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Does Investor Sentiment Influence Stock Price Crash Risk? Evidence from Saudi Arabia*

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Abstract

This paper examines the relationship between investor sentiment and the risk of a stock price crash at the firm level. Our dataset includes 131 firms listed on the Saudi stock exchange (Tadawul) from 2011 to 2019, as well as 953 firm-year observations. To evaluate crash risk, we employ two distinct proxies and propose an index for measuring firm-level sentiment which we use for the first time in our study. The average turnover rate, price-earnings ratio, and overnight return are the three sentiment proxies we utilize in our index. Our findings show that high levels of investor emotion increase managers' proclivity to withhold unfavorable news from investors, which aggravates the risk of a stock price crash. We undertake cross-sectional regressions by sector to ensure the robustness of our findings, and our findings are confirmed. After accounting for any endogeneity issues with the GMM technique, the results remain the same. Furthermore, we analyze the liquidity effect by dividing our sample into subsamples with better and worse liquidity and find that firms with worse liquidity have a considerably greater positive impact of investor mood. Overall, our findings help investors and regulators recognize the significance of this downside risk and how to manage it in the stock market.

Keywords: Investor Sentiment, Stock Price Crash Risk

JEL Classification Code: G1, G3, G4

1. Introduction

Recent years have witnessed a growing interest in researching and investigating the factors contributing to crash risk. Previous researches have provided evidence that managers' propensity to suppress unfavorable news from investors is the major cause of the risk of future crashes when agency problems may be present (Kothari et al., 2009; Yuan et al., 2016). When the concealed news accumulates, it will become public at one time, generating

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an unusual negative change in stock prices, and thus causing a crash.

Among the growing body of stock crash literature, earnings smoothing, debt financing, stock liquidity, management discussion and analysis, and employee welfare have been documented to have an influence on such risk risk (Ben-Nasr & Ghouma, 2018; Chauhan et al. 2017; Chen, et al., 2017; Lee & Chae 2018 and Wang et al., 2020). However, few researchers have focused on the behavioral finance framework.

In this study, we examine the relationship between one of behavioral finance's pillars, namely investor sentiment, and the likelihood of future crashes. According to behavioral theories, investors may develop optimistic or pessimistic beliefs as a result of sentiment, which leads to uninformed (noise) trading and, as a result, financial asset prices drift away from their fundamental values (De Long et al., 1990). Non-fundamental signals are used by noise traders, and they overreact to both positive and bad news. When reasonable arbitrageurs step in to counter the noise traders' irrational activities, the influence these traders have can be minimized. They are concerned, however, that sentimental traders may become even more illogical,

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causing asset prices to deviate even further from real value (De Long et al., 1990).

The cost of arbitrage limits arbitrageurs' operations, which may limit their ability to intervene more. As a result, arbitrage fails to totally eliminate irrational traders' mispricing, and sentiment has an impact on stock prices. However, there are reasons to suspect that irrational trading is more common during periods of positive sentiment than during periods of negative sentiment. As a result, during periods of high optimism, bad information is suppressed and accumulates until it is exposed, generating the crash risk.

We utilize firm-level proxies of crash risk and sentiment since we aim to examine the firm-level relation between the two. We employ "the negative coefficient of skewness" (NCSKEW), and "the down-to-up volatility" (DUVOL) to measure crash risk. In contrast, to measure firm-level sentiment, we construct a sentiment index that includes the following sentiment proxies: average turnover rate, priceearnings ratio, and overnight return.

We examined 131 firms that traded on the Saudi stock exchange from 2011 to 2019. (Tadawul). Our findings show that high levels of investor sentiment increase the likelihood of a stock market meltdown. We further conduct crosssectional regressions by sector and continue to find support for our empirical evidence. Moreover, our results hold after we address endogeneity issue that could arise in the analysis of the relation between our primary variables using the dynamic panel GMM technique. In addition, we conduct a secondary investigation. We investigate the influence of liquidity of investor sentiment and discover that firms with less liquidity have a more positive impact than firms with more liquidity.

