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Article

From fear to recovery: Investor sentiment, macroeconomic shocks, and tourism stock volatility in China

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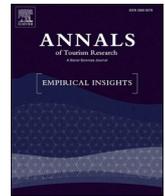


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From fear to recovery: Investor sentiment, macroeconomic shocks, and tourism stock volatility in China

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ABSTRACT

This research investigates the impact of investor sentiment and macroeconomic shocks on the volatility of China's tourism stocks during the COVID-19 recovery period, specifically from March 2020 to December 2022. By analyzing daily data from 20 publicly listed tourism companies using GARCH family models, the study distinguishes between a Crisis Phase (from March 2020 to February 2022) and a Recovery Phase (from March to December 2022). The findings indicate that during the Crisis Phase, investor sentiment and anxiety related to the pandemic heightened volatility, resulting in a 6.2 % contraction in tourism GDP. After March 2022, the impact of pandemic-related fears began to diminish. The analysis also reveals bidirectional volatility spillovers among different tourism subsectors, indicating that market sentiment plays a significant role in contributing to this volatility. The study highlights the importance of investor education and institutional reforms in mitigating herd behavior and stabilizing a key sector of China's economy.

1. Introduction

The post-pandemic era has profoundly reshaped the tourism industry, a sector uniquely vulnerable to external shocks due to its reliance on discretionary spending and mobility. Psychological factors, such as market fear and investor sentiment, play a significant role in shaping economic outcomes, as evidenced by their impact on stock market volatility during crises (Wang et al., 2022). For instance, Yahya (2022) reported how shifts between bullish and bearish market trends are deeply connected with investor psychology. Sorić (2021) emphasizes that its impacts were uneven across sectors. Tourism, as a luxury-driven industry, proved exceptionally sensitive: the pandemic triggered a 6.2 % contraction in China's tourism GDP within the first quarter of 2020 alone, decimating revenues and destabilizing the sector (Seraphin, 2021).

A critical unresolved challenge in China's tourism stock market is the amplification of volatility due to irrational investor behavior and pandemic-driven fear, particularly during the post-pandemic economic resumption phase (March 2020 to December 2022). While prior studies (e.g., Peng et al., 2023; Zargar & Kumar, 2023) have examined the

impact of sentiment during the pandemic, they overlook the evolving role of investor psychology and macroeconomic factors during the recovery period. This gap limits policymakers' ability to devise strategies for stabilizing China's tourism stocks, which contribute 11.3 % to GDP and are dominated by inexperienced retail investors prone to herd mentality.

Addressing this gap is critical because China's tourism industry lost 6.2 % of its GDP in early 2020, with volatility persisting even after borders reopened in 2022. Unlike studies focusing on pre-pandemic or peak-pandemic periods (e.g., Bouteska et al., 2022; Kumari & Mahakud, 2016), this work examines how sentiment-driven noise trading and fading pandemic fear shape volatility during recovery. The findings directly inform strategies to stabilize a sector critical to China's economy, where 38.5 million retail investors dominate the trading market.

While prior studies link COVID-19 to heightened stock volatility (Ullah et al., 2024) and identify stabilizing policy effects (Bakry et al., 2022), few examine how investor sentiment and macro-economic factors interact during post-pandemic recovery, particularly in China's tourism sector, dominated by retail investors (Peng et al., 2023; Zargar & Kumar, 2023). Prominent studies have assessed the influence of

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investor sentiment on stock price volatility prior to the pandemic (Kumari & Mahakud, 2016), while Bouteska et al. (2022) investigated the period from pre- to post-pandemic. Recently, Xie et al. (2023) highlighted that noisy behavior is noteworthy in the deviation of the stock's intrinsic value.

Hence, this study aims to quantify the impact of individual and market-level investor sentiment, as well as macroeconomic shocks, on tourism stock volatility during China's post-pandemic recovery. First, this article segments the analysis into two critical phases: (a) the COVID-19 crisis (March 2020 to February 2022) and (b) the economic resumption period (March to December 2022), to identify shifts in volatility drivers as pandemic fears subside. Second, the study develops a novel Fear Index (FI) and PCA-based sentiment indices to disentangle pandemic-specific anxiety from broader behavioral influences. Finally, this study examines volatility spillovers across tourism sectors (Travel & Transport, Hotels, and Scenic Spots) using univariate and multivariate GARCH models, providing actionable insights into how sectoral interdependencies amplify or mitigate risk.

This study advances existing research through four key innovations. First, while prior work often treats the post-pandemic period as a single phase, this study divides it into two distinct eras: (1) the "Coronanic" crisis phase (March 2020–February 2022), marked by the WHO's pandemic declaration, and (2) the economic resumption phase (March to December 2022), initiated by China's border reopening. This phased approach reveals how the drivers of volatility shifted as pandemic fears subsided. Second, the article deepens the understanding of retail investor behavior. Earlier studies (e.g., Peng et al., 2023; Wang et al., 2020) have highlighted that China's tourism stocks are prone to a herd mentality. This study builds on this by developing PCA-based sentiment indices that integrate emojis, emoticons, and social media data from platforms like XUEQIU, providing an unfiltered view of how individual and market sentiments contribute to volatility. Third, it introduces a novel Fear Index (FI) tailored to the impact of COVID-19 on tourism, extending methodologies from Salisu and Akanni (2020). This index quantifies pandemic-specific anxiety using variables such as daily cases and mortality rates, thereby disentangling health crises from broader market sentiment. Finally, it adopts Vo et al.'s (2022) framework to model volatility dynamics, employing asymmetric GARCH models. Combining univariate and multivariate GARCH analyses uncovers bidirectional spillovers and dynamic correlations across tourism sub-sectors (Travel, Hotels, Scenic Spots), providing policymakers with actionable insights to mitigate systemic risks.

2. Literature review

2.1. COVID-19 pandemic and the tourism market

The World Travel and Tourism Corporation (WTTC) reported that the pandemic caused a \$2.1 trillion decrease in global tourism GDP in 2020, while China's GDP dropped from 6.2 % to 2.2 % (Mensi et al., 2023). The COVID-19 pandemic triggered an unprecedented collapse in global tourism demand, with international tourist arrivals declining by 74 % in 2020 (Sharma & Nicolau, 2020). Travel restrictions, lockdowns, and health-related anxiety devastated global trends, as tourism revenue losses exceeded \$2.1 trillion worldwide. The crisis exposed structural vulnerabilities in tourism sectors, such as over-reliance on discretionary spending and sensitivity to exogenous shocks (Assaf & Scuderi, 2020).

China's tourism industry faced unique challenges due to its dual role as a global tourism hub and a frontline COVID-19 containment zone. While strict lockdowns initially curbed outbreaks, they also disrupted domestic travel and investor confidence. Despite a gradual recovery following 2021, driven by China's border reopening and events such as the Beijing Winter Olympics, volatility persisted due to recurring pandemic waves and shifting consumer behavior (Assaf & Scuderi, 2020). These dynamics underscore the need to examine how pandemic-induced disruptions interact with investor psychology to

amplify the volatility of tourism stocks.

2.2. Investor sentiment

The efficient market hypothesis (EMH) suggests that stock prices always reflect all available market information perfectly. The Dutch tulip and internet bubbles demonstrate that investor behavior may not always be consistent (Okorie & Lin, 2021). Sun et al. (2021) employed the event study approach and demonstrated that investor sentiment during the pandemic led to market anomalies. Cheema and Fianto (2024) stated that rational investors sell stock when prices deviate from the intrinsic value, while noise traders contradict EMH. Investor sentiment can be categorized into limited rationality, efficiency, emotions, and cognitive biases, which influence expectations. During the outbreak, the use of TVP-VAR revealed that postponing trading activities had a significant impact on the tourism industry (Hu, Shao, et al., 2021). Yeh (2021) employed the TGARCH model and reported that tourism declined significantly once governments imposed strict measures on travel and leisure activities during the outbreak.

Further, Carter et al. (2022) suggested that during the outbreak, cash reserves and corporate actions have played an essential role in the US travel and tourism industry. Few studies reveal that behavioral finance was more sensitive amid the outbreak in the tourism industry (Wu, Cai, & Zhang, 2021; Zheng & Osmer, 2021). The famous PCA method was employed to develop a sentiment index, and a multivariate DCC-GARCH model was utilized to investigate the sentiment volatility spillover effect and dynamic conditional correlation across markets (Mundra & Bicchall, 2021). Additionally, this study applied a univariate GARCH model to examine the conditional variance during the pessimistic and optimistic periods, and their finding demonstrates that any change in sentiment amplifies stock market volatility (Chen & Haga, 2021).

