Firm Specific Investor Sentiments and Stock Price Crash Risk: Evidence from Pakistan

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Abstract

The aim of this study was to investigate the effect of firm-specific investor sentiments (FSIS) on stock price crash risk (SPCR). The study also examines the effect of stock liquidity on the relationship between FSIS and SPCR in context of Pakistan. For this purpose, we selected non-financial firms from KSE-100 index, listed in PSX for the period covering from 2009 to 2017. The financial statements' data was obtained from the websites of PSX, SBP and SECP. The findings of this study suggest there is a negative relationship between FSIS and SPCR. The empirical results are found to be consistent in robustness analysis. Furthermore, our findings reveal that the negative relationship is more pronounced for the firms with better liquidity. This study would be helpful for investors, policy maker and Regulators in making of informed and rational decision.

Keywords: Stock Price Crash Risk, Firm Specific Investor Sentiment, Stock Liquidity

1. Introduction

Managers withhold bad news about stock prices to pursue their personal objectives. When a wide range of negative information is exposed in market at once, the prices of stocks decrease abruptly, result in a crash. The asymmetric stock return volatility (fall in prices are more likely than rising prices) not only threatens the wealth of investors, but also it hurts the capital markets development and stability. Hong & Stein, (2003) explains a new model for traits which aren't addressed by volatility feedback models. This model is based on two concepts: investor disagreements owing to overconfidence and short-sale constraint. Short-sale constraint, stock price reflects optimistic rather than pessimistic investor expectations. When the markets fall, unfavorable news hits the market, leading to crash in the stock prices.

In the 1980s, multiple investigations into stock price crashes were initiated. Earliest investigations were based on rational models and extensive data aggregation, with volatility feedback models serving as the workhorse in explaining asymmetric fluctuations in the prices of stock (Campbell & Hentschel, 1992). However, these models were unable to account for the unique aspects of the crashes, such as stock values declining systematically in the lack of information (Romer, 1993 ; Cao, Coval & Hirshleifer, 2002). Insiders' intensive dissemination of private information and pushing outsiders as a result (Barlevy & Veronesi, 2003), risk of decline in prices of stocks is caused by rational models with insufficient information aggregation. Grech & Mazur, (2004) showed that information asymmetry and efficiency had an effect on the crash risk. They demonstrated that poorer information efficiency correlates with high probability of crashing stock prices.

In asset pricing, SPCR has played a vital role. A various researches has attempted to link a variety of factors to the SPCR, includes Chief Financial Officer equity incentives (Kim, Li & Zhang, 2011a), corporate tax-avoidance (Kim et al., 2011b), optimism of analyst (Xu et al., 2013), opacity in financial reports, (Hutton et al., 2009; Kim & Zhang, 2013), directors' or officers' accounting conservatism (Kim & Zhang, 2016), institutional investor and liability insurance (Yuan et al., 2016), debt financing (Wang et al., 2020). These factors also have recognized by the empirical and theoretical investigations according to the concept of agency (Jin & Myers, 2006).

Previous literature explains that the more individual investors pay attention, the lower the probability of a firm-level crisis in the future. In this way, investors can avoid suffering a significant loss on their investment. Evidence from Wen et al., (2019) reveals that enterprises with high new investors' interest

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have low chance of future stock price drop. Additional forms of retail investor attentiveness and FPCR provide similar findings. Kumar and Lee (2006) examined the impact of retail trading habits on stock return co-movement. They show that retail investors' trading actions have a similar directed element: when they purchase (or sell) shares, they usually buy (or sell) another grouping. Likewise, when some other investors purchase (or sell) shares, other people likely to do the same (selling). This research implies that changes in retail sentiment at the product level can cause stock market returns to move down.

