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Article

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How does investor sentiment affect stock market crash risk? Evidence from Asia-Pacific markets

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ABSTRACT

This study aims to examine the effect of investor sentiment on stock market crash risk in the Asia–Pacific region. The research employs principal components analysis (PCA) to construct an investor sentiment index, while the Method of Moments Quantile Regression (MMQR) is used to analyze monthly data of 16 Asia-Pacific stock markets. The findings show that investor sentiment positively impacts on crash risk in the middle to higher quantities. Moreover, regional sentiment significantly increases stock market crash risk, particularly at higher quantiles, while local sentiment generally reduces crash risk at the lower to middle quantiles. Besides, the magnitude and direction impact of investor sentiment on stock market crash risk is heterogeneous across market levels. Specifically, the results indicate that at higher quantiles of risk, investor sentiment increases crash risk in developed and emerging markets, while it decreases crash risk in frontier markets.

IMPACT STATEMENT

This paper not only provides support for behavioral theories but also have implications for global investors, portfolio managers, and policymakers.

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D53; G21; G40

1. Introduction

Investing in the stock market carries certain risks due to specific risks or market risks, with the possibility of occurrence of such risks being higher during a financial crisis (Wang et al., 2009). Financial crises have historically had far-reaching economic, social, and political ramifications (Fu et al., 2020). Stock market crashes, which are rapid and often unforeseen declines in stock prices, can be a side effect of a major catastrophic event, economic crisis, or the collapse of a long-term speculative bubble (Kustina et al., 2024). In particular, stock and bond markets play an essential roles in the financial stability of national capital markets (Zhou et al., 2022). Past decades have experienced many stock market crashes, such as the collapse in 1929 in the United States, the 2018 financial crisis leading to a drop in the value of subprime mortgage stocks, and the COVID-19 pandemic in March 2020. Understanding the risk of a stock price collapse is critical for portfolio investment, risk management, and stakeholder safety monitoring (Vo, 2020).

In theory, a stock market crash is defined as a sudden decline in stock returns in most stocks, leading to a significant decrease in investors' asset values (Wang et al., 2009). Mishkin and White (2002) state that a stock market crash quantifies a 20% decline in the market index over a period of time (between a day and a year). Patel and Sarkar (1998) define 'collapse' as a significant drop in a market index relative to its historical maximum over an observed period, such as one or two years. These authors classify a stock market crash as a relative decline in the regional price index of more than 20% for developed markets and more than 35% for emerging markets. Furthermore, Hong and Stein (2003) argue that a 'crash'

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must consist of three elements, including: (i) a collapse, characterized by an abnormally large movement in the market without a corresponding major mass news event; (ii) that this large price change is negative; and (iii) the crash constitutes a market-wide 'contagion' phenomenon. This means that a crash is not only a sudden drop in the price of a stock but also a fall strongly correlated with the price of an entire class of stocks. In addition, crash risk is defined as the conditional deviation of the return distribution, which shows an asymmetry in risk and is significant for investment and risk management choices (Kim et al., 2014). According to Zhang et al. (2021), crash risk is a type of extreme risk or tail risk, which can be also defined as extreme events, whose probability of occurring is shown in the tail of a distribution and is capable of influencing valuation results. In general, stock market crash risk is an extreme type of risk that indicates the likelihood of a sudden market crash caused by cumulative negative information that has been made public for an extended period.

A stock market crash risk comes from the stock price crash risk of firms where managers tend to hide accumulated bad news over a long period (Habib et al., 2018). If company executives successfully prevent the flow of negative information into the market, the distribution of stock returns will be disproportionate (Hutton et al., 2009; Kothari et al., 2009). When the amount of bad information crosses a threshold, it is revealed to the market immediately, leading to a stock price crash. In addition, stock price crash risk is also affected by individualism, especially during the global financial crisis (An et al., 2018). This impact can be eliminated through enhanced financial information transparency. The Efficient Market Hypothesis (EMH) of Fama (1970) states that stock prices react to information and interpret relevant information to form good and bad expectations about stock price movements. As a result, the buy and sell orders of all participants in the market are pooled to establish the equilibrium price of shares at a certain point in time. However, investors are always constrained in their reasoning and cannot effectively evaluate all types of information. This means that their biases can lead to an increase in market sentiment. Stock markets are prone to price bubbles, leading to a crash in the market. Moreover, the asymmetric information theory explains that information asymmetry occurs when different people know different things. This means that an asymmetric capital market emerges when one market player (management) knows more about the company's internal information while investors or shareholders know little about the business's information, leading to an incentive for executives to take action. Cao et al. (2002) propose the 'information blockade' model to account for price collapse through information congestion and the asymmetric release of information in the stock market at the cost of setting up fixed trades. The increasing price trend drives well-informed investors to initiate aggressive trading in line with this pattern. Conversely, less knowledgeable investors often doubt the true nature and accuracy of the signal, thus delaying trade until the price falls. As a result, price corrections are unavoidable if the economic outlook turns negative and investors join the market with less knowledge. Furthermore, because investors might postpone trading until price movements corroborate their private signals, insider trading generates even more market news. In particular, inheriting the signal theory of French et al. (1987) and Ross (1973), Campbell and Hentschel (1992) propose the volatility feedback effect to explain stock crash price risk. In particular, a large volume of good news indicates an increase in market volatility. Therefore, the immediate benefit of positive news is somewhat offset by a rise in the risk premium. On the other hand, when large amounts of bad news emerge, the direct impact and risk-offset effect will go in the same direction, leading to an amplification of the influence. Extreme price movements might induce investors to rethink market volatility and raise the necessary risk compensation, which lowers the equilibrium price by building up the effect of adverse news and balancing the influence of good news, resulting in a negative skewness about return (Hutton et al., 2009).

Besides the above-mentioned arguments of traditional finance theories, behavioral finance theory states that a stock market crash risk also results from psychological factors (Zouaoui et al., 2011). According to Blajer-Gołębiewska et al. (2018) and Lucey and Dowling (2005), asset prices are not only driven by reasonable expected returns but also irrational decisions that are affected by investor emotions, sentiments, or states of mind. In fact, investor sentiment is defined as participants' expectations regarding future cash flows (returns) and investment risk (De Long et al., 1990). When sentiment is considered as high, stocks have comparatively poor subsequent returns, and when sentiment is low, these cross-sectional patterns are inverted (Baker & Wurgler, 2006). Furthermore, sentiment-based mispricing is caused by uninformed demand from investors, noise traders, and an arbitrage limit. Therefore, there

have been several empirical investigations on the role of investor sentiment in stock market crash risk which can be divided into three main topics as follows: (i) Studies on the effect of market sentiment on individual stock price crash risk, such as those of Cui and Zhang (2020), Yin and Tian (2017), and Wu et al. (2021); (ii) Studies on the effect of firm-specific investor sentiment on stock price crash, such as those of Alnafea and Chebbi (2022), Fan et al. (2021), Fu et al. (2021), and Shin and Choi (2022); and (iii) Studies on investor sentiment in early warning systems of stock market crashes, such as those of Fu et al. (2020) and Zouaoui et al. (2011). However, it can be seen that most previous studies focus on the impact of investor sentiment on stock price crash risk at the firm level but ignore the country level. One of the few closest studies focused on cross-sectional countries is that of Kustina et al. (2024) but investor sentiment indexes are measured by a simple formula based on the highest high, lowest low, and closing price of an asset (Zhou, 2018), which does not fully reflect market sentiment as the composite index of Baker and Wurgler (2006). Besides, these authors only use logistic regression and OLS regression, which leads to bias in results because panel data requires consideration of cross-sectional dependence and stationarity. Furthermore, previous studies have not considered market development as one of the factors influencing the relationship between investor sentiment and stock market crash risk. Meanwhile, Chui et al. (2010) claim that market development and market integrity can affect information flow and market efficiency.

