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Spillover of fear among the US and BRICS equity markets during the COVID-19 crisis and the Russo-Ukrainian conflict

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A B S T R A C T

This study examines volatility contagion between the US and five BRICS stock markets during the COVID-19 pandemic and the Russo-Ukrainian crisis. We first use the Markov-switching dynamic regression method to endogenously identify various phases of market evolution. Then, we employ a dynamic conditional correlation process to uncover time-varying volatility spillovers relying on the implied volatility induced by daily changes in the investigated markets. Empirical results indicate that market spillover during the two crises presents quite different scenarios. The US has a more significant and persistent contagion effect on the BRICS markets during COVID-19. However, only a short-lived and pulse-like market response is detected in the initial stage of the Russo-Ukrainian crisis, and the volatility interdependency structures do not follow a specific pattern across all implied volatility pairs.

1. Introduction

In recent years, the global financial markets have experienced considerable disruptions caused by the COVID-19 pandemic and the ongoing military conflict between Russia and Ukraine. These disruptions have caused significant fluctuations, both positive and negative, within the markets, as well as cross-market spillover risks. Even as the world moves into a post-pandemic era, the uncertainty surrounding the Russo-Ukrainian conflict continues to pose risks to the global financial market. Therefore, it is crucial for investors and regulators to have a better understanding of the connections between market volatility and its impacts against this background. This will enable them to make informed decisions regarding portfolio holdings, financial stability, and policy coordination.

There is a significant body of literature that examines market integration in the context of the COVID-19 pandemic, focusing mainly on volatility spillovers across various markets and asset categories (Zorgati & Garfatta, 2021; Guo, Li & Li, 2021; Pineda, Cortés & Perote, 2022; Benkraiem et al., 2022; Ben Amar, Bouattour & Carlotti, 2022; Yousfi, Farhani & Bouzgarrou, 2023; Taera et al., 2023; Almansour et al., 2023; Zhang et al., 2024). However, most of these studies rely on volatility estimates based on historical data to examine spillovers, and very few studies focus on implied volatility connections between markets. Compared to historical volatility estimates, the implied volatility derived from financial options provides a forward-looking estimation of market volatility that reflects investors' fear of future market crashes (Kostakis et al., 2011). Therefore, it offers better volatility forecasts than realized volatility or some other parametrical volatility estimators, particularly during periods of turbulence (Blair, Poon & Taylor, 2001).

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It is well documented in the literature that implied volatility indices show non-normal distribution patterns with excess kurtosis and heavy tails (Ammann & Süss, 2009; Aboura & Wagner, 2016). Additionally, they display volatility clustering and leverage effects, meaning that they react asymmetrically to positive shocks versus negative shocks (Kenourgios, 2014). This requires the modeler to effectively capture these distribution patterns to set up robust models for the analysis of volatility linkages. In this context, Kenourgios (2014) proposes using the asymmetric dynamic conditional correlation (A-DCC) specification developed by Cappiello, Engle, and Sheppard (2006) in an autoregressive (AR) asymmetric GARCH model. The author argues that this process can effectively capture the non-normal and asymmetric properties of implied volatility indices, making it suitable for analyzing asymmetric reactions in conditional correlations during times of market stress. Therefore, this study applies the AR-GJR-GARCH-A-DCC model to assess the time-varying behavior of volatility linkages and reveal the patterns of interdependence changes during normal and turbulent periods, as well as across various stages of market crisis.

This study contributes to the existing literature by examining the contagion of implied volatility between the US Chicago Board Options Exchange Volatility Index (VIX) and the implied volatility indices of the BRICS markets, which include Brazil, Russia, India, China, and South Africa. Previous studies, such as Jin and An (2016), focus on contagion during the global financial crisis. Similarly, Batondo and Uwilingiye (2022) investigate co-movement across BRICS and US stock markets using wavelet analysis. While these studies have provided valuable insights, the sample data used are outdated, failing to reveal the new patterns of risk spillover among the markets in the context of contemporary crises. In comparison to these related studies, the present research utilizes the most recent data to investigate the dynamics of implied volatility spillovers specifically in the context of the COVID-19 pandemic and the ongoing Russo-Ukrainian conflict. By employing daily changes in volatility indices and segmenting the observation period into four sub-samples based on distinct market phases identified through statistical analysis, this study offers a timely and relevant understanding of how these contemporary crises impact volatility interdependencies.

The contagion test method employed here is grounded in the standard definition of contagion, which refers to significant co-movement between volatility indices across different markets during periods of financial turbulence, extending beyond mere interdependence in fundamentals (Forbes & Rigobon, 2002). This research highlights the contagion effect from the US VIX index to the implied volatilities of BRICS markets, emphasizing the sensitivity of these emerging markets to shifts in macroeconomic and global market conditions (Ozoguz, 2009; Mensi et al., 2014). By focusing on the implications of implied volatility during these distinct crisis periods, this study provides valuable insights into the dynamics of volatility spillovers, enhancing our understanding of market interdependencies in a rapidly changing global landscape and offering practical implications for risk management and investment strategies in the context of emerging markets.

The empirical findings indicate that the two crises generate distinct time-varying dynamics of cross-market volatility linkage. Specifically, the US VIX and the implied volatility of the BRICS countries appear to have been more contagious and persistent during COVID-19, especially in the early phase. This suggests that market participants' attitudes towards the prospects of the markets tend to be consistent during this turbulent period. However, volatility contagion during the Russo-Ukrainian conflict is weak and short-lived, and the volatility interdependency structures do not follow a specific pattern across all implied volatility pairs.

The findings of the study offer valuable insights into the interdependence among implied volatility indices, which has significant implications for managing risks and achieving portfolio diversification goals. As stable cross-market correlations enhance international portfolio diversification, any increase in volatility spillover risk could reduce the effectiveness of volatility products. The findings could also assist in calculating value-at-risk, given that volatility contagion during crisis periods impacts the portfolio's extreme losses, and enable the implementation of innovative investment and trading strategies in the option markets. Lastly, considering dependencies among implied volatilities across various markets could lead to improvements in the use of prediction methods with implied volatilities.

The rest of the paper is outlined as follows: Section 2 provides a review of the relevant literature, Section 3 introduces the research methodology, Section 4 presents the sample data and discusses the specification of financial turmoil, Section 5 presents empirical findings, and Section 6 concludes the paper.

2. Related literature

The existing literature on market integration is prominent and extensive. Here, we mainly provide a brief review of two strands of literature that are highly relevant to this study.