Understanding the causes of collapse risk is crucial for regulators and investors to plan effective ways for reducing it. Because of the severe loss in equity value induced by this downside risk, investors' wealth and firm value have plummeted. It has an impact on investor decision-making, risk management, and the stability of financial markets. This was, in fact, our reason for researching this topic.

Our study offers several contributions. First, we extend the strand of literature that has explored numerous causes of future crashes. Second, as far as we are aware, this is the first study to attempt to forecast crash risk in Gulf Cooperation Council (GCC) markets. Third, this study is one of the very few studies that directly link investor sentiment with future crash risk. Yin and Tian (2017) created a sentiment index using market-wide sentiment proxies and showed that sentiment is associated with a higher likelihood of price crashes. In our paper, we form a new index, first used for this study that captures firm-level sentiment using principal component analysis, which differs from Baker and Wurgler's (2006) market-wide index and the indexes proposed in the related studies. Finally, we enrich the sparse literature on investor sentiment in emerging markets.

2. Literature Review and Hypothesis Development

2.1. Stock Price Crash Risk

An emerging stream of literature has investigated a variety of underlying factors that aggravates the risk of crashes. One strand of this literature focuses on stock market determinants of such risk. Hong and Stein (2003) demonstrated that the increasing trading volume caused by investor heterogeneity causes a price crash. Short-sales constraints decrease trading activities of both experienced and inexperienced investors which, as a result, trigger stock crashes. Liquidity of shares increases managers' motivations to suppress negative information which raises crash risk (Habib & Hasan, 2017) argued that corporate unconventional strategies can lower the potential of future crashes. Park and Park (2020) documented that using derivatives for the purpose of hedging generates a larger possibility of crash occurrence in stock prices.

Another strand of literature links corporate governance mechanisms with the risk of future crashes. Chae et al., (2020) argue that when auditor quality is high, crash risk decreases because auditors play an important part in corporate governance. Xu et al. (2017) found that firms with more analyst herding and less effective corporate governance face a higher risk of extreme declines in prices. Using non-financial performance measures in CEO compensation contracts reduces managers' propensity to suppress bad news, which reduces future crashes. Yuan et al. (2016) documented a linkage between directors' and officers' insurance and the likelihood of a crash.

2.1. Investor Sentiment

Trading activities of sentimental uninformed investors affect stock prices and, therefore, affect expected returns. Congruent with this notion, Brown and Cliff (2004) provided evidence that there is an effect of sentiment on weekly and monthly stock returns. Qiang and Shu-e (2009) found that the effect of investors' optimistic beliefs is strong and causes stock prices to fluctuate which enhances the volatility of stock returns. Kumar and Lee (2006) argued that return comovements are explained by trading activities of sentimental retail investors. Kumari and Mahakud (2015) documented that sentiment impacts stock market volatility which influences future stock returns.

Several scholars, on the other hand, have examined the relationship between emotions and stock mispricing. Cornell et al. (2017) show that high-quality accounting information

reduces mispricing in stock markets caused by sentiment. Miwa (2016) showed that in bull markets, high levels of sentiment cause investors to discriminate aggressively between corporations with high-growth potential and other firms, resulting in mispriced equities. Qian (2014) revealed that when retail investor sentiment is high and there is a large difference of opinion among investors, securities prices become inflated.

2.3. Hypothesis Development

In financial markets, sentiment investors (also known as ignorant or noise traders) trade on non-fundamental information. When sentimental traders' trading activity increases in the financial market, asset values vary from their intrinsic worth, according to Black (1986). Baker and Wurgler (2006) looked at whether mood has an impact on the cross-section of returns and found evidence that uninformed traders had an impact on stock prices. When noisy traders are overconfident, they buy more stocks, causing stock prices to skyrocket. Intuitively, positive investor attitudes during high-sentiment times may lead to expensive equities.

Furthermore, when analysts are overly optimistic, they tend to transmit positive recommendations and profit forecasts to the market, making it difficult for bad news about the companies they cover to reach outside investors quickly (Xu et al., 2013). After the suppressed news accumulates, it will come to a critical point where it will all be revealed at one time, which leads to unusual negative stock returns and causes a crash. Consequently, we conclude that high levels of investor sentiment trigger future stock crashes. We construct our hypothesis as follows:

H1: Firm-level investor sentiment is related positively to the possibility of crash occurrence in stock prices.

