Tail risk transmission from the United States to emerging stock Markets: Empirical evidence from multivariate quantile analysis

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ABSTRACT

This paper explores the transmission of risk from the United States equity market to the equity markets of the BRICS countries using a multivariate quantile process. The focus is on the contagion effect at the extreme quantiles, both upside and downside. In addition, a pseudo-impulse-response function (PIRF) analysis is conducted to investigate the responses of the five emerging stock markets to a shock in the US market. We conduct an empirical study against the backdrop of the COVID-19 event and the Russia-Ukraine conflict, finding that risk spillovers between the US stock market and the five emerging stock markets are significantly enhanced during the COVID-19 period. Moreover, a shock in the US market produces a stronger and more persistent negative effect at the downside quantiles compared to upside quantiles. However, we find little evidence of cross-market risk spillovers among the investigated variables during the Russia-Ukraine conflict period. We also discuss the implications of these findings for investors and policymakers in terms of portfolio holdings and policy coordination.

1. Introduction

With the increasing globalization of financial markets, a structural shock originating in one market can rapidly propagate to other markets, increasing the systemic exposure to risk. Therefore, the study of contagion effects across international financial markets has always been of keen interest in financial economics. A better understanding of the dynamics of financial market contagion and their impact is becoming increasingly relevant for investors, policymakers, and regulators in terms of portfolio holdings, financial stability, and policy coordination.

In parallel, the unexpected COVID-19 pandemic and the Russia-Ukraine conflict are impacting the global financial system, putting financial market spillovers on the research agenda of many economists. In this context, Arfaoui and Yousaf (2022) study the asymmetric volatility spillover across stock, Bitcoin, gold and oil markets before and during the COVID-19 pandemic. The authors find that the interdependency across the examined markets intensified during the recent health crisis. Jin et al. (2023) investigate the dynamic features of multiscale spillovers between oil and BRICS stock markets during the COVID-19 crisis. Some studies also examine the risk contagion among international financial markets in the context of the Russia-Ukraine war. See, among others Yang et al. (2023), Umar et al. (2023) and Zhang, He and Hamori (2023). According to the conclusions of these works, the presence of significant increases in correlations among international financial market returns after the inception of the crisis events was validated, indicating contagion

effects.

For emerging markets, including the BRICS countries, market illiquidity and the slow development of financial institutions and regulatory systems are increasing their potential vulnerability to external shocks from developed markets (Prasad et al., 2005). As a result, global investors must seek to understand the functioning of BRICS stock markets, their dynamic risk/return trade-off relative to major developed stock markets (e.g., the United States), and the potential return and volatility spillovers between these markets and their economies. The extent of recent crises as well as the associated portfolio losses support further research into the spillovers between these major emerging and developed markets.

The related empirical literature on market relationship has come a long way, with the most common and straightforward one being correlation-based tests for contagion (Forbes and Rigobon, 2002; Luchtenberg and Vu, 2015; Wang et al., 2014). However, examining only mean or variance linkages between markets may result in an incomplete analysis that fails to reveal the full picture of market contagion. As ample evidence shows that financial asset returns do not follow a normal distribution; instead, they exhibit leptokurtosis and heavy tails due to being highly affected by frequent extreme events and crises. This means that there is a likelihood of an asymmetric pattern of contagion effect across different locations of the return distribution. To this end, a stream of studies has particularly focused on the tail risk spillover among markets (Wang, Wang and Huang, 2015; Aboura and Chevallier, 2018; Fong, Li and Fu, 2018; Miguel, Ugolini and Zambrano, 2018; Salisu et al., 2022; Stoja et al., 2023; Dai and Harris, 2023). Compared to volatility risk, tail risk represents an extreme type of risk with a greater potential for destruction not only in financial markets but also for entire economies, as seen in market crashes, bank failures, and sovereign debt crises. Consequently, we should give particular attention to tail risk and take measures to prevent its contagion.

Against this background, the present study aims to examine the interrelationship of the US stock market and the stock markets of the BRICS countries (Brazil, Russia, India, China, and South Africa) amidst the COVID-19 pandemic and the Russia-Ukraine war. The reason for selecting the BRICS markets as the subject is because, similar to other emerging markets, these markets have several unique features in common. For instance, they have historically generated high average returns while exhibiting relatively low correlations with the stock markets of developed countries. These features demonstrate that emerging markets have evolved into a significant asset class, and their inclusion in international and specialized investment portfolios has gained increasing importance due to the diversification benefits they offer to international investors. Therefore, emerging markets deserve greater attention and should be considered an important investment option to be included in investment portfolios.

Our study is closely related to the extant literature in the following three aspects: market contagion between BRICS countries and the US market, the temporal effect of a US market shock on the other markets' reactions, and the role of the crisis event in market risk spillover, with a particular focus on the tailed risk transmission from the US to BRICS markets. These problems have been thoroughly examined in the past with the aid of efficient tail-linkage detection tools based on the heavy-tailed distribution (Nasri and Rémillard, 2019; Tiwari, Raheem and Kang, 2019; Yousaf, Pham and Goodell, 2023). Among these methods, the quantile regression model is favored due to its capacity to offer greater flexibility in analyzing diverse market conditions. Additionally, the quantile analysis is semi-parametric, which means that it does not require the imposition of too many prior assumptions about the underlying data-generating process (Engle and Manganelli, 2004). As a result, the quantile analysis is highly robust to outliers, making it especially valuable in analyzing financial time series.

In comparison to previously contributions, the present work advance the literature by utilizing a multivariate quantile model to describe market relationships, rather than a conventional vector autoregression (VAR) model. Unlike traditional VAR models, which capture the dependency structure across markets on the entire return distributions, the multivariate quantile model allows the modeler to specifically focus on the correlation at certain percentiles. This, in turn, enables us to conduct a pseudo-impulse-response function (PIRF) analysis, which outperforms the conventional impulse response function by identifying the variable response to a unit shock at various distribution quantiles, such as upside quantiles and downside tail quantiles. Overall, as far as our knowledge goes, our study is among the first to investigate the possible asymmetry and shift structure in tail dependence between the US and BRICS stock markets, based on the most updated temporal background. These contributions provide a comprehensive understanding of the dynamics of risk spillovers between the US stock market and the BRICS markets, offering valuable implications for both investors and policymakers.

In general, we document strong evidence of tail spillovers from the US stock index to BRICS market indices, particularly at the downside quantiles. However, we find an asymmetric market reaction to shocks originating from the US market depending on the conditioning quantile investigated. Specifically, a positive shock in the US produces a negative response in other markets in the downside tail, whereas it is followed by a positive reaction in the upside tail. We attribute this phenomenon to the presence of liquidity spillovers in a rising market and the flight-to-quality phenomenon operating in a fallen market. We also show that market spillovers are highly event-specific. The turmoil in the market caused by the crisis events has significantly increased market tail codependence, with the most notable effects being observed in the downside tail.

The rest of the paper is structured as follows: Section 2 provides a brief review of related studies. Section 3 introduces our employed methodology. Section 4 describes the sample data for empirical research. Section 5 presents the empirical findings. The last section concludes the paper.

2. A brief literature review

The literature on market contagion is abundant and prominent, and many empirical models have been developed regarding the spillovers of returns, volatility, or even higher-order moments across regional or international financial markets. We mainly focus on and provide a short review of the existing literature from the following two strands, which are most relevant to the scope of this study.