Investor sentiments and volatilities in investor attitudes are two aspects of behavioral finance that explain crash risk. Case and Shiller (1989) analyzed economic fundamentals of investor sentiments by studying the risk of crashing stock prices around the 1987 market crisis. According to their findings investor's sentiments, rather than economic realities, is the driver that caused crash. The economic fundamentals remained unchanged, however sentiments shifted abruptly from overconfidence prior to the stock market crisis to pessimism after the crash. Fu et al. (2021) believed that sentiment of investor is a broader term that refers to a belief in future investment risks which is not based on facts. External investors have a major role in SPCR but most researches internally focus firm characteristics that impact on the possibility of a stock market crash. Poor financial performance expectancy, inability to disclose company information, and lack of conviction all affect the likelihood of a crash risk. They find that investors attitude to behavior (irrational) are significantly related to SPCR. Wen et al. (2019) explains that sentiments of retail investor are negatively associated with SPCR. They investigated that enterprises with high new investor interest have a lower chance of a future crashing of stock price. Tzomakas et al. (2023) investigated the relationship between crises sentiments and SPCR by focusing on European banks and they found that crises sentiment positively affects SPCR and investors own perception of risk plays a vital role.

This study was aimed to examine the link among firm-specific investor sentiment (FSIS) and SPCR. We collected data of non-financial companies listed in KSE-100 index from the website of Pakistan Stock Exchange (PSX), State Bank of Pakistan (SBP) and Securities and Exchange Commission of Pakistan (SECP), covering period from 2009 to 2017. Data was filtered by applying various measures. Regression analysis was performed to investigate the link among FSIS and stock market crashes. Our research investigates the link among firm-specific sentiment of investor and crashing of stock prices in context of Pakistan. To the best of researchers' knowledge, insufficient attention has been paid in context of Pakistan and a very few studies are available focusing on relationship between FSIS and SPCR. Further, it is yet to explore that how stock liquidity impacts the link among FSIS and SPCR in Pakistan.

2. Literature Review

According to Diamond & Verrecchia, (1987) even though short sales are more expensive and riskier than extended money transfers, small investors will only short-sell shares if they are confident that the price of stock would decrease in future, paying at least the extra expenses. Hong & Stein, (2003) suggest a new model for traits that aren't addressed by volatility feedback models. This model is predicated on two concepts: investor disagreements owing to overconfidence and short-sale constraint. In short-sale constraint, stock price reflects optimistic rather than pessimistic investor expectations. As a result, bearish private data is buried in greater extent. When the markets fall, unfavorable news floods the market, increasing the chance of a crash. Investors undertake security financing trades to reveal negative information if there was no short-sale constraint and resultantly, other investors learn about the unfavorable news. Gradual decline in stock prices indicates a lesser likelihood of a crash. According to Stein, (2009) overconfidence of an experienced investor may worsen industry inefficiencies. Short sellers value his own data and observations, and then make an instinctive jump depending on the info at hand," according to the book "the Art of Short Selling." Often, the symptoms lead to major issues that will not be fully recognized until after the breakdown." Money managers gather and evaluate data from a range of sources, including election, insider's filings and financial statements, markets, chart analysis, press, and many others, to "put together the tale of a firm". Short sellers, according to Callen & Fang, (2015), are skilled investors who can spot news holding actions by companies whose shares they sell in preparation of price collapses. If this is the case, the amount of short interest should represent the capacity for corporations to store negative news, and short (interest rate) to be significantly correlated with the probability of a stock price fall in future. With consideration to a large sample of U.S. public companies, this study investigates the empirical connection among speculative trading and future SPCR. Short position is significantly connected to ahead on annual basis share price collapse risk (Callen & Fang, 2015). Even after accounting for accrual manipulation, this positive relationship remains substantial, indicating that short sellers can detect unfavorable news hoarding by management, which leads to future market collapses.

According to Berkman et al., (2012) attention-getting events (very large gains or significant net purchase by small investors) during a trading session promoting heightened demand from investors (individual) around the start of upcoming trade (daily). This leads to higher returns overnight, which are then reversed throughout the trading session, resulting in a small rise in inflation at the start. They show that for enterprises that are difficult to analyze and arbitrage, just one turnaround is more prominent, showing that this return pattern is impacted by retail investment choices.

Basu (1997) describes conservative as "accountants' predisposition to seek a greater level of confirmation for identifying positive news in accounting records than for recognizing negative news". Conservative, as per Watts (2003), is a governance which limits that is managerial in nature motivations and capabilities to inflate accounting information in contracts. LaFond and Watts (2008) looked at the need for conservative in the stock market. They argue that asymmetric information between business insiders (executives) and outside equity investors contribute to economic accounting conservativeness. Since conservative limits managers' motives, prospects, and capacity to misrepresent revenue and net asset values, it decreases imperfect information. De Long et al. (1990) present two types of investors that are arbitrageurs and noise investors. Noise investors have a high sentiment about a single stock because they have the ability to easily modify price at high level. Noise creates risk itself that why arbitrageurs sell stock short because they worry about if the noise trader creates circumstances, they could not remove the effect of noise.