The first strand of studies pertains to the use of implied volatility indices in examining linkages across markets and financial assets (Wagner & Szimayer, 2004; Korkmaz & Cevik, 2009; Peng & Ng, 2012; López, 2014). Implied volatility, compared to other volatility variables such as realized volatility or GARCH-based volatility estimates, reflects investors' anticipation of future market uncertainties. Hence, it provides more information for predicting financial contagion (Maghyereh et al., 2016). Jiang, Konstantinidi and Skiadopoulos (2012) show evidence that spillovers of implied volatility between the US and European markets significantly increase in the face of news announcements in the US market. Min and Hwang (2012) find that the increase in the US VIX exacerbates the volatility spillover effect on OECD countries. MacDonald, Sogiakas and Tsopanakis (2018) provide evidence of volatility spillovers across a number of strategic assets after accounting for economic fundamental variables. Badshah (2018) furthers the analysis of volatility linkage into a higher-order framework and suggests that the second moment of volatility offers informative content that should not be ignored in modeling volatility linkages. Using an autoregressive conditional jump intensity model, Chen et al. (2020a,b) reveal strong contagion effects of sentiment responses between the US and European countries, as well as within European nations. Similar results are reported by Quoreshi, Uddin and Jienwatcharamongkhol (2019), who confirm the existence of cross-market volatility spillovers at a smaller time scale.

The second strand of research refers to the market integration between developed stock markets and emerging stock markets. Over the past 20 years, with the deepening of global economic integration, emerging economies represented by the BRICS countries are not only active but also useful for investment diversification. Consequently, the connectedness between emerging markets and developed markets is continuously strengthening (Bhar & Nikolova, 2009; Dimitriou et al., 2013a,b; Bhuyan et al., 2016; Samargandi & Kutan, 2016). Mensi et al. (2014) provide evidence of interdependence between BRICS equity markets and the US equity market using a quantile regression framework. Bouri et al. (2018) confirm through the BGSVAR model that the implied volatility of developed stock markets has significant predictive power for the implied volatility of BRICS stock markets. Jin and An (2016) conduct an impulse response analysis and find that there exist contemporaneous and lagged spillover effects between the volatilities of the US and BRICS equity markets. The authors also provide evidence of a strong contagion effect from the US to the BRICS markets during the global financial crisis period, although the degree varies across specific market pairs. Batondo and Uwilingiye (2022) analyze the co-movement of stock markets between BRICS countries and the US during major financial crises since 2000. The study finds that market integration has deepened co-movement among equity markets and China's market offers lucrative opportunities for short-term investors. A stream of studies investigates the market connectedness between developed and emerging countries from the perspective of behavioral finance. For example, Caetano and Yoneyama (2011) describe the dynamics of herding behavior and the contagion effect in financial markets using particle swarm techniques. Ghorbel, Snene and Frikha (2022) examine the presence of herding contagion among developed countries and the BRICS markets in the context of the COVID-19 pandemic. Using wavelet coherence analysis, they discover various patterns of herding interaction among the herding estimators across markets. Dash and Maitra (2019) study the causal relationship between investor sentiment in developed and emerging markets, concluding that investor psychology is an important channel for market risk transmission. The recent financial turbulence caused by the COVID-19 pandemic has attracted researchers' attention to shed light on market linkages during this special period (Ledwani, Chakraborty & Shenoy, 2021; Yu et al., 2021; Li, Zhuang & Wang, 2021; Yarovaya et al., 2022; Amar et al., 2023). Malik, Sharma and Kaur (2022) use a multivariate GARCH framework to examine pairwise contagion and volatility transmissions in stock market returns of BRICS nations and the US during the pandemic. Zhang, Sha and Xu (2021) investigate the dynamic spillover effects between BRICS and G7 countries, indicating that the global financial market's spillover network is enhanced after events such as the China-US trade war and the COVID-19 pandemic.

Our study extends the related studies by examining the implied volatility spillovers across the US and the BRICS markets against the background of the COVID-19 and Russo-Ukrainian crises. This significant issue has not been explored in previous studies. Specifically, we employ a robust contagion test model that can effectively capture the patterns of the implied volatility and dynamically estimate the time-varying spillovers of volatility across different phases of market evolution. In this way, the analysis provides a comprehensive understanding of the volatility interdependence between the examined markets. This information is valuable for regulators in preventing the spread of financial risks, and can also serve as a guide for investment diversification.

3. Methodological framework

The model employed in this paper consists of two stages to estimate the conditional covariance matrix. Firstly, univariate GARCH models are used to fit each implied volatility index's daily changes. Then, the daily changes are transformed by their estimated standard deviations and used to estimate conditional correlation parameters with the A-DCC model. The A-DCC model, proposed by Cappiello et al. (2006), is an extension of Engle's (2002) DCC-GARCH model. It considers the asymmetry in the impact of positive and negative news on volatility and correlation dynamics. The model also includes the use of series-specific news impact and smoothing parameters, which can account for idiosyncratic effects in a more flexible way.

For the application of the DCC paradigm, we first introduce the AR(1) process to express the process of the implied volatility indices as follows:

$$r_t = c_0 + c_1 r_{t-1} + \varepsilon_t \varepsilon_t \sim n.d.(0, H_t) \tag{1}$$

with $H_t = E\left[\varepsilon_t, \varepsilon_t'\right]' = D_t P_t D_t$.where $r_t = [r_{it}, r_{2t}]'$ is a 2×1 vector including VIX and each of the other implied volatility index sequences, and $\varepsilon_t = [\varepsilon_{it}, \varepsilon_{2t}]'$ is a 2×1 residual vector. H_t denotes the variance–covariance matrix, in which P_t is the correlation matrix with time-varying characteristics.D_t is the diagonal matrix whose diagonal elements $h_{i,t}^{1/2}$ represent the conditional variance derived from the estimation of the first stage. To capture the asymmetry and clustering features of the volatility series, we specify $h_{i,t}$ to follow the GJR-GARCH (1, 1) process of Glosten et al. (1993) as:

$$h_{i,t} = \omega + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_i \varepsilon_{i,t-1}^2 I_{t-1} \tag{2}$$

where ω is the intercept term, α_i is the ARCH-coefficient, β_i describes the autocorrelation structure of the volatility, and γ_i captures the asymmetry in the pricing process. $I(\cdot)$ is the indicative function, which is equal to unity when $\varepsilon_{i,t-1} < 0$, otherwise zero. It should be noted that α_i is a non-negative coefficient, and $\alpha_i + \beta_i < 1$ to ensure positive conditional variances.

In the second stage, we use the residuals estimated from Equation (2) to estimate the DCC model. The standard DCC model presented by Engle (2002) is written as:

$$Q_t = (1 - a - b)\overline{P} + a z_{t-1} z_{t-1}' + b Q_{t-1} \tag{3}$$

where $z_{i,t} = \left(r_{i,t}/\sqrt{h_{i,t}}\right)$ is the standardized form of the residuals, $\overline{P} = E\left[z_t z_t'\right]$ and a and b are non-negative parameters satisfying $a +$

$b < 1$.