3. Research Methods

3.1. Sample

The sample initially includes all firms traded on the Saudi Stock Exchange (Tadawul) for the period 2011–2019. We acquire our data from two different sources, firm-specific accounting, and financial data are acquired from the Bloomberg database, while stock prices and trading volume are obtained from the official site of the Saudi stock exchange.

We exclude firm-year observations using the following data filters; (i) financial firms, (ii) firm-years with fewer than thirteen weeks of stock return data in a year, (iii) firmyears with missing data. Our final sample consists of 953 firm-year observations, corresponding to 131 listed firms from different industries.

3.2. Measurement of Stock Price Crash Risk

We use two proxies of crash risk. Before constructing these measures, we estimate the firm-specific weekly returns using the expanded market model regression for each firm and year as follows:

$$R_{i,t} = a_i + B_{1,i}R_{m,t-2} + B_{2,i}R_{m,t-1} + B_{3,i}R_{m,t}$$

$$+ B_{4,i}R_{m,t+1} + B_{5,i}R_{m,t+2} + \varepsilon_{i,t}$$
(1)

Where $R_{i,t}$ is the return of stock *i* during week *t* and $R_{m,t}$ is the return on the value-weighted market index during week *t*.

Then the firm-specific weekly return is calculated using the residual return in eq. (1) for each firm and year:

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

Based on $W_{i,t}$, we construct our first measure of crash risk which is the "negative coefficient of skewness" of weekly stock returns (NCSKEW). NCSKEW for each firm *i* during year *t* is computed as:

NCSKEW_{*i*,*t*} =
$$-\frac{n(n-1)^{\frac{3}{2}} \sum_{t=1}^{n} W_{i,t}^{3}}{(n-1)(n-2) \left(\sum_{t=1}^{n} W_{i,t}^{2}\right)^{\frac{3}{2}}}$$
 (3)

Where n is the number of weekly observations of firmspecific weekly returns for firm i during year t.

The "down-to-up volatility" (DUVOL) is the second measure of crash risk. To compute this measure, we divide weekly returns into two different groups; the up weeks and the down weeks. For firm *i* during year *t*, if weekly returns are above the annual mean it is defined as an 'up week' and as a 'down week' if otherwise. We calculate the standard deviation for each individual group. DUVOL is then calculated using the following equation:

$$\text{DUVOL}_{i,t} = \ln \frac{(n_u - 1) \sum_{\text{down}} W_{i,t}^2}{(n_d - 1) \sum_{\text{up}} W_{i,t}^2}$$
(4)

Where $n_u(n_d)$ is the number of up (down) weeks during year *t*.

3.3. Measurement of Investor Sentiment

Investor sentiment measures are not specific or inarguable and in several cases are country-specific and mainly based on data availability and data consistency. Consequently, we utilize sentiment proxies that are available for the Saudi market during our sample period to form a new firm-level sentiment index. Following Baker and Wurgler (2006), we build our index using principal component analysis (PCA). The new index contains three sentiment proxies: average turnover rate (ATR), priceearnings ratio (PE), and overnight return (OR).

The first proxy is turnover rate, which is based on the ratio of the trading volume to the total number of shares outstanding. Baker and Stein (2004) imply that turnover rate is a suited proxy of investor sentiment. In a market that is full of irrational investors participating, the trading increases when those investors are optimistic and they add more liquidity to the market, high liquidity refers to the overvaluation of the stocks. Therefore, we use ATR as our first sentiment proxy.

The price-earnings ratio is our second proxy, which is defined as the ratio of a company's share price to the company's earnings per share. The price earnings ratio is a good measure of sentiment because it has low values in bear markets and high values in bull markets, indicating a positive relationship with the investor emotions. Thus, we employ PE as a sentiment proxy.