Motivated by the above-mentioned research gap, this research aims to investigate the impact of investor sentiment on stock market crash risk among Asia–Pacific markets. In fact, Asia-Pacific markets are sub-categorised into frontier, emerging, and developed markets, which allows the research to compare this effect among markets of different development levels. Despite their ongoing evolution and improvements, Asia-Pacific stock markets face challenges, such as undeveloped market structures, a low number of institutional investors, and incomplete transparency, highlighting the need for research in this region. In addition, this study also employs the Method of Moments Quantile Regression (MMQR) on panel data of 16 stock markets spanning from January 2006 to December 2023 to examine the dependence of the relationship between investor sentiment and the probability of stock market crash by levels of market development. This research makes the following two contributions. Firstly, this study adds to the literature review by showing that investor sentiment impacts the different quantiles of crash risk in Asia-Pacific stock markets. Moreover, the magnitude and direction impact of investor sentiment on stock market crash risk is heterogeneous across market levels. Secondly, this study proposes some recommendations for policymakers and investors for a stable market and an effective portfolio diversification strategy, respectively.

The remainder of this article is structured as follows: Section 2 provides a literature review on the effect of investor sentiment on the crash risk of the stock market. Section 3 explains methods of measuring variables and collecting and analyzing the data. Section 4 describes empirical results before they are discussed in section 5. Finally, conclusions with implications, limitations, and orientation for future studies are presented in section 6.

2. Literature reviews

Topics about the impact of investor sentiment on stock market crash risk have attracted the attention of many scholars. There are three strands of literature review, including (i) the effect of market sentiment on individual stock price crash risk; (ii) the effect of firm-specific investor sentiment on stock price crash risk; and (iii) the effect of investor sentiment in early warning systems of stock market crashes.

In terms of the effect of market sentiment on individual stock price crash risk, Yin and Tian (2017), based on the method proposed by Baker and Wurgler (2006), construct a market sentiment index and investigate the effect of market sentiment on stock price crash risk in China. The results demonstrated that there is evidence of positive impacts of investor sentiment on the future stock price crash risk, and this nexus is strengthened by poorer financial reports, the absence of short-sales constraints, and the bull market state. Similar conclusions are reached by Cui and Zhang (2020) for the U.S. enterprises between 1991 and 2014. Besides, Wu et al. (2021) also demonstrate rising holistic investor sentiment in the current period can increase stock price crash risk in the next period in both Shanghai and Shenzhen A-share markets. Moreover, their results reveal that investor pessimism will increase stock price crash risk

in the Shenzhen A-share market from the perspective of heterogeneous sentiment. With a large sample of A-share listed companies on the Shanghai and Shenzhen Stock Exchanges in the period of 2004–2019, Bashir et al. (2024) outline the mediating role of analyst herding in deepening market sentiment which results in crash risk. However, the market-wide investor sentiment index is invariant in the cross-section and cannot correctly represent investor sentiment with individual firms, making it inappropriate for dealing with firm-level issues (Aboody et al., 2018).

Regarding the impact of firm-specific investor sentiment on stock price crash risk, this effect is developed in an attempt to address the limitations of the market-wide sentiment index. Fu et al. (2021) find that firm-specific investor sentiment is significantly and positively related to the possibility of crash occurrence in stock prices. Additionally, the effect of firm-specific investor sentiment on crash risk is more pronounced for firms with worse liquidity, which is supported by Alnafea and Chebbi (2022) who argue that firms with worse liquidity have a considerably greater positive influence of investor sentiment on future crashes than firms with better liquidity. Shin and Choi (2022) indicate that firms listed on the KSE from 2011 to 2019 that also have high levels of foreign ownership reduce the high stock price crash risk attributable to high sentiment. Besides the above, the impact of investor sentiment on future stock price crash risk is more significant for stocks eligible for margin trading (Fan et al., 2021). In addition, Zhang et al. (2023) show that stock price synchronicity which is defined as firm-specific information or noise in the stock price, can harm investor attitude to obtain firm-specific information, leading to a higher crash risk.

Concerning the impact of investor sentiment on stock market crash risk, Zouaoui et al. (2011) use a logit model to show investor sentiment has a significantly positive influence on the probability of occurrence of stock market crash. Additionally, they reveal that investor sentiment has a stronger impact on stock markets in countries where herding and overreaction are common, while institutional involvement is limited. This finding is entirely supported by Zhang et al. (2019) who confirm that investor sentiment is a better predictor of the stock market crisis within a 1-year horizon than macroeconomic variables, and Fu et al. (2020) who focus on the important role of sentiment factors in early warning models. Recently, Kustina et al. (2024), who define country index crash risk as the possibility of the significant and rapid decline of the stock index, give evidence of a negative impact of investor sentiment and exchange rate on the country index crash risk. Furthermore, a higher net foreign trading value does not improve the impact of investor sentiment but reduces the influence of exchange rate volatility on the country index crash risk.

3. Methodology

3.1. Measuring variables

3.1.1. Dependent variable

As regards methods used to measure stock market crash risk, there are two approaches, including (i) CMAX index; and (ii) Asymmetric returns. The CMAX index measures current prices against the highest in the past 12 or 24 months, with a crash occurring when it falls below two standard deviations from its historical average (Patel & Sarkar, 1998). To assess return asymmetry, Chen et al. (2001) use the negative coefficient of skewness (NCSKEW) and down-to-up volatility (DUVOL), while Liu et al. (2021) enhance the conditional skewness with the GARCH-S model for daily deviations over six months.

In this study, asymmetric return measures, specifically NCSKEW and DUVOL, are chosen over CMAX for detecting stock market crash risk due to their focus on left-tail risk and volatility asymmetry. NCSKEW captures extreme negative returns, making it more effective at identifying early warning signs of market downturns, while DUVOL emphasizes market reactions to negative news by comparing the volatility on down days *vs.* up days. Both measures rely on daily data, allowing for quicker responses to emerging risks compared to CMAX, which focuses on longer-term trends and may overlook short-term fluctuations. This sensitivity to market dynamics, particularly in volatile conditions, makes NCSKEW and DUVOL more suitable for assessing crash risk.

Therefore, the negative coefficient of skewness (NCSKEW) and down-to-up volatility (DUVOL) are used to measure stock market crash risk. The idiosyncratic daily market return is defined as

$W_{i,t} = \ln(1 + R_{i,t})$, where $R_{i,t}$ is the return of stock market index i on day t. The negative coefficient of skewness (NCSKEW) is the ratio of the third moment of stock market returns over the standard deviation of stock market returns raised to the third power and then multiplied by −1, as shown below:

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

where n is the trading days of stock market index i in month T. Adding a negative sign on the right side of the equation will make the negative coefficient of skewness positively correlate with the stock price crash. In other words, the higher the negative skewness coefficient is, the higher the stock price crash risk is.

The down-to-up volatility (DUVOL) is calculated as the following formula:

$$DUVOL_{i,T} = \ln\frac{(n_{up}-1)\sum_{down} W_{i,t}^2}{(n_{down}-1)\sum_{up} W_{i,t}^2}$$

where n_{up} and n_{down} are the up and down days. For returns in month T, we separate all the days with returns below the monthly mean (down days) from those with returns above the monthly mean (up days) and calculate the standard deviation for each of these sub-samples separately. Then, the DUVOL measure is the log of the ratio of the standard deviation of the down days to the standard deviation of the up days. An increase in DUVOL corresponds to a stock being more likely to crash and vice versa.

3.1.2. Independent variable

From the literature review, there are three methods to build an investor sentiment index, including: (i) The survey-based approach allows for the analysis of different investor groups but is limited by time and space; (ii) The text-based method provides high-frequency indicators but risks inaccurate correlations due to vast data and cross-country complexities due to language differences; (iii) The market-based method, favored for its data availability, struggles to separate rational from psychological behavior. Since a composite sentiment index better captures investor irrationality compared to a single sentiment index (Yang & Gao, 2014), we apply the Baker and Wurgler (2006) method. This approach involves capturing the first principal component of sentiment proxies to measure investor sentiment across Asia-Pacific stock markets. The process of calculating the investor sentiment index is shown in the following steps:

(i) ***Step 1:*** Collect stock market-level data on technical indicators. This study utilizes four key technical indicators that can represent investor sentiment on Asia-Pacific stock markets, including: (i) The relative strength index (RSI) is a technical indicator that helps investors detect overbought or oversold conditions in the market, to show the investors' beliefs in the markets; (ii) Williams %R (WRI) measures market extremes by comparing the current closing price to the highest and lowest prices over a set period, (iii) The psychological line index (PLI) measures investor volatility during market fluctuations and captures short-term price reversals, reflecting short-term trends and psychological stability; and (iv) The share turnover velocity (VOL) can capture the liquidity of a stock market and investors' heterogeneous beliefs on a stock market, as higher turnover suggests optimism and expectations of rising prices. These four indicators are chosen because of their high pairwise correlations (Supplementary Appendix 1).