The standard DCC model mentioned above can be augmented by incorporating the asset-specific news and the asymmetrical features of the volatility process, thereby creating the AG-DCC model, expressed as:

$$Q_t = (\overline{P} - A'\overline{P}A - B'\overline{P}B - G'\overline{N}G) + A'z_{t-1}z_{t-1}'A + G'n_{t-1}n_{t-1}'G + B'Q_{t-1}B \tag{4}$$

in which A, B and G are coefficient matrices of size $k \times k$, $\overline{P}$ and $\overline{N}$ are correlation matrices for z_t and n_t, respectively. The asymmetric impact of n_t is measured by its negative standardized residuals, which are given by $n_t = I[z_t < 0] \otimes z_t$, where the symbol "$\otimes$" represents the Hadamard product and $I(\cdot)$ is an indicator function that equals one if the argument is true and zero otherwise. The A-DCC specification can be viewed as a special condition of the AG-DCC specification once A, B and G are substituted by scalars a, b and g.

Finally, the time-varying correlation matrix in the framework of the A-DCC model can be given as:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

where Q_t^* is a diagonal matrix whose diagonal elements correspond to the square root of the corresponding elements in Q_t.

4. Sample data and specification of turmoil periods

4.1. Sample data

We use the multivariate AR-GJR-GARCH-A-DCC model discussed in Section 3 to examine the volatility interdependence between the US equity markets and the BRICS equity markets, namely Brazil, Russia, India, China, and South Africa. The selection of these countries is particularly compelling due to their diverse economic contexts and significant global influence. The BRICS nations represent a unique group of emerging economies, each with distinct political, economic, and market characteristics. This diversity allows for a comprehensive analysis of how different markets respond to global shocks, enhancing our understanding of financial contagion and market integration. We rely on the daily prices of the implied volatility of the S&P 500 index (VIX), the Bovespa index (IV-BOVESPA), the RTS index (IV-RTS), the SENSEX index (IV-SENSEX), the HIS index (IV-HIS), and the JSE index (IV-JSE). All volatility indices are calculated based on options on the selected market index with a maturity of thirty days. The sample period spans from January 3, 2013, to April 30, 2023, incorporating the prominent financial turmoil period caused by the COVID-19 event and the Russo-Ukrainian conflict. The COVID-19 pandemic and the Russo-Ukrainian conflict exemplify two distinct crisis types—one primarily a health crisis with widespread economic ramifications, and the other a geopolitical conflict that disrupts global stability. Analyzing these events allows for a nuanced understanding of how various crises impact market volatility and interdependencies. We collect all stock indices from Bloomberg and calculate the log returns of their prices for our estimation.

Fig. 1 displays the changes over time of the selected volatility indices for both closing prices and first-order differences throughout the entire observation period. The figure exhibits some interesting patterns with regard to the fluctuations in volatility. Firstly, all volatility indices show a sharp increase in the first quarter of 2020, primarily due to the outbreak of the COVID-19 pandemic, which induced panic across the globe. Although the volatility indices have since fluctuated and returned to normal levels, they still remain higher than before the pandemic. Secondly, another significant increase in all volatility indices occurred in February 2022 during the Russo-Ukrainian war. The war's negative impact on the global energy market's supply led to increased market panic. Among the direct parties to the crisis, the Russian market's volatility index experienced the most significant and longest-lasting increase, followed by the

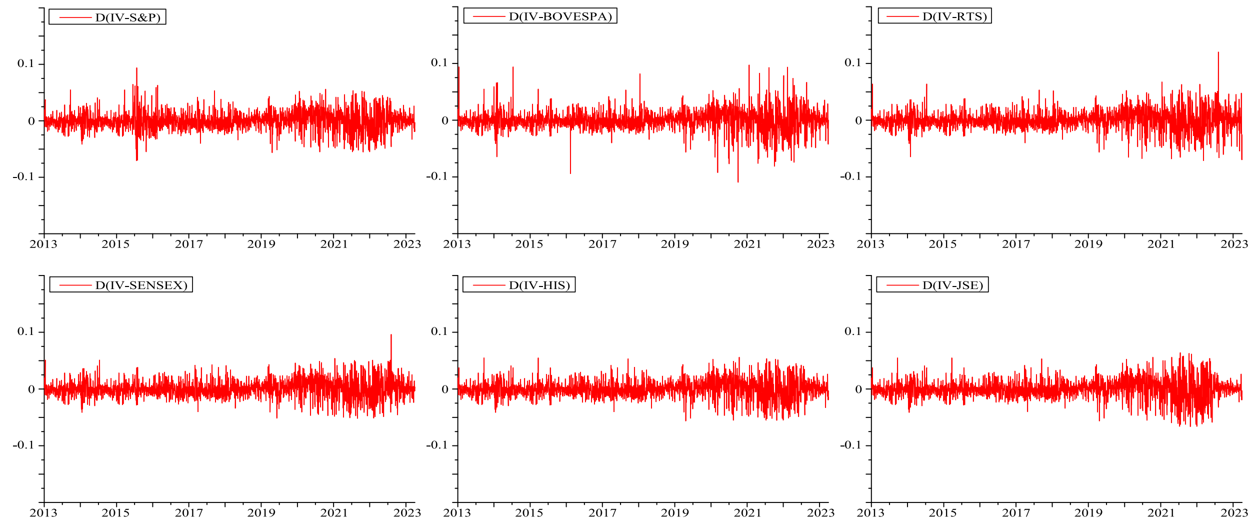

Fig. 1. Time series of the six investigated variables, January 2013 to April 2023.

US market. However, we find that the other four emerging market indices experienced only short-lived pulse-like increases, returning to pre-crisis levels shortly after. Lastly, the volatility indices display an evident feature of volatility clustering, particularly around the crisis breakpoint.

4.2. Specification of turmoil periods

For empirical analysis, it is vital to effectively identify the period of the financial crisis and its duration, as the empirical study of market contagion is sensitive to the specification of the crisis period. The literature in contagion usually identifies market breakpoints and the duration of different stages using either qualitative or quantitative methods (Kalbaska & Gatkowski, 2012; Akhtaruzzaman, Boubaker & Sensoy, 2021). This study relies on quantitative analysis methods to endogenously identify different market regimes. We further use ad-hoc (economic) analysis to verify the results of the statistical approach and ensure their appropriateness.

It is widely known that the US stock market holds an important and dominant position in the global financial system, and its volatility is often a source of risk for other markets globally (Arouri et al., 2016). Therefore, we use the VIX indicator from the US market in our statistical analysis to identify different market regimes. Specifically, we apply a Markov-switching dynamic regression (MS-DR) technique to the VIX indicator to capture the breakpoints endogenously and define the starting and ending times of different regimes. A Markov-switching dynamic regression (MS-DR) model is a statistical model that assumes that data is generated from different regimes, and the regime is determined by an underlying Markov process. In our analysis, the market state is classified into two categories: "stable" (regime 0) and "volatile" (regime 1), which correspond to the lower and higher values of VIX, respectively. The identification of crisis regimes is dependent on the presence of high persistence of excess volatility, which is identified by the smoothed regime probability approaching 1. However, any regime with low persistence of excess volatility is not considered in the identification process.