2.1 Investor’s Sentiment

Investor sentiment is defined that volatility attitude generated by an ignorant set of investors has been popular perspective in finance in recent years as negative predictor of future stock market returns over almost horizons of all time (Fisher & Statman, 2000; Baker & Wurgler, 2006). At very basic level, lack of clarity about the best timeframe for evaluating the relationship between investor interest and company's future returns to fact that investor sentiments described long-run contrarian anticipation does not hold short time frequency weekly, monthly. In shorter term, however, investor sentiment is expected to have a persistently favorable effect on the returns. A variety of real-world event or social factors might lead to favorable relationship between investor interest and future stock returns (Han & Li, 2017). Li and Li (2021) further indicate that both optimistic and pessimistic sentiments of invests reflect long-term poor performance.

2.2 Stock Price Crash Risk

A growing number of researchers targeted the firm-level crash risk of stock price, which are evaluated by using return distributions with negative skewness. Crash risk has been studied from the perspective of the financial sector procedures in prior research. The agency theory framework is the focus of some other researches, which is the most essential part of contemporary investigations. These researches reveal that managers conceal bad information for a variety of reasons. It’s hard for investors to figure out what information is being kept hidden due to asymmetric information. As a result, the stock price would be overvalued by investors. When a wide range of negative information is exposed in market at same time the prices of stocks decrease abruptly, resulting a crash. The biggest contribution to the crash risk is the disparity between managers and external investors.

Stock price crashes have historically been associated with fresh knowledge about a company's future, according to financial analysts and auditors. However, Roll, (1988) shows that only a tiny part of price changes can be described by current public announcements, and suggests that returns might be driven by traders reacting on non - public company intelligence. The relationship between information and stock inflationary pressures, particularly the R2 from a revised indicator regression and the revelation of company news, had sparked a lot of attention as a result of these findings. According to Morck et al., (2000), individuals with abundant intellectual property conferred to intermediaries who barter on firm-specific data have lower R2 (equivalently, company return variability is greater). According to Jin & Myers, (2006), weaknesses in accountability regarding firm's performance allows managers to capture a fraction of working capital, soaking up part of the variability in organizational value. R2 is increased as a result. To keep their positions, managers are ready to take personal tragedies case of temporary poor performance. However, after a sufficiently terrible run of news, they are reluctant or unable to tolerate any further damages; in other respects, they have the choice of abandoning the project. While the exact kind of opacity is mostly unimportant in Jin and Myers' work, Kirschenheiter & Melumad, (2002) concentrated on a specific source of inaccurate information: earnings averaging. Greater reported income, according to their model, raises the inferred level of persistent income and, as a result, the firm's worth. The impact is stronger when reported profits are seen to be more accurate, therefore managers are likely to smooth results, inadequately earnings in reaction to good shocks and over-reporting profits in reaction to adverse unexpected. Management (or, to use their concept more broadly, employees) must accept some danger from stockholders for R2 to drop. The timeliness of information disclosures is influenced by the Kirschenheiter et al., (2002) framework, but not the level of risk absorbed by investors over time. Institutional investors' substantial stock ownership, according to Cornett et al., (2008), also restricts reported earnings. They demonstrate, on the other hand, that economic incentives to maintain a high company's stock (in the form of opportunity pay like option awards) induce earnings management. Financial performance is also found to react to paybacks linked with a momentarily high share price in other research.