Table 1 presents a detailed description of sentimental proxies.

(ii) ***Step 2:*** Use the principal components analysis (PCA) approach to assign weights to all four proxies of investor sentiment in Table 1 and then construct a composite investor sentiment index based on the first principal component (F_i) for each stock market i. investor sentiment indicator ($SENT_{i,t}$) is calculated as:

$$SENT_{i,t} = F_{i,1} \times RSI_{i,t} + F_{i,2} \times WRI_{i,t} + F_{i,3} \times PLI_{i,t} + F_{i,4} \times VOL_{i,t}$$

Table 1. Description of sentiment proxies.

Proxy	Code	Measure	References
Relative strength index	RSI	$RSI_{i,t} = \frac{RS_{i,t}}{1+RS_{i,t}} \times 100$ where $RSI_{i,t} = \frac{\sum_{t=1}^{14} \max(0, P_{i,t} - P_{i,t-1})}{\sum_{t=1}^{14} \max(0, P_{i,t-1} - P_{i,t})}$, and $P_{i,t}$ is closing price of stock market at month t.	Zhou et al., 2023
%William R indicator	WRI	$WRI_{i,t} = \frac{P_{highest,i,t} - P_{i,t}}{P_{highest,i,t} - P_{lowest,i,t}} \times -100$ where $P_{highest,i,t}$ and $P_{lowest,i,t}$ are the highest high and lowest low prices of stock index i, the past n = 14 periods are used, and closing price is the closing price today.	Kustina et al., 2024; Zhou, 2018
Psychological line index	PLI	$PLI_{i,t} = 100 \times \sum_{t=1}^{12} \left\{ \frac{Max(0, P_{i,t} - P_{i,t-1})}{P_{i,t} - P_{i,t-1}} \right\} / 12$ where $P_{i,t}$ is closing price of stock market i at month t.	Yang & Gao, 2014; Zhou et al., 2023
Share turnover velocity	VOL	$VOL_{i,t} = \frac{1}{12} \sum_{j=0}^{11} TURN_{i,t-j}$ Where $TURN_{i,t} = \frac{Total\ of\ shares\ trade_{i,t}}{Maket\ capitalization_{i,t}}$, and $TURN_{i,t}$ represents share turnover velocity of equity market i at month t.	Baker & Wurgler, 2006

Source: Authors.

Besides, sentiment contagion spreads across markets within a geographic region, forming regional sentiment (Baker et al., 2012). Regional sentiment is derived by performing the PCA on investor sentiment indicators from 16 countries in the sample, while local sentiment for each market is calculated as the residual after orthogonalizing total sentiment concerning regional sentiment. Detailed results of the PCA approach are shown in Supplementary Appendix 2.

3.1.3. Control variables

This study employs an expanded set of market characteristics and macroeconomic conditions as control variables to isolate the 'irrational' component of market sentiment measures, acknowledging that changes in these factors can affect overall economic conditions and market sentiment. To be precise, the four factors considered include market return (RET), market volatility (SIGMA), inflation (INF), and interest rate (INT). Market return is determined by the change in the natural logarithm of the stock index from month t to month t-1, while market volatility is assessed through the standard deviation of daily returns in month t. Inflation is represented by the change in the natural logarithm of the monthly consumer price index, and the monthly money market rate indicates the interest rate (INT).

The main variables are summarized in Supplementary Appendix 3.

3.2. Data and sampling

This study uses panel data of 16 stock markets (Supplementary Appendix 4) with 216 months from January 2006 to December 2023, giving a sample of data that includes $16 \times 216 = 3456$ observations. Since the stock market index changes daily, but macroeconomic data is recorded monthly, quarterly, or yearly, it is appropriate to determine monthly data. Secondary data on the stock index extracted from Bloomberg consists of 16 stock market indices classified from the MSCI catalog and internationally recognized as benchmark indices, which are the most closely watched by analysts in the Asia-Pacific region. In addition, macro factors are compiled from the International Financial Statistics of IMF and Investing.com.

Table 2 shows the summary statistics for the entire sample, such as minimum values, standard deviation, mean value, maximum values, and number of observations used in the study. The main variable of interest is stock market crash risk which is measured by the negative coefficient of skewness (NCSKEW) and down-to-up volatility (DUVOL). NCSKEW has an average of −0.020, a slight negative skewness in stock returns, suggesting that extreme negative returns are more likely than extreme positive returns. DUVOL also reflects downside risk, with a mean of −0.066, implying that downside volatility tends to be more pronounced than upside volatility, making losses sharper than gains on average.

Table 2. Summary statistics.

Variables	Obs	Mean	Std. Dev	Min	Max
NCSKEW	3456	−0.020	0.976	−4.278	3.905
DUVOL	3456	−0.066	1.120	−8.517	4.505
SENT	3456	0.000	1.607	−4.693	4.070
RET	3456	0.005	0.059	−0.449	0.326
SIGMA	3456	0.010	0.006	−0.027	0.070
INF	3456	0.004	0.008	−0.054	0.158
INT	3456	0.041	0.039	−0.001	0.800

Source: Authors.

The mean value of investor sentiment (SENT) is 0.000, implying that the data contains equal occurrences of positive and negative sentiment. The large standard deviation of 1.607 and the range from −4.693 to 4.070 indicate significant swings in market sentiment, reflecting periods of both extreme pessimism and optimism. Countries in the sample have average levels of inflation (INF) of 0.004, reflecting a low inflationary environment, while interest rates (INT) average 4.1%, but exhibit significant variation, ranging from −0.001 to 0.800, reflecting different economic conditions. On average, market returns are slightly positive at 0.5%, but with noticeable fluctuations, as indicated by a standard deviation of 0.059. Finally, market volatility (SIGMA) averages 1.0%, with minimum and maximum values of −0.027 and 0.07, respectively, suggesting that while most markets are relatively stable, some experience considerable fluctuations.

3.3. Econometrics approach

For the empirical modeling, we employ panel co-integration techniques which are based on (i) checking the cross-sectional dependence (CD); (ii) testing the order of integration corresponding to each variable; and (iii) the existence of long-run co-integration among the variables is checked using panel co-integration tests.

Once the long-run cointegration is confirmed, we need to estimate the long-run coefficients by innovative estimate methodology as MMQR, to investigate the relationship between variables. Machado and Silva (2019) came up with this approach. The reason for using the MMQR methodology is that it outperforms other methods, such as conventional panel quantile regression, DOLS, and FMOLS. MMQR is suited since other linear estimating approaches cannot handle distributions of data and hence only address averages. Moreover, basic quantile regression is inadequate for non-crossing estimates when measuring estimators for multiple percentiles, resulting in an invalid distribution. On the other hand, the MMQR with fixed effects introduced by Machado and Silva (2019) fully addresses the drawbacks that are associated with panel quantile regression. The conditional quantile $QY(\tau|X_{i,t})$ for a location-scale model is expressed as:

$$Y_{it} = \alpha_i + \beta X'_{it} + \left(\xi_i + \psi Z'_{it}\right)U_{it}$$

In this context, Y_{it} and X_{it} represent the dependent and independently and identically distributed explanatory variables, respectively. Additionally, $\alpha, \beta, \xi,$ and ψ are the coefficients to be estimated. Here, the probability $P\left\{\xi_i + \psi Z'_{it} > 0\right\} = 1$. Moreover, Z is a k-vector of the known components, while $i = 1, \ldots\ldots, n$ denotes the individual fixed effects. U_{it} is independently and identically distributed across individuals i over time t and is orthogonal to X_{it}, which are standardized to satisfy the moment conditions. Thus, the equation can be rewritten as:

$$QY(\tau|X_{it}) = (\alpha_i + \xi_i q(\tau)) + X'_{it}\beta + Z'_{it}\psi q(\tau)$$