Table 1 displays the descriptive statistics for the six volatility indices being analyzed. The results show that all of the volatility indices exhibit excess kurtosis and are skewed to the right. The Jarque-Bera statistics reject the normality hypothesis for all cases. Therefore, the AR(1)-GJR-GARCH model is appropriate to account for these distribution patterns. The augmented Dickey-Fuller tests indicate that there is no unit-root present; however, there is a significant ARCH effect for all of the indices.

Fig. 2 displays the smoothed regime probabilities of VIX for the entire sample period. Based on Fig. 2, three sustained high volatility regimes of VIX have been identified, which correspond to the periods from February 27, 2020 to May 29, 2020; from September 13, 2020 to January 20, 2021; and from February 17, 2022 to August 23, 2022. The identification results of the statistical approach are highly consistent with the evolution of the two crises as marked by major economic and financial events during this period.[1] Therefore, we divide the financial market evolution since 2020 due to the pandemic and geopolitical conflicts into four continuous and distinct phases. Phase 1, occurring from February 27, 2020 to May 29, 2020, is characterized by a sharp market crash caused by the COVID-19 shock. Phase 2, spanning from May 30, 2020 to February 16, 2022, is defined by economic difficulties resulting from lockdown measures and supply chain disruptions under the pandemic. Phase 3, occurring from February 17, 2022 to August 23, 2022, is marked by severe financial market turbulence due to pressure from both the pandemic and the Russo-Ukrainian conflict. Finally, Phase 4, which lasts from August 24, 2022 onwards, is characterized by the gradual stabilization of financial markets coupled with a sluggish recovery in the real economy. Accordingly, the crisis period, which covers the first three stages as defined above, lasts from February 27, 2020 to August 23, 2022.

5. Empirical findings

5.1. Estimation results of the AR(1)-GJR-GARCH(1,1)-A-DCC specification

Table 2 presents the estimation results for the univariate AR(1)-GJR-GARCH(1,1) model for each individual volatility index on level changes. The volatility for each index exhibits a significant auto-correlated structure pattern, as evidenced by the parameters $(\alpha_i + \beta_i)$ in each case being close to unity. The parameters γ_i are significantly negative, which suggests the leverage effect of volatility in response to positive and negative shocks. The Ljung-Box Q statistics demonstrate the absence of auto-correlated relations in the time series residuals.

Table 3 presents the estimation results from the bivariate A-DCC model of US-emerging market volatility pairs. We apply the quasi-maximum likelihood approach to estimate the model and generate robust and consistent standard residuals. It suggests that the estimates of a_i and b_i are significantly positive for all cases. Additionally, the estimate of g_i is positive and statistically significant, indicating the presence of asymmetry. The results of the autocorrelation tests do not reject the null hypothesis of no autocorrelated

[1] It is widely known that the COVID-19 pandemic originated in Wuhan, China, in December 2019 and spread to the US in March 2020, causing massive disruption to the US financial markets. The Dow Jones Industrial Average (DJIA) index dropped sharply from its peak of 29,551.42 points to a low of 18,591.93 points, experiencing four circuit breakers. As the death toll rose and medical resources became scarce, the financial markets continued to experience extreme volatility. Although the markets eventually stabilized, the global supply chain disruption caused by lockdown measures exerted enormous pressure on the real economy, resulting in slow economic growth and an increase in unemployment rates. In February 2022, the conflict between Russia and Ukraine erupted, exacerbating war fears and pandemic uncertainty, prompting significant fluctuations in currency and commodity markets. Despite the financial markets remaining calm afterwards, the increase in commodity prices caused inflation pressures in many countries, posing new threats to the real economy.

Table 1
Descriptive statistics of VIX and volatility indices of the BRICS stock markets (daily changes).

	VIX	IV-BOVESPA	IV-RTS	IV-SENSEX	IV-HIS	IV-JSE
Mean	−0.0035	−0.0065	−0.0078	−0.1142	−0.0013	−0.0009
Max.	31.5251	21.5451	19.8465	20.5451	17.8492	23.5412
Min.	−16.8545	−20.4515	−19.8645	−32.5141	−29.8412	−18.7454
St. dev.	1.7845	1.6845	2.0541	1.6948	1.3567	1.5541
Skewness	0.6215	1.1254	0.7154	0.5124	0.3356	0.7682
Kurtosis	21.6854	23.4682	26.9854	32.4658	26.8454	13.8763
Jarque-Bera	363.546*	298.512*	330.548*	318.652*	415.855*	423.525*
ADF statistics	−33.5412	−29.5452	−35.5412	−32.8456	−33.8454	−36.8451
ARCH (5)	1.2351	1.2255	1.2384	1.2463	1.2387	1.2115

Note: The table presents the descriptive statistics of the daily changes in the implied volatility indices of the investigated markets. The sample period spans from January 3, 2013, to April 30, 2023. "*" indicates statistical significance at the 10% level.

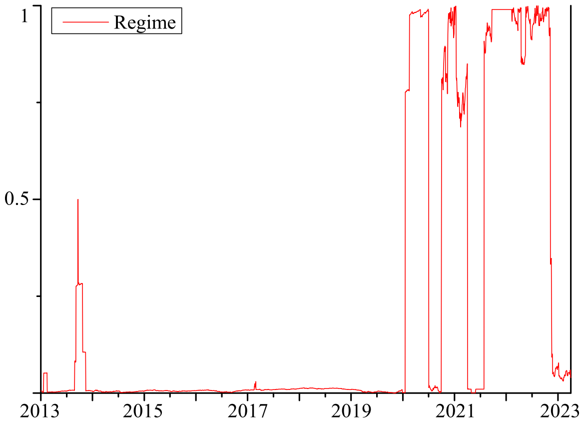

Fig. 2. Regime switch of VIX volatility characterized by the MS-DR technique.

Table 2
AR(1)-GJR-GARCH(1,1) model estimation for the investigated variables.

	VIX	IV-BOVESPA	IV-RTS	IV-SENSEX	IV-HIS	IV-JSE
c_0	0.0358**	0.4124*	0.3412**	0.2986**	0.3015**	0.1839*
t statistics	2.3125	1.8549	1.9654	1.7985	2.4125	2.2285
c_1	−0.0514**	−0.0498****	−0.0345**	−0.0452*	−0.4521**	−0.3658*
t statistics	−3.1254	−2.1541	−2.2351	−4.1625	−3.2151	−1.2142
ω	0.0235***	0.0314**	0.0158***	0.0251***	0.0351**	0.0153***
t statistics	2.6125	2.7125	1.9854	2.2012	2.3546	2.6851
α_i	0.1251***	0.1125***	0.1395***	0.1214***	0.1025***	0.1125***
t statistics	6.5212	5.3125	6.3213	5.3646	4.1231	3.9456
β_i	0.8745***	0.8874***	0.8604***	0.8785***	0.8974**	0.8873***
t statistics	44.5261	45.5465	46.8546	40.4582	41.5931	42.7534
γ_i	−0.2545**	−0.1987***	−0.1625***	−0.1756***	−0.1864***	−0.1423***
t statistics	−7.4514	−6.9823	−7.5495	−8.4582	−7.7712	−6.5813
$Q(5)$	19.8545	14.4874	16.8124	19.1325	12.5415	11.5415
	[0.7345]	[0.4152]	[0.3526]	[0.6845]	[0.8845]	[0.5912]
$Q^2(5)$	0.8874	1.9856	2.0546	0.9865	−0.5693	3.0529
	[0.6582]	[0.6283]	[0.4829]	[0.6346]	[0.4685]	[0.5934]