The first strand is related to studies on international spillovers in financial markets. The concept of financial contagion, also known

as market spillover or propagation, came into use during the 1997 Asian financial crisis and gained even more attention after the 2008 subprime mortgage crisis. The existence of financial contagion has been widely demonstrated through empirical evidence. However, it is difficult to determine with certainty whether contagion has occurred or not, as the answer to this question would largely depend on the testing methodology used (Pericoli and Sbracia, 2003). Earlier studies primarily searched for evidence of contagion by relying on the most common and straightforward correlation-based analysis. The occurrence of contagion was suggested by a statistically significant increase in the correlation coefficient following the breakpoint. For example, Calvo and Reinhart (1996) determined the occurrence of financial contagion during 1994 Mexican Crisis through a correlation-based test. In what is considered to be the most central study in the correlation-based contagion literature, Forbes and Rigobon (2002) argued that the linear correlation-based tests of market contagion suffered from heteroscedasticity bias. The authors maintained that market volatility tended to increase during periods of turmoil, creating an upward bias in the correlation measures. Therefore, the correlation-based test is prone to identifying normal market interdependence as evidence of contagion occurrence. After accounting for that bias, there is no supportive evidence of contagion during financial crisis periods. In the same vein as Forbes and Rigobon (2002), Luchtenberg and Vu (2015) used a heteroscedasticity-adjusted test to investigate the 2008 subprime mortgage crisis, showing significant evidence for market contagion. Many scholars applied the VAR framework to examine the transmission of financial shocks across different markets and the potential for financial contagion. Georgoutsos and Moratis (2017) used a panel VAR model to reveal the distinctive behavior of the Eurozone market during financial turmoil and distinguish between contributors and recipients of risk. Dynamic conditional correlation (DCC) analysis is another popular method to detect the presence of financial contagion. This method enables the phenomenon of financial contagion to be captured by modeling the time-varying correlations between assets and estimating how they change in response to market conditions (Celık, 2012; Dimitriou, Kenourgios and Simos, 2013; Bello, Guo and Newaz, 2022). Ahmad, Sehgal, and Bhanumurthy (2013) employed the DCC-GARCH model to examine the contagion effect of the Eurozone stock market shock on global emerging economies during the Eurozone crisis, showing that the BRICS countries experienced the strongest contagion effects, while other emerging economies only showed an increase in interdependence. Mollah, Quoreshi and Zafirov (2016) used the dynamic conditional correlation framework to examine the contagion effect across global equity markets due to the 2008 global financial crisis and the 2011 European zone crisis, showing that contagion spread from the US market to the international markets during both crises.

A main drawback of the methods mentioned above is their inability to effectively characterize the tail behavior of the return distribution, yet this tail behavior represents extreme risk which is essential in measuring financial contagion. Therefore, a considerable body of literature places attention on the examination of extreme risk spillover based on theories of heavy-tailed distributions, with copula function (Fenech and Vosgha, 2019; Niţoi and Pochea, 2020; Abduraimova, 2022), value-at-risk (VaR) estimations (Ye, Luo and Liu, 2017), and quantile analysis (Chuliá, Guillén and Uribe, 2017; Wen et al., 2019) being among the most commonly used methods. Ning (2010) applied copulas to account for the spillover between the equity market and the foreign exchange market, finding that there exists an apparent symmetric upside and downside tail relationship between the two markets. Using a vine-copula model, Yu, wang and Jin (2020) investigated the dynamic dependence structure between the crude oil market and stock indices of both the US and China. The findings indicated variations in the dependence structure under different market conditions. The quantile regression framework proposed by Koenker and Bassett (1978) provides us with a promising tool for better understanding the way in which market contagion occurs. Wen et al. (2019) investigated the transmission of risk between the crude oil market and the equity market using a multivariate quantile approach, finding that shocks in the crude oil market have a significant asymmetric effect on the upper and lower tails of the equity market, and that tail dependence between the two markets is strengthened after structural breaks in the financial market. Quantile analysis has the advantage of enabling the modeler to study the correlations between variables at different percentiles across the entire distribution, which provides a more comprehensive view of the dependency structure rather than being limited to the center. Moreover, quantile analysis can be used to model the behavior of the tail without the need to estimate the first two moments of the distribution. Due to these reasons, this study proposes multivariate quantile analysis, which captures the extreme distribution quantile dependency and accounts for the tail risk spillovers across the markets of our interest.

The second strand is the literature related to the role of the COVID-19 and Russia-Ukraine crises in market dependence. Given that financial markets could become more synchronized during a bearish market (Hartmann et al., 2004), the market downturn associated with the evolution of this health event offers an ideal backdrop to test this hypothesis (Chevallier, 2020; Yousaf, Ali and Wong, 2020; Akhtaruzzaman, Boubaker and Sensoy, 2021; Benkraiem et al., 2022; Yousaf et al., 2023). Yuan, Wang and Jin (2022) established a market contagion network through a dynamic combined copula-EVT process, suggesting the presence of epidemic-driven market contagion during the pandemic period. Uddin et al. (2022) examined the tail dependence structure between the US stock market and the stock markets of BRICS countries during the pandemic, concluding that the COVID-19 pandemic could be considered as a new source of global financial contagion. Although it has been pointed out that market dependence could shift significantly due to the pandemic, the research on the impact of COVID-19 on tail risk spillover between the US market and the markets of the BRICS bloc remains scarce so far.

3. Methodology

As noted by a number of studies, causal relationships can only be identified once any exogenous issues have been appropriately addressed in a structural modeling procedure (Pearl, 2012). However, in practice, this condition is difficult to fulfill in the situation of deepening global financial integration. International investors can quickly adjust their positions by reallocating their assets, which has a feedback effect on global markets and undermines the exogeneity requirement. Some studies propose the structural vector autoregression model and allege that the introduction of this multivariate time series tool can effectively deal with the problem of exogenous conditions (Sims, 1980). In this context, White, Kim and Manganelli (2015) proposed the multivariate multiquantile models (MVMQ)

and used them to study the vulnerability of financial institutions in the face of financial distress. The MVMQ model is a multivariate augmentation of the CAViaR model established by Engle and Manganelli (2004), which is built on the assumption that the quantiles of the distribution of a data series may depend on the lags of its own and certain related variables of interest. The MVMQ (1,1) model utilized in our study can be expressed as:

$$q_{1,t} = c_1(\theta) + a_{11}(\theta)r_{1,t-1} + a_{12}(\theta)r_{2,t-1} + b_{11}(\theta)q_{1,t-1} + b_{12}(\theta)q_{2,t-1} \tag{1}$$

$$q_{2,t} = c_2(\theta) + a_{21}(\theta)r_{1,t-1} + a_{22}(\theta)r_{2,t-1} + b_{21}(\theta)q_{1,t-1} + b_{22}(\theta)q_{2,t-1} \tag{2}$$

For notational simplicity, the reduced form of models (1) and (2) is written as:

$$q_t = c + AR_{t-1} + Bq_{t-1} \tag{3}$$

in which $q_{i,t}$ denotes the conditional quantile regression equation on the τ th quantile, defined as $Pr[r_{i,t} \leqslant q_{i,t} | \mathbb{F}_{t-1}]$. $r_{i,t-1}$ is the value of the first lag of the returns, and $q_{i,t-1}$ is the first lag of the distribution quantiles in the bivariate structure. A and B are the reduced-form lag coefficient matrices. It should be noted that B is the binary connectivity matrix whose elements on the main diagonal describe the temporal dependence structure of the distribution quantile, while the non-diagonal elements in matrix B measure the tail interdependence between the distribution quantiles of two variables.

As suggested by White, Kim and Manganelli (2015), we can recover the structural innovations and deduce quantile PIRFs, provided that a suitable exogeneity restriction holds in the system. The restriction condition in this study is based on the fact that the US stock market shock has been extensively proven to be a main source of risk to international equity markets (Ehrmann, Fratzscher and Rigobon, 2011). Additionally, as the largest and most liquid stock market in the world, the performance of the US market mainly reflects information from its own market (Brazys, Duyvesteyn and Martens, 2015). Therefore, we impose the restriction condition that the US stock price is contemporaneously immune from external shocks, while all other markets contemporaneously respond to the US stock market's performance. This assumption is supported by empirical literature, which provides a plausible and straightforward option, much better than strictly supposing the global factors to be exogenous (Chevallier et al., 2018; Das et al., 2019).