Where X'_{it} is a vector of the independent variable and control variables, $\alpha_i + \delta_i q(\tau)$ is the scalar coefficient of the quantile-τ fixed or distributional effect at τ, which is time invariant. Following Machado and Silva (2019), the MMQR specification of the basic model is as follows:

$$QNCSKEW_{it}(\tau|\alpha_i, \varepsilon_{it}, X_{i,t}) = \alpha_i + \varphi_{1\tau} SENT_{it} + \sum_{k=2}^{5} \varphi_{k\tau} CV_{k,it} + \varepsilon_{it}$$

$$QDUVOL_{it}(\tau|\alpha_i, \varepsilon_{it}, X_{i,t}) = \alpha_i + \varphi_{1\tau}SENT_{it} + \sum_{k=2}^{5} \varphi_{k\tau}CV_{k,it} + \varepsilon_{it}$$

Where $QNCSKEW_{it}(\tau|\alpha_i, \varepsilon_{it}, X_{i,t})$ and $QDUVOL_{it}(\tau|\alpha_i, \varepsilon_{it}, X_{i,t})$ are the conditional quantile of $QNCSKEW_{it}$ and $QDUVOL_{it}$ with the scalar coefficient $(\alpha_i(\tau))$ for the distributional effect at τ. To analyse the effect of the individual independent variables on the dependent variable, the dependent variable is set between 0 and 1 to capture the effect of each of the independent variable (SENT) and control variables (RET, SIGMA, INF, and INT) at the selected point in the conditional distribution of NCSKEW(DUVOL). Setting $\tau = 0.1, 0.2, \ldots, 0.9$ enables evaluation of the effects of the independent variable and control variables on the distributional NCSKEW(DUVOL) at the 10th, 20th … and 90th quantiles respectively.

Apart from the main MMQR method, we utilize traditional regression models, such as dynamic ordinary least squares (DOLS), and fully modified ordinary least squares (FMOLS) estimators to provide a comparative analysis of the results. FMOLS, focusing on nonparametric methods, addresses endogeneity and heterogeneity across various units within a dataset (Phillips & Hansen, 1990). In contrast, DOLS, a parametric method, is known for generating unbiased estimates and effectively handling issues related to endogeneity (Kao & Chiang, 2001). Therefore, both FMOLS and DOLS are considered more robust than OLS regression.

In the final stage of our econometric analysis, we apply the Dumitrescu and Hurlin (D-H) panel causality test (2012) to determine the direction of causality between crash risk and its key determinants. The test uses two statistics: the W-bar, which averages the test statistics, and the Z-bar, based on the standard normal distribution. The null hypothesis assumes no causality, and the test identifies three possible outcomes: unidirectional causality, bidirectional causality, or no causality.

4. Empirical results

4.1. Preliminary analyses

Firstly, the study runs the correlation matrix that exposes the correlation among the variables. Table 3 presents the Person correlation coefficients for the main variables. The correlation matrix reveals a strong positive relationship between NCSKEW and DUVOL (0.9427), both significant at the 5% level. Higher sentiment (SENT) correlates negatively with NCSKEW (−0.1809) and DUVOL (−0.2057), suggesting that better sentiment reduces crash risk. Returns (RET) are also negatively correlated with NCSKEW (−0.6480) and DUVOL (−0.6859), indicating that higher returns are linked to lower crash risk. SIGMA shows a weak positive correlation with NCSKEW (0.2091) and DUVOL (0.2134), while INF and INT have weaker, mostly insignificant correlations. Moreover, all VIFs are below 4, well below the threshold of 10, indicating that multicollinearity is not a concern in our dataset.

Once the empirical data has confirmed non-multicollinearity, this study analyses the panel data issue as cross-section dependence. The estimated results for this issue are provided in Table 4. From the results, Pesaran CD tests are applied with estimated *p*-values of <1% lead to rejecting the null hypothesis of no cross-sectional dependence. It means that there exists a cross-sectional dependence defect in most variables.

Since first-generation unit root tests have been strongly criticized for being inefficient and biased in the presence of cross-sectional dependence, this study performs the second-generation unit root test:

Table 3. Correlation matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) NCSKEW	1						
(2) DUVOL	0.9427*	1					
(3) SENT	−0.1809*	−0.2057*	1				
(4) RET	−0.6480*	−0.6859*	0.3153*	1			
(5) SIGMA	0.2091*	0.2134*	−0.2468*	−0.3090*	1		
(6) INF	0.0194	0.0208	0.0127	−0.0121	0.0108	1	
(7) INT	−0.0443*	−0.0417*	−0.0860*	−0.0034	0.0561*	0.2635*	1

Note: * shows a statistical significance level of 5%.
Mean VIF = 1.128 [1.128] when using NCSKEW [DUVOL] as the dependent variable.
Source: Authors.

Table 4. Cross-sectional dependence.

Variables	CD-test	*p*-Value
NSKEW	41.881***	0.000
DUVOL	42.49***	0.000
SENT	83.054***	0.000
RET	76.979***	0.000
SIGMA	89.085***	0.000
INF	21.793***	0.000
INT	71.584***	0.000

Note: ***shows a statistical significance level of 1%.
Source: Authors.

Table 5. Panel unit root test.

	Level		First difference	
Variables	Constant	Constant + Trend	Constant	Constant + Trend
NSKEW	−6.190***	−6.420***	−6.190***	−6.420***
DUVOL	−6.190***	−6.420***	−6.190***	−6.420***
SENT	−3.117***	−3.451***	−6.190***	−6.420***
RET	−6.190***	−6.420***	−6.190***	−6.420***
SIGMA	−6.111***	−6.378***	−6.190***	−6.420***
INF	−6.179***	−6.420***	−6.190***	−6.420***
INT	−2.032	−2.605	−5.963***	−6.155***

Notes: H_0 states that there is non-stationarity. ***shows a statistical significance level of 1%.
Source: Author.

the cross-sectional augmented Dickey-Fuller (CADF) test. The estimated outputs of the said test are given in Table 5. The results show that no variables hold units at the leveled data, but INT satisfies the null hypothesis of non-stationarity. Therefore, these variables are tested on the first difference, where all these variables become significant and thus the null proposition can be rejected. Hence, all the variables are found to be stationary, allowing this study to examine the long run co-integration relationship between the variables considered.

This study performs the panel co-integration test of Westerlund (2007). The estimated results of the said test are provided in Table 6. In Panels A and B, the Westerlund co-integration test results show that most statistics reject the null hypothesis. This implies the presence of co-integration. Therefore, this research can conclude that investor sentiment (SENT), stock market crash risk (NCSKEW or DUVOL), market return (RET), market volatility (SIGMA), inflation (INF), and interest rate (INT) share a long-run equilibrium.

4.2. Baseline results

Table 7 shows the outcomes of MMQR examining the effect of investor sentiment on crash risk in Asia-Pacific. In Panel A, the results of panel MMQR indicated that investor sentiment (SENT) relates to stock market crash risk (NCSKEW) positively in the lower middle to upper quantiles (Q60–Q90). Meanwhile, there is no evidence that there exists a relationship between investor sentiment (SENT) and stock market crash risk (DUVOL) in all quantiles of DUVOL in Panel B.

Overall, this study gives evidence of the significantly positive impact of investor sentiment on the stock market crash risk in the Asia-Pacific region. This finding contributes to understanding the behavior of noisy traders as described by De Long et al. (1990). These traders often build irrational expectations based on positive external information, leading to the overvaluation of stocks. Arbitrageurs frequently fix price errors; however, their efforts are impeded by regulatory restrictions, liquidity constraints, and substantial transaction costs. These obstacles diminish market efficiency, elevate volatility, and increase the likelihood of market crashes. These outcomes are completely consistent with the conclusions of Cui and Zhang (2020) and Zouaoui et al. (2011), but different from the findings of Kustina et al. (2024) who argue that investor sentiment reduces the probability of country index crash risk. Furthermore, investor sentiment positively influences stock market crash risk at the middle and higher quantiles (Q60–Q90), indicating that stock markets with elevated crash risk are significantly affected by investor sentiment.