2.3 Stock Liquidity

According to previous studies, the crash risk of stock price can occur when unfavorable information's of huge volume has been hidden by management is published all at once. Chang et al., (2017) established that liquidity of stock can affect the risk of crashing price by altering one or more factors listed below: the possibility of receiving unfavorable news, the level to which managers hide bad news, as well as the markets react when bad news is presented. According to governance theory, increased stock liquidity improves block holder oversight of business management, discouraging managers from engaging on value-destroying activities. This decreases the chances of bad news spreading. Greater stock liquidity, as per governance theory, lessens the danger of a crash by enabling block holders to supervise firm management. Increased stock liquidity improves information creation and informed trading (Holmström & Tirole, 1993; Holden et al., 2014). They found that liquidity encourages shareholders to gather more confidential business information stocks. As a result, liquidity is closely linked to ownership concentration. Higher (lower) liquidity makes it simpler for investment banks to sell (hold) shares and prevent (earn) larger losses (profits) in stocks with a greater (lower) SPCR. As per Rao & Zhou, (2019), increased liquidity helps corporate investors to trade shares easily and prevent greater loss from companies with a higher chance of collapsing.

2.4 Hypothesis Formation

Manager withhold bad news that effect investor sentiment. Hong and Stein (2003) argued that stock prices only indicate optimistic investors' expectations, not pessimistic. The negative information is therefore ignored and accumulates, increasing the probability of a market crash when the market falls. To release negative information, investors would engage in security financing trades, and then various types of investors would learn to recognize negative information. The price of information and stock falls gradually, lowering the crash risk.

H1: *investor sentiment has a negative relationship with stock price crash risk.*

Chang et al. (2017) according to governance theory, increased stock liquidity improves block holder supervision of company management, prohibiting managers from engaging on projects that will drain the company's value. This decreases the probability of negative information breaking. Stock liquidity can affect financial market stability by increasing managers' incentives to hide negative news. Nonetheless, past research has shown that stock liquidity has a variety of positive implications on business management, the environment information, and value of company. The manager benefits can be raised by the liquidity of stock to keep bad information away from the public, placing financial market stability at risk.

H2: *Stock liquidity effect the relationship between investor's sentiment and stock price crash risk.*

3. Research Methods

This is a quantitative study based on secondary data. In order to examine the relationship between FSIS and SPCR, the sample of all non-financial firms of KSE-100 index listed in Pakistan Stock Exchange (PSX), was taken. The data related to financial statements was collected from the website of PSX, SBP and SECP, covering period from 2009 to 2017. The stock prices data for weekly returns calculations was obtained from the website of PSX.

Following Alnafea and Chebbi (2021), various data filters were applied for cleaning the data and making it useful. First, we excluded all financial firms because the characteristics of financial firms are different from non-financial firms. Contrary to non-financial firms, high leverage is normal for financial firm and it does not represent the stress of the firm (Fama & French, 1992). Second, in order to be included in the sample, in a fiscal year, a corporation should have 30 weeks' data of stock return at least. The data was filtered by removing the firms having age less than 7 years. Finally, we removed missing PSX data with firm-year observations from the estimated variables. Our final sample consists of 700 firm-year observations. Our variables of interest are SPCR and first-specific investor sentiments. The SPCR is employed as dependent variable, FSIS as independent variable whereas stock liquidity is used as moderator. After that the regression equation is used to investigate relation of company related investor sentiment and crash risk of stock price. We use STATA software for analysis.

3.1 SPCR

The crash risk has a major issue in asset pricing since it evaluates risk asymmetry, particularly the risk decline. The skewness of stock prices is examined by assessing degree of its crash (Chen et al., 2001). For measuring the SPCR, we used NCSKEW and DUVOL, we started by measuring firm-specific weekly returns (FSWR) for each year using the expanded market model (Yin & Tian, 2017). We collected weekly market prices data to calculate return of firms and market index from PSX.

$$r_{i,t} = \alpha_i + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \varepsilon_{i,t} \tag{1}$$

In the above equation $r_{i,t}$ is the return of company *i* in week *t* and $r_{m,t}$ is the market index return in week t, $r_{m,t+1}$ and $r_{m,t-1}$ is the lag and lead of market returns.

$$w_{i,t} = ln(1 + \varepsilon_{i,t}) \tag{2}$$

The residual series $\varepsilon_{i,t}$ was estimated by using equation (1), subsequently, we calculated firm specific weekly return by using equation 2.