We apply the PIRFs instead of conventional functions, because while conventional functions impose a one-time intervention on the error term, PIRFs suppose that the one-time intervention on the error term is given only to the asset return of the current period (Gourieroux and Lu, 2019; Lee, Kim and Mizen, 2021). The PIRFs within the quantile regression framework are defined as:

$$\Delta_{i,s}\left(\widetilde{r}_{1,t}\right) = \widetilde{q}_{i,t+s} - q_{i,t+s}, \; s = 1, 2, 3 \cdots T \tag{4}$$

in which $\widetilde{q}_{i,t+s}$ and $q_{i,t+s}$ refer to the $\theta-$th conditional quantile of the affected series $\widetilde{r}_{it}$ and the $\theta-$th conditional quantile of the unaffected series r_{it}, respectively. The PIRFs can be calculated for various quantiles of the distribution of a given return series, while still preserving the conventional interpretation of IRFs. This enables the examination of extreme interdependencies between pairs of data series, addressing the challenge of measuring tail dependencies directly, rather than obtaining them indirectly through first and second conditional moment models.

4. Data description

We use the multivariate quantile model discussed in Section 3 to examine the tail interdependence between the US equity markets and the BRICS equity markets, namely Brazil, Russia, India, China, and South Africa. Specifically, we rely on the daily S&P 500 index price for the US market, the Bovespa index for Brazil, the RTS index for Russia, the SENSEX index for India, the HIS index for China, and the JSE index for South Africa. The sample period runs from January 3, 2015, December 30, 2023, incorporating the prominent financial turmoil period caused by the COVID-19 health and Russia-Ukraine conflict events. All stock indices are collected from Bloomberg, and we calculate the log returns of the prices for our estimation.

Panel A of Table 1 displays the descriptive statistics of the US index and five emerging market indices. The mean values of returns are found to be close to zero, while the standard deviations are significantly larger. The skewness and kurtosis statistics reveal that all

Table 1
Summary descriptive statistics of the sample data. This table displays the statistical characteristics of each country's log return over the period from January 3, 2015 to December 31, 2022. The J-B statistic represents the Jarque-Bera test of normality. KPSS is the statistic of the Kwiatkowski et al. (1992) stationary test. ** and *** indicate statistical significance at 5% and 1% level, respectively.

	S&P 500	Bovespa	RTS	SENSEX	HIS	JSE
Mean	0.00321	0.00393	−0.00141	0.00342	0.00126	0.00192
Median	0.00447	0.00464	0.00022	0.00542	0.00342	0.00301
Std. Dev	3.323	3.550	4.103	3.887	3.653	3.462
Skewness	−0.066	−0.652	−0.669	−0.463	−0.992	−0.079
Kurtosis	20.963	16.531	35.537	16.887	9.524	10.201
J-B statistic	331.54[***]	336.522[***]	340.662[***]	298.493[***]	277.815[***]	409.306[***]
Probability	0.00	0.00	0.00	0.00	0.00	0.00
KPSS	0.0601	0.0369	0.0685	0.0528	0.0859	0.0133
P-B correlations with US	1	0.52[***]	0.35[**]	0.44[**]	0.33[**]	0.48[***]

return series exhibit a leptokurtic and heavy-tailed pattern. This is further confirmed by the Jarque-Bera statistic, which rejects the null hypothesis of normality at a 1 % level for all cases. The KPSS test fails to reject the null hypothesis that the series is stationary in any case, allowing us to model their joint behaviors directly without any further processing. The Pearson correlations between the US index and each of the BRICS indices are all significant, with the highest correlation observed for the US − Brazil pair and the lowest for the US − China pair.

5. Empirical findings

In this section, we test the contagion hypothesis between the series of quantiles of the US and BRICS stock market indices, with the US market serving as the common risk source market. We first present the estimation results of the multivariate quantile model over the entire period and three sub-periods separated by the outbreaks of the COVID-19 pandemic and the Russia-Ukraine conflict. Next, we perform the pseudo-impulse response analysis to investigate the temporal spillover effects at the extreme percentile locations of the return distribution. Lastly, we assess the performance and robustness of the model.

5.1. VAR quantile regression results

Tables 2 and 3 present the estimation results of the MVMQ model over the entire sample period. The coefficients associated with Eq. (2) are estimated at five quantiles, including 0.01, 0.10, 0.50, 0.90 and 0.99. The 1st and 10th percentiles indicate downside risk, while the 90th and 99th percentiles denote upside risk. The 50th percentile represents the median risk. We estimate a bivariate VAR structure between the US market index and each BRICS market index. Notably, we are particularly interested in the estimation results of coefficients a_{21} and b_{21}, as these two factors best demonstrate the relationship of each variable with the US index.

We first focus on the coefficient estimates for the 50th percentile, as displayed in Table 2. Our analysis shows that only Brazil has a negative and statistically significant coefficient a_{21} at the 10 % level. For the remaining cases, no significant cross-sectional effects exist between the US index and the other four market indicators. In other words, the performances of BRICS stock market indices are relatively independent of the US markets at this percentile. Additionally, we also observe a weak autocorrelation structure in the median for the majority of both the US and BRICS indicators, as evidenced by positive and significant estimates of b_{11} and b_{22}. This, to some extent, negates the efficient market hypothesis in these markets.

When turning to the extreme quantiles reported in Table 3, we find more evidence of tail-linkage patterns between markets, especially at the downside quantiles. The estimations of the coefficient b_{21} are statistically significant at the 0.01 and 0.10 quantiles for all cases, with a significance level of 5 % or higher. Since the extreme downside quantiles of the return distribution can be interpreted as the VaR measures, this finding implies a higher probability of crash risk for the BRICS markets led by the lagged VaR of the US market. The a_{21} estimations are statistically significant at the 1 % quantile for the Brazil index and the 10 % quantile for the South Africa index, suggesting that the downside tail risk of these two markets is affected by the lagged returns of US indices. For other markets, the influence of the lagged US index returns on their downside risk is insignificant. We also notice significant estimations of b_{11} and b_{22} for the majority of the indices, suggesting the persistence of VaRs for these markets.

Regarding upper quantiles, there are significant risk spillover effects among markets, although the degree is relatively smaller than that of the downside scenario. The estimations of b_{21} indicate that the upside risks of the Brazilian, Indian, and South African markets significantly depend on the lagged upside risk of the US index, which only occurs under very extreme conditions (0.99 quantile) for the Russian and Chinese markets. The coefficient estimations of a_{21} are statistically insignificant for most cases, except for the Indian indicators at the 90th percentile, suggesting that the overnight return of the US index has very little influence on the upside risk of the BRICS markets. Additionally, the US index presents a significant autocorrelation structure of the upper tail distribution, supported by the estimations of b_{11}, whereas for the BRICS market indices, the auto-dependence structure changes from being significant to insignificant in many cases.

The joint test results suggest significant cross-dependence for the majority of cases, with a few exceptions at the upper percentiles. All this evidence suggests that shocks to the US market have increased the probability of tail risks occurring in the BRICS market in an

Table 2
Estimation results of the MVQM model at the 50% quantile. The table reports the parameter estimation results of the MVQM model for the bivariate analysis of the US index and the BRICS indices over the entire period. The statistic *js* represents the joint significance of the cross-coefficients. ** and * denote the significance level at 5% and 10%, respectively.

