stock price crashes.

CRediT authorship contribution statement

Usman Bashir: Conceptualization, Formal analysis. **Umar Nawaz Kayani:** Methodology. **Shoaib Khan:** Data curation, Resources. **Ali Polat:** Project administration, Resources. **Muntazir Hussain:** Validation, Writing – review & editing. **Ahmet Faruk Aysan:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abbreviations

(CR) Stock price crash risk
(SI) Sentiment Index
(CSMAR) China Securities market and Accounting Research
(CEFD) Closed-end fund discount
(TURN) A Share Turnover
(PE) Price to earnings ratio
(OP) Investors opening account
(CCI) Consumer confidence index
(DHI) Degree of Herding Index approach

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