3.1.1 NCSKEW

NCSKEW is measured by taking the negative third movement of every stock related weekly return for every year and dividing it by the standard deviation of company related weekly returns rose to third power. NCSKEW was calculated by using equation (3) for each firm *i* in year *t*

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

3.1.2 DUVOL

DUVOL is used to calculate the log of the ratio of the standard deviation on down weeks to the standard deviation of up week returns. For a particular firm in a specific year, all the weeks that have weekly returns below the annual average are "down" weeks and that weekly returns above average are "up" weeks.

$$\mathrm{DUVOL_{i,t}} = \log\{\frac{[(n_u - 1)\sum_{down} w_{i,t}^2]}{[(n_d - 1)\sum_{up} w_{i,t}^2]}\} \tag{4}$$

3.2 Firm-Specific Investor Sentiment

Brown and Cliff (2004) illustrated that investor sentiment is defined as the degree of optimism or pessimism. However, providing a reliable assessment is difficult, and various literatures choose different proxy variables to characterize investor interest. We create a composite index of FSIS using principal component analysis and that composite are based on, turnovers rate and price earnings ratio (PER).

The PER is the relation between the price of a corporate stock and their EPS. Han and Li (2017) establishes that the ratio of earning price have higher cost in positive companies and lower cost in negative company, suggesting it as a useful indicator of investor sentiment. The share turnover to total number of shares during a certain time period is the turnover rate and it is an indicator of economic transactions that might be used to gauge public mood. Baker & Wurgler, (2006) indicates that turnover rate might be used as an index of interest. An increase in turnover rate implies strong desire from investors' sentiment, which drives logical investor out of the industry, causing the prices of asset to become unstable. We run a principal component analysis and obtain 0.7071 value from component 1 that have an eigenvalue above 1.00

$$SENT_{i,t} = 0.7071PE_{i,t} + 0.7071ATR_{i,t} \tag{5}$$

PE= Price earnings ratio ATR: Average turnover rate

3.3 Control Variables

Our control variables were based on previous research. Many studies use different control variables. We followed Chen et al., (2001); Yin & Tian, (2017) for selecting our control variables that includes Leverage, Size, Dturn, BMratio, ROA, RET and SIGMA. Leverage (LEV) is the ratio of Total debt to total assets, SIZE is the measured as natural logarithm of total assets. Dturn is the detrended turnover of stock which is measured by the average monthly share turnover in year t minus the same from previous year. BMratio is calculated by taking ratio equity's book value to its market value. Return on Assets (ROA) is measured by dividing the net profit to the book value of total assets. RET is the average of FSWR in year t. SIGMA is the standard derivation of firm FSWR.

3.4 Empirical Model

$$Crash\ Risk_{i,t+1} = \alpha + \beta_1 \times SENT_{i,t} + \sum_{i=1}^{m} r_i \times \left(control\ variables_{i,t} \right) + \epsilon_{it} \tag{6}$$

To estimate the relationship between FSIS and SPCR, the above regression model in Eq. (6) is used. In this equation crash risk is the dependent variable with one lead to the SENT which is the independent variable. As above described the control variables are the SD of FSWR, detrended share turnover, the average FSWR over the past year, book-to-market ratio, firm size, return on assets, financial leverage. We maintain a one-year difference between DV and IV for testing the relation between future SPCR and FSIS. We also include fixed effect in regression.

3.5 Descriptive Statistics

Table 1 shows the descriptive summary of the variables. Total number of firm-year observations used in this study is 700. The SPCR is measured by two proxies that are $NCSKEW_{t+1}$ and $DUVOL_{t+1}$. In table 1 the mean of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ are -0.001 and -0.03 respectively. The SD of $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ is 0.845 and 0.145, respectively. The FSIS has 4.056 mean values with 0.917 SD. The means values of control variables are measured which do not show any anomalies with firm leverage as 0.533, SIZE as 22.825, DTurnt as 0.001, BMratiot as 0.214, ROA as 0.093, RET as -0.003 and SIGMA as 0.066. It is also interesting to note that the standard derivations (SD) of control variables in our sample are not inconsistent with prior research of the same nature. The SD of firm leverage is 0.232, SIZE is 1.542, DTurnt is 0.024, BMratio is 0.284, ROA is 0.136, RET is -0.011 and SIGMA is 0.049.