The third proxy we utilize is the overnight return. The overnight return is a suitable investor sentiment proxy that can powerfully predict firm-specific sentiment. The overnight return is based on the daily close-to-close return, calculated using the total return of closing prices, and the intraday return which is calculated as the return of opening price over the return of closing price for each day.

$$R_{\text{close to close, }t}^{i} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1$$
(5)

Where $RI_{i,t}$ is the total return of the closing price for the stocks of firm *i* during day *t* and $RI_{i,t-1}$ is the total return of the closing price for the stocks of firm *i* during day *t*-1.

$$R_{\text{intraday},t}^{i} = \frac{P_{i,t}}{PO_{i,t}} - 1 \tag{6}$$

Where $P_{i,t}$ is the closing price for the stocks of firm *i* during day *t* and $PO_{i,t}$ is the opening price for the stocks of firm *i* during day *t*.

Therefore, the overnight return is computed as the closeto-close return divided by the intraday return:

$$OR_{i,t} = \frac{1 + R_{close to close, t}^{i}}{1 + R_{intraday, t}^{i}} - 1$$
(7)

The annual overnight return for each firm and year is then computed as the average of the daily overnight returns.

We conduct the principal component analysis which results in the following index:

$$SENTINDEX_{i,t} = 0.34ATR_{i,t} + 0.33PE_{i,t} + 0.32OR_{i,t}$$
(8)

3.4. Empirical Model

We design our empirical regression model to investigate whether investor sentiment contributes to crash risk in individual firms as follows:

$$\operatorname{CrashRisk}_{i,t+1} = a + B_1 \times \operatorname{SENTINDEX}_{i,t} + \sum_{i=1}^{m} \gamma_i \left(\operatorname{ControlVariable}_{i,t} \right) + \varepsilon_{i,t}$$
(9)

Where CrashRisk is the dependent variable measured by NCSKEW and DUVOL, while the independent variable is SENTINDEX. A variety of control variables are employed in our regression. We measure the independent and control variables in year t, while we measure the dependent variable in year t + 1.

4. Empirical Results

4.1. Descriptive Statistics

Table 1 displays an overview of descriptive statistics for the key variables. The proxies of crash risk, NCSKEW_{*t*+1} and DUVOL_{*t*+1}, have a mean value of -0.663 and -0.065, respectively. The standard deviations of NCSKEW_{*t*+1} and DUVOL_{*t*+1} are 1.801 and 0.177, respectively, which implies that crash risk measures in our sample have large differences, showing that crash risk can be measured in various ways. The mean value of the sentiment index SENTINDEX_{*t*} is 0.010, while the standard deviation is equal to 1.440. The firms included in the sample have an average size of 9.293, average leverage of 2.239, an average book-to-market ratio of 0.432, and an average return on assets of 6.737. The other variables are within reasonable ranges.

Variables	Obs.	Mean	Std. dev.	25%	Min	75%	Max
NCSKEW	1139	-0.663	1.801	-1.161	-18.527	-0.105	13.698
DUVOL	1139	-0.065	0.177	-0.107	-2.105	-0.008	0.772
SENTINDEX _t	989	0.010	1.440	-0.273	-21.905	-0.078	17.594
BETA	1179	0.959	0.164	0.851	0.349	1.079	1.370
LEV _t	1179	2.239	4.628	1.297	-70.736	2.413	83.413
ROA _t	1179	6.737	12.134	1.420	-164.067	11.690	58.946
SIZE	1179	9.293	0.699	8.842	6.929	9.576	11.667
BM _t	1152	0.432	0.330	0.247	-2.200	0.583	2.278
	1161	0.279	1.082	-0.045	-1.971	0.152	10.648
RET _t	1134	-0.191	1.812	-0.500	-17.361	0.392	10.017
ABACC	1179	0.037	0.092	0.005	-0.557	0.035	1.268
SIGMA _t	1134	0.050	0.036	0.003	-0.163	0.061	0.377

Table 1: Descriptive Statistics

This table represents descriptive statistics for the key variables over the period 2011–2019 for the 953 firm-year observations of the sample.