2.3. PCA and machine learning-based sentiment indices

Two standard techniques have been used for sentiment index: (a) machine learning (ML) and (b) the market proxy base called the indirect method. The PCA technique is used to reduce data dimensionality by amalgamating interconnected variables into a single index. These notable studies employed PCA on market proxies and developed sentiment indexes (Peng et al., 2023; Zhang et al., 2021). Dash and Maitra (2022) reported that sentiment has a negative influence on volatility during the outbreak. In contrast, the machine learning approach has also made a substantial contribution; for instance, Das et al. (2019) noted that emojis and emoticons are graphical languages that effectively convey individual emotions. In the domain of behavioral finance (📊), which is known as greed, similarly, jet✈️ with speaker 🗣️ denotes boosting up stock, and insect 🐛 with red apple 🍏 indicates negative sentiment toward stock price. CSI-300 has over 90 % of retail, young, and inexperienced individual investors. Several notable studies have argued that ignoring the role of emojis and emoticons in sentiment research is unjustifiable, as they effectively convey individuals' emotions (Liu et al., 2020). China has various social media groups, such as WeChat and Weibo (like Facebook and Twitter). Generally specialized in financial news, XUEQIU, referred to as the "Chinese stock Twitter," focuses primarily on financial professionals and provides information related to stock trading, market trends, and investment strategies. It was introduced in 2010, and its top three articles garnered the highest readership, with a count of 16.341 million users in 2018, now surpassing 20.7 million. Famous studies conducted on emojis and emoticons, along with microblogs on Xueqiu, have found that they effectively authenticate the expression of individual investor emotions (Wu et al., 2022; Zhang et al., 2021). XUEQIU offers a realistic overview of individual investors in the stock market.

2.4. Macro factors' impact during the outbreak

Recent studies suggest that during the pandemic, macroeconomic factors amplified stock market volatility and diminished stock returns (El Khoury et al., 2023; Li et al., 2021). Conversely, Anderson (2022) uses TVP-VAR and contends that COVID-19 should no longer be blamed for stock market volatility. Qin et al. (2021) reported that other factors also affect stock volatility, such as oil prices and the impact of economic policy; however, the effect varies across different sectors, including tourism. In their famous study, Feng et al. (2022) employed the continuous wavelet coherence (CWC) approach and indicated that EPU has a significant impact, while oil prices have a partial impact on China's travel and leisure industry. Similarly, Song et al. (2022) assessed the intensity of macroeconomic factors in the tourism sector in China. They found that amid the pandemic, the real exchange rate has been negative, and the oil price has had no effect in the short run. Vo et al. (2022) analyzed the post-pandemic stock market volatility, and they segmented the period from the WHO pandemic declaration to December 2020 and the calm period from January 2021 to January 2022. The variables are categorized into two groups: variables of interest (EPU, daily new COVID-19 cases, and daily newly vaccinated people) and control variables (oil price and gold price). Univariate GARCH family models are employed. Their finding indicate that control measures have reduced market volatility, and the COVID-19 impact on volatility faded with time. The above analyses demonstrate that COVID-19 has had a significant impact on various aspects of the economy.

If a retail investor sells the current one and quickly wants to buy another, it signifies overconfidence, which leads the market toward frequent trading (Peng et al., 2023). Therefore, this study proposes four research hypotheses to test the behavioral finance theory on the sentiment index that could influence China's tourism industry.

H1. News sentiment has a greater impact on the volatility of Chinese tourism stocks than market sentiment does.

H2. Stocks in the tourism industry are particularly sensitive to changes in the COVID-19-related Fear Index.

H3. Domestic and international shocks have a significant impact on the tourism industry.

H4. The volatility spillover effect is present across various sectors during the post-pandemic period.

To this end, it is observed that the financial markets are sensitive to crises. Tourism is a luxury and entertainment business and is mostly studied from a qualitative perspective. This study observed some studies examining the macro-economic factors, such as exchange rate, oil price, and interest rate impact the tourism industry (Ullah et al., 2024, Ullah et al., 2025). If the focus is shifted from macroeconomics, negligible attention is paid to psychological variables in the context of the Chinese tourism industry. This study focuses on a highly relevant issue, as China is the world's second-largest stock market and has a large number of individual investors. They are mostly inexperienced and exhibit herding behavior, which leads the market to fluctuate. This article chooses the pivotal event of this century to investigate the tourism stock volatility and devise strategies for policymakers to recover investors' confidence, sentiment, and trading interest in this lucrative industry.

3. Methodology

3.1. Data collection

This study collected daily data from twenty firms listed in the tourism sector, sourced from CSMAR. The selection criteria were as follows: (a) the firm must have continuously operated throughout the selected period; (b) the firm's primary business should be closely related to tourism, with over 60 % of its revenue derived from direct tourism

activities; and (c) the firm's market capitalization must be at least 10 billion at the end of the selected period. The sample is divided into three sectors: Travel & Transport, Hotel, and Scenic Spots. The Travel & Transport sector includes six firms, while the Hotel and Scenic Spot sectors each consist of seven firms. Daily exchange rates, oil prices, and COVID-19 statistics, including new cases, total cases, daily deaths, and total deaths, were collected. In addition, monthly variables such as Economic Policy Uncertainty (EPU), Consumer Confidence Index (CCI), Net Oil Assets (NOA), and the London Interbank Offered Rate (LIBOR) were gathered. To facilitate more precise regression analysis, the monthly variables were converted to a daily frequency using EViews 12. Table A1 present the emojis emoticons along with microblogs, while the details of the data sources and the firms, along with their respective symbols, are presented in Appendix Table A2.

Segment A corresponds to the World Health Organization's declaration of a pandemic, while Segment B refers to the period of economic resumption. For news sentiment analysis (NS), we used the English version of Python (Jupyter Notebook), and for multivariate analysis, we utilized R Studio (Jing-ya, 2021). Additionally, microblog data from the XUEQIU platform, a Chinese social media site focused on stock trading and investment, was collected to gauge individual investor sentiment. This aspect of the data collection was facilitated by support from the CISU (Chinese International Student Union) at Hainan University. The collected Chinese microblogs were first translated from Chinese to English using the Google Translate API via Python to ensure consistency in initial processing. Subsequently, these automated translations were manually reviewed and refined by a bilingual research team to accurately capture nuanced investor sentiments and financial slang, ensuring the translations were contextually appropriate for sentiment analysis (Hota et al., 2021). The stationarity table has been excluded for brevity.

3.2. Principal component analysis (PCA)

Different studies have established varying threshold values for Principal Component Analysis (PCA), but many researchers concur that a threshold of 50 % or higher is generally acceptable. In this context, Appendix Table A3 shows the Kaiser-Meyer-Olkin (KMO) values for all indices, which are significantly higher than Peng et al. (2023) by 0.56 %, and compared to the well-known studies by Baker and Wurgler (2007) and Lycheva et al. (2023), which report values around 53 %. Furthermore, Fig. 1 illustrates the relationships between investor sentiment proxy variables both graphically and numerically. The legend on the right side indicates the correlation magnitude, ranging from 1 to -1', while the color intensity reflects the strength and weakness of the correlations. Figure 2 shows the investor sentiment and fear index, while Fig. 3 the conceptual framework. The KMO values and correlation analysis confirm that using Principal Component Analysis is appropriate

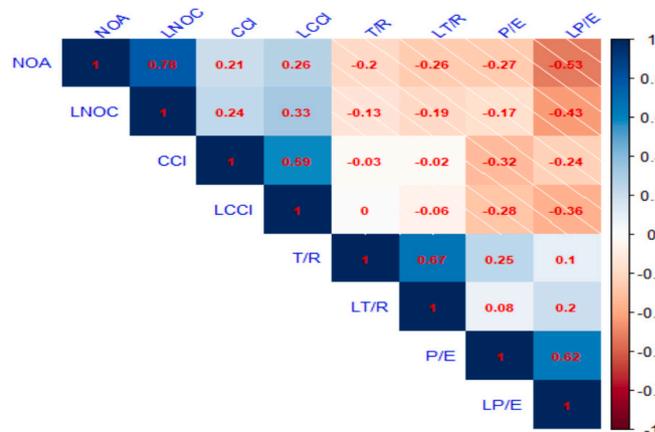


Fig. 1. Correlation between market sentiment proxies.

for these proxies (Field, 2018).

3.3. Individual sentiment (IS) construction

The literature mentioned above offers a comprehensive overview; however, this study conducted a thorough analysis of the entire population and collected a sample of 15 relevant positive and negative emojis, five distinct emoticons, and various microblogs. To maintain consistency, the microblogs were translated into English (Montariol & Allauzen, 2021). In this study, Python utilized the Valence Aware Dictionary and Sentiment Reasoner (VADER) lexicon. VADER is based on supervised human-labeled data and does not require additional training data (Hutto & Gilbert, 2014). A well-known library in natural language processing (NLP) is the Natural Language Toolkit (NLTK), which includes the VADER module featuring a Sentiment Intensity Analyzer (SIA) function. This dictionary accounts for the intensity of exclamation marks and the capitalization of words. It categorizes each outcome as positive, negative, or neutral, with polarity values ranging from -1 to 1, where 1 represents positive sentiment and -1 signifies negative sentiment. This study applied this methodology to each emoji, emoticon, and microblog, and the final observations for further analysis were calculated using the following equation.

$$NS_t = \frac{pos_t - neg_t}{comp_t} \tag{1}$$

Where, $pos_t, neg_t, comp_t$ exhibit the positive, negative, and compound values for news sentiment or individual investor sentiment. To enhance the observation frequency in logarithmic form for better regression analysis, EIEWS-12 is employed. Subsequently, Principal Component Analysis is utilized to develop news sentiment as an exogenous variable news sentiment as an exogenous variable (Paramanik & Singhal, 2020).