4. Results

4.1 Correlation Matrix

Table 2 explains the Pearson-Spearman correlation matrix of our variable that is used to examine the relationship of FSIS and SPCR. Pearson correlations are displayed upward the diagonal, whereas Spearman correlations are displayed downward the diagonal. There are two variables that is used for measuring crash risk $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ and that variables are positively correlated. The coefficients correlation between $NCSKEW_{t+1}$ and $DUVOL_{t+1}$ (0.854 and 0.873) are significant at 1% level. On the other hand, firm specific investor sentiment (SENT) has a negative correlation coefficient with crash risk ($NCSKEW_{t+1}$ and $DUVOL_{t+1}$) that shows SENT is significantly correlated at 1%.

Table 1: Descriptive Statistics

Variables	Observations	Mean	Standard dev.	Min	Max
$NCSKEW_{t+1}$	700	-0.001	0.845	-2.064	4.869
$DUVOL_{t+1}$	700	-0.03	0.145	-0.386	0.839
$SENT_t$	700	4.056	0.917	3.058	5.171
LEV_t	700	0.533	0.232	0.007	1.647
$SIZE_t$	700	22.825	1.542	17.775	26.643
$DTurn_t$	700	0.001	0.024	-0.304	0.178
$BMratio_t$	700	0.214	0.284	-0.543	2.425
ROA_t	700	0.093	0.136	-1.603	0.58
RET_t	700	-0.003	0.011	-0.177	0.026
$SIGMA_t$	700	0.066	0.049	0.015	0.824

4.2 Regression Analysis

Table 3 shows the regression results of relationship between FSIS on SPCR. The SPCR is measured by two proxies $NCSKEW_{t+1}$ and $DUVOL_{t+1}$. In this regression $NCSKEW_{t+1}$ and $DUVOL_{t+1}$are the dependent variable and $SENT_t$ is the independent variable. Column 1 in table 3 shows that the $SENT_t$ has negative relationship using $NCSKEW_{t+1}$ as dependent variable at 5% significance level. Column 2 in table 3 shows the result of $SENT_t$ with control variables still have significant negative relationship using $NCSKEW_{t+1}$ as dependent variable at 5%. Column 3 in table 3 shows that $SENT_t$ has negative relationship using $DUVOL_{t+1}$ as dependent variable at 5% significance level. Column 4 in table 3 shows the result of $SENT_t$ with control variables present in model still have negative relationship using $DUVOL_{t+1}$ as dependent variable at 1%. Overall the regression analysis concludes that the company related investor emotion has a negative relationship on future SPCR. That shows the positive investor sentiments reduce the chances of stock price crashes. That result is consistent with our established hypothesis H1.

4.3 Liquidity Effect Analysis

Chauhan et al. (2017) studied the impact of stock liquidity on crash risk. Liquidity, in theory, is a measure for the cost of trade. This cost can be calculated using either market volatility or the price of stock. To test the relationship, we use illiquidity measure which is calculated by the annual average ratio of weekly absolute return to weekly volume. The lower ILLIQ value implies higher liquidity of stocks and the higher ILLIQ value implies lower liquidity of stocks.

$$\mathrm{ILLIQ}_{i,t} = 1/\mathrm{N}_{i,t} \sum_{k=1}^{\mathrm{N}_{i,t}} |\mathrm{R}_{i,t,k}| \backslash \mathrm{V}_{i,t,k}$$

Where $N_{i,t}$ is the number of weeks for which data exist for stock *i* and year *t*, $R_{i,t,k}$ is the return of stock *i* in week *k* of year *t* and $V_{i,t,k}$ is the volume of stock *i* in week *k* of year *t*.

For measuring the liquidity effect we divide our sample in two categorized as better liquidity and worse liquidity. ILLIQ value below its median is taken as Better liquidity subsample whereas above the median as worse liquidity subsample. After dividing into sub sample we run again regression model using subsamples. Table 5 explains the result after subsample.