	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_2	a_{21}	a_{22}	b_{21}	b_{22}	js
Bovespa	−0.113**	0.164*	0.004	0.113*	0.018	−0.511*	0.112*	0.212	0.117	0.126*	4.32
	(0.103)	(0.056)	(0.226)	(0.004)	(0.017)	(0.004)	(0.301)	(0.107)	(0.109)		
RTS	−0.111	0.151	0.021	0.182*	0.213	−0.332	0.021	0.329*	0.008	0.139*	6.33
	(0.271)	(0.109)	(0.313)	(0.069)	(0.046)	(0.166)	(0.005)	(0.007)	(0.141)	(0.028)	
SENSEX	−0.134	0.211*	0.142	0.132*	0.113	−0.414*	0.019	0.166	−0.023	0.241*	4.01
	(0.201)	(0.016)	(0.221)	(0.081)	(0.051)	(0.021)	(0.312)	(0.006)	(0.018)	(0.029)	
HIS	−0.041	−0.182	0.007	0.211*	0.007	−0.303	−0.027	0.212*	0.134	0.213*	3.02
	(0.133)	(0.219)	(0.231)	(0.132)	(0.114)	(0.214)	(0.333)	(0.032)	(0.049)	(0.017)	
JSE	−0.119	0.073	0.007	0.108**	0.013	0.117	−0.141	0.029	−0.124	0.2038*	4.98
	(0.207)	(0.171)	(0.158)	(0.004)	(0.034)	(0.252)	(0.329)	(0.112)	(0.029)	(0.019)	

Table 3

Estimation results of the MVQM model. The table reports the parameter estimation results of the MVQM model on the conditional quantiles 0.01, 0.10, 0.90 and 0.99 over the entire period. The statistic *js* represents the joint significance of the cross-coefficients. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_2	a_{21}	a_{22}	b_{21}	b_{22}	js
1 % quantile											
Bovespa	−0.234**	0.243*	0.003	0.711***	0.013	−0.422*	−0.112**	0.113	−0.123***	0.832***	23.34***
	(0.021)	(0.013)	(0.359)	(0.002)	(0.142)	(0.331)	(0.004)	(0.211)	(0.002)	(0.002)	
RTS	−0.169	0.112	0.012	0.693**	0.101	−0.333	0.011	0.162	−0.236***	0.741**	22.67**
	(0.221)	(0.229)	(0.354)	(0.004)	(0.046)	(0.216)	(0.036)	(0.031)	(0.012)	(0.002)	
SENSEX	−0.162	0.203*	0.035	0.801***	0.155	−0.324*	0.011	0.198	−0.121***	0.713**	32.84***
	(0.207)	(0.021)	(0.173)	(0.009)	(0.161)	(0.016)	(0.233)	(0.029)	(0.001)	(0.011)	
HIS	−0.151	−0.213	0.015	0.503**	0.011	−0.241	−0.016	0.232*	−0.122**	0.602*	13.44*
	(0.149)	(0.311)	(0.362)	(0.005)	(0.092)	(0.242)	(0.121)	(0.163)	(0.004)	(0.009)	
JSE	−0.316	0.0107	0.007	0.619**	0.032	0.151	−0.321	0.029	−0.317***	0.918***	26.35***
	(0.241)	(0.211)	(0.204)	(0.006)	(0.087)	(0.363)	(0.231)	(0.143)	(0.031)	(0.001)	
10 % quantile											
Bovespa	−0.169**	0.162*	0.014	0.702**	0.009	−0.313*	0.083	0.203	−0.121**	0.639**	25.24***
	(0.0011)	(0.081)	(0.132)	(0.003)	(0.139)	(0.116)	(0.103)	(0.212)	(0.003)	(0.009)	
RTS	−0.142	0.153	0.009	0.693**	0.143	−0.251	0.021	0.261*	−0.213**	0.041	27.37***
	(0.351)	(0.221)	(0.524)	(0.012)	(0.115)	(0.206)	(0.116)	(0.007)	(0.008)	(0.311)	
SENSEX	−0.143	0.153*	0.177	0.701*	0.132	−0.294*	0.019	0.189	−0.121***	0.313*	31.84***
	(0.027)	(0.001)	(0.183)	(0.009)	(0.161)	(0.007)	(0.133)	(0.006)	(0.001)	(0.004)	
HIS	−0.023	−0.232	0.010	0.203*	0.029	−0.281	−0.038	0.181*	−0.132**	0.102	14.24*
	(0.179)	(0.169)	(0.312)	(0.211)	(0.432)	(0.193)	(0.111)	(0.009)	(0.002)	(0.212)	
JSE	−0.131	0.061	0.007	0.519*	0.021	0.132	−0.193**	0.026	−0.197**	0.718**	26.15**
	(0.469)	(0.212)	(0.254)	(0.005)	(0.132)	(0.338)	(0.004)	(0.116)	(0.011)	(0.004)	
90 % quantile											
Bovespa	−0.314**	0.221*	0.021	0.682**	0.031	−0.214*	−0.134	0.104	0.201**	0.539**	15.34*
	(0.018)	(0.008)	(0.541)	(0.003)	(0.539)	(0.016)	(0.213)	(0.247)	(0.008)	(0.011)	
RTS	−0.162	0.123	0.014	0.576**	0.061	−0.214	0.041	0.123	0.106	0.241	10.33
	(0.351)	(0.211)	(0.294)	(0.013)	(0.537)	(0.116)	(0.145)	(0.141)	(0.212)	(0.413)	
SENSEX	−0.151	0.222*	0.035	0.601*	0.013	−0.321*	0.111*	0.098	0.121**	0.213	12.32*
	(0.342)	(0.016)	(0.203)	(0.009)	(0.211)	(0.014)	(0.013)	(0.129)	(0.009)	(0.321)	
HIS	−0.233*	−0.149	0.012	0.544**	−0.009	−0.321	−0.006	0.112*	0.021	0.102	6.34
	(0.201)	(0.336)	(0.454)	(0.007)	(0.172)	(0.192)	(0.728)	(0.263)	(0.044)	(0.079)	
JSE	−0.141	0.217	0.008	0.598**	0.042	0.153	−0.032	0.029	0.117**	0.323**	19.42*
	(0.241)	(0.221)	(0.314)	(0.010)	(0.097)	(0.183)	(0.138)	(0.213)	(0.003)	(0.009)	
99 % quantile											
Bovespa	−0.179**	0.142*	0.014	0.694**	0.011	−0.143*	−0.083	0.103	0.111*	0.549**	21.43**
	(0.003)	(0.071)	(0.176)	(0.002)	(0.165)	(0.158)	(0.174)	(0.232)	(0.005)	(0.009)	
RTS	−0.143	0.123	0.009	0.599**	0.021	−0.101	0.065	0.160*	0.123*	0.261	17.36*
	(0.251)	(0.241)	(0.684)	(0.009)	(0.035)	(0.366)	(0.186)	(0.107)	(0.010)	(0.011)	
SENSEX	−0.213	0.175*	0.037	0.622*	0.051	−0.184*	0.021	0.117	0.121***	0.303*	24.09**
	(0.079)	(0.012)	(0.293)	(0.004)	(0.521)	(0.011)	(0.103)	(0.076)	(0.001)	(0.004)	
HIS	−0.133	−0.117	0.002	0.573**	0.026	−0.153	0.041	0.251*	0.132*	0.132	16.36*
	(0.329)	(0.139)	(0.581)	(0.008)	(0.472)	(0.204)	(0.322)	(0.004)	(0.012)	(0.267)	
JSE	−0.141	0.072	0.006	0.618**	0.021	0.146	−0.165	0.035	0.147**	0.418**	28.62*
	(0.531)	(0.179)	(0.644)	(0.009)	(0.154)	(0.298)	(0.084)	(0.176)	(0.011)	(0.008)	

asymmetric manner. Similar findings were reported by Kang et al. (2022). The authors investigated the market linkage across a variety of international equity markets using a VAR model with robust coskewness estimators, and found directional systematic skewness spillovers between the US market and emerging stock markets. Using copula and conditional VaR approaches, Hanif et al. (2021) showed evidence of asymmetric tail dependence between the US and Chinese stock markets.

5.2. Subsample analysis

In this subsection, we examine the time-varying tail codependence structures by separating the entire sample into three subsamples based on the inception of the 2020 COVID-19 crisis and the 2022 Russia-Ukraine conflict. Specifically, we define Period I as the stable period covering January 3, 2015, to January 31, 2020, Period II as the turbulent period associated with the spread of the pandemic, covering February 1, 2020, to February 23, 2022, and Period III from February 24, 2022, to December 30, 2023 as the turmoil period caused by the Russia-Ukraine war. We solely present the estimation results of parameters a_{21}, b_{21} and the joint test statistics in Table 4 to highlight the cross-sectional spillover effects.