3.4. Uni-multivariate PCA index

This study developed six indices: MS (Market Sentiment), NS (News Sentiment), and FI (Fear Index), along with CT, CS, and CH. In this context, ‘‘C’’ represents China, ‘‘T’’ denotes the travel and transport sector index, ‘‘S’’ indicates the scenic sector index, and ‘‘H’’ refers to the hotel sector index. A univariate model was employed to investigate the impact of NS, MS, and FI on the current conditional volatility of firm stocks. Additionally, a multivariate DCC-GARCH model was used to examine the spillover effects and dynamic conditional co-movement between MS and the sector-based indices. MS is composed of four proxies: CCI (Consumer Confidence Index), P/E (Price-to-Earnings Ratio), NOA (Net Operating Assets), and T/R (Total Revenue), along with their lagged values Shen et al. (2022). Further, Salisu and Akanni (2020) followed and took daily new and total cases, similar daily deaths, and total death cases, and developed a fear index. Subramaniam and Chakraborty (2021) stated that these metrics directly reflect pandemic

severity and trigger immediate public anxiety. Lagged values capture temporal dependencies in fear propagation, while combining deaths (mortality risk) cases ensures a comprehensive assessment of crisis-driven fear, aligning with methodologies that link health data to behavioral or financial impacts. The following are the raw sentiments after the component rotation matrix is applied.

$$MS = -0.079CC + 0.006CC_{t-1} + 0.518NOA + 0.596NOA_{t-1} - 0.600P/E - 0.051P/E_{t-1} + 0.08T/R - 0.04 T/R_{t-1} \tag{2}$$

$$NS = 0.541Pp - Np0.435Np + 0.584 \log Pp + 0.419 \log Np \tag{3}$$

$$FI = 0.661NC + 0.059DC + 0.054TNC - 0.459TDC \tag{4}$$

$$CT\ Index = 0.508CT1 - 0.099CT2 + 0.050CT3 - 0.128CT4 - 0.455CT5 + 0.710CT6 \tag{5}$$

$$CH\ Index = 0.035CH1 - 0.698CH2 + 0.040CH3 - 0.008CH4 + 0.646CH5 + 0.301CH6 + 0.009CH7 \tag{6}$$

$$CS\ Index = 0.417CS1 + 0.240CS2 - 0.313CS3 - 0.051CS4 + 0.409CS5 + 0.684CS5 + 0.176CS7 \tag{7}$$

Fig. 2 illustrates the cumulative variation of the Eigenvalue basis for all indices, and Fig. 3 presents the study’s flowchart.

3.5. Econometric specification

Investor sentiment can be a significant risk factor, as individual emotions often follow herd mentality, leading to mispricing in the market. This phenomenon underscores the importance of continuously monitoring price fluctuations to inform rational decision-making. Among the various time-series models, the GARCH family is effective for analyzing conditional variance by incorporating lagged shocks and volatility, as well as assessing the effects of leverage and unexpected news on stock volatility.

3.5.1. Exponential GARCH model

The E-GARCH model was proposed by Nelson (1991) to capture the leverage effect in firm operations.

$$\log h_t = \omega + \alpha_i \sum_{i=1}^p \left[\left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-j}}} - E \left(\frac{\varepsilon_{t-i}}{\sqrt{h_{t-j}}} \right) \right| \right] + \sum_{i=1}^p \gamma_k \frac{\varepsilon_{t-i}}{\sqrt{h_{t-j}}} + \sum_{j=1}^q \beta_j \ln(\log h_{t-j}) + \phi_1 ISI + \phi_2 FI + \phi_3 IS + \phi_4 DS \tag{8}$$

$\left[\left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-j}}} - E \left(\frac{\varepsilon_{t-i}}{\sqrt{h_{t-j}}} \right) \right| \right]$ represents the size effect of the news and $\gamma_k \frac{\varepsilon_{t-i}}{\sqrt{h_{t-j}}}$ represents the sign effect.

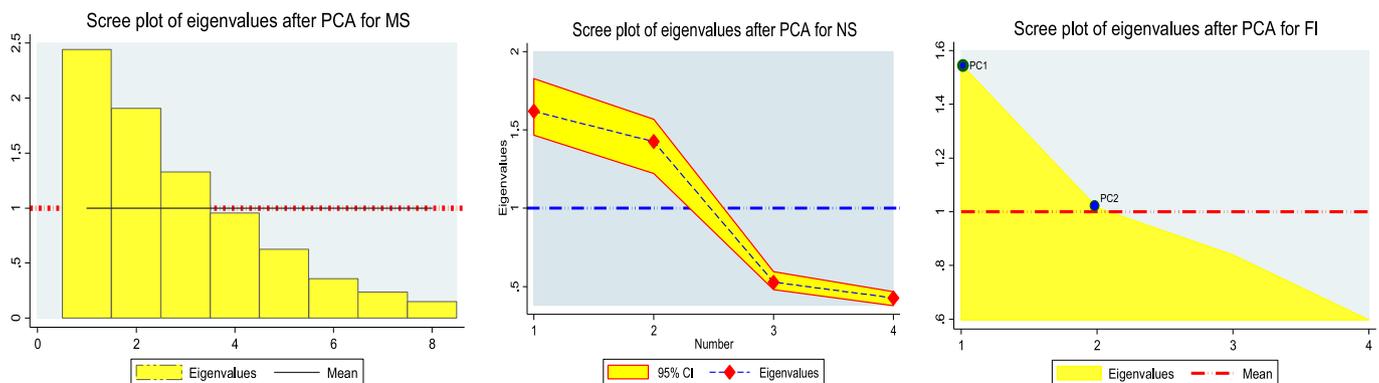


Fig. 2. The Scree plots of MS (market sentiment), NS (news sentiment), and FI (fear index).

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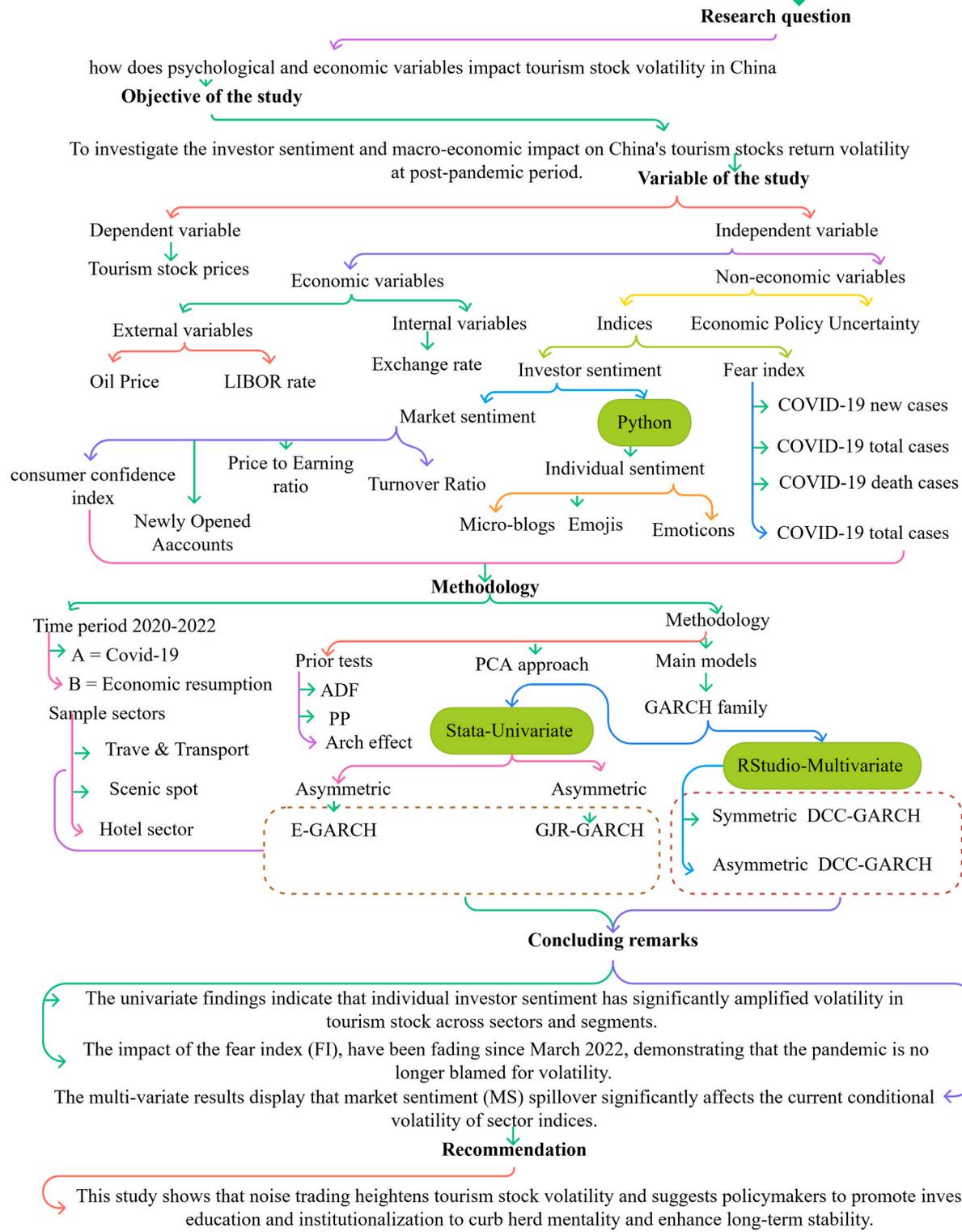


Fig. 3. The flow chart of the study.