Table 5 column 1 shows the result of better liquidity subsample using dependent variable NCSKEW_{t+1}. The SENT_t coefficient -5.217 in better liquidity using NCSKEW_{t+1} is significant at 10%. Column 2 explains the result of worse liquidity subsample using NCSKEW_{t+1}. The SENT_t coefficient

Table 2: Pearson-Spearman Correlation Matrix

Variables	NCSKEW	DUVOL	SENT	LEV	SIZE	DTurn	BMratio	ROA	RET	SIGMA
$NCSKEW_{t+1}$	1.000	0.873***	-0.115***	0.052	-0.102*	-0.19***	0.137***	-0.087**	-0.61***	0.258***
$DUVOL_{t+1}$	0.854***	1.000	-0.152***	0.031	-0.12***	-0.12***	0.124***	-0.031	-0.43***	0.308***
$SENT_t$	-0.138***	-0.14***	1.000	-0.038	0.405***	-0.015	-0.112***	-0.002	0.108***	-0.262***
LEV_t	0.048	0.026	-0.030	1.000	0.155***	0.039	-0.012	-0.38***	-0.17***	0.278***
$SIZE_t$	-0.118***	-0.13***	0.363***	0.119***	1.000	-0.065*	-0.179***	0.090**	0.112***	-0.353***
$DTurn_t$	-0.237***	-0.13***	0.034	0.063	-0.11***	1.000	0.025	-0.045	0.134***	0.086**
$BMratio_t$	0.140***	0.101**	-0.033	0.018	-0.28***	0.086**	1.000	-0.17***	-0.11***	0.235***
ROA_t	-0.106***	-0.032	-0.066	-0.48***	0.117***	-0.101**	-0.405***	1.000	0.22***	-0.285***
RET_t	-0.655***	-0.29***	0.113***	-0.12***	0.074*	0.292***	-0.163***	0.242***	1.000	-0.587***
$SIGMA_t$	0.035	0.079*	-0.264***	0.279***	-0.55***	0.279***	0.343***	-0.42***	-0.046	1.000

The t-statistics represented in brackets which are standard errors clustered by both firm and year.
*, **, and *** explain the level of significance at the 10%, 5% and 1% levels, respectively.

Table 3: Regression Analysis of Firm Specific Investor Sentiment and Crash Risk

	(1) $NCSKEW_{t+1}$	(2) $NCSKEW_{t+1}$	(3) $DUVOL_{t+1}$	(4) $DUVOL_{t+1}$
$SENT_t$	-2.916**	-3.034**	-0.564**	-0.479***
	(-1.93)	(-2.14)	(-2.24)	(-3.47)
LEV_t		-0.195		-0.0828
		(-0.55)		(-1.42)
$SIZE_t$		0.0220		-0.0169
		(0.17)		(-0.79)
$DTurn_t$		0.259		0.0688
		(0.16)		(0.25)
$BMratio_t$		0.0524		0.0273
		(0.30)		(0.95)
ROA_t		0.928***		0.141***
		(2.65)		(2.42)
RET_t		-2.598		-0.478
		(-0.69)		(-0.77)
$SIGMA_t$		2.038*		0.501***
		(1.78)		(2.64)
Constant	11.83	11.67	2.259*	2.291
	(1.93)	(1.49)	(2.21)	(1.76)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	700	700	700	700
Adjust R^2	0.0173	0.0188	0.0245	0.0288

The t-statistics are represented in parentheses. *, **, and *** explain the level of significance at the 10%, 5% and 1% levels, respectively.

Table 4: Robustness Analysis

	(1) $NSCKEW_{t+1}$	(2) $DUVOL_{t+1}$
$SENT_t$	-3.941**	-0.660**
	(-1.97)	(-1.99)
LEV_t	0.0168	-0.0438
	(0.04)	(-0.70)
$SIZE_t$	0.0809	-0.00536
	(0.63)	(-0.25)
$DTurn_t$	2.139	0.478
	(0.93)	(1.26)
$BMratio_t$	0.0443	0.0277
	(0.21)	(0.81)
ROA_t	1.711***	0.283***
	(3.38)	(3.37)
RET_t	-4.760	-0.894
	(-1.22)	(-1.38)
$SIGMA_t$	1.608	0.412**
	(1.38)	(2.12)
Constant	13.84	2.728*
	(1.75)	(2.08)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
N	700	700
Adjust R^2	0.0180	0.0270

The t-statistics are represented in parentheses. *, **, and *** explain the level of significance at the 10%, 5% and 1% levels, respectively.

in worse liquidity subsample using NCSKEW_{t+1} is not significant. Table 5 column 3 explain the result of better liquidity subsample using dependent variable DUVOL_{t+1}. The SENT_t coefficient in better liquidity using DUVOL_{t+1} is -0.931 which is significant at 10%. The results indicate that stocks with better liquidity are more likely to react stronger for the effect of FSIS on SPCR. That suggests the existence of moderating effect of liquidity on relationship between FSIS and SPCR.