Table 6. Westerlund co-integration test.

Statistics	Value	*Z*-value	*p*-Value
Panel A			
Gt	−13.551***	−45.774	0.000
Ga	−263.531***	−106.108	0.000
Pt	−59.597***	−48.654	0.000
Pa	−266.202***	−111.073	0.000
Panel B			
Gt	−14.570***	−50.203	0.000
Ga	−260.185***	−104.655	0.000
Pt	−60.082***	−49.140	0.000
Pa	−263.139***	−109.715	0.000

Notes: H_0 states that there is no co-integration. ***denotes significance at the level of 1%.
Source: Authors.

Table 7. The outcomes of MMQR.

	Lower quantile			Middle quantile			Higher quantile		
Variables	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Panel A: NCSKEW									
SENT	−0.0114	−0.00264	0.00340	0.00920	0.0142	0.0191**	0.0245***	0.0311***	0.0394***
	(0.0125)	(0.0106)	(0.00961)	(0.00899)	(0.00877)	(0.00888)	(0.00934)	(0.0103)	(0.0120)
RET	−10.07***	−10.33***	−10.51***	−10.69***	−10.84***	−10.98***	−11.14***	−11.34***	−11.59***
	(0.384)	(0.325)	(0.294)	(0.275)	(0.269)	(0.272)	(0.286)	(0.317)	(0.369)
SIGMA	−12.47***	−7.313**	−3.776	−0.379	2.567	5.442**	8.561***	12.46***	17.29***
	(3.830)	(3.231)	(2.927)	(2.741)	(2.673)	(2.705)	(2.849)	(3.150)	(3.673)
INF	4.703*	4.095*	3.679*	3.279*	2.933*	2.594	2.227	1.769	1.200
	(2.498)	(2.113)	(1.914)	(1.790)	(1.747)	(1.768)	(1.860)	(2.058)	(2.399)
INT	−3.393***	−2.672***	−2.178***	−1.703***	−1.292***	−0.890*	−0.455	0.0895	0.764
	(0.707)	(0.597)	(0.541)	(0.506)	(0.494)	(0.500)	(0.526)	(0.582)	(0.678)
Constant	−0.636***	−0.402***	−0.241***	−0.0860**	0.0480	0.179***	0.321***	0.498***	0.718***
	(0.0492)	(0.0409)	(0.0371)	(0.0350)	(0.0341)	(0.0344)	(0.0363)	(0.0400)	(0.0469)
Observations	3456	3456	3456	3456	3456	3456	3456	3456	3456
Panel B: DUVOL									
SENT	−0.00323	−0.000192	0.00195	0.00381	0.00549	0.00699	0.00870	0.0105	0.0132
	(0.0153)	(0.0127)	(0.0112)	(0.0102)	(0.00961)	(0.00946)	(0.00969)	(0.0104)	(0.0120)
RET	−12.78***	−12.90***	−12.99***	−13.07***	−13.14***	−13.20***	−13.27***	−13.35***	−13.46***
	(0.473)	(0.391)	(0.344)	(0.314)	(0.297)	(0.292)	(0.299)	(0.319)	(0.372)
SIGMA	−16.20***	−9.976***	−5.586	−1.776	1.673	4.750*	8.274***	11.92***	17.54***
	(4.670)	(3.857)	(3.399)	(3.095)	(2.928)	(2.881)	(2.952)	(3.155)	(3.678)
INF	3.486	3.487	3.487	3.488	3.488*	3.488*	3.489*	3.489	3.490
	(3.197)	(2.647)	(2.328)	(2.121)	(2.007)	(1.974)	(2.022)	(2.161)	(2.514)
INT	−3.844***	−2.975***	−2.362***	−1.830***	−1.349**	−0.919*	−0.427	0.0819	0.867
	(0.872)	(0.721)	(0.635)	(0.578)	(0.547)	(0.538)	(0.552)	(0.589)	(0.686)
Constant	−0.694***	−0.431***	−0.246***	−0.0849**	0.0607	0.191***	0.339***	0.493***	0.731***
	(0.0598)	(0.0489)	(0.0433)	(0.0395)	(0.0374)	(0.0367)	(0.0375)	(0.0401)	(0.0474)
Observations	3456	3456	3456	3456	3456	3456	3456	3456	3456

Notes: Standard errors are in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10%, respectively.
Source: Authors.

The findings highlight that the impact of investor sentiment varies with crash risk levels, particularly emphasizing that as crash risk increases, the influence of sentiment becomes more pronounced.

Regarding control variables, the market return (RET) shows a consistent negative correlation with stock market crash risk (NCSKEW or DUVOL) across all quantiles. This indicates that higher returns are associated with a lower risk of a market crash, emphasizing that strong market performance generally reduces crash risk. These findings align closely with the conclusions drawn by Zouaoui et al. (2011). However, it diverges from the findings of Cui and Zhang (2020), Fu et al. (2021), Shin and Choi (2022), and Wu et al. (2021), who suggest a positive relationship between returns and stock price crash risk. This difference can be attributed to these studies examining the impact of returns on crash risk at the firm level and using annual data frequencies, which can lead to differing outcomes. The outcomes also indicate that market volatility (SIGMA) has a negative and significant effect on crash risk in lower quantiles (Q10–Q20), indicating that during stable periods, higher volatility may reduce the likelihood of a crash, likely due to normal market adjustments. However, in higher quantiles (Q60–Q90), the relationship turns positive, meaning that in more volatile or stressed market conditions, rising volatility increases the probability of a crash. This suggests volatility can be stabilizing in calm markets but signals higher crash risk during turbulent times. These results are consistent with the conclusions of Fu et al. (2021), Shin

and Choi (2022), and Wu et al. (2021). In contrast, they differ from the findings of Zouaoui et al. (2011), who did not find evidence supporting the impact of market volatility on financial crisis forecasting models.

Concerning macroeconomic variables, inflation (INF) has a positive and significant effect on crash risk in the lower quantiles (Q10–Q50), suggesting that higher inflation increases the likelihood of a crash during stable market conditions. However, in the higher quantiles (Q60–Q90), this effect weakens and becomes insignificant, indicating that inflation plays a smaller role in influencing crash risk during more volatile periods. These findings support the conclusion of Moradi et al. (2021), who argue that inflation reduces individual purchasing power while increasing product costs, both of which significantly affect company sales. When real revenues decline, company managers may hesitate to disclose negative news about performance, fearing it could negatively affect investor perceptions and lead to stock price declines. Besides, the interest rate (INT) has a negative impact on stock market crash risk within the lower to middle quantiles (Q10–Q60), suggesting that higher interest rates decrease the likelihood of a crash during stable market conditions. This effect may reflect how tighter monetary policy can help limit excessive risk-taking and speculative behavior. This is consistent with the findings of Zouaoui et al. (2011), who explain that monetary authorities frequently lower interest rates to stabilize the economy and alleviate the adverse effects of market downturns.

4.3. Robustness check

4.3.1. Robustness to alternative methods

This subsection conducts robustness checks on the main findings of the research. Specifically, it employs fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) as alternative estimators. These methods are chosen for their ability to estimate long-run cointegrating relationships between variables, providing further validation and insights into the main results. The results are presented in Table 8.

As shown in Table 8, the effect of investor sentiment on crash risk differs significantly depending on the estimation method used. In Column 1 of Panel A (NCSKEW), FMOLS shows a positive and significant effect, suggesting that higher sentiment increases the likelihood of a crash in the long term. However, in Column 2, DOLS reveals an insignificant negative effect, indicating a weaker or even opposite relationship in the short term. Similarly, in Panel B (DUVOL), Column 3 using FMOLS indicates a weakly positive and significant impact on investor sentiment, while Column 4 with DOLS shows a significant negative effect, implying that sentiment might reduce crash risk over shorter periods. These results suggest that the impact of investor sentiment on crash risk varies depending on the estimation method used. This highlights the importance of using multiple estimation methods to fully understand how sentiment influences crash risk in both the short and long term.

The inconsistencies between FMOLS, DOLS, and MMQR arise because FMOLS and DOLS focus on long-term averages and short-term dynamics, respectively, while MMQR captures effects across the

Table 8. Robustness tests.