The coefficients $\phi_1, \phi_2, \phi_3,$ and ϕ_4 represent the influence of external shocks on current volatility. Here, ϕ_1 and ϕ_2 are the variables of interest (VOI), capturing investor sentiment and the Fear Index, respectively.

The coefficients ϕ_3 and ϕ_4 represent control variables for international and domestic shocks. The model ensures the non-negativity constraint of $\log h_t$, and the persistence of volatility will be less than 1. Furthermore, a

statistically significant and negative $\gamma_k < 0$ indicates the presence of a leverage effect, where negative news has a greater impact on volatility than positive news. Conversely, a positive $\gamma_k > 0$ suggests an absence of this typical asymmetric response (Van Hoang & Syed, 2021).

3.5.2. GJR-GARCH model

GJR-GARCH, proposed by Glosten et al. (1993), incorporates asymmetric shocks through a dummy variable.

$$h_t = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \lambda_r \varepsilon_{t-i}^2 I_{t-i} + \sum_{j=1}^q \beta_j h_{t-j} + \phi_1 ISI + \phi_2 FI + \phi_3 IS + \phi_4 DS \tag{9}$$

$$I_{t-1} = \begin{cases} 1, & \varepsilon_{t-i} < 0 \text{ (Bad News)} \\ 0, & \varepsilon_{t-i} \geq 0 \text{ (Good News)} \end{cases} \tag{10}$$

if $\varepsilon_{t-1}^2 > 0$, and $\alpha_1 + \lambda_r \geq 0$. Further, if $\lambda_r > 0$, the shock is significant; the shock will be equal to $\alpha_1 + \lambda_r$, which means the negative shock will have more impact on the current conditional variance; otherwise, if $\lambda_r < 0$, it is equal to α , indicating the absence of a bad news impact.

3.6. Multivariate GARCH model

The DCC-GARCH model, proposed by Engle (2002), captures time-varying dynamic conditional co-movement.

3.6.1. DCC-GARCH

$$H_t = D_t R_t D_t \tag{11}$$

Where, H_t is the conditional variance-covariance matrix, which must be positive, and it decomposes into D_t the conditional standard deviation.

$$D_t = \text{diag}(q_{11,t}^{-1/2}, \dots, q_{kk,t}^{-1/2})$$

$$R_t = \text{diag}\left(\frac{-\frac{1}{2}}{q_{11,t}}, \dots, \frac{-\frac{1}{2}}{q_{kk,t}}\right) Q_t \text{diag}\left(\frac{-\frac{1}{2}}{q_{11,t}}, \dots, \frac{-\frac{1}{2}}{q_{kk,t}}\right) \tag{12}$$

Table 1
E-GARCH (1, 1).

	ω	α	β	$\alpha + \beta$	γ_k	ϕ_1		ϕ_2		ϕ_3		ϕ_4	
						MS	NS	FI	OP	IR	EU	ER	
CT1	0.195 ^a	0.230 ^a	0.648 ^b	0.879	-0.237 ^a	0.113	-6.24 ^a	-0.042 ^b	-0.24	1.309	33.80 ^b	-0.67 ^b	
CT2	2.11 ^a	0.261 ^a	0.641 ^a	0.902	0.688 ^a	-0.086 ^b	0.834 ^b	0.182 ^b	-0.175	2.923 ^a	27.24 ^b	-0.86 ^a	
CT3	0.507 ^b	0.208 ^b	0.624 ^b	0.833	-0.083 ^b	-0.05 ^b	-0.012 ^b	0.001	-0.003	0.012 ^b	0.211 ^c	-0.001	
CT4	0.447 ^a	0.699 ^b	0.156 ^c	0.856	0.936 ^a	0.068	-0.243 ^a	-0.151 ^b	0.114 ^c	-0.92	30.41 ^a	0.508 ^a	
CT5	0.003 ^b	0.110 ^b	0.843 ^a	0.954	-0.020	-0.800 ^b	-0.002 ^b	-0.009 ^b	-0.001	0.016 ^b	-0.249	-0.003 ^b	
CT6	0.001	0.580 ^a	0.21 ^a	0.791	0.229 ^a	-0.001 ^b	-0.036 ^a	-0.223 ^a	-0.020 ^b	0.026	0.585	0.004 ^b	
CH7	0.009 ^a	0.349 ^a	0.428 ^a	0.778	0.822 ^a	0.015	-0.032 ^a	-0.025 ^b	0.005	-0.056 ^b	-0.648 ^b	-0.039 ^b	
CH8	0.483 ^a	0.310 ^a	0.321 ^a	0.631	-0.77 ^a	-0.005 ^b	-0.134 ^a	-0.425 ^b	-0.001	0.004	-0.225	-0.008	
CH9	0.620 ^a	0.125 ^a	0.361 ^a	0.486	0.902 ^a	-0.53 ^a	0.169 ^b	0.285 ^b	0.547 ^b	-0.905	-1.905 ^b	-0.003	
CH10	1.042 ^b	0.233 ^a	0.863 ^a	1.096	0.057	-0.001 ^a	0.007	-0.058 ^b	0.020 ^a	0.032 ^b	0.264 ^b	-0.008 ^b	
CH11	0.002 ^a	0.265 ^b	0.785 ^a	0.871	-0.08 ^c	0.002 ^a	-0.011	0.021 ^b	-0.003	-0.014	-0.026	-0.492 ^b	
CH12	0.010 ^a	0.459 ^a	0.185 ^b	0.644	-0.194 ^b	-0.23 ^b	-0.041 ^b	-0.053 ^b	0.014	0.021	-1.029 ^a	0.243 ^a	
CH13	0.013 ^a	0.369 ^a	0.063 ^a	0.432	1.456 ^a	0.012 ^a	0.242 ^a	-0.15 ^a	0.012 ^a	-0.107 ^b	0.077 ^c	-0.154 ^a	
CS14	0.482 ^b	0.099 ^a	0.276 ^b	0.375	0.926 ^b	-0.008	-0.654 ^a	0.023 ^b	-0.002	0.056 ^a	0.347	-0.009	
CS15	0.992 ^b	0.031	0.461 ^b	0.492	0.633 ^a	-0.001 ^b	-0.370 ^b	0.008 ^c	-0.020	0.020	0.357	-0.085 ^b	
CS16	0.468 ^a	-0.060	0.613 ^a	0.552	1.053 ^a	0.007 ^b	0.173 ^b	-0.07 ^a	-0.123 ^a	-0.001	0.152 ^b	-0.210 ^a	
CS17	0.110 ^b	0.132 ^a	0.292 ^b	0.424	0.979 ^a	-0.203 ^b	-0.581 ^a	0.074 ^b	-1.529 ^a	-1.713 ^a	0.846 ^b	-1.33 ^a	
CS18	0.004 ^a	0.856 ^a	0.008 ^b	0.865	-0.138	-0.004 ^b	-0.083 ^a	-0.405 ^b	0.004	-0.520	2.040 ^a	-0.014	
CS19	0.008 ^a	0.133 ^b	0.901 ^b	1.034	0.932 ^a	-0.001 ^b	0.059 ^a	-0.12 ^a	0.008	0.065 ^a	1.191 ^a	0.012 ^a	
CS20	2.387 ^a	0.121 ^b	0.805 ^a	0.926	-0.022	0.055 ^a	3.818 ^b	-0.189	-0.418	-3.804	37.48 ^a	0.031 ^b	

Note: a, b, c subscript 1,5,10%, CT (China Travel & Transport), CH (China Hotel tourism), CS (China scenic tourism), MS (market sentiment), NS (news sentiment), FI (fear index), OP (oil price) IR (interest rate), EU (economic policy uncertainty), ER (exchange rate).

$$Q_t = \left(1 - \sum_{m=1}^M \alpha_m - \sum_{n=1}^N \beta_n\right) \bar{Q}_t + \alpha_m \varepsilon_{t-m} \varepsilon'_{t-m} + \sum_{n=1}^N \beta_n Q_{t-1} \tag{13}$$

Where, R_t is the DCC coefficients matrix, Q_t and \bar{Q}_t are $K \times K$ dimensional positive matrices. Further, ε_{t-m} , is the standardized lagged order m , and α_m is the coefficient for squared residuals, β_n is the conditional variance coefficient, α_m and β_n , are non-negative scalars, $\sum_{m=1}^M \alpha_m + \sum_{n=1}^N \beta_n < 1$. The dynamic conditional coefficient between two financial variables is given by:

$$\rho_{12,t} = \frac{q_{12t}}{\sqrt{q_{11t} q_{22t}}} \tag{14}$$

The larger $\rho_{12,t}$, the greater the risk and the greater the risk spillover effect.