Table 2 reports the Pearson and Spearman correlation matrix of the key variables. We report Pearson correlations on the bottom side of the table and Spearman correlations on the upper side. We show that the two crash risk variables NCSKEW_{*t*+1} and DUVOL_{*t*+1} are positively related (0.2583 Pearson; 0.2599 Spearman), implying that these two crash risk measures are consistent. We also show that both crash risk measures are related positively to the sentiment index SENTINDEX_{*t*}. The correlation coefficients are small, which eliminates the concern of the presence of multicollinearity that might impact our results. Therefore, we conduct the variance inflation factors (VIF) and find that the corresponding values are weak and do not outpace the critical value of 10, which indicates that multicollinearity is not an issue.

4.2. Regression Analysis

Table 3 displays the results of regressing investor sentiment on crash risk using OLS regression. In Table 3, we show that whether the crash risk is proxied by NCSKEW_{*t*+1} or DUVOL_{*t*+1}, the estimated coefficients of SENTINDEX_{*t*} are both significantly positive at the 10% and 1% levels, respectively. This suggests that investor sentiment is positively related to the possibility of crash occurrence in stock prices, which supports hypothesis 1. The result is robust with two different measures of crash risk.

4.3. Robustness Test

4.3.1. Cross-sectional Regressions by Sector

We select four major sectors of the Saudi market to run cross-sectional regressions presented in Table 4. The selected sectors are materials, consumer discretionary, industrials, and consumer staples. Our main inference on the positive firm-level relation between investor sentiment and price crashes does not change. This supports our hypothesis that sentiment is associated positively with future crashes.

4.4. Endogeneity

Our results so far suggest a positive impact of sentiment on the future potential of crashes. However, our findings could be driven by potential concerns related to the endogeneity issue. This positive relation might be impacted by some factors that cannot be observed which affect investor sentiment and crash risk. Therefore, we conduct a test to alleviate endogeneity concern which is the dynamic panel GMM approach.

The GMM approach is generally used for panel data, it provides unbiased results of major sources of endogeneity, namely dynamic endogeneity, unobserved heterogeneity, and simultaneity. The GMM estimator is widely used in various

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NCSKEW ⁺¹	-	1.0000	0.2599	0.3054	0.0077	0.0179	0.0633	0.1206	-0.0101	-0.1291	0.0114	-0.0744	-0.0883
DUVOL _{#1}	2	0.2583	1.0000	0.3001	0.0157	-0.0552	-0.0252	0.0501	0.0025	-0.0280	0.0613	-0.0399	-0.0188
SENTINDEX _{I+1}	ო	0.1341	0.1371	1.0000	-0.0123	-0.0418	0.0881	-0.0191	-0.0190	0.0072	0.0770	0.0344	-0.0366
BETA _t	4	0.0340	0.0242	0.0097	1.0000	0.1497	-0.2387	0.0343	-0.0747	0.1081	0.1152	0.0306	0.2962
LEV	5	0.0658	0.0324	0.0157	0.0366	1.0000	-0.2339	0.3484	-0.4646	0.0562	-0.1582	-0.0315	0.1362
ROA	9	-0.0059	-0.0572	0.0493	-0.1827	-0.0031	1.0000	-0.0288	-0.1254	0.0694	0.1543	0.0962	-0.2531
SIZE	7	0.1106	0.2040	0.0141	0.0857	0.0772	-0.0188	1.0000	0.0071	-0.0972	0.0269	-0.0539	-0.1851
BM_t	∞	0.0594	0.0038	-0.0420	0.0241	-0.0661	-0.1533	0.0286	1.0000	-0.1354	-0.1036	-0.0377	-0.0763
DTURN	6	-0.0843	-0.0757	-0.0350	-0.0321	0.0517	-0.0339	-0.1854	-0.2469	1.0000	-0.0336	0.0286	0.2273
RET	10	0.1676	0.0934	0.0281	0.2611	-0.0967	-0.1004	0.1101	0.2280	-0.0016	1.0000	0.0039	0.0396
ABACC,	7	-0.0314	0.0154	0:0050	-0.0263	-0.0269	0.0855	-0.0877	-0.0331	0.0636	-0.0510	1.0000	-0.0347
SIGMA	12	0.0409	-0.0088	-0.0028	0.1353	0.1777	-0.2051	-0.1168	-0.0113	0.0892	0.1163	0.0320	1.0000
This table reports the	ne Pea	Irson and Sp	earman corr	elation matri	x of the kev	variables ov	ver the nerio	d 2011–2019	9 for the 953	firm-vear ob	servations o	of the sample	a