Note: This table reports the estimated results of model (1) and (2) using the daily changes of the implied volatility indices from the US and five BRICS stock markets over the period of January 2013 to April 2023. The lag order is determined based on the AIC and SIC criteria. Parameters α_i and β_i describe the ARCH and GARCH effects, respectively. γ_i stands for the asymmetry in the pricing process. Q and Q^2 are the Ljung-Box Q-statistics in the standardized and the squared standardized residuals, respectively. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

relationship, which suggests that the chosen specification captures the distribution features of the implied volatility indices well. Therefore, we can proceed with the calculation of the dynamic correlation coefficients based on these findings.

Fig. 3 depicts the time-varying conditional correlation dynamics (DCCs) between the volatility indices of the US and the BRICS markets. The DCCs display significant fluctuations throughout the entire sample period. Furthermore, a clear regime shift pattern in

Table 3
The estimation results of the DCC model.

	US–BOVESPA	US–RTS	US–SENSEX	US–HIS	US–JSE
COR_{ij}	0.4854	0.3951	04,264	0.3041	0.3825
a_i	0.2112***	0.1701***	0.1952***	0.1115**	0.1825***
t statistics	5.4521	5.1452	3.1582	3.9125	3.7825
b_i	0.7815***	0.8236***	0.8012***	0.8864**	0.8142***
t statistics	63.5124	48.1274	47.3482	50.6384	51.4629
g_i	0.5362***	0.6184***	0.5934***	0.3845***	0.4358***
t statistics	6.4521	4.1582	4.3845	4.9685	6.2546
H(20)	49.8545	80.6348	62.5458	39.4825	49.5625
	[0.3351]	[0.4125]	[0.1985]	[0.2435]	[0.3846]
$H^2(20)$	5.6845	3.6826	4.256	6.3946	11.5214
	[0.8894]	[0.9364]	[0.8216]	[0.7752]	[0.9236]

Note: This table reports the estimated results of the DCC model using the daily changes of the implied volatility indices from the US and five BRICS stock markets over the period of January 2013 to April 2023. H() and H^2() are the Ljung-Box statistics proposed by Hosking (1980). ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

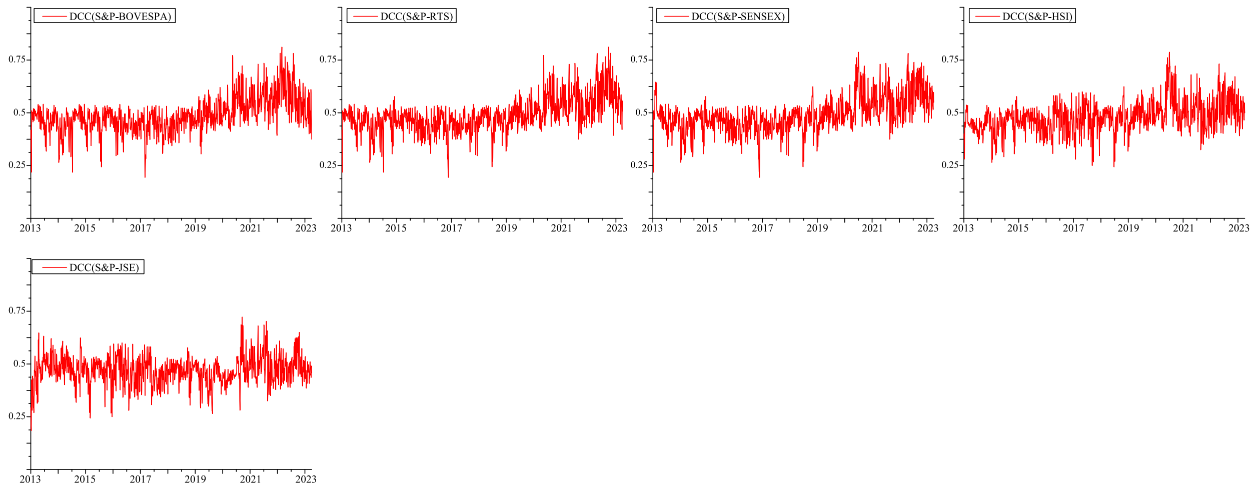

Fig. 3. DCCs between the US and BRICS market volatilities during the sample period.

market interdependence can be observed across stable and crisis conditions. For example, we observe that co-movements among volatility indices are much more significant during downside movements than upside movements. This motivates us to conduct a more extensive investigation into contagion dynamics during different market phases.

5.2. DCCs across non-crisis and crisis periods

This subsection tests for variations in dynamic correlations between market volatilities during calm and turbulent periods. We

Table 4
Structure changes in correlations across normal and turbulent periods.

	US–BOVESPA	US–RTS	US–SENSEX	US–HIS	US–JSE
Mean equation in model (6)					
c_0	0.5121***	0.4715**	0.5493***	0.3581**	0.4128***
L_1	0.0421***	0.0412**	0.0512***	0.0312*	0.8984***
Variance equation in model (7)					
a_0	0.0031***	0.0041***	0.0009***	0.0015***	0.0024***
a_1	0.7316***	0.7254***	0.7936***	0.7101**	0.7425***
v_1	0.1625***	0.1435***	0.1382***	0.1184**	0.1825***
a_2	0.2241***	0.2238**	0.1382***	0.2245*	0.2012***
L_1	−0.0013***	−0.0008***	−0.0012***	−0.0021***	−0.0006***

Note: This table reports the test results of the structural changes in correlations across normal and turbulent periods. L_1 is the dummy variable which equals 1 during the turbulent period (COVID-19 and Russo-Ukrainian crises). The lag order is selected based on the AIC and SIC criteria. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

establish the following specification to estimate the dynamic changes in DCC:

$$\rho_{ij,t} = c_0 + L_1 DM + \eta_{ij,t} \tag{6}$$

where $\rho_{ij,t}$ is the conditional correlation between US VIX and each BRICS volatility index estimated from Eq. (5). DM is a dummy variable specified to be unity during the crisis period and 0 otherwise. We also introduce the dummy variable into an extended GARCH (1,1) model to account for the ARCH effects as well as asymmetry features in the conditional variance dynamics of the DCCs:

$$h_{ij,t} = \alpha_0 + \alpha_1 \eta_{ij,t-1}^2 + L_1 DM + \alpha_2 h_{ij,t-1} + \nu_1 \eta_{ij,t-1}^2 I_{t-1} \tag{7}$$

As indicated by the model, the significance of the estimated parameter on the dummy variable suggests a change in the structure of volatility interdependence caused by external shocks during the periods of market crises.