4. Results and discussion

Table 1 presents the estimated results of the EGARCH model, where the β coefficient is greater than the α coefficient. Furthermore, the asymmetric coefficient is not equal to zero for sixteen firms. Specifically, for firms CT1, CT3, CH8, CH11, CH12, and CS18, this indicates the presence of the leverage effect. The hotel sector demonstrates a greater sensitivity, suggesting that investors are more susceptible to adverse shocks. This finding is consistent with Fakhfekh and Jeribi (2020), who argue that financing increases a firm's operational volatility.

The market sentiment and news sentiment parameters are significant in fifteen and eighteen firms, respectively, while the CT and CS sectors show negative values. In the CH sector, one factor is the most statistically significant, characterized by five negative coefficients. In the OP and IR groups, eight and ten factors were identified as significant. Additionally, the EU and ER parameters are relevant in fifteen firms. The summary indicates the presence of bad asymmetry, or the leverage effect, while the external factors (VOI) have a profound link with volatility. However, individual emotions have a significant impact on tourism stock prices during the outbreak. The results demonstrate a significant mixed impact, consistent with the observation (Sadorsky, 2022), that the market remained highly volatile during the outbreak. As a result, the tourism industry, being on the front line, experienced 70 % of the financial losses.

Table 2 presents the GJR-GARCH results, showing that β (past

Table 2
GJR-GARCH (1, 1).

	ω	α	β	$\alpha + \beta$	λ_r	ϕ_1		ϕ_2	ϕ_3	ϕ_4		
						MS	NS	FI	OP	IR	EU	ER
CT1	3.537 ^a	0.314 ^a	0.684 ^a	0.998	0.493 ^a	0.141	-2.446 ^a	0.476 ^c	1.318	-1.947	-23.40 ^b	1.743 ^a
CT2	0.005 ^a	0.278 ^a	0.522 ^b	0.801	1.110 ^a	0.002 ^c	-0.023	-0.004 ^a	-0.002	0.004	-0.885 ^b	-0.204 ^a
CT3	0.004 ^b	0.060	0.750 ^a	0.811	0.030 ^c	-0.004 ^b	-0.009 ^b	-0.108 ^b	-0.003	0.013	0.250 ^b	-0.044
CT4	0.001 ^b	0.092 ^b	0.824 ^a	0.915	0.078 ^b	0.079 ^b	-2.985 ^a	0.415 ^a	-0.692 ^a	-2.45 ^a	15.91	2.282 ^a
CT5	0.002 ^b	0.15 ^b	0.79 ^a	0.944	-0.037	-0.006 ^b	-0.038	-0.010	-0.001	0.011 ^c	-0.136	-0.002
CT6	2.829 ^a	0.317 ^a	0.284 ^c	0.601	0.339 ^b	0.005 ^b	4.137 ^a	-0.698 ^a	-0.213	-0.885	-18.6 ^a	-0.161 ^a
CH7	0.004 ^b	0.137 ^a	0.634 ^a	0.771	0.702 ^a	0.001 ^b	-0.021 ^b	0.001 ^c	0.013	-0.063 ^a	-0.781 ^a	-0.014 ^a
CH8	0.002 ^b	0.28 ^b	0.49 ^b	0.772	0.48 ^a	-0.001 ^c	-0.069 ^a	-0.342 ^b	0.002	-0.012	-0.177 ^b	-0.035
CH9	7.769 ^a	0.34 ^a	0.177 ^b	0.521	0.002	-1.307 ^a	0.336 ^a	-0.048 ^b	-0.074 ^c	-2.138 ^b	-24.74 ^a	-0.49
CH10	0.019 ^b	0.194 ^a	0.789 ^a	0.985	-0.685 ^b	0.001	0.009 ^c	-0.005 ^b	0.020 ^a	0.030 ^b	0.246 ^c	-0.008 ^b
CT11	0.003 ^c	0.048 ^b	0.928 ^a	0.977	0.043 ^c	0.003 ^a	-0.040 ^a	-0.01	0.001	0.007	0.377 ^b	-0.040 ^a
CT12	0.006 ^b	0.099 ^b	0.862 ^a	0.961	-0.099 ^b	-0.009	-0.011	-0.036 ^b	0.009	0.028	-0.128	0.009
CT13	0.001 ^a	0.573 ^b	0.255 ^a	0.828	0.576 ^b	0.003 ^c	0.001	0.008 ^b	0.003	0.025 ^c	-0.246 ^b	-0.008
CS14	0.004 ^a	0.246 ^a	0.830 ^b	1.076	0.148 ^b	-0.009 ^c	-0.065 ^a	0.003 ^b	-0.002	0.057 ^a	0.262	-0.013 ^c
CS15	0.052 ^a	0.303 ^a	0.136 ^b	0.440	0.054	-0.04 ^b	0.192 ^b	-0.489 ^a	-0.006 ^b	0.230	1.797	-0.228 ^a
CS16	0.002 ^b	0.191 ^a	0.744 ^a	0.935	1.071 ^a	0.179 ^a	0.409 ^a	-0.341 ^b	0.037	-0.104	1.68 ^a	0.002 ^a
CS17	0.006 ^b	0.175 ^a	0.731 ^a	0.906	0.774 ^a	0.003 ^a	-0.611 ^a	-0.019 ^b	-0.006 ^b	-0.04 ^a	-0.95 ^b	0.006 ^b
CS18	0.001 ^a	0.508 ^a	0.138 ^b	0.646	0.170	-0.003	0.091 ^a	0.001	0.004	-0.045 ^b	1.583 ^a	-0.228 ^a
CS19	0.034 ^a	0.144 ^a	0.709 ^a	0.893	0.620 ^a	-0.01 ^a	-0.001 ^b	-0.551 ^a	0.012 ^b	0.055 ^b	-0.80 ^a	-0.037
CS20	16.328 ^a	-0.035 ^b	0.970 ^a	0.934	0.070 ^a	0.157 ^b	28.87 ^a	-0.774 ^b	1.555 ^a	-0.933	-14.67	6.503 ^a

See Table 1.

volatility) consistently influences current volatility in the Chinese tourism market. The parameter λ_{r-i} is non-zero $\lambda_{r-i} \neq 0$ in sixteen firms. With the exception of CH10 and CH12, all other parameters are positive. This shock specification ($\alpha + \lambda$) indicates an asymmetric effect, meaning that unknown bad news shocks have an impact on current conditional volatility. Interestingly, it is notable that $\lambda_{r-i} < 0$ for CH10, 12, the shock is equal to α , and it is a good gesture for investors; these firms play a dominant role and exhibit a more stable situation during COVID-19.

The market sentiment in sixteen and news sentiment in fifteen firms are significant and similar to those reported, indicating that individual sentiment can better forecast future returns. The ϕ_2 is significant in seventeen firms, with more negative coefficients, indicating that the pandemic has exacerbated the conditional volatility of these stocks. The ϕ_3 , OP, and IR show rare significance. In contrast, ϕ_4 , (EU and ER) significantly influences fourteen and thirteen firms, respectively, particularly with four negative coefficients in the CH sector. The summary of GJR-GARCH shows the harmful asymmetry, notably the VOI ϕ_1 , ϕ_2 , CV ϕ_4 carries mostly negative coefficients, while ϕ_3 with limited in-

fluence, it also confirms H1 and H3 of our study, and these findings are aligned with (Elgharib, 2023).

Table 3 presents the results of the E-GARCH (1,1) model, which indicates asymmetry in eleven firms. Evidence of the leverage effect is observed in firms CT6, CH10, 12, and CS16, 20. Despite the negative correlation between past and present returns, it appears that the shock will not have a detrimental impact, as the Chinese tourism firms involved operate with comparatively less debt (Fakhfekh & Jeribi, 2020).

The external shocks, ϕ_1 , on market sentiment and news sentiment in fifteen and sixteen firms exhibit significant results. Individual sentiment consistently has a significant influence, with parameters mostly positive, reflecting an optimistic trend (Ur Rehman, 2021). The ϕ_2 parameter is insignificant in ten out of twenty cases; the estimated ϕ_2 result indicates that the COVID-19 impact on the tourism industry is waning over time (Mazur et al., 2021). Now the ϕ_3 OP is significant in fourteen firms, which is more than IR. Similarly, Qin et al. (2021) concluded that the impact of oils is mostly rare but positive. The ϕ_4 shock (EU and ER)

Table 3
E-GARCH (1, 1) B(Resumption period).