According to Table 4, during Period I, the estimations of b_{21} shift from being significant in the entire sample to becoming

Table 4

Estimation results of the MVQM model during three subperiods. Subperiod I is defined as the stable period from January 3, 2015, to January 31, 2020, Period II covers the turbulent period associated with the spread of the pandemic from February 1, 2020, to December 31, 2022, while Period III from February 24, 2022, to December 30, 2023, as the turmoil period caused by the Russia-Ukraine war. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

	Bovespa	RTS	SENSEX	HIS	JSE
Panel A: Subperiod I					
a) 1 % quantile					
a_{21}	−0.154**	0.014	0.012	−0.009	−0.187
	(0.003)	(0.136)	(0.313)	(0.143)	(0.152)
b_{21}	−0.132***	0.204***	−0.243**	−0.092*	−0.215**
	(0.002)	(0.009)	(0.0044)	(0.009)	(0.003)
js	21.67**	19.34**	26.54**	9.56	18.69**
b) 10 % quantile					
a_{21}	0.079	0.033	0.015	−0.024	−0.159*
	(0.033)	(0.121)	(0.305)	(0.154)	(0.008)
b_{21}	−0.111**	−0.183**	−0.213**	−0.124*	−0.235**
	(0.002)	(0.006)	(0.003)	(0.009)	(0.010)
js	19.54**	17.77**	26.67**	11.36	18.33**
c) 90 % quantile					
a_{21}	−0.121	0.039	0.223*	−0.003	−0.026
	(0.119)	(0.233)	(0.016)	(0.128)	(0.115)
b_{21}	0.161*	0.134	0.119*	0.043	0.109**
	(0.010)	(0.313)	(0.009)	(0.284)	(0.006)
js	9.67	9.87	7.56	4.84	15.31*
d) 99 % quantile					
a_{21}	−0.069	0.087	0.004	0.032	−0.136
	(0.122)	(0.216)	(0.09)	(0.562)	(0.104)
b_{21}	0.123*	0.145*	0.116**	0.126	0.132**
	(0.008)	(0.009)	(0.013)	(0.212)	(0.009)
js	14.67*	9.57	19.68*	9.98	18.78**
Panel B: Subperiod II					
a) 1 % quantile					
a_{21}	−0.213***	0.178**	0.141*	−0.132*	−0.231**
	(0.002)	(0.006)	(0.013)	(0.091)	(0.005)
b_{21}	−0.221***	0.287***	−0.121***	−0.143**	−0.341***
	(0.001)	(0.012)	(0.002)	(0.006)	(0.011)
js	36.67***	28.67***	38.67***	19.65**	30.76***
b) 10 % quantile					
a_{21}	0.121*	0.121*	0.191**	−0.198**	−0.223**
	(0.013)	(0.116)	(0.003)	(0.006)	(0.003)
b_{21}	−0.202**	−0.333***	−0.201***	−0.212**	−0.207***
	(0.006)	(0.001)	(0.001)	(0.003)	(0.002)
js	27.54***	26.87***	35.67***	17.31*	26.78**
c) 90 % quantile					
a_{21}	−0.244*	0.061	0.154*	−0.176*	−0.142
	(0.013)	(0.164)	(0.011)	(0.018)	(0.018)
b_{21}	0.213**	0.146*	0.145*	0.221*	0.197**
	(0.005)	(0.011)	(0.011)	(0.014)	(0.009)
js	16.44**	9.87*	13.54*	7.97*	20.41*
d) 99 % quantile					
a_{21}	−0.097	0.059	0.151*	0.041	−0.105
	(0.154)	(0.198)	(0.101)	(0.322)	(0.184)
b_{21}	0.134*	0.213*	0.191***	0.132*	0.199**
	(0.009)	(0.009)	(0.008)	(0.012)	(0.009)
js	23.83**	18.96*	25.71**	16.64***	27.32**
Panel C: Subperiod III					
a) 1 % quantile					
a_{21}	−0.133**	0.009	0.013	−0.011	−0.211
	(0.002)	(0.125)	(0.254)	(0.133)	(0.149)
b_{21}	−0.141**	0.183**	−0.213**	−0.093*	−0.223**
	(0.001)	(0.008)	(0.004)	(0.008)	(0.002)
js	33.51**	20.56**	23.69**	10.56	16.39**
b) 10 % quantile					
a_{21}	0.081	0.029	0.013	−0.023	−0.161*
	(0.035)	(0.133)	(0.296)	(0.136)	(0.007)
b_{21}	−0.112**	−0.191**	−0.222**	−0.133*	−0.215**
	(0.003)	(0.005)	(0.002)	(0.008)	(0.009)

Table 4 (*continued*)

	Bovespa	RTS	SENSEX	HIS	JSE
js	17.33[**]	18.05[**]	30.85[**]	12.96	17.95[**]
c) 90 % quantile					
a_{21}	−0.109	0.041	0.241*	−0.002	−0.031
	(0.201)	(0.243)	(0.013)	(0.117)	(0.113)
b_{21}	0.221*	0.124	0.117*	0.039	0.112[**]
	(0.021)	(0.324)	(0.008)	(0.301)	(0.004)
js	8.89	10.86	6.79	6.89	14.85*
d) 99 % quantile					
a_{21}	−0.071	0.079	0.003	0.034	−0.141
	(0.131)	(0.222)	(0.08)	(0.552)	(0.112)
b_{21}	0.134*	0.151*	0.176[**]	0.127	0.142[**]
	(0.007)	(0.008)	(0.015)	(0.232)	(0.011)
js	13.69*	8.78	17.86*	10.63	19.84*

insignificant for many cases, especially in the lower quantiles. This suggests that the tail risk of BRICS markets is relatively less dependent on the US markets in normal market conditions. Furthermore, the estimations of a_{21} indicate that lagged returns in the US market have a very small effect on the tail risk of the BRICS index. Twelve out of 20 cases present statistically significant cross-dependence effects (joint test statistics), with four cases for the upside quantiles and eight cases for the downside quantiles. Both figures are lower than those observed in the analysis of the whole period.

During Period II, a quite different landscape emerges, revealing a significant increase in the tail linkage between the US index and the five emerging markets during market turbulent periods. The estimations of b_{21} are highly significant for all cases at the 0.01 and 0.10 quantiles and are notably larger than the estimations based on the whole sample and the first subsample. This trend also appears for upper quantile situations, despite the codependencies being relatively weaker than those of the downside quantiles. The results of the joint hypothesis statistics further confirm the strong tail-codependence between markets during this market phase. The estimates of a_{21} suggest clear cross-sectional spillovers from the lagged return of the US index to the tail risk of the remaining markets, and their effect varies depending on the percentiles of the distribution.