	Panel A: NCSKEW		Panel B: DUVOL	
	(1)	(2)	(3)	(4)
Variables	FMOLS	DOLS	FMOLS	DOLS
SENT	0.0257***	−0.0146	0.0168*	−0.0250**
	(0.00882)	(0.00948)	(0.00968)	(0.0105)
RET	−10.15***	−3.849***	−12.37***	−5.799***
	(0.245)	(0.555)	(0.270)	(0.616)
SIGMA	4.953**	5.480**	4.307*	5.334*
	(2.213)	(2.566)	(2.431)	(2.845)
INF	1.786	0.908	2.743	2.167
	(1.658)	(2.342)	(1.822)	(2.597)
INT	−1.449***	−1.542***	−1.610***	−1.746***
	(0.351)	(0.361)	(0.385)	(0.400)
Constant	0.0295	0.000673	0.00384	−0.0307
	(0.0298)	(0.0324)	(0.0328)	(0.0359)

Notes: Standard errors are in parentheses. ***, **, and * denote statistical significance at 1, 5, and 10%, respectively.
Source: Authors.

entire distribution of crash risk. FMOLS estimates long-run relationships, and DOLS accounts for short-term variations but lacks sensitivity to different risk levels. In contrast, MMQR reveals that investor sentiment significantly impacts crash risk primarily in higher quantiles (Q70–Q90), indicating a stronger effect during extreme market conditions, which FMOLS and DOLS do not capture. Additionally, MMQR shows that market volatility stabilizes crash risk in lower quantiles but increases it in higher quantiles, highlighting nuances missed by FMOLS and DOLS. Despite these variations, market return and inflation show a more stable relationship with crash risk across different methodologies, likely due to their consistent behavior across time horizons and quantiles. The inconsistencies are primarily due to sentiment analysis of market conditions, while other variables show a more uniform effect. Overall, MMQR excels in revealing how factors like sentiment or volatility affect crash risk across various market conditions, including extreme states, by analyzing the entire distribution of risk. This provides deeper insights into risk behavior than FMOLS and DOLS, which focus on average or long-term trends and may overlook critical variations.

4.3.2. Panel causality test results

This study further examines the causal relationship between stock market crash risk and its selected determinants, exploiting the causal experiment of Dumitrescu and Hurlin (2012); the results are shown in Supplementary Appendix 5. The findings indicate that SENT has a significant causal impact on NCSKEW, with a Z-bar statistic of 3.390 and a p-value of 0.001, suggesting that changes in SENT drive changes in NCSKEW. Conversely, NCSKEW does not significantly influence SENT (Z-bar $= -0.715$, $p = 0.475$). Additionally, NCSKEW significantly affects SIGMA, INF, and INT, and these variables also have a significant impact on NCSKEW. Regarding DUVOL, the results show a marginally significant causality from SENT to DUVOL (Z-bar $= 1.688$, $p = 0.091$), indicating a potential influence, though it is not robust. DUVOL significantly influences RET, SIGMA, INF, and INT, highlighting its substantial role in driving changes in these variables. Overall, while SENT exerts a clear influence on NCSKEW, the causality involving DUVOL is less pronounced, reflecting varied dynamics across different financial metrics.

5. Further analysis

5.1. Regional, local sentiment, and stock market crash risk

In this part, we split the total sentiment indicator into regional and local indices and discover their influence on stock market crash risk.

The results from Table A6.1 (Supplementary Appendix 6) reveal that regional sentiment has a significantly positive impact on stock market crash risk across various quantiles, particularly at higher quantiles. This suggests that regional sentiment plays a crucial role in increasing the likelihood of stock market crashes, especially under extreme market conditions. These findings align with Baker et al. (2012), who assert that regional sentiment has a more substantial impact on stock markets compared to local sentiment. Moreover, the positive and significant coefficients for regional sentiment across different quantiles underscore its consistent influence on crash risk, with the effect intensifying at higher quantiles. However, this contrasts with Vuong and Suzuki (2020), who argue that the effect of regional sentiment is relatively minor and does not significantly impact Asia-Pacific markets.

Besides, Table A6.2 (Supplementary Appendix 6) indicates that local sentiment generally has a negative and decreasing impact on stock market crash risk, with significant negative effects observed in lower to middle quantiles. This suggests that local sentiment can reduce crash risk, particularly during less extreme market conditions. This finding is supported by Jang and Kang (2019) who propose that sentiment-driven arbitrageurs can correct mispriced equities, thereby reducing the likelihood of stock price crashes. Similarly, Jiang and Zhu (2023) highlight the role of rational arbitrageurs in stabilizing the market by capitalizing on mispricing and restoring equilibrium. The significant difference between regional and local sentiment may stem from the broader, more uniform nature of regional sentiment, which captures a wider economic and market perspective. In contrast, local sentiment tends to be more volatile and less impactful on a larger scale. Therefore, while regional sentiment reflects global economic

conditions and broader investor behavior, local sentiment appears to have a more contained and less consistent influence on stock market stability.

5.2. Investor sentiment in developed, emerging, and frontier markets

Investors across various markets, particularly those in different market categories (developed, emerging, or frontier), may allocate misperceptions differently due to cultural aspects, market integrity, intelligence, and education. These factors can significantly influence investor behavior (Chui et al., 2010; Zouaoui et al., 2011). Consequently, this study investigates the relationship between investor sentiment and crash risk in 16 Asia-Pacific stock markets. The analysis includes five developed markets (Australia, New Zealand, Japan, Singapore, and Hong Kong), eight emerging markets (China, India, Korea, Taiwan, Indonesia, Malaysia, Philippines, and Thailand), and three frontier markets (Pakistan, Sri Lanka, and Vietnam). Supplementary Appendix 7 shows the results of MMQR with sub-samples of these three market types.

In terms of developed markets, the MMQR results in Table A7.1 (Supplementary Appendix 7) demonstrate the dual effects of investor sentiment on stock market crash risk, depending on the level of crash risk. At the lowest quantiles (Q10–Q20) of crash risk, investor sentiment has a negative and significant impact, indicating that in these lower-risk states, positive sentiment tends to mitigate the risk of a crash. It demonstrates a stabilizing effect of investor sentiment in developed markets, where high investor sentiment can foster positive market behaviors and confidence, thereby reducing the perceived risk of crashes. This finding is consistent with Kustina et al. (2024) that investor sentiment stabilizes markets and lessens the likelihood of market crashes. This can be attributed to the stability of developed markets, such as Australia, New Zealand, Japan, Singapore, and Hong Kong, where transparency and robust financial systems lead to more cautious investment decisions. Additionally, advanced market institutions enhance information flow, making stock markets more efficient and reducing the influence of investor sentiment (Zouaoui et al., 2011).

Conversely, at higher quantiles (Q70–Q90) of crash risk, the effect of sentiment turns positive and statistically significant, with the strongest impact observed at Q90, implying that in more extreme market states, higher investor sentiment is associated with an increased risk of market crashes. In markets with advanced financial systems, high liquidity, and significant institutional participation, investor sentiment significantly impacts market dynamics. Developed markets, in particular, can be affected when investors become overly confident about ongoing market growth. Akarsu and Süer (2022) show that this overconfidence can lead to abnormal returns, as investor sentiment often results in overreactions and price deviations from fundamentals (Peng & Xiong, 2006). As a result, during extreme market conditions—whether driven by excessive optimism, which creates speculative bubbles, or excessive pessimism, which deepens downturns—investor sentiment has a stronger impact, raising the likelihood of a crash. Interestingly, at middle quantiles (Q30–Q50), investor sentiment does not significantly affect crash risk, suggesting that during moderate risk phases, when market conditions are balanced, sentiment has little impact on altering the likelihood of a crash.

About emerging markets, Table A7.2 (Supplementary Appendix 7) shows that the impact of sentiment becomes statistically significant starting at the middle quantile (Q50) and increases in magnitude at higher quantiles, grows stronger at higher quantiles, indicating its importance in both moderate and extreme market scenarios. This pattern suggests that positive investor sentiment is associated with increased crash risk, especially during extreme market conditions. Similar findings have been observed in emerging markets in the Asia-Pacific region, with studies by Shin and Choi (2022) in the Korean stock market and by Fan et al. (2021), Fu et al. (2021), Wu et al. (2021), and Zhang et al. (2023) in the Chinese stock market.