areas of finance and economics to detect the endogeneity issue. Our dynamic GMM model is designed as follows:

$$CrashRisk_{i,t+1} = \partial CrashRisk_{i,t} + SENTINDEX_{i,t} + Xn_{i,t} + \mu_{i,t} + \varepsilon_{i,t}$$
(10)

Where CrashRisk_{*i*,*t*+1} represents our dependent variable, CrashRisk_{*i*,*t*} is a one-period lag operator of the dependent variable, SENTINDEX_{*i*,*t*} represents the dependent variable, $Xn_{i,t}$ represents our control variables, $\mu_{i,t}$ is firm-specific fixed effects, and $\varepsilon_{i,t}$ represents the error term.

From the results presented in table 5 of the dynamic GMM estimation, we can see that the coefficients of SENTINDEX, are positive for both NCSKEW_{*t*+1} and DUVOL_{*t*+1}, which indicates that the evidence of a positive association between sentiment and crash risk remains unaffected.

Table 5 also displays the results of the AR(1) first-order serial correlation test, the AR(2) second-order correlation test, and the Hansen *J* test for over-identification. In the AR(1) and AR(2) tests, we see that the *p*-value for both crash risk proxies does not equal zero, which means that the null of no serial correlation in the residuals cannot be rejected. This confirms the absence of first and second-order serial correlation. In addition, the *p*-value of the Hansen *J* test for NCSKEW_{*t*+1} and DUVOL_{*t*+1} is 91.53 and 80.06, respectively. This implies that the hypothesis that our instruments are exogenous cannot be rejected. These findings show that the instruments included in the GMM estimator are indeed valid and exogenous.

Overall, the specification tests reveal no evidence that the instruments used in our estimation process are endogenous. Based on the dynamic GMM approach, we provide support for a positive association between sentiment and the possibility of a crash, confirming hypothesis 1.

4.5. Additional Analysis – Liquidity Effect

Prior research offers evidence that stock liquidity decreases future crash risk. Higher stock liquidity augments informed trading and information production. Hiding negative information becomes difficult for managers when stock prices are informational about a firm's fundamentals, which in turn lowers crash risk. Hence, we infer that liquid stocks have lower crash risk, which means that firms with bad liquidity face a higher possibility of a future crash.

To measure liquidity, we utilize the Amihud (2002) illiquidity ratio (ILLIQ), which is calculated as:

$$\text{ILLIQ}_{i,t} = \frac{1}{N_{i,t}} \sum_{w=1}^{N_{i,t}} \frac{\left| R_{i,t,w} \right|}{V_{i,t,w}}$$
(11)

Table 2: Correlation Matrix

We report Pearson correlations on the bottom side of the table and Spearman correlations on the upper side

	Expected Sign	NCSKEW	DUVOL
SENTINDEX,	+	0.1423* (2.55)	0.0150*** (3.40)
BETA _t	+	-0.1300 (-0.36)	-0.0786* (-2.02)
LEV _t	-	0.0327* (2.05)	0.0011 (0.99)
ROA _t	±	0.0012 (0.20)	-0.0005 (-1.31)
SIZE,	±	0.1149 (1.40)	0.0592*** (3.29)
BM,	+	0.4143 (0.86)	-0.0406* (-2.21)
DTURN,	+	-0.2254* (-2.56)	-0.0136 (-0.88)
RET _t	+	0.1585 (1.54)	0.0064 (1.36)
ABACC	+	-0.4177 (-0.87)	0.1461* (2.35)
SIGMA _t	+	-1.0522 (-0.41)	0.0240 (0.12)
Constant		-2.0632 (-1.82)	-0.5654*** (-3.82)
N		953	953
Adj. R ²		0.1133	0.2131
Year		Yes	Yes
Industry		Yes	Yes