	ω	α	β	$\alpha + \beta$	γ_k	ϕ_1		ϕ_2	ϕ_3	ϕ_4		
						MS	NS	FI	OP	IR	EU	ER
CT1	0.251 ^b	0.461 ^a	0.195 ^b	0.713	0.540 ^a	-0.016 ^b	0.008 ^a	0.105	0.004	-0.634	0.089	-0.065 ^a
CT2	2.411 ^b	0.081	0.214 ^c	0.296	-0.484	0.743 ^b	-0.457 ^b	-0.067	0.177 ^a	-1.340 ^b	-0.182 ^b	-0.214
CT3	0.022 ^b	0.733 ^a	0.098 ^c	0.832	-0.006	0.157 ^b	0.003 ^b	-0.001	-0.007	-0.010	0.055 ^b	0.055 ^a
CT4	0.006 ^b	0.174 ^a	0.943 ^a	1.117	-0.806	-0.022	0.032	-0.011	0.003 ^a	0.026 ^a	-0.185 ^c	0.009 ^b
CT5	0.013 ^b	0.292 ^b	0.573 ^a	0.865	0.353 ^a	0.008 ^a	0.564 ^a	0.002 ^b	0.025 ^a	-0.037 ^b	0.303 ^a	0.015 ^b
CT6	0.007 ^b	0.176 ^a	0.706 ^b	0.882	-0.326 ^a	0.049 ^b	0.030 ^b	-0.006 ^b	0.062 ^c	0.006	0.014	0.204 ^a
CH7	0.027 ^b	0.689 ^a	0.216 ^a	0.906	0.012	-0.138 ^b	0.002	-0.001	-0.038 ^b	0.027	-0.361 ^b	0.060 ^a
CH8	0.241 ^b	0.688 ^b	0.237 ^b	0.926	0.687 ^a	0.116 ^b	0.001	0.001	-0.002 ^b	0.424	0.107	0.030 ^b
CH9	0.027 ^a	0.216 ^b	0.701 ^a	0.918	0.660 ^a	1.683	0.034	0.120 ^b	0.101 ^b	-1.410 ^b	2.314 ^a	-1.490 ^b
CH10	0.022 ^a	0.114	0.349 ^b	0.464	-0.825 ^a	0.044 ^b	0.076 ^b	0.094	-0.037 ^b	-0.015	3.013 ^b	0.413 ^b
CH11	0.066 ^a	0.206 ^b	0.193 ^b	0.400	0.732 ^b	-0.020 ^b	0.002 ^a	0.064 ^b	-0.070 ^b	-0.72 ^a	0.004	-0.066 ^a
CH12	2.807 ^b	0.318 ^b	0.554 ^b	0.872	-0.267 ^a	-0.133	0.002 ^b	-0.007 ^b	0.002 ^b	-0.06 ^b	-0.368 ^b	0.009
CH13	0.004 ^b	0.047	0.580 ^b	0.635	-0.033	0.052 ^b	-0.004 ^b	-0.04 ^b	0.022 ^c	0.012	-0.243 ^c	0.006
CS14	0.062 ^a	0.100	0.066	0.167	-0.230	0.075 ^a	0.295 ^c	-0.006 ^a	0.063	-0.003 ^a	0.838	0.038 ^a
CS15	0.001	0.825 ^a	0.142	0.968	0.034	-0.055	0.422 ^b	0.023	0.002 ^b	0.051	-0.140 ^c	0.041 ^b
CS16	0.014 ^b	0.112	0.689 ^a	0.801	-0.231 ^b	-0.080 ^b	0.145 ^b	-0.007	0.018	0.038	0.225 ^b	0.129
CS17	0.007 ^b	0.196 ^a	0.610 ^a	0.807	0.059 ^b	0.042	0.467 ^b	0.004 ^c	0.004 ^a	-0.088	0.126	0.467 ^b
CS18	0.025 ^b	0.141 ^b	0.761 ^a	0.902	0.029	-0.109 ^b	-0.001 ^a	-0.004 ^c	-0.32	0.017	0.347 ^b	0.014
CS19	0.025 ^c	0.340 ^b	0.528 ^b	0.869	0.061	0.161 ^b	0.109 ^a	-0.007 ^c	-0.003 ^a	0.583	-0.049	-0.049 ^b
CS20	0.006	0.465 ^b	0.024	0.489	-0.407 ^b	-0.040 ^b	0.125 ^b	0.001	0.082	0.010	0.061	-0.014 ^b

See Table 1.

Table 4
GJR-GARCH (1,1) B

	ω	α	β	$\alpha + \beta$	λ_r	ϕ_1	ϕ_2	ϕ_3	ϕ_4			
						MS	NS	FI	OP	IR	EU	ER
CT1	0.031 ^b	0.376 ^a	0.274 ^b	0.650	-0.530 ^b	0.196 ^a	0.078 ^a	0.009	0.010	-0.066	0.056	-0.066 ^a
CT2	0.062 ^a	0.327 ^a	0.589 ^b	0.916	-0.172	-0.049 ^b	0.618 ^b	0.058 ^b	-0.124	-0.462 ^b	-1.096 ^a	-0.038
CT3	0.145 ^c	0.431 ^b	0.589 ^a	1.020	0.190	-0.145 ^c	0.004 ^b	-0.001	-0.006	-0.007	-0.104 ^b	0.053 ^a
CT4	0.033 ^a	-0.156 ^a	0.935 ^b	0.779	0.249 ^a	3.761 ^a	-0.085 ^a	-0.119 ^b	0.007 ^a	-0.566 ^a	0.004	0.098 ^b
CT5	0.043 ^a	0.279	0.713 ^a	0.992	-0.495 ^b	-0.176 ^b	0.002	0.178	0.021 ^b	-0.010	0.207 ^b	0.027 ^b
CT6	0.016 ^b	0.238 ^b	0.60 ^a	0.842	-0.731	0.129 ^b	0.071 ^b	-0.190	0.014	0.007	-0.445 ^b	0.058
CH7	0.004 ^a	0.224 ^b	0.550 ^a	0.774	-0.573 ^b	-0.363 ^a	0.006 ^b	0.002 ^b	-0.004 ^b	0.030	1.378 ^a	-0.051 ^a
CH8	0.275 ^b	0.311 ^b	0.237 ^b	0.549	0.806 ^b	-0.145 ^b	0.005 ^b	0.014	-0.002 ^b	0.053	0.104	0.377 ^a
CH9	0.001 ^b	0.370 ^b	0.611 ^a	0.998	0.093	-0.281 ^a	0.036 ^c	0.009	-0.066	-0.018 ^b	-0.431 ^a	-0.006
CH10	0.006	0.295 ^b	0.420	0.715	0.065	0.198 ^b	0.012 ^b	-0.328	-0.004	0.328	-0.204 ^b	-0.044 ^b
CH11	0.847 ^a	0.071	0.692 ^a	0.764	0.558 ^a	-0.303	0.22 ^a	0.016 ^b	-0.064 ^a	-1.578 ^a	-2.259 ^a	1.391 ^b
CH12	0.003 ^b	-0.315 ^a	0.980 ^a	0.665	0.345 ^a	-0.054 ^b	-0.262 ^b	-0.038 ^a	0.182	-0.047 ^b	-0.268 ^a	0.028 ^b
CH13	0.901 ^a	0.264 ^b	0.299 ^b	0.564	0.453	0.033 ^b	0.224 ^b	-0.219	-0.011	-0.682 ^b	2.664	-1.711 ^b
CS14	0.024 ^b	0.069	0.841 ^a	0.911	0.062	0.137 ^b	0.084 ^b	0.304	0.002 ^b	-0.039 ^a	0.254	0.450
CS15	0.021 ^c	0.777 ^b	0.145 ^b	0.922	-0.287	-0.063 ^b	0.441 ^b	0.001	0.002 ^b	0.015	0.098	0.033 ^b
CS16	0.045 ^b	0.809 ^b	0.244 ^b	1.223	0.280	-0.234 ^b	0.062 ^b	0.004 ^b	0.026	-0.041	-0.210 ^c	-0.220 ^b
CS17	0.023 ^b	0.615 ^a	0.362 ^b	0.977	0.589	-0.120 ^b	-0.001	-0.341	0.003 ^a	0.057 ^a	0.037	-0.039 ^b
CS18	0.002 ^c	0.249	0.651 ^b	0.909	-0.253 ^c	-0.015	0.045 ^b	-0.037	-0.004	0.077	0.420 ^b	0.044
CS19	0.024 ^b	0.108 ^c	0.871 ^a	0.979	-0.260	-0.139 ^c	0.563 ^b	-0.093 ^b	-0.003 ^b	0.097 ^a	0.198	-0.638 ^b
CS20	0.006 ^a	0.173 ^a	0.54 ^a	0.714	0.944 ^b	-0.041	0.013 ^b	0.005	0.851 ^c	0.027	0.067	-0.147 ^b

See Table 1.

exhibits significance in twelve and fifteen firms, but the ER remains significant. The overall summary indicates that γ_k is less than 0. In some firms, there is a lower level of leverage or debt financing in their operations. Most external parameters are significant, except for $\text{CV}\phi_3$, which suggests that the aftershocks of the pandemic have diminished to some extent.