Compared to developed markets, emerging markets exhibit greater sensitivity to investor sentiment. This is evident as investor sentiment amplifies crash risk at medium to upper quantiles (Q50–Q90) in emerging markets, while in developed markets, this effect is observed primarily at higher quantiles (Q70–Q90). Zouaoui et al. (2011) emphasize that investor sentiment is particularly significant in countries with higher herd-like behavior and lower market integrity. The heightened sensitivity in emerging markets can be attributed to their higher volatility, lower liquidity, and weaker regulation, which cause

investor behavior to react more strongly to news and events, leading to more pronounced fluctuations even during moderate or extreme risk phases. Furthermore, Choi and Yoon (2020) reveal that investor sentiment is significantly shaped by herding behavior during market downturns or extreme conditions, with this herding effect being most pronounced in emerging markets. This trend for investors to follow the crowd during panic market periods exacerbates sentiment-driven fluctuations, making emerging markets particularly susceptible to these fluctuations.

As regards frontier markets, Table A7.3 (Supplementary Appendix 7) reveals a significantly negative relationship between investor sentiment and stock market crash risk in the higher quantiles (Q60 to Q90). This indicates that, as sentiment increases, the likelihood of a market crash decreases, particularly in scenarios where crash risk is higher. This finding is particularly insightful for frontier markets, which are characterized by less developed market structures and higher volatility. In these markets, investor sentiment plays an important role in influencing market dynamics, with declines in sentiment significantly increasing the probability of market crashes. Speidell (2009) highlights that individual investors represent a substantial portion of transactions in frontier markets. These investors often favor low-priced stocks, viewing the quantity of shares they can acquire as a measure of value. Additionally, they typically have a higher risk appetite compared to investors in developed markets (Statman, 2008). Their propensity for speculative behavior, or 'gambler's' mindset, significantly impacts market stability. During periods of high sentiment, these investors are less likely to exit the market despite apparent risks. Instead, their willingness to embrace higher risks for the potential of greater rewards contributes to market stability and mitigates the risk of crashes. This behavior is particularly relevant at higher quantiles of crash risk (Q70–Q90), where the increased optimism and speculative tendencies among investors help buffer against severe market declines, thus reducing the likelihood of a crash.

6. Conclusions and implications

By analysing panel data of 16 stock markets in the Asia-Pacific region through the Method of Moments Quantile Regression (MMQR) approach, this study shows a positive effect of investor sentiment on crash risk at the middle-higher quantiles (Q60–Q90). It also shows that the magnitude and direction of the impact of investor sentiment on crash risk is heterogeneous across levels of market development. To the best of the authors' knowledge, this is the first quantitative study on the influence of investor sentiment on the quantiles of crash risk in stock markets, and therefore this research potentially has important theoretical and practical contributions.

In terms of theory, this paper provides support for behavioral theories by giving evidence of a positive effect of investor sentiment on the middle and higher quantiles of stock market crash risk in the Asia-Pacific region. It clarifies the intricate relationship between sentiment and market stability, offering insights into how sentiment influences crash risk differently across developed, emerging, and frontier markets. The findings reveal a positive relationship between investor sentiment and crash risk in higher quantiles for developed and emerging markets, while a negative relationship is observed in frontier markets. Additionally, the investigation of global and local sentiment effects highlights that regional sentiment significantly increases crash risk, particularly in extreme market conditions, while local sentiment generally reduces crash risk in less severe markets. Furthermore, the study constructs investor sentiment indexes using Principal Component Analysis (PCA).

As regards practical aspects, the results of this study have implications for global investors, portfolio managers, and policymakers. For global investors, portfolio managers, and policymakers, adapting strategies to the distinct characteristics of developed, emerging, and frontier markets is crucial for mitigating risks and optimizing returns. In developed markets, where market efficiency and regulatory frameworks are more robust, investors should focus on dynamic risk management techniques and incorporate investor sentiment metrics to predict potential market downturns. For emerging markets, which often experience higher volatility and rapid economic changes, portfolio managers should emphasize diversification and stay attuned to regional sentiment shifts, as these can significantly impact market stability. In frontier markets, characterized by their nascent financial systems and higher risk profiles, investors should prioritize thorough local market research and consider the effects of both global and local sentiment on market movements. Policymakers across all market types should enhance transparency,

strengthen financial regulations, and promote investor education to foster market resilience and stability. Tailoring strategies to the specific attributes and risks of each market segment will help in better managing investment risks and achieving more favorable financial outcomes.

However, the study has certain limitations. The first stems from not considering the influence of investor sentiment on stock market crash risk while experiencing different states of sentiment (i.e. optimistic/pessimistic). The second concern is that many other determinants affect stock market crash risk but have not been considered in the model. Finally, there is a discrepancy between the number of observations between market groups, which reduces credibility. These gaps are expected to be filled in future studies.

Author contributions

Methodology: An Tuan Nguyen and Nhung Thi Nguyen; software, An Tuan Nguyen; validation, An Tuan Nguyen and Nhung Thi Nguyen; data curation, An Tuan Nguyen; writing-original draft, An Tuan Nguyen and Nhung Thi Nguyen; writing-review and editing, Nhung Thi Nguyen; visualization, An Tuan Nguyen; supervision, Nhung Thi Nguyen.

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Data availability statement

The data can be made available upon request.

References

Aboody, D., Even-Tov, O., Lehavy, R., & Trueman, B. (2018). Overnight returns and firm-specific investor sentiment. *Journal of Financial and Quantitative Analysis*, *53*(2), 485–505. https://doi.org/10.1017/S0022109017000989

Akarsu, S., & Süer, Ö. (2022). How investor attention affects stock returns? Some international evidence. *Borsa Istanbul Review*, *22*(3), 616–626. https://doi.org/10.1016/j.bir.2021.09.001

Alnafea, M., & Chebbi, K. (2022). Does investor sentiment influence stock price crash risk? Evidence from Saudi Arabia. *The Journal of Asian Finance, Economics and Business*, *9*(1), 143–152.

An, Z., Chen, Z., Li, D., & Xing, L. (2018). Individualism and stock price crash risk. *Journal of International Business Studies*, *49*(9), 1208–1236. https://doi.org/10.1057/s41267-018-0150-z

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics*, *104*(2), 272–287. https://doi.org/10.1016/j.jfineco.2011.11.002

Bashir, U., Kayani, U. N., Khan, S., Polat, A., Hussain, M., & Aysan, A. F. (2024). Investor sentiment and stock price crash risk: The mediating role of analyst herding. *Computers in Human Behavior Reports*, *13*, 100371. https://doi.org/10.1016/j.chbr.2024.100371

Blajer-Gołębiewska, A., Wach, D., & Kos, M. (2018). Financial risk information avoidance. *Economic Research*, *31*(1), 521–536. https://doi.org/10.1080/1331677X.2018.1439396

Campbell, J. Y., & Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics*, *31*(3), 281–318. https://doi.org/10.1016/0304-405X(92)90037-X

Cao, H. H., Coval, J. D., & Hirshleifer, D. (2002). Sidelined investors, trading-generated news, and security returns. *Review of Financial Studies*, *15*(2), 615–648. https://doi.org/10.1093/rfs/15.2.615

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*(3), 345–381. https://doi.org/10.1016/S0304-405X(01)00066-6

Choi, K. H., & Yoon, S. M. (2020). Investor sentiment and herding behavior in the Korean stock market. *International Journal of Financial Studies*, *8*(2), 34. https://doi.org/10.3390/ijfs8020034

Chui, A. C., Titman, S., & Wei, K. J. (2010). Individualism and momentum around the world. *The Journal of Finance*, *65*(1), 361–392. https://doi.org/10.1111/j.1540-6261.2009.01532.x

Cui, H., & Zhang, Y. (2020). Does investor sentiment affect stock price crash risk? *Applied Economics Letters*, *27*(7), 564–568. https://doi.org/10.1080/13504851.2019.1643448

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy*, *98*(4), 703–738. https://doi.org/10.1086/261703

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, *29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

Fama, E. F. (1970). Efficient capital markets. *Journal of Finance*, *25*(2), 383–417.