When turning to period 3, we notice a similar pattern of interconnectedness as in period 2, such as asymmetry and tail dependency structure. However, we also observe that the number of significantly statistics is lower compared to the COVID-19 period, and the significance level has decreased, though it still remains higher than in normal market periods. From this, we can infer that while the
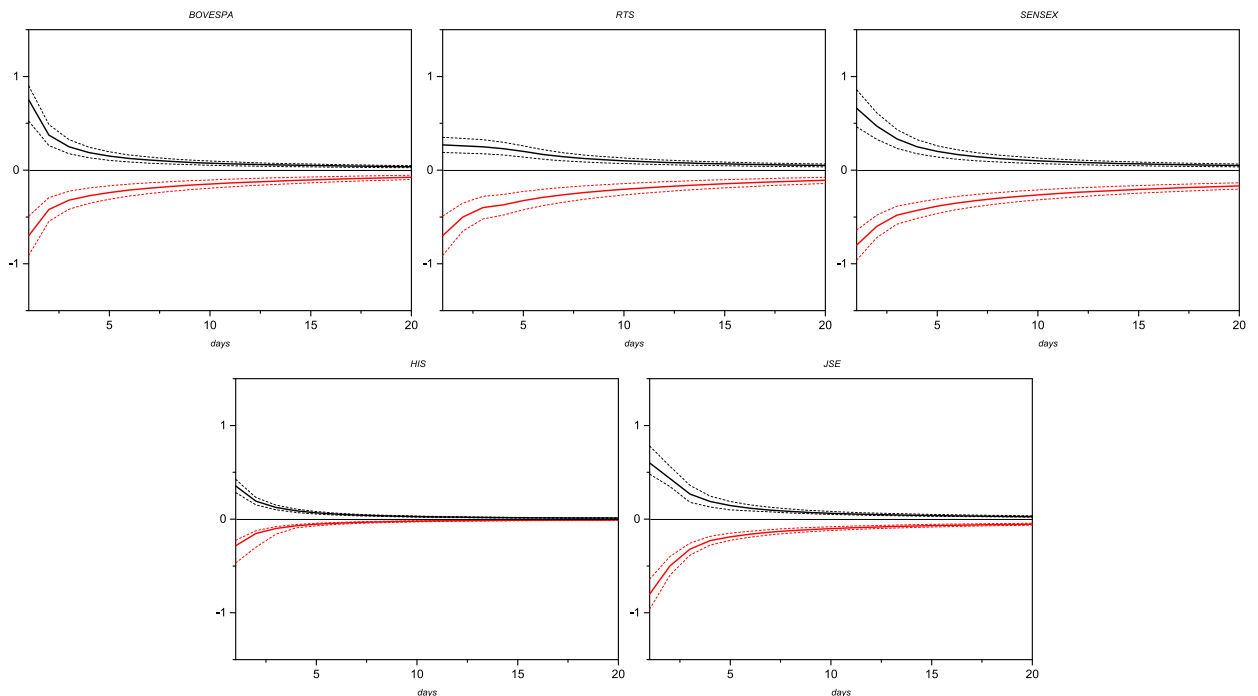

Fig. 1. Impulse-response functions of the BRICS market induced by a specific shock in the US market index over the whole sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals at the 95% level. The results at the 0.90 and 0.10 quantiles (not present) are very similar to the results at the 0.99 and 0.01 quantiles, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

contagion risk appears to have decreased during this period, it remains elevated above its normal level.

The above findings provide supportive evidence of shift tail-codependence between the US index and the five emerging market indices during different market conditions. The COVID-19 event of 2020 and Russia-Ukraine war of 2022 have significantly altered the inter-market dependence structure, making it more probable that the tail risks of the US stock market will impact the emerging markets.

5.3. Pseudo-impulse-response analysis

To further examine the risk spillovers between the US index and BRICS stock indices, we employ the PIRFs derived from the MVMQ model that we have established. As discussed earlier, the advantage of the PIRF approach over the conventional IRF is that it enables us to precisely examine the responses of a specific distribution quantile to a shock to the predictor variable, thereby better revealing the instantaneous and delayed dependent structures of tail risk spillovers. We perform the PIRF analysis on the upper quantiles of 0.90 and 0.99, and the lower quantiles of 0.10 and 0.01 on the entire sample as well as two sub-samples. We specify the imposed shock to the predictive variable to be two standard deviations of the US index return.

Fig. 1 displays the main results of the PIRF analysis for the distribution quantiles over the entire sample period. Two notable findings can be observed from Fig. 1. Firstly, a structural shock to the US market produces a tail reaction that is completely opposite in direction between the upper and lower tails for all of the remaining five markets. Specifically, the indices of the five emerging markets react positively to a shock to the US index at the upside quantiles, while the responses of the BRICS indices to a shock to the US index are negative at the downside quantiles. This indicates that a significant positive shock to the US market increases the likelihood of observing either very high or very low values in other markets by expanding the entire range of unconditional return distributions.

Second, in addition to the directions of the tails, we also observe asymmetries in the cumulative responses of an individual market in response to a shock to the predictive variable. Specifically, the indices of Brazil, India, and South Africa are significantly more affected by the US index shock in the upside quantiles than in the downside quantiles in the initial time; however, the effects decay faster in the upside quantiles for these three indices. However, a different appearance is documented in the case of Russia. The cumulative response of the Russian stock index to a US shock is heavier in the downside quantiles than in the upside quantiles. As for the China index, it seems that the tail risk of the Chinese market is rather independent from the US market, as evidenced by the reactions of both the upper and the lower quantiles, which die out to the zero line in a few days after an initially observable reaction to the US index shock.

Fig. 2 illustrates the results of the PIRF analysis during Period I, referring to a stable market phase; while Fig. 3 and Fig. 4 show the results of the PIRF analysis during Period II and Period III, identified as the market turbulent periods. Consistent with the findings
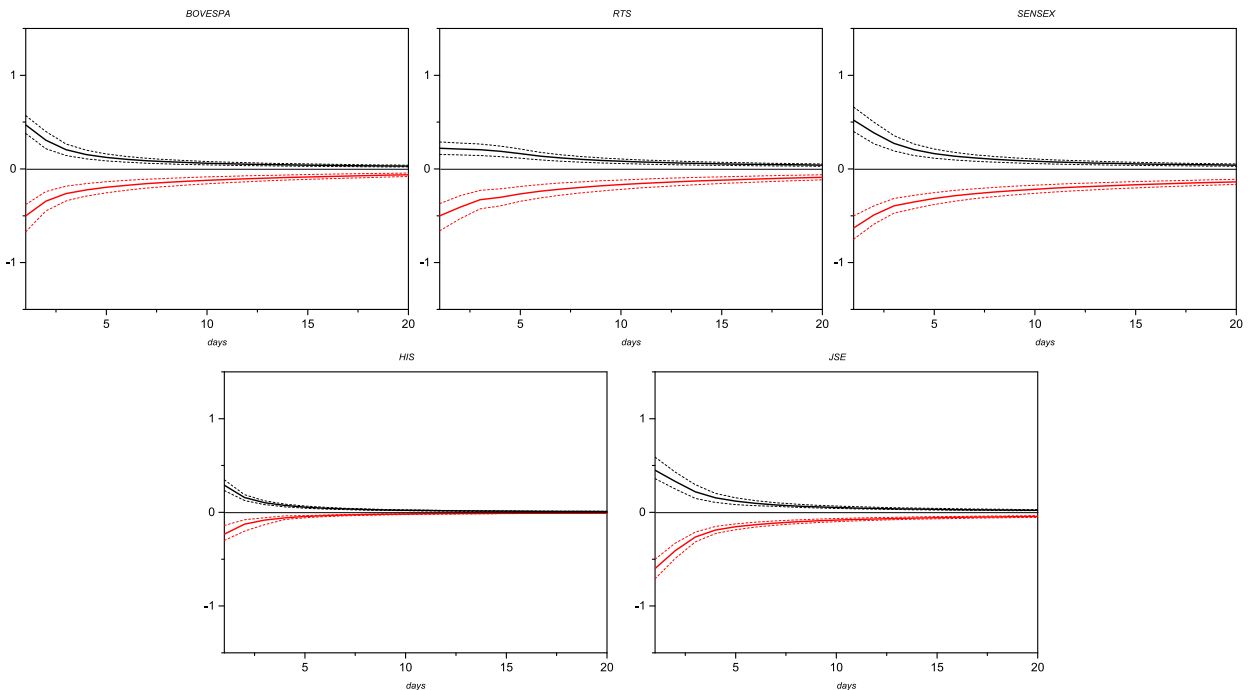

Fig. 2. Impulse-response functions of the BRICS market induced by a specific shock in the US market index during the first sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals at the 95% level. The results at the 0.90 and 0.10 quantiles (not present) are very similar to the results at the 0.99 and 0.01 quantiles, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

reported in Table 4, we observe obvious shift structure in tail dependence across the two sub-periods. In all cases, a relatively larger and more persistent accumulated effect from a shock originating in the US is observed during the second subperiod for both the lower and upper quantiles of the distribution. This indicates that the financial market turmoil triggered by the crisis events has significantly increased the spillover of extreme risk from the US market to BRICS markets.