Similarly, [Qin et al. \(2021\)](#) reported that the parameter response was dynamic to different industries in the stock market. As time passes, optimism increases, and investors become actively engaged in buying and selling, helping to shift the market from bearish to bullish.

[Table 4](#) examines GJR-GARCH. The asymmetry parameter $\lambda_r \neq 0$ for nine firms, although $\lambda_r > 0$, in CT4, CH8, 9, 11, 12, CS20, there are a few firms where an unknown shock has a detrimental impact on current conditional volatility ([Kumari & Mahakud, 2015](#)).

Regarding external shocks ϕ_1 , MS and NS significantly influence seventeen and eighteen firms; moreover, the outcomes are aligned with previous-period GARCH and E-GARCH, and ϕ_1 consistently confirms the influence on stock price fluctuation ([Cui & Zhang, 2020](#)).

Thirteen out of twenty firms yielded insignificant results, indicating that the influence has diminished over time; however, its occasional impact persists in tourism stocks in China ([He et al., 2020](#)). Furthermore,

Table 5
DCC-ADCC-GARCH models.

GARCH	EGARCH		GJR-GARCH							
	α	β	α	β	γ_k	λ_r				
CT	0.217 ^a	0.701 ^a	CT	0.283 ^b	0.883 ^a	0.412 ^a	CT	0.189 ^a	0.780 ^a	0.057
CH	0.225 ^a	0.753 ^a	CH	0.025 ^b	0.967 ^a	0.449 ^a	CH	0.236 ^a	0.744 ^a	-0.022 ^a
CS	0.214 ^a	0.764 ^a	CS	0.09 ^b	0.905 ^a	0.539 ^a	CS	0.208 ^a	0.765 ^b	0.050
DCC	0.023 ^a	0.956 ^a		0.028 ^a	0.951 ^a			0.024 ^a	0.935 ^a	
AIC	1.744		1.503				1.744			
HQ	1.787		1.553				1.794			
GARCH			EGARCH				GJR-GARCH			
	α	β		α	β	γ_k		α	β	λ_r
MS	0.001 ^c	0.926 ^a	MS	-0.091 ^c	0.861 ^a	2.45 ^a	MS	0.919 ^a	0.042 ^a	0.033
CT	0.186 ^a	0.780 ^a	CT	0.028	0.908 ^a	0.449 ^a	CT	0.189 ^a	0.780 ^a	0.057 ^b
CH	0.157 ^b	0.803 ^a	CH	-0.052 ^b	0.967 ^a	0.412 ^b	CH	0.236 ^a	0.704 ^a	-0.225
CS	0.203 ^b	0.705 ^a	CS	-0.098	0.995	0.539 ^a	CS	0.208	0.765	0.050 ^b
DCC	0.032 ^b	0.947 ^a	DCC	0.04 ^b	0.917 ^a		DCC	0.032 ^b	0.935 ^a	
AIC	2.333		2.080				2.337			
HQ	2.392		2.150				3.639			

Note: a, b, c subscript 1%, 5%, 10 significance level, CT (China T&T Sector Index), CH (China Hotel Sector Index), CS (China Scenic Tourism Index), MS (Market Sentiment).

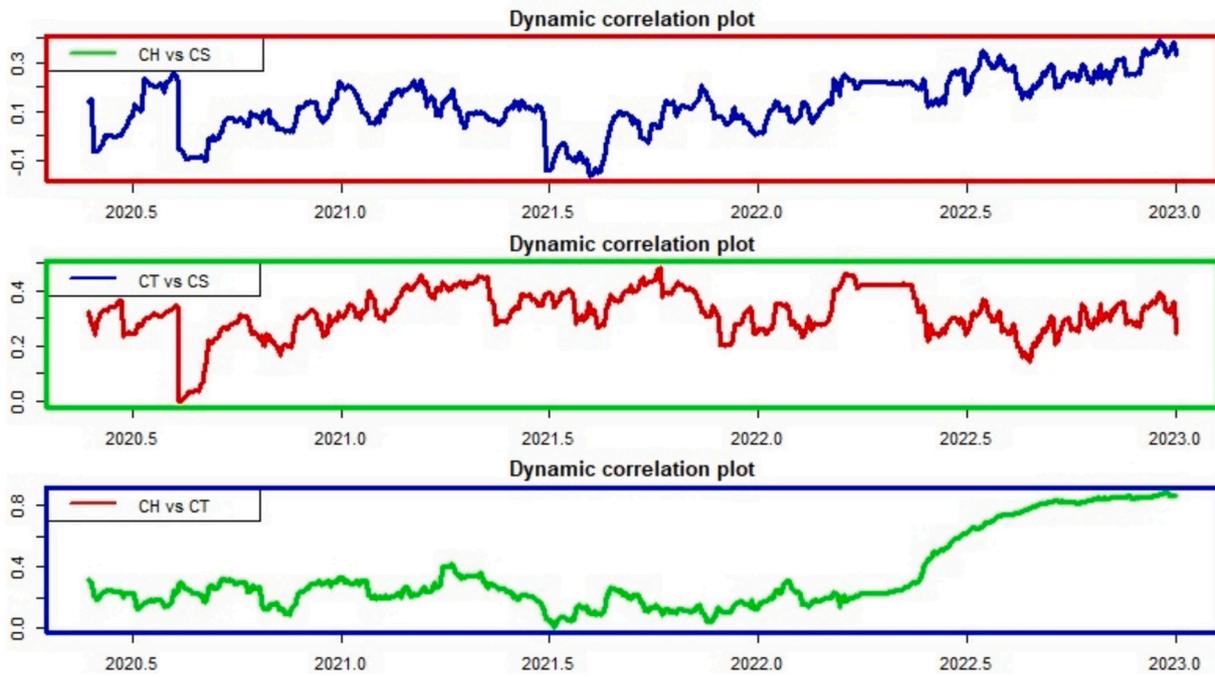


Fig. 4. The correlation between CH vs CT, CT vs CS, and CH vs CS.

volatility of the tourism sector.

Further, the γ_k Shows the presence of the leverage effect, but it is not harmful; in contrast, the coefficients of λ_r is positive in the CT and CS sectors, which displays that the market sentiment is asymmetrically transmitted to the tourism stock prices of these sectors (J. Cui & Maghyreh, 2023). Further residuals are standardized using an asymmetric E-GARCH model, which performs better across multivariate analyses, as indicated by the lowest AIC and HQ values.

Fig. 4 illustrates the dynamic conditional correlation among the

three sectors. Initially, during the outbreak era, the CH-CS correlation was high, but it gradually declined, reaching -0.1 by mid-2020, and continued to decline thereafter. Similarly, the CT-CS and CH-CT correlations are almost positive until mid-2020. The CT-CS peaked at 0.4 in Q2 2021, while the CH-CT relation surged after Q1 2022 but observed a positive trend. The relation between CH and CS indicates sectoral instability and a higher risk during the outbreak. The low-high values serve as a source of instability across the period, confirming our hypothesis, H4. These findings align with those of Mundra and Bichal