Table 5 column 4 presents the result of worse liquidity subsample using dependent variable DUVOL_{t+1}. The SENT_t coefficient in worse liquidity using DUVOL_{t+1} is -0.887 which is not significant. Overall results explain that with the better liquidity sample firm specific investor sentiment has a significant negative impact on future SPCR. This shows that firms with better stock liquidity are more likely to have impact of investor sentiments on SPCR, whereas in worse liquidity sample that effect does not exist.

4.4 Robustness

To test the sensitivity of our findings, we run regression by including winsorized variables. In order to remove the outliers effect, we winsorized LEV, ROA, BMratio, Dturnt at 1% level and after winsorization we run regression on winsorized variables. Table 4 show the regression result for winsorized variables. Column 1 in table 5 shows that the SENT_t with control variables has negative relationship using $NCSKEW_{t+1}$ as dependent variable at 5% significance level. Column 2 in table 5 shows the result of SENT_t with control variables has still negative relationship using DUVOL_{t+1} as dependent variable at 5% significance level. The result states that after winsorizing some variables there is still negative relationship between firm specific investor sentiment and SPCR. That shows all results are consistent to actual analysis.

Table 5: Regression to Measure Stock Liquidity Effect

	Better liquidity NCSKEW_{t+1}	Worse liquidity NCSKEW_{t+1}	Better liquidity DUVOL_{t+1}	Worse liquidity DUVOL_{t+1}
SENT_t	-5.217***	-5.246	-0.931***	-0.887
	(-2.74)	(-1.57)	(-2.93)	(-1.57)
LEV_t	0.639	-0.261	0.0704	-0.0587
	(1.14)	(-0.47)	(0.78)	(-0.62)
SIZE_t	-0.0779	0.169	-0.0209	-0.00453
	(-0.37)	(0.96)	(-0.62)	(-0.15)
DTurn_t	3.621	2.216	0.619	0.773
	(1.41)	(0.46)	(1.50)	(0.94)
$\mathrm{BMratio}_t$	-0.0382	0.207	0.0109	0.0930*
	(-0.14)	(0.72)	(0.25)	(1.90)
ROA_t	2.326***	0.404	0.449***	0.0375
	(3.00)	(0.98)	(3.61)	(0.54)
RET_t	5.817	-5.249	1.770	-1.471*
	(0.76)	(-1.03)	(1.43)	(-1.70)
SIGMA_t	-3.668	1.712	-0.781	0.350
	(-0.80)	(1.23)	(-1.05)	(1.48)
Constant	25.27*	14.97	4.667**	3.224
	(1.87)	(1.28)	(2.14)	(1.62)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	340	360	340	360
Adjust R^2	0.0006	0.0216	0.0014	0.0363

The t-statistics are represented in parentheses. *, **, and *** explain the level of significance at the 10%, 5% and 1% levels, respectively.

5. Conclusion

This study is based on secondary data and this is quantitative study. The aim of this study is to investigate relation of company related investor sentiment and crash risk of stock price. We select companies that are listed in Pakistan stock exchange and State bank of Pakistan. We collect data from financial statement of non-financial firms in the Pakistan for the time 2009 to 2017. We collect data from 100 companies. Our study finds that the firm specific investor sentiment is negatively associated with SPCR. Our results explain that high investor sentiment have lower crash risk. Our empirical results are still valid after a robustness analysis and winsorization of some variables. Furthermore, our findings reveal that the negative relationship is more pronounced for firms with better liquidity. This study contributes in the literature related to relationship between investor's sentiment and SPCR, and how this relationship be effected by stock liquidity in context of developing economy such as Pakistan. This result would be helpful for investors, policy maker and Regulators to make decision better. The scope of the study is limited because it only reflects the perspective of Pakistan which hinders the generalization of its findings.

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