5.4. Interpretation of the finds

In conclusion, the empirical findings highlight the asymmetric characteristics of tail risk interdependence between the US market and the BRICS markets from three perspectives: the sign of the effect in response to an external shock at different quantiles, the extent and persistence of the effect, and a shift in dependency structure across different market phases. One possible explanation for the former two aspects could be associated with the potential for liquidity spillovers in higher quantiles and episodes of "flight-to-quality" in lower quantiles. Specifically, at high quantiles, a positive shock to the US market may signal greater liquidity in the global financial market, which could potentially cause the positive trend to spill over into other markets, including the BRICS markets (Koulakiotis, Babalos and Papasyriopoulos, 2015). In contrast, at low quantiles, following a positive shock to the US markets, investors prefer to shift their assets to safer, lower-risk investments in the face of market uncertainty or increased risk to reduce the risk of losses (Kaul and Kayacetin, 2017; Perras and Wagner, 2020). The latter suggests that the tail relationship is rather event-specific. The COVID-19 crisis has significantly increased the extreme risk connections between global financial markets, as extensively supported by existing literature (Abuzayed and Al-Fayoumi, 2021; Guo, Li and Li, 2021; Cao, 2022; Lashkaripour, 2023). However, the empirical results also indicate that after March 2022, the tail spillover from the US stock markets to the emerging market indicators gradually dies out, but it remains higher than the interdependence levels under normal market conditions. This suggests that compared to the pandemic event, the impact of the Russia-Ukraine conflict on financial contagion is very limited.

In addition to the common features illustrated, we should also note the heterogeneities in the reactions within the BRICS markets. This implies the need to conduct a careful analysis of the idiosyncratic characteristics of each market prior to pursuing opportunities for diversification. For example, China's market seems to be a good hedge against the US market most of the time: the Chinese market's performance is rather independent from the US market in its median and tail quantiles, and the cumulated response of the PIRFs is among the lowest observed in the candidate markets. As for policymakers, policymakers in BRICS nations should pay attention to the potential impact of systemic risks coming from the US market and coordinate policy efforts to mitigate these risks. Specifically, when a decline in investors' appetite for risk occurred after a period of high risk appetite, markets are more likely to react negatively to events that would not usually cause a significant reaction. In such situations, it might be suitable to promptly offer funding to stabilize sentiments and impose less stringent conditions (Kumar and Persaud, 2001). Swiftly increasing liquidity could greatly lessen the
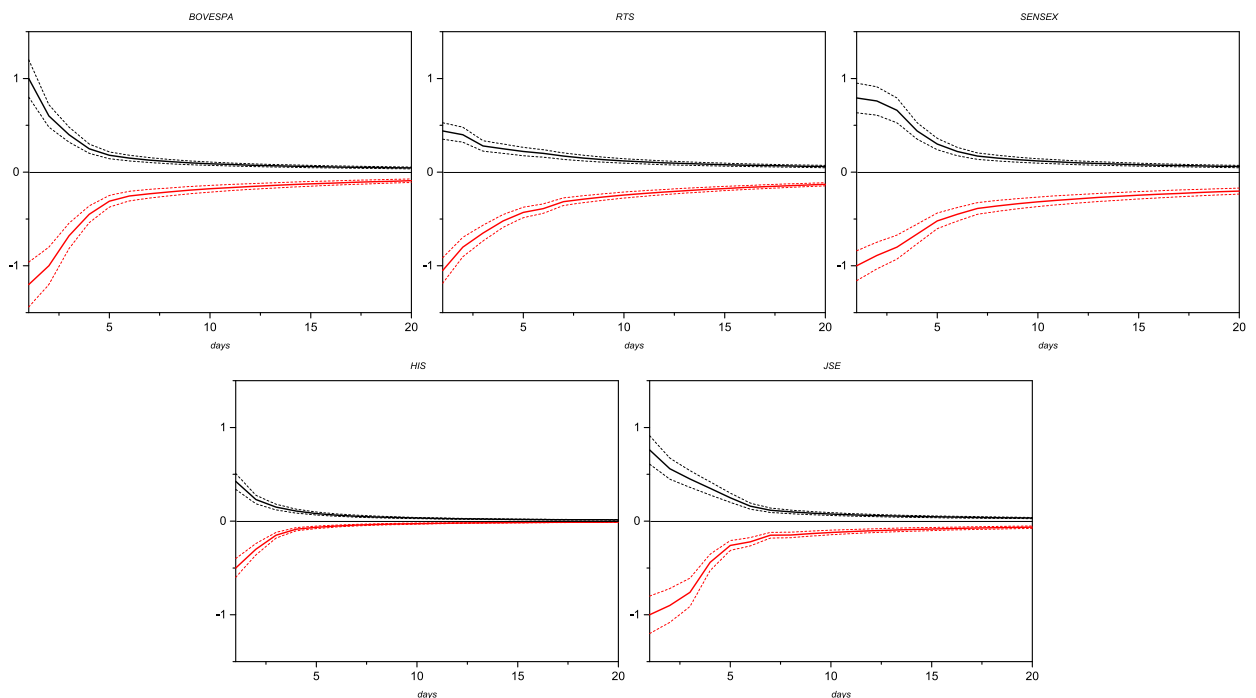

Fig. 3. Impulse-response functions of the BRICS market induced by a specific shock in the US market index during the second sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals at the 95% level. The results at the 0.90 and 0.10 quantiles (not present) are very similar to the results at the 0.99 and 0.01 quantiles, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
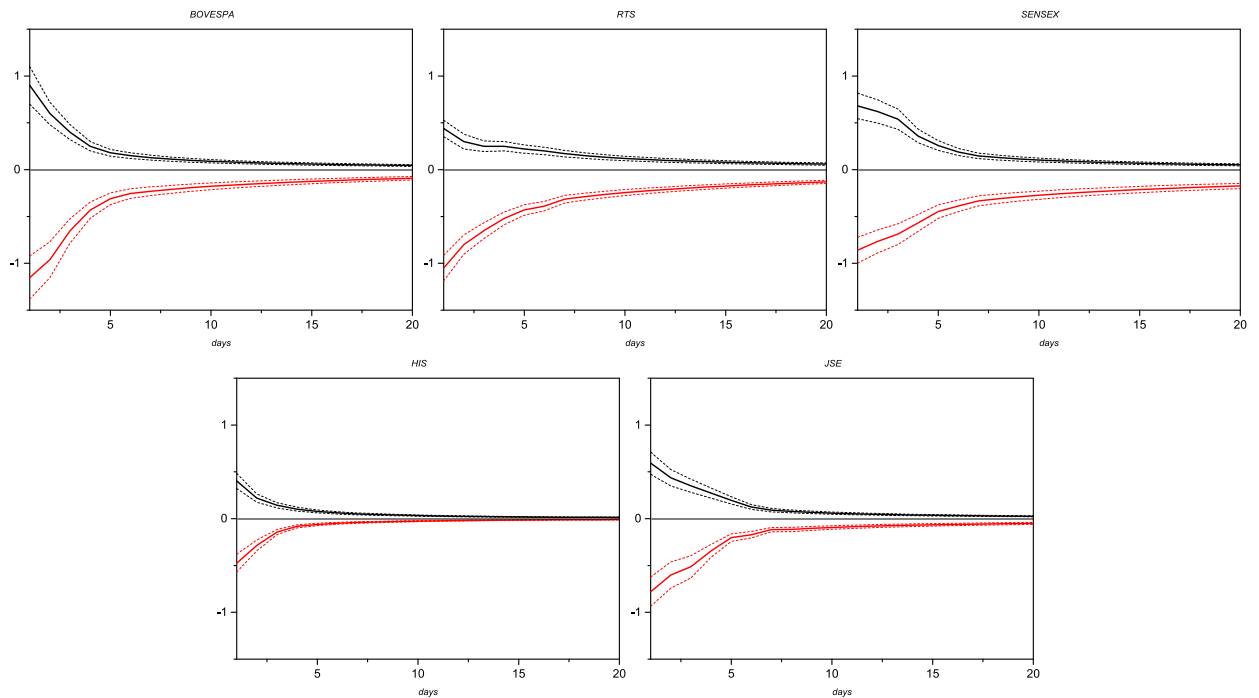
Fig. 4. Impulse-response functions of the BRICS market induced by a specific shock in the US market index during the third sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals at the 95% level. The results at the 0.90 and 0.10 quantiles (not present) are very similar to the results at the 0.99 and 0.01 quantiles, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

severity of a crisis and the possibility of its spreading.