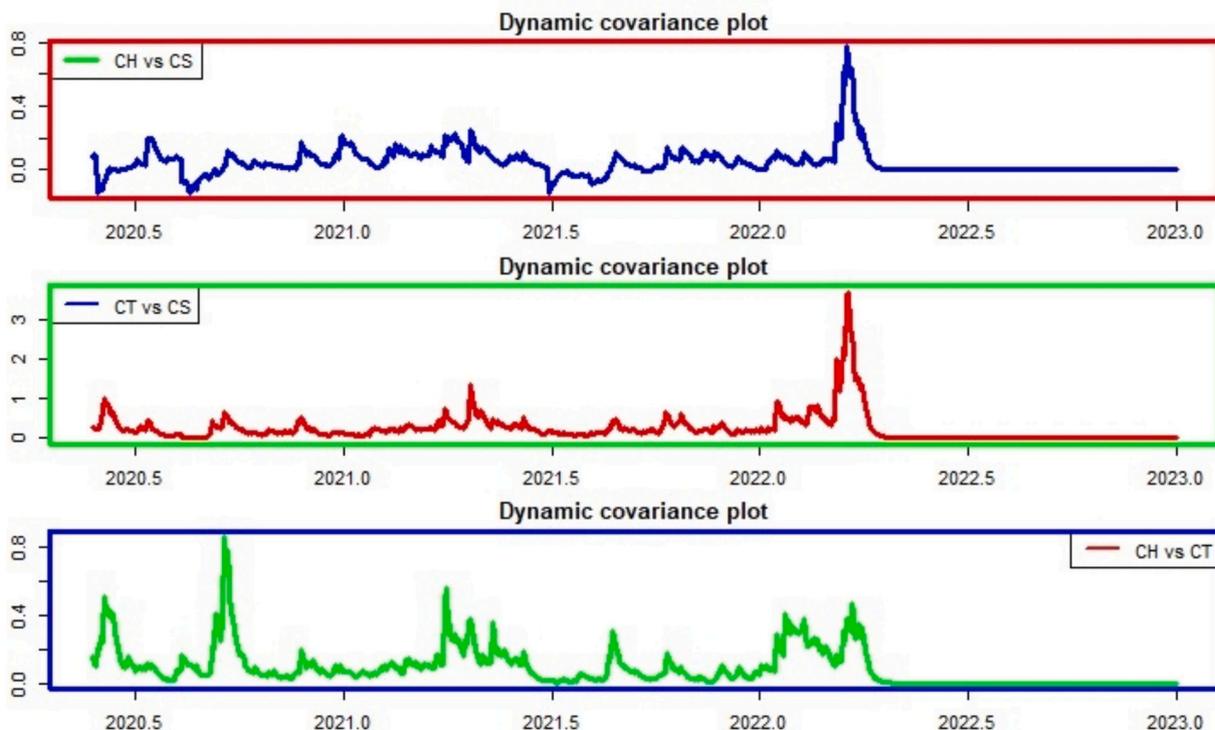


Fig. 5. The covariance between CH vs CT, CT vs CS, and CH vs CS.

(2021), highlighting the significant presence of dynamic conditional correlation among the sector's indices. Fig. 5 depicts the time-varying covariance among CT, CH, and CS sectors. The outbreak in China led to an increase in the covariance among all industries. However, CH and CT exhibited significant fluctuation over time, peaking during the 2nd quarter of 2020 and mid-2021. This indicates a considerable impact on CT by the CH sector; notably, a co-movement pattern was observed across all figures, with a sudden increase in the initial quarter, and it remained calm once China opened its borders in 2022. Results are consistent with Ringim et al. (2022), who reported the volatile and smooth covariance under various conditions.

5. Conclusion and policy implications

This study investigates the impact of investor sentiment and macroeconomic shocks on the volatility of tourism stocks in China during the COVID-19 recovery period, specifically from March 2020 to December 2022. The analysis is divided into two phases: the Crisis Phase (March 2020 to February 2022) and the Recovery Phase (March to December 2022). The findings indicate that the conditional volatility of tourism stocks is primarily driven by historical patterns (GARCH effects) rather than recent shocks, highlighting the significant impact of market memory. During the Crisis Phase, pandemic-related fear (measured by the Fear Index) and news sentiment played a crucial role in amplifying volatility, which contributed to a 6.2 % contraction in China's tourism GDP. However, the influence of the Fear Index diminished after March 2022, reflecting a decrease in concerns related to the pandemic.

Multivariate analysis revealed bidirectional volatility spillovers among tourism subsectors, travel, hotels, and scenic spots, with market sentiment spillovers accounting for 60 % of the conditional volatility in high-frequency trading firms. Additionally, asymmetric shocks, such as leverage effects, decreased during the Recovery Phase, indicating a reduction in debt-related vulnerabilities.

These insights suggest that policymakers should prioritize investor education programs for China's 38.5 million retail investors, implement institutional reforms to mitigate herd behavior, and integrate non-traditional sentiment indicators such as social media data into regulatory frameworks. Such measures are crucial for stabilizing a sector that accounts for 11.3 % of China's GDP.

6. Theoretical and practical implications

This study advances the field of behavioral finance by integrating PCA-based sentiment indices with emojis and microblogs, offering a clearer understanding of the psychology of retail investors in emerging markets. By dividing the post-pandemic period into Crisis and Recovery Phases, the research challenges traditional crisis frameworks and highlights how market dynamics evolve over time.

Practically, the findings emphasize the importance of risk managers focusing on historical volatility patterns rather than short-term shocks. Policymakers are also urged to address cross-sector spillovers, such as the transmission of volatility from the hotel sector to the travel sector, through diversified stimulus strategies. The diminishing relevance of the Fear Index after 2022 suggests that pandemic-specific metrics should gradually be replaced by broader sentiment indicators during the recovery phase.

For executives in the tourism industry and Destination Management Organization (DMO) managers, this study offers several actionable insights. First, incorporating social media and news sentiment analysis into market intelligence dashboards is crucial, as a sudden surge in negative emoji usage or fear-driven discussions on platforms like XUE-QIU can serve as an early warning signal for potential stock volatility and drops in consumer confidence, allowing for proactive public relations and marketing campaigns. Second, it is vital to acknowledge the interconnectedness of tourism subsectors; for instance, hotel chains should develop contingency plans that address not only their own operations but also volatility originating from major travel or transport companies, since negative shocks can quickly spill over. During future health or economic crises, DMOs and large firms should implement targeted communication strategies that directly address investor and consumer anxieties. Providing transparent information about safety protocols and financial health can help counter irrational fear and stabilize market perceptions. Finally, given the evidence of bidirectional spillovers, it is important to promote collaborative marketing and stabilization funds among hotels, transportation companies, and tourist attractions. By enabling these industry groups to work together, they can launch joint initiatives that enhance overall sector sentiment during recovery phases.

7. Limitations and future research

This study has several limitations. Methodologically, GARCH models assume linear relationships, potentially overlooking non-linear sentiment dynamics (e.g., panic-buying thresholds), while structural breaks in volatility regimes may bias results. PCA-based indices, although innovative, prioritize textual data (such as emojis and microblogs) and overlook non-textual factors, including geopolitical events. Contextually, the findings are anchored in China's post-pandemic setting, which limits their generalizability to non-crisis periods or other regions. Future research should explore cross-market comparisons in emerging tourism economies using Diebold-Yilmaz spillover and TVP-VAR models, as well as non-linear machine learning techniques (e.g., LSTM networks) to capture sentiment thresholds, and intraday data to refine aggregation biases. A case study on the China-Pakistan Economic Corridor (CPEC) could shed light on volatility spillovers at the intersection of tourism and infrastructure development, providing valuable insights for regional policy coordination.

CRedit authorship contribution statement

Aziz Ullah: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **He biao:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Mahfuzur Rahman:** Writing – review & editing, Visualization, Resources. **Assad Ullah:** Formal analysis, Conceptualization.

Declaration of competing interest

At this moment, I declare on behalf of all co-authors that submitting a manuscript is entirely our work, and this article has not been submitted or published in any other journal, and we have no conflict of interest.

Table A2
Variable Definitions, Data Sources, and Sample Firms by Tourism Subsector.

Firms	Transport sector	Hotel sector	Scenic spot sector
1	ZGGH -601,111	HTJD -428	HQCA -69
2	HHKG -600,221	LNKG -524	STSD -2159
3	NFHK -600,029	QJD -2186	SCYY -300,144
4	ZGDH -600,115	ZKYW -2306	HSLY -600,054
5	XMKG -600,897	SLJD -600,258	DSLY -600,593
6	HXHK -2928	JJJD -600,754	QJWL -600,706
7		JLFD -601,007	HSBG -900,942
Variable	Definition	Sources	Reference
Variables of interest (VOI)			
Firm CP	The closing price for firms	CSMAR	(Gao et al., 2022)
DDC	Daily COVID-19 death cases	Our world in data	(Vo et al., 2022)
DNC	Daily COVID-19 new cases	Our world in data	(Vo et al., 2022)
NS	News sentiment	Xueqiu.com	(W. Zhang et al., 2021)
Market proxies			
P/E	Price-to-earnings ratio	RESSET	(Peng et al., 2023)
CCI	Consumer confidence index	RESSET	(Peng et al., 2023)
T/R	Turnover ratio	CSMAR	(Peng et al., 2023)
NOA	Newly open accounts	CSMAR	(Peng et al., 2023)
Control variables (CV)			
E-Rate	Daily Exchange rate	CSMAR	(Vo et al., 2022)
EPU	Economic policy uncertainty	FRED economic data base	(Peng et al., 2023)
OP	Crude oil prices WTI	FRED economic data base	(Vo et al., 2022)
LIBOR	London Interbank offered a rate	Market watch	(Vo et al., 2022)

Table A3
KMO and Bartlett's test for PCA.

Kaiser-Meyer-Okine		Bartlett's Test Of Sphericity		
Index	Measurement of sampling adequacy	\$ Chi Sq	DF	significance
MS	0.76	7161.17	40	0.000 ^a
NS	0.61	324.438	19	0.000 ^a
FI	0.57	243.497	12	0.000 ^a
CT	0.80	1780.32	15	0.000 ^a
CH	0.65	351.751	21	0.000 ^a
CS	0.81	1200.724	21	0.000 ^a

Note: a,b,c subscript level of significance MS (Market Sentiment), NS (News Sentiment), FI (Fear Index).
CT (China Travel & Transport), CH (China Hotel Sector), CS (China Scenic Sector).

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