Table 4 shows the estimates of models (6) and (7). The results indicate that the parameter estimates of the dummy variables in Eq. (6) are significantly different from the calm market period for all cases. This suggests that during crises, there is a significant increase in the correlation between the volatility indices of the US and BRICS, confirming the presence of contagion effects. The positive and significant estimate of parameter ν_1 indicates a higher level of volatility of the DDCs associated with crises. Finally, the coefficient L_1 in equation (7) is negative and significant for all cases, indicating that the volatility relationships are more stable in market stress conditions. The above findings provide helpful insights for investors in managing investment portfolios. On the one hand, the risk diversification effect of volatility indices is significantly undermined during financial crises. On the other hand, the stable structure of volatility index correlations provides a potential guide for asset allocation decisions during crisis periods.

5.3. DCCs across different market phases

As discussed in section 3.2, the turmoil periods triggered by the two crises can be identified as four distinct stages of evolution. To investigate market contagion behavior across different phases of market evolution, we use four dummy variables corresponding to each phase of the crisis. Dummy variable is set to 1 during the crisis period and 0 otherwise. This approach allows us to identify and measure the contagion effect during different market regimes by testing the significance of the coefficient on the dummy variables. Based on equations (6) and (7), we establish the following specifications:

$$\rho_{ij,t} = c_0 + \sum_{k=1}^{4} \beta_k dum_{k,t} + \eta_{ij,t} \tag{8}$$

$$h_{ij,t} = \alpha_0 + \alpha_1 \eta_{ij,t-1}^2 + \sum_{k=1}^{4} d_k dum_{k,t} + \alpha_2 h_{ij,t-1} + \nu_1 \eta_{ij,t-1}^2 I(\eta_{ij,t-1} < 0) \tag{9}$$

where $\rho_{ij,t}$ denotes the DCC between the volatility indices of the US and the BRICS countries. $dum_{k,t}$ corresponds to the k-th phase of the crisis periods.

Table 5 presents the estimated results of the dummy variables in model (8). The coefficients β_1 in the model are positive and significantly different from the non-crisis period for all US-BRICS volatility index pairs, indicating that the initial panic caused by the spread of the virus had a significant impact on these financial markets, leading to significant contagion effects between the volatility indices.

In the second phase, the coefficients β_2 are only statistically significant for the volatility pairs of US–Brazil and US–South Africa, and there are no significant volatility relationships detected for the rest of the cases. This suggests that some markets are decoupling their risks from the US market after the initial chaos caused by the pandemic. A plausible explanation for this phenomenon could be that the pandemic has permanently shifted investors' common appetite for risk, and that the performance of each country's market mainly reflects the fundamental factors of the respective country.

During phase 3 of the financial stress period, when geopolitical conflicts once again shook the financial markets, we observe that the estimated results of the coefficient β_3 are quite mixed for different volatility index pairs. The estimated β_3 is positive and highly significant for the US–Russian case. β_3 is also positively significant for the US–Brazil and US–South Africa pairs, although the sig-

Table 5
Structure changes in correlations across various phases of the Covid-19 and Russo-Ukrainian crises.

	US–BOVESPA	US–RTS	US–SENSEX	US–HIS	US–JSE
c_0	0.5456***	0.3358**	0.4658***	0.3946**	0.5758***
β_1	0.4632***	0.5017**	0.3349***	0.6121**	0.5705***
β_2	0.0021***	0.0412	0.0512	−0.0002	0.0079***
β_3	0.3231*	0.4051***	−0.0009	0.0011	0.1024*
β_4	0.0312	−0.1105	0.0925	0.0034	0.0023*

Note: This table presents the test results of the structural changes in correlations during different phases of the COVID-19 and Russo-Ukrainian crises. β_i (i=1, 2, 3, 4) is the dummy variable corresponding to the i-th phase of the financial crisis evolution process. The lag order is selected based on the AIC and SIC criteria. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

nificance level is lower than that of the US–Russia case. However, the estimated β_3 is insignificant for the US–India and US–China volatility pairs during this market stress period, suggesting that the global financial market impact caused by the Russo-Ukrainian conflict did not reach these two countries.

In phase 4, as the impact of the pandemic gradually faded and the Russo-Ukrainian conflict become prolonged, the volatility correlation between markets once again shows a relatively stable structure. Among them, only the coefficient β_4 between the South African and US volatility indices is positive and significant at the 10 % level, while the remaining cases are all insignificant.

Finally, the estimated results for the dummy coefficients of Equation (9) are presented in Table 6. The results show that the coefficients d_k of the variance of DCCs between US and emerging markets volatility are either negative or insignificant during each stage of the crisis. This implies that the dynamic correlation structure of the market's volatility does not undergo a structural change with the change in market conditions. Therefore, investors can continue to use the stable interdependence structure of volatility indices for risk management during the crisis period.

5.4. *Interpretation of the findings*

The analysis of the dynamic conditional correlations between the US and five BRICS stock market volatilities reveals significant synchronization at the beginning of the COVID-19 crisis. However, the observed pattern is a mix of decoupling from US markets for the five emerging markets during the subsequent stage of the crises. Moreover, the impact of the Russo-Ukrainian conflict on emerging markets, except those involved in the conflict, seems markedly different from the effects seen from the COVID-19 pandemic on financial markets. This can be interpreted as an indication of varying degrees of interdependence and integration between the US and BRICS stock markets during different phases of financial crises.

When the epidemic hit the US in March 2020, it had a significant impact on the healthcare system. The medical infrastructure faced challenges due to overcrowding and a sharp increase in the death toll, which lead to panic in the capital markets. Furthermore, the US stock market had just emerged from a significant rise, and there was mounting pressure for accumulated market risks to be released. With the combined effect of these twin factors, the US stock market plummeted by nearly 40 % in just one month, experiencing rare circuit breakers four times during this period. This panic also spread globally like a tsunami, affecting stock markets worldwide. Many emerging markets, including Brazil, joined the wave of circuit breaks, leading to a significant increase in market volatility correlation.

After experiencing initial chaos, the proactive measures taken by governments around the world gradually calmed the market down from the panic of the early days of the pandemic. The one-sided market crash came to an end, and was replaced by an increase in the frequency of wide-ranging fluctuations. However, at this stage, different countries took varying measures to address the long-term economic and social impacts of the pandemic. For example, the US market did not take excessive measures to restrict economic activity, instead using stimulus policies like fiscal and monetary policies to mitigate the pandemic's negative impact on the economy. Some emerging markets, such as Brazil, Russia, and South Africa, also adopted similar strategies to the US, where they coexisted with the virus. As a result, the stock markets in these countries quickly recovered their prosperity with liquidity increasement. In contrast, China did not implement excessive economic stimulus plans but instead relied on public health management measures, including strict lockdowns, isolation, and dynamic clearing policies, to address the pandemic. Therefore, during this period, the Chinese stock market and other emerging markets showed different trends, which are also reflected in the volatility relationship with the US market.