Table 3: Investor Sentiment and Crash Risk

This table reports the results from regressing investor sentiment on crash risk and other control variables using OLS regression over the period 2011–2019 for the 953 firm-year observations of the sample. The t-statistics reported in parenthesis are based on standard errors clustered by both firm and year. *,**, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Table 4: The Impact of Investor	Sentiment on Crash Risk:	Cross-Sectional Regressions by	/ Sector
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	Panel A:	Materials	Panel B: Consumer Discretionary		
	NCSKEW,+1	DUVOL ₁₊₁	NCSKEW	DUVOL ₁₊₁	
SENTINDEX,	0.0997* (2.17)	0.0202*** (3.38)	0.6953* (2.27)	0.0180* (2.02)	
Ν	309	309	164	164	
Adj. <i>R</i> ²	0.2090	0.4962	0.1120	0.4474	
Constant and controls	Yes	Yes	Yes	Yes	
Year	Yes	Yes	Yes	Yes	
Industry	Yes	Yes	Yes	Yes	
	Panel C: I	ndustrials	Panel D: Con	sumer Staples	
	NCSKEW,+1	DUVOL ₁₊₁	NCSKEW	DUVOL ₁₊₁	
SENTINDEX,	0.2983 (1.13)	0.0322* (2.32)	0. 9760* (2.91)	0. 1516*** (6.33)	
Ν	152	152	93	93	
Adj. <i>R</i> ²	0.3421	0.2074	0.2089	0.4454	
Constant and controls	Yes	Yes	Yes	Yes	
Year	Yes	Yes	Yes	Yes	
Industry	Yes	Yes	Yes	Yes	

This table presents the cross-sectional regression results of the impact of investor sentiment on crash risk for four major sectors of the Saudi Stock Exchange over the period 2011–2019 for the 953 firm-year observations of the sample. The t-statistics reported in parenthesis are based on standard errors clustered by both firm and year. *,**, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	GMM	GMM
	NCSKEW,	DUVOL
NCSKEW,	0.4281*** (61.18)	
		0.6954*** (65.62)
SENTINDEX,	0.1284*** (8.57)	0.0026* (2.32)
BETA _t	-0.1789 (-1.50)	-0.0350** (-2.88)
LEV _t	-0.0034*** (-3.88)	-0.0032*** (-51.07)
ROA,	-0.0003 (-0.17)	-0.0001 (-1.30)
SIZE,	0.4498*** (7.57)	0.0422*** (8.97)
BM,	0.0695 (0.98)	-0.0166** (-2.59)
DTURN,	0.1491*** (6.51)	0.0215*** (15.66)
RET	0.0157 (1.76)	-0.0009 (-1.56)
ABACC	0.9674*** (4.10)	-0.0432* (-2.43)
SIGMA,	3.5148*** (18.43)	0.1423*** (7.83)
Constant	-4.6665*** (-8.83)	-0.3706*** (-7.66)
Ν	848	848
AR(1) test (p-value)	-3.33***	-5.69***
AR(2) test (p-value)	1.36	1.05
Hansen-J test of over-identification (p-value)	91.53	80.06
Year	Yes	Yes
Industry	Yes	Yes

	Table	5: Re	aression	Analysis	s to Ad	dress Er	ndoaenei	tv Concerns
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This table reports the analysis to address the endogeneity issue on the impact of investor sentiment on crash risk over the period 2011–2019 for the 953 firm-year observations of the sample. We show the results of the GMM approach. The *z*-statistics reported in parenthesis are based on standard errors clustered by both firm and year. *,**, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

Where $N_{i,t}$ represents the number of weeks within year *t* for stock *i*, $R_{i,t,w}$ represents the absolute return on week *w* within year *t* for stock *i*, and $v_{i,t,w}$ represents the weekly trading volume.