Fan, Y., Zhou, F., An, Y., & Yang, J. (2021). Investor sentiment and stock price crash risk: Evidence from China. *Global Economic Review*, *50*(4), 310–339. https://doi.org/10.1080/1226508X.2021.1947340

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, *19*(1), 3–29. https://doi.org/10.1016/0304-405X(87)90026-2

Fu, J., Wu, X., Liu, Y., & Chen, R. (2021). Firm-specific investor sentiment and stock price crash risk. *Finance Research Letters*, *38*, 101442. https://doi.org/10.1016/j.frl.2020.101442

Fu, J., Zhou, Q., Liu, Y., & Wu, X. (2020). Predicting stock market crises using daily stock market valuation and investor sentiment indicators. *The North American Journal of Economics and Finance*, *51*, 100905. https://doi.org/10.1016/j.najef.2019.01.002

Habib, A., Hasan, M. M., & Jiang, H. (2018). Stock price crash risk: review of the empirical literature. *Accounting & Finance*, *58*(S1), 211–251. https://doi.org/10.1111/acfi.12278

Hong, H., & Stein, J. C. (2003). Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies*, *16*(2), 487–525. https://doi.org/10.1093/rfs/hhg006

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics*, *94*(1), 67–86. https://doi.org/10.1016/j.jfineco.2008.10.003

Jang, J., & Kang, J. (2019). Probability of price crashes, rational speculative bubbles, and the cross-section of stock returns. *Journal of Financial Economics*, *132*(1), 222–247. https://doi.org/10.1016/j.jfineco.2018.10.005

Jiang, M., & Zhu, B. (2023). The nonlinear relationship between investor sentiment and stock crash risk under the regime of EPU-evidence from China's individual stock and market. Available at SSRN 4439527.

Kao, C., & Chiang, M. H. (2001). On the estimation and inference of a cointegrated regression in panel data. In *Nonstationary panels, panel cointegration, and dynamic panels* (pp. 179–222). Emerald Group Publishing Limited.

Kim, Y., Li, H., & Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, *43*, 1–13. https://doi.org/10.1016/j.jbankfin.2014.02.013

Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research*, *47*(1), 241–276. https://doi.org/10.1111/j.1475-679X.2008.00318.x

Kustina, L., Sudarsono, R., & Effendi, N. (2024). Does foreign portfolio investment moderate the impact of exchange rate volatility and investor sentiment on country index crash risk? *Cogent Economics & Finance*, *12*(1), 2305481. https://doi.org/10.1080/23322039.2024.2305481

Liu, Z., Huynh, T. L. D., & Dai, P. F. (2021). The impact of COVID-19 on the stock market crash risk in China. *Research in International Business and Finance*, *57*, 101419. https://doi.org/10.1016/j.ribaf.2021.101419

Lucey, B. M., & Dowling, M. (2005). The role of feelings in investor decision-making. *Journal of Economic Surveys*, *19*(2), 211–237. https://doi.org/10.1111/j.0950-0804.2005.00245.x

Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, *213*(1), 145–173. https://doi.org/10.1016/j.jeconom.2019.04.009

Mishkin, F. S., & White, E. N. (2002). *US stock market crashes and their aftermath: Implications for monetary policy* (NBER Working Paper 8992). https://doi.org/10.7551/mitpress/1459.003.0011

Moradi, M., Appolloni, A., Zimon, G., Tarighi, H., & Kamali, M. (2021). Macroeconomic factors and stock price crash risk: Do managers withhold bad news in the crisis-ridden Iran market? *Sustainability*, *13*(7), 3688. https://doi.org/10.3390/su13073688

Patel, S. A., & Sarkar, A. (1998). Crises in developed and emerging stock markets. *Financial Analysts Journal*, *54*(6), 50–61. https://doi.org/10.2469/faj.v54.n6.2225

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics*, *80*(3), 563–602. https://doi.org/10.1016/j.jfineco.2005.05.003

Phillips, P. C., & Hansen, B. E. (1990). Statistical inference in instrumental variables regression with I (1) processes. *The Review of Economic Studies*, *57*(1), 99–125. https://doi.org/10.2307/2297545

Ross, S. A. (1973). The economic theory of agency: The principal's problem. *The American Economic Review*, *63*(2), 134–139.

Shin, H., & Choi, S. Y. (2022). Firm-specific investor sentiment and stock price crash risk: The role of foreign investors in Korea's stock market. *Investment Management and Financial Innovations*, *19*(4), 309–326. https://doi.org/10.21511/imfi.19(4).2022.25

Speidell, L. S. (2009). Investing in the unknown and the unknowable—Behavioral finance in frontier markets. *Journal of Behavioral Finance*, *10*(1), 1–8. https://doi.org/10.1080/15427560902719323

Statman, M. (2008). Countries and culture in behavioral finance. *CFA Institute Conference Proceedings Quarterly*, *25*(3), 38–44. https://doi.org/10.2469/cp.v25.n3.6

Vo, X. V. (2020). Foreign investors and stock price crash risk: Evidence from Vietnam. *International Review of Finance*, *20*(4), 993–1004. https://doi.org/10.1111/irfi.12248

Vuong, N. B., & Suzuki, Y. (2020). Impact of financial development on sentiment-return relationship: Insight from Asia-Pacific markets. *Borsa Istanbul Review*, *20*(2), 95–107. https://doi.org/10.1016/j.bir.2020.01.003

Wang, J., Meric, G., Liu, Z., & Meric, I. (2009). Stock market crashes, firm characteristics, and stock returns. *Journal of Banking & Finance*, *33*(9), 1563–1574. https://doi.org/10.1016/j.jbankfin.2009.03.002

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, *69*(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Wu, B., Cai, Y., & Zhang, M. (2021). Investor sentiment and stock price crash risk in the Chinese stock market. *Journal of Mathematics*, *2021*, 1–10. https://doi.org/10.1155/2021/6806304

Yang, C., & Gao, B. (2014). The term structure of sentiment effect in stock index futures market. *The North American Journal of Economics and Finance*, *30*, 171–182. https://doi.org/10.1016/j.najef.2014.09.001

Yin, Y., & Tian, R. (2017). Investor sentiment, financial report quality and stock price crash risk: Role of short-sales constraints. *Emerging Markets Finance and Trade*, *53*(3), 493–510. https://doi.org/10.1080/1540496X.2015.1093844

Zhang, P., Gao, J., Zhang, Y., & Wang, T. W. (2021). Dynamic spillover effects between the US stock volatility and China's stock market crash risk: a TVP-VAR approach. *Mathematical Problems in Engineering*, *2021*, 1–12. https://doi.org/10.1155/2021/6616577

Zhang, R., Xian, X., & Fang, H. (2019). The early-warning system of stock market crises with investor sentiment: Evidence from China. *International Journal of Finance & Economics*, *24*(1), 361–369. https://doi.org/10.1002/ijfe.1667

Zhang, Z., Chen, R., & Luo, Q. (2023). Firm-specific investor sentiment, stock price synchronicity, and crash risk. *Applied Economics Letters*, *30*(4), 450–455. https://doi.org/10.1080/13504851.2021.1991562

Zhou, G. (2018). Measuring investor sentiment. *Annual Review of Financial Economics*, *10*(1), 239–259. https://doi.org/10.1146/annurev-financial-110217-022725

Zhou, L., Chen, D., & Huang, J. (2023). Stock-level sentiment contagion and the cross-section of stock returns. *The North American Journal of Economics and Finance*, *68*, 101966. https://doi.org/10.1016/j.najef.2023.101966

Zhou, W., Zhong, G. Y., & Li, J. C. (2022). Stability of financial market driven by information delay and liquidity in delay agent-based model. *Physica A: Statistical Mechanics and Its Applications*, *600*, 127526. https://doi.org/10.1016/j.physa.2022.127526

Zouaoui, M., Nouyrigat, G., & Beer, F. (2011). How does investor sentiment affect stock market crises? Evidence from panel data. *Financial Review*, *46*(4), 723–747. https://doi.org/10.1111/j.1540-6288.2011.00318.x