By early 2022, although the pandemic had gradually subsided, new geopolitical conflicts once again caused turbulence in the international financial markets. Compared with the COVID-19 pandemic, the impact of the Russo-Ukrainian conflict on the market is more reflected in the international energy and commodity markets. However, when looking back at this period, it can be found that besides Russia, the conflicting party, the impact on other emerging markets was short-lived and limited, but the impact on developed economies such as Europe was relatively persistent and profound. This can be attributed to the fact that the conflict between Russia and Ukraine has had a greater impact on the markets of developed economies that are heavily dependent on Russian energy. However, for emerging markets, represented by China and India, there have been no energy supply issues from Russia, and their stock markets have had a relatively muted response to geopolitical conflicts. As a result, we have not found much evidence of significant increases in market correlation during this period.

The findings of the present study largely corroborate existing studies on market integration and volatility spillovers. For instance, Mensi et al. (2014) find significant interdependence between BRICS equity markets and the US equity market, while Bouri et al. (2018) further confirm that the implied volatility of developed markets has predictive power for BRICS markets. However, this study specifically examines the volatility spillover dynamics between the US and the BRICS markets, tracing the timing patterns and the magnitude of the transmission. By doing so, we uncover additional patterns of volatility connectedness, particularly during periods of market distress, thereby contributing to a deeper understanding of the interdependencies in times of crisis.

6. Conclusion

This study examines the spread of market fear across the US and the five BRICS stock markets, namely Brazil, Russia, India, China, and South Africa, during the periods of the COVID-19 pandemic and the Russo-Ukrainian conflict. Relying on implied volatility, we investigate the time-varying co-movement of variables across different market phases using an asymmetric DCC process based on the multivariate GJR-GARCH representation. The results show a mixed contagion pattern with respect to the COVID-19 event and the Russo-Ukrainian event. Specifically, the implied volatility correlation between the US and the BRICS countries is more pronounced during the pandemic and lasts longer, experiencing two significant increases in correlation associated with the evolution of the pandemic. However, no significant volatility spillover effects are detected during the Russo-Ukrainian conflict. The five emerging

Table 6
Structure changes in volatility of correlations across various phases of the COVID-19 and Russo-Ukrainian crises.

	US–BOVESPA	US–RTS	US–SENSEX	US–HIS	US–JSE
α_0	0.0007***	0.0013***	0.0006***	0.0004***	0.0011***
α_1	0.8024***	0.7812***	0.7385***	0.7518**	0.8246***
v_1	0.1632***	0.1352**	0.1145***	0.0968*	0.1849***
α_2	0.1452***	0.1596***	0.1105***	0.1896**	0.1213***
d_1	0.0004	0.0003	−0.0025**	−0.0018*	0.0022
d_2	−0.0013**	−0.0014*	0.0021	−0.0006**	0.0015
d_3	−0.0054**	0.0031	−0.0035**	0.0009	−0.0023**
d_4	−0.0306**	−0.0121**	−0.0023*	0.0012	0.0009

Note: This table presents the test results of the structural changes in volatility of correlations during different phases of the COVID-19 and Russo-Ukrainian crises. d_i (i=1, 2, 3, 4) is the dummy variable corresponding to the *i*-th phase of the financial crisis evolution process. The lag order is selected based on the AIC and SIC criteria. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

markets only briefly respond to the US market in the early stages of the conflict, and the volatility of the interdependency structures does not follow a specific pattern across all implied volatility pairs. This evidence suggests that investors' expectations regarding the prospects of the markets are significantly different during these two crises.

Based on our findings, it is recommended that policy-makers in selected BRICS countries closely monitor the sources of significant volatility, as these can serve as leading indicators of market sentiment and potential volatility spillovers. Understanding these indices can help in anticipating market movements and adjusting strategies accordingly. Given the distinct patterns of volatility spillover observed during different crises, investors should consider diversifying their portfolios across various asset classes and geographical markets. This can mitigate risks associated with sudden market shocks and enhance overall portfolio stability.

For future study, exploring the long-term effects of geopolitical events on market volatility is essential. Additionally, investigating the role of emerging technologies in predicting volatility and expanding the analysis to include more emerging markets could enhance understanding of global financial interconnectedness and risk management strategies.

CRediT authorship contribution statement

Yi Zhang: Investigation, Formal analysis. **Long Zhou:** Conceptualization. **Zhidong Liu:** Project administration, Methodology. **Baoxiu Wu:** Validation, Software.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

References

Aboura, S., & Wagner, N. (2016). Extreme asymmetric volatility: Stress and aggregate asset prices. *Journal of International Financial Markets, Institutions and Money, 41*, 47–59.
Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID-19 crisis. *Finance Research Letters, 38*, Article 101604.
Almansour, B. Y., Elkrghli, S., Gaytan, J. C. T., & Mohnot, R. (2023). Interconnectedness dynamic spillover among US, Russian, and Ukrainian equity indices during the COVID-19 pandemic and the Russian-Ukrainian war. Heliyon, 9(12), 2405-8440.
Amar, A. B., Bouattour, M., Bellalah, M., & Goutte, S. (2023). Shift contagion and minimum causal intensity portfolio during the COVID-19 and the ongoing Russia-Ukraine conflict. *Finance Research Letters, 103853*.
Ammann, M., & Süss, S. (2009). Asymmetric dependence patterns in financial time series. *European Journal of Finance, 15*, 703–719.
Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters, 18*, 136–141.
Badshah, I. U. (2018). Volatility spillover from the fear index to developed and emerging markets. *Emerging Markets Finance and Trade, 54*(1), 27–40.
Batondo, M., & Uwilingiye, J. (2022). Comovement across BRICS and the US stock markets: A multitime scale wavelet analysis. *International Journal of Financial Studies, 10*(2), 27.
Benkraiem, R., Garfatta, R., Lakhal, F., & Zorgati, I. (2022). Financial contagion intensity during the COVID-19 outbreak: A copula approach. *International review of financial analysis, 81*, Article 102136.
Ben Amar, A., Bouattour, M., & Carlotti, J. E. (2022). Time-frequency analysis of the comovement between wheat and equity markets. *The Journal of Risk Finance, 23* (4), 368–384.
Bhar, R., & Nikolova, B. (2009). Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate EGARCH framework. *Global finance journal, 19*(3), 203–218.