To examine the liquidity effect, we split our sample into two subsamples; the better liquidity and the worse liquidity. Firms with better liquidity have an ILLIQ that is above the median, while firms with worse liquidity have an ILLIQ that is below the median. We then run eq. (9) to explore the liquidity effect on the impact of investor sentiment on future crashes.

Table 6 displays the regression results of the liquidity effect. Using NCSKEW_{*t*+1} as our crash proxy, we show that the coefficients estimated on SENTINDEX, for the better (worse) liquidity subsample is 0.0695 (0.2488), statistically significant at the 10% and 1% levels, respectively. On the other hand, the estimated coefficients of SENTINDEX, when we utilize DUVOL_{*t*+1} as a crash proxy in both subsamples equal to 0.0128 and 0.0151, which are

significant at the 1% and 10% levels, respectively. These findings discussed above indicate that firms with worse liquidity exhibit a more positive influence of investor sentiment on future crashes than firms with better liquidity.

5. Conclusion

We investigate the firm-level relationship between investor mood and future crashes in this study. Based on a sample of 131 companies traded on the Saudi stock exchange (Tadawul) and 953 firm-year observations from 2011 to 2019, we find a significant positive relationship between investor mood and the likelihood of a stock market meltdown. After doing a robustness check and accounting for potential endogeneity, our empirical results remain valid. Furthermore, our research shows that companies with lower liquidity have a considerably higher positive impact of market mood. Investors and authorities who want to manage stock market collapses should be interested in our findings. First, our

	The Better Liqu	idity Subsample	The Worse Liqu	idity Subsample
	(1) NCSKEW	(2) DUVOL _{t+1}	(3) NCSKEW	(4) DUVOL
SENTINDEX _t	0.0695* (2.32)	0.0128*** (5.59)	0.2488*** (3.22)	0.0151* (2.06)
BETA _t	0.4959 (1.25)	0.0576 (1.90)	-0.8932 (-1.43)	-0.1241* (-2.09)
LEV _t	-0.0819 (-1.36)	-0.0011 (-0.25)	0.0301* (2.13)	0.0003 (0.27)
ROA _t	0.0180*** (3.22)	0.0002 (0.61)	-0.0040 (-0.54)	-0.0009 (-1.38)
SIZE	0.0283 (0.31)	0.0003 (0.04)	0.2250 (1.13)	0.1308*** (6.87)
BM _t	-0.3171 (-1.35)	-0.0055 (-0.31)	0.6559* (2.17)	-0.0730* (-2.54)
DTURN,	-0.1160 (-1.26)	-0.0002 (-0.03)	-0.2355** (-2.71)	-0.0230** (-2.78)
RET _t	-0.1201 (-1.71)	0.0070 (1.32)	0.1913*** (4.44)	0.0058 (1.43)
ABACC	-0.5940 (-0.41)	-0.1169 (-1.04)	0.0371 (0.04)	0.2097* (2.49)
SIGMA _t	1.1000 (0.46)	-0.2543 (-1.38)	-1.9190 (-0.91)	0.0510 (0.25)
Constant	-1.4183 (-1.41)	-0.1210 (-1.58)	-2.6442 (-1.14)	-1.2089*** (-5.49)
Ν	425	425	528	528
Adj. R ²	0.0823	0.1092	0.1451	0.2689
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes

Table 6: The Impact of Investor Sentiment on Crash Risk: Liquidity Effect

This table reports regression results of liquidity effect on the impact of investor sentiment on crash risk over the period 2011–2019 for the 953 firm-year observations of the sample after splitting the sample into two subsamples; the better liquidity and the worse liquidity. The *t*-statistics reported in parenthesis are based on standard errors clustered by both firm and year. *,**, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

findings help investors assess the accuracy of predicted stock returns, as well as the potential of price crashes in the near future, which is more likely in bull markets. Second, while making an investment during moments of high sentiment, investors must consider the high costs of an extreme drop in stock prices caused by crash risk. Third, authorities can gain a better understanding of how investors behave when they are too optimistic or pessimistic. This knowledge can be used to regulate or educate sentimental traders to avoid the economic implications of investor emotions. Future research could look into the research question in a different setting or use different sentiment proxies.

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