The spillover testing results for the indicators under investigation appear to be unrelated to their trade and financial profiles. Table 5 provides an overview of the trade and financial features of five emerging countries over the period 2020–2023. The economic performance of India, China, and South Africa heavily relies on the export of manufactured goods, whereas Brazil and Russia are more dependent on revenue generated from commodity exports. Additionally, it should be noted that both China and South Africa demonstrate a high level of economic openness, as indicated by their trade to GDP ratios, while India and Brazil exhibit lower levels of economic openness. Our findings do not show a contagion pattern across all markets that can be attributed to their common trade characteristics. Nevertheless, insights can be derived from the net capital inflows data. It appears that countries experiencing significant financial contagion effects, such as Brazil and Russia, also have substantial net capital outflows. On the other hand, markets with capital controls, like China, exhibit less pronounced contagion effects.

5.5. Performance evaluations

In this section, we evaluate the overall fitness of the models at specific quantiles of 0.01, 0.10, 0.90, and 0.99. To achieve this, we count the number of actual returns that exceed the upper quantiles and the number that fall below the lower quantiles. We expect exceedances to be around 1 % of the total number of occurrences for the 0.01 and 0.99 quantiles, and 90 % for the 0.10 and 0.90 quantiles.

Table 6 reports the percentage of exceedances for the four specific quantiles. The results of the models appear to be quite impressive, performing well in both the upside and downside quantiles. We observe exceedance percentages that are aligned with theoretical expectations for the chosen confidence level.

6. Conclusion

In this paper, we investigate the cross-sectional extreme risk spillovers from the US stock market to BRICS markets by using the MVMQ models framework. We further investigate the effect of a positive shock occurring in the US market on the remaining five markets using PIRF analysis. We rely on daily data over the period from January 3, 2015 to December 30, 2023 for our empirical study, and some crucial findings emerge. Generally, the spillover effect exhibits significant asymmetry, showing more significance in the downside quantiles than in the upside quantiles. Notably, a positive shock to the US index produces a positive response for the five emerging market indices at the upside quantiles; conversely, it produces a stronger and more persistent negative effect at the downside quantiles. This result can be linked to the notion of international liquidity overshooting during bullish market periods and a flight-to-

Table 5

Trade and financial profiles of the markets under examination. The table provides the trade profiles and some financial characteristics of the five emerging markets from 2020 to 2024. The total exports of commodity products account for the combined exports of energy and bulk commodities. The trade to GDP ratio represents the combined value of goods and services exports and imports as a percentage of the gross domestic product. The market capitalization of listed companies is expressed as a percentage of GDP. The turnover ratio corresponds to the value of shares traded in a year divided by the average market capitalization for that year. The data used are .

	2020	2021	2022	2023
Brazil				
Exports of commodities — % of merchandise exports	52.14	52.96	53.04	52.09
Exports of manufactures — % of merchandise exports	47.12	46.98	46.13	47.13
Trade to GDP ratio (%)	26.58	21.52	22.56	29.86
Market capitalization (% of GDP)	100.63	62.54	102.85	101.52
Turnover ratio (%)	83.54	79.52	63.85	70.52
Net capital inflow (billion US dollar)	46.52	50.45	42.64	46.98
Russia				
Exports of commodities — % of merchandise exports	73.54	72.64	64.85	54.85
Exports of manufactures — % of merchandise exports	25.84	26.85	34.95	44.85
Trade to GDP ratio (%)	56.56	51.52	38.52	40.85
Market capitalization (% of GDP)	121.52	108.65	34.65	98.56
Turnover ratio (%)	61.52	59.85	100.52	33.65
Net capital inflow (billion US dollar)	21.52	22.65	8.21	13.62
India				
Exports of commodities — % of merchandise exports	28.68	30.45	31.45	26.85
Exports of manufactures — % of merchandise exports	70.58	68.96	68.02	72.13
Trade to GDP ratio (%)	42.52	32.52	42.12	40.65
Market capitalization (% of GDP)	123.52	118.45	130.85	112.52
Turnover ratio (%)	76.45	96.85	73.85	66.15
Net capital inflow (billion US dollar)	81.52	83.54	100.21	103.56
China				
Exports of commodities — % of merchandise exports	6.37	6.08	6.54	6.13
Exports of manufactures — % of merchandise exports	92.87	92.65	92.86	91.87
Trade to GDP ratio (%)	66.85	74.54	68.54	54.18
Market capitalization (% of GDP)	53.65	54.62	46.85	44.16
Turnover ratio (%)	118.54	133.68	150.85	118.54
Net capital inflow (billion US dollar)	128.65	131.52	132.32	131.52
South Africa				
Exports of commodities — % of merchandise exports	51.63	53.45	52.46	51.86
Exports of manufactures — % of merchandise exports	47.58	45.86	46.85	47.56
Trade to GDP ratio (%)	60.52	42.85	49.85	63.54
Market capitalization (% of GDP)	131.52	99.52	126.85	136.95
Turnover ratio (%)	56.95	57.46	88.85	60.85
Net capital inflow (billion US dollar)	57.52	54.25	64.52	63.21

Sourced from the World Development Indicators database

Table 6

Percentage of exceedances. This table presents the results of the calculation of the percentage of exceedances for the 0.01, 0.10, 0.90, and 0.99 quantiles. Theoretically, the values should equal 10% for the 0.10 and 0.90 quantiles and 1% for the 0.01 and 0.99 quantiles. The closer the results of the calculation are to these values, the better the fitness of the model.

	S&P 500	Bovespa	RTS	SENSEX	HIS
1 % quantile	1	1	1.01	1.01	1
10 % quantile	1	0.98	1.02	1	0.99
90 % quantile	1.01	1.02	1	1	0.99
99 % quantile	1	1	1	0.99	0.99

quality effect among the US market and international markets during bearish market periods. The subsample analysis indicates that the COVID-19 event that took place in 2020 significantly increased the degree of tail codependence, especially at the downside tail. Despite the common patterns described above, divergent patterns are also detected for each individual market, such as China's market being relatively less dependent on US market performance. We also notice that the impact of the Russia-Ukraine conflict on financial risk spillovers is not very significant.

The main findings of this study provide helpful insights for investors regarding asset allocation and for regulators regarding policy

formulation. For investors looking to balance their assets in the global market, the asymmetry and event-specific characteristics of tail-codependence between the US and BRICS markets can be leveraged to increase investment diversity. On the other hand, investors should also take note of the heterogeneous reactions of individual markets in the face of shocks from the US market in order to improve their asset allocation efficiency. For regulators in BRICS nations, it is important for policymakers to pay extra attention to the potential impact of systemic risks coming from the US market on their own markets. In future studies, it would be intriguing to broaden the scope of cross-country comparisons that were carried out in this study to encompass additional developed and emerging economies. This would enable an analysis of diversification strategies that are global, stretching beyond the BRICS markets, by employing an endogenous multivariate setup.

CRediT authorship contribution statement

Yi Zhang: Data curation, Formal analysis. **Long Zhou:** Conceptualization. **Baoxiu Wu:** Methodology, Supervision, Validation. **Fang Liu:** Validation, Writing – original draft.

Data availability

Data will be made available on request.

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