Bhuyan, R., Robbani, M. G., Talukdar, B., & Jain, A. (2016). Information transmission and dynamics of stock price movements: An empirical analysis of BRICS and US stock markets. *International Review of Economics & Finance, 46*, 180–195.
Blair, B., Poon, S., & Taylor, S. (2001). Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high-frequency index returns. *Journal of Econometrics, 105*, 5–26.
Bouri, E., Gupta, R., Hosseini, S., & Lau, C. K. M. (2018). Does global fear predict fear in BRICS stock markets? Evidence from a Bayesian Graphical Structural VAR model. *Emerging Markets Review, 34*, 124–142.
Caetano, M. A. L., & Yoneyama, T. (2011). A model for the contagion and herding. *Physica A: Statistical Mechanics and its Applications, 390*(23–24), 4445–4450.
Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics, 4*(4), 537–572.
Chen, C. D., Chiang, S. M., & Huang, T. C. (2020a). The contagion effects of volatility indices across the US and Europe. *The North American Journal of Economics and Finance, 54*, Article 101234.
Chen, C. D., Chiang, S. M., & Huang, T. C. (2020b). The contagion effects of volatility indices across the U.S. and Europe. *The North American Journal of Economics & Finance, 54*, Article 101234.
Dash, S. R., & Maitra, D. (2019). The relationship between emerging and developed market sentiment: A wavelet-based time-frequency analysis. *Journal of Behavioral and Experimental Finance, 22*, 135–150.
Dimitriou, D., Kenourgios, D., & Simos, T. (2013a). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis, 30*, 46–56.
Dimitriou, D., Kenourgios, D., & Simos, T. (2013b). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH-DCC approach. *International Review of Financial Analysis, 30*, 46–56.
Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20*(3), 339–350.
Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market co-movements. *Journal of Finance, 57*, 2223–2261.
Ghorbel, A., Snene, Y., & Frikha, W. (2022). Does herding behavior explain the contagion of the COVID-19 crisis?. Review of Behavioral. *Finance.*
Guo, Y., Li, P., & Li, A. (2021). Tail risk contagion between international financial markets during COVID-19 pandemic. *International Review of Financial Analysis, 73*, Article 101649.
Jiang, G. J., Konstantinidi, E., & Skiadopoulos, G. (2012). Volatility spillovers and the effect of news announcements. *Journal of Banking and Finance, 36*(8), 2260–2273.
Jin, X., & An, X. (2016). Global financial crisis and emerging stock market contagion: A volatility impulse response function approach. *Research in International Business and Finance, 36*, 179–195.
Kalbaska, A., & Gatkowski, M. (2012). Eurozone sovereign contagion: Evidence from the CDS market (2005–2010). *Journal of Economic Behavior and Organization, 83*, 657–673.
Kenourgios, D. (2014). On financial contagion and implied market volatility. *International Review of financial analysis, 34*, 21–30.
Korkmaz, T., & Cevik, E. I. (2009). Volatility spillover effect from volatility implied index to emerging markets. *Journal of BRSA Banking and Financial Markets, 3*(2), 87–106.
Kostakis, A., Panigirtzoglou, N., & Skiadopoulos, G. (2011). Market timing with option-implied distributions: A forward-looking approach. *Management Science, 57*(7), 1231–1249.
Ledwani, S., Chakraborty, S., & Shenoy, S. S. (2021). Spatial tale of G-7 and Brics stock markets during COVID-19: An event study. *Investment Management and Financial Innovations, 18*(2), 20–36.
Li, Y., Zhuang, X., & Wang, J. (2021). Analysis of the cross-region risk contagion effect in stock market based on volatility spillover networks: Evidence from China. *The North American Journal of Economics and Finance, 56*, Article 101359.
López, R. (2014). Volatility contagion across commodity, equity, foreign exchange and Treasury bond markets. *Applied Economics Letters, 21*(9), 646–650.
MacDonald, R., Sogiakas, V., & Tsopanakis, A. (2018). Volatility co-movements and spillover effects within the Eurozone economies: A multivariate GARCH approach using the financial stress index. *Journal of International Financial Markets, Institutions and Money, 52*, 17–36.
Maghyereh, A. I., Awartani, B., & Bouri, E. (2016). The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes. *Energy Economics, 57*, 78–93.
Malik, K., Sharma, S., & Kaur, M. (2022). Measuring contagion during COVID-19 through volatility spillovers of BRIC countries using diagonal BEKK approach. *Journal of Economic Studies, 49*(2), 227–242.
Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review, 19*, 1–17.
Min, H. G., & Hwang, Y. S. (2012). Dynamic correlation analysis of US financial crisis and contagion: Evidence from four OECD countries. *Applied Financial Economics, 22*(24), 2063–2074.
Ozoguz, A. (2009). Good times or bad times? Investors' uncertainty and stock returns. *The Review of financial studies, 22*(11), 4377–4422.
Peng, Y., & Ng, W. L. (2012). Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. *Annals of Finance, 8*(1), 49–74.
Pineda, J., Cortés, L. M., & Perote, J. (2022). Financial contagion drivers during recent global crises. *Economic Modelling, 117*, Article 106067.
Quoreshi, A. M. M., Uddin, R., & Jienwatcharamongkhol, V. (2019). Equity market contagion in return volatility during euro zone and global financial crises: Evidence from FIMACH model. *Journal of Risk and Financial Management, 12*(2), 94.
Samargandi, N., & Kutan, A. M. (2016). Private credit spillovers and economic growth: Evidence from BRICS countries. *Journal of International Financial Markets, Institutions and Money, 44*, 56–84.
Taera, E. G., Setiawan, B., Saleem, A., Wahyuni, A. S., Chang, D. K. S., Nathan, R. J., & Lakner, Z. (2023). The impact of Covid-19 and Russia-Ukraine war on the financial asset volatility: Evidence from equity, cryptocurrency and alternative assets. *Journal of Open Innovation: Technology, Market, and Complexity, 9*(3), 2199–8531.
Wagner, N., & Szimayer, A. (2004). Local and spillover shocks in implied market volatility: Evidence for the US and Germany. *Research in international Business and Finance, 18*(3), 237–251.
Yarovaya, L., Brzeszczyński, J., Goodell, J. W., Lucey, B., & Lau, C. K. M. (2022). Rethinking financial contagion: Information transmission mechanism during the COVID-19 pandemic. *Journal of International Financial Markets, Institutions and Money, 79*, Article 101589.
Yousfi, M., Farhani, R., & Bouzgarrou, H. (2024). From the pandemic to the Russia-Ukraine crisis: Dynamic behavior of connectedness between financial markets and implications for portfolio management. *Economic Analysis and Policy, 81*, 1178–1197.
Yu, H., Chu, W., Ding, Y. A., & Zhao, X. (2021). Risk contagion of global stock markets under COVID-19: A network connectedness method. *Accounting & Finance, 61*(4), 5745–5782.
Zhang, P., Sha, Y., & Xu, Y. (2021). Stock market volatility spillovers in G7 and BRIC. *Emerging Markets Finance and Trade, 57*(7), 2107–2119.
Zhang, Y., Zhou, L., Wu, B. X., & Liu, F. (2024). Tail risk transmission from the United States to emerging stock Markets: Empirical evidence from multivariate quantile analysis. *The North American Journal of Economics and Finance, 73*, 1062–9408.
Zorgati, I., & Garfatta, R. (2021). Spatial financial contagion during the COVID-19 outbreak: Local correlation approach. *The Journal of Economic Asymmetries, 24*, e00223.