North American Journal of Economics and Finance 70 (2024) 102067

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

journal homepage: www.elsevier.com/locate/najef

Extreme risk contagion from the United States to BRICS stock markets: A multivariate quantile analysis

Yi Zhang [a], Long Zhou [b,*], Baoxiu Wu [a], Fang Liu [c]

[a] School of Economics, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China
[b] Centre for Energy Policy, University of Strathclyde, Glasgow G1 1XQ, UK
[c] Business School, Cardiff University, Cardiff CF10 3EU, UK

ARTICLE INFO

JEL Code:
G15
G31
G11
G19

Keywords:
Extreme risk contagion
Multivariate quantile models
Pseudo-impulse-response functions
BRICS markets

ABSTRACT

This paper explores the transmission of risk from the United States equity market to the equity markets of the BRICS countries (Brazil, Russia, India, China, and South Africa) 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. The results reveal an asymmetric pattern of underlying tail dependence from three different perspectives: the sign of the effect in response to external shocks at various quantiles, the extent and persistence of the effect, and a shift in dependency structure across different market phases. The paper also discusses 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. Particularly in recent years, the ongoing international trade conflicts, the pandemic crisis, and geopolitical conflicts have intensified the volatility of financial markets, making this issue even more prominent.

Over the past few decades, numerous studies have been conducted to investigate contagion effects using various empirical models, with a stream of studies 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). Ample evidence shows that financial asset returns do not follow a normal distribution, instead exhibiting leptokurtosis and heavy tails, which significantly increase the likelihood of extreme risks occurring. 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 to 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, this study aims to examine the interrelationship of the US stock market and the stock markets of the BRICS

* Corresponding author.
E-mail address: long.zhou@strath.ac.uk (L. Zhou).

https://doi.org/10.1016/j.najef.2023.102067
Received 21 September 2023; Accepted 3 December 2023
Available online 6 December 2023
1062-9408/

countries (Brazil, Russia, India, China, and South Africa) amidst the Covid-19 pandemic. 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 COVID-19 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.

We expand on existing related studies through the following perspectives. Firstly, we utilize 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 US and BRICS stock markets, based on the most updated temporal background.

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 COVID-19 pandemic 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 et al. (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 event 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; Akhtaruzzaman, Boubaker and Sensoy, 2021; Benkraiem et al., 2022). 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 $Pr\left[r_{i,t} \leqslant q_{i,t} | \mathbb{F}_{t-1}\right]$. $r_{i,t-1}$ 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

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	0.00314	0.00423	−0.00123	0.00331	0.00133	0.00185
Median	0.00468	0.00514	0.00026	0.00536	0.00398	0.00298
Std. Dev	3.315	3.541	4.051	3.987	3.641	3.546
Skewness	−0.065	−0.645	−0.687	−0.451	−0.987	−0.084
Kurtosis	21.456	16.548	35.687	16.987	9.684	10.187
J-B statistic	330.51***	336.541***	340.542***	298.548***	277.815***	408.516***
Probability	0.00	0.00	0.00	0.00	0.00	0.00
KPSS	0.0591	0.0372	0.0675	0.0536	0.0867	0.0131
P-B correlations with US	1	0.51***	0.34**	0.43**	0.32**	0.49***

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	−0.112**	0.175*	0.003	0.102*	0.008	−0.503*	0.103*	0.223	0.118	0.139*	4.44
	(0.101)	(0.061)	(0.231)	(0.003)	(0.079)	(0.016)	(0.003)	(0.312)	(0.111)	(0.011)	
RTS	−0.103	0.133	0.013	0.193*	0.123	−0.321	0.019	0.332*	0.006	0.141*	6.87
	(0.211)	(0.221)	(0.344)	(0.072)	(0.055)	(0.196)	(0.006)	(0.008)	(0.132)	(0.039)	
SENSEX	−0.122	0.203*	0.165	0.101*	0.124	−0.404*	0.021	0.168	−0.021	0.213*	3.94
	(0.119)	(0.018)	(0.213)	(0.079)	(0.061)	(0.017)	(0.303)	(0.007)	(0.021)	(0.031)	
HIS	−0.037	−0.192	0.006	0.203*	0.009	−0.321	−0.036	0.201*	0.122	0.202*	2.84
	(0.125)	(0.211)	(0.212)	(0.121)	(0.112)	(0.233)	(0.321)	(0.013)	(0.054)	(0.019)	
JSE	−0.121	0.087	0.008	0.119**	0.011	0.121	−0.123	0.031	−0.117	0.218*	5.45
	(0.211)	(0.166)	(0.164)	(0.006)	(0.032)	(0.243)	(0.332)	(0.103)	(0.031)	(0.021)	

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 θ-th conditional quantile of the affected series $\widetilde{r}_{it}$ and the θ-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, to December 31, 2022, incorporating the prominent financial turmoil period caused by the COVID-19 event. 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 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

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	−0.212**	0.235*	0.005	0.702***	0.012	−0.413*	−0.103**	0.103	−0.121***	0.839***	24.44***
	(0.019)	(0.011)	(0.361)	(0.001)	(0.139)	(0.326)	(0.003)	(0.212)	(0.001)	(0.001)	
RTS	−0.172	0.101	0.012	0.693**	0.101	−0.333	0.011	0.162	−0.236***	0.741**	21.87**
	(0.231)	(0.232)	(0.354)	(0.004)	(0.046)	(0.216)	(0.036)	(0.031)	(0.012)	(0.002)	
SENSEX	−0.151	0.193*	0.035	0.801***	0.155	−0.324*	0.011	0.198	−0.121***	0.713**	33.94***
	(0.218)	(0.016)	(0.173)	(0.009)	(0.161)	(0.016)	(0.233)	(0.029)	(0.001)	(0.011)	
HIS	−0.148	−0.202	0.015	0.503**	0.011	−0.241	−0.016	0.232*	−0.122**	0.602*	12.84*
	(0.162)	(0.313)	(0.362)	(0.005)	(0.092)	(0.242)	(0.121)	(0.163)	(0.004)	(0.009)	
JSE	−0.332	0.097	0.007	0.619**	0.032	0.151	−0.321	0.029	−0.317***	0.918***	25.45***
	(0.232)	(0.206)	(0.204)	(0.006)	(0.087)	(0.363)	(0.231)	(0.143)	(0.031)	(0.001)	
10 % quantile											
Bovespa	−0.171**	0.155*	0.014	0.702**	0.009	−0.313*	0.083	0.203	−0.121**	0.639**	24.44***
	(0.008)	(0.079)	(0.132)	(0.003)	(0.139)	(0.116)	(0.103)	(0.212)	(0.003)	(0.009)	
RTS	−0.116	0.141	0.009	0.693**	0.143	−0.251	0.021	0.261*	−0.213**	0.041	26.87***
	(0.342)	(0.311)	(0.524)	(0.012)	(0.115)	(0.206)	(0.116)	(0.007)	(0.008)	(0.311)	
SENSEX	−0.154	0.183*	0.177	0.701*	0.132	−0.294*	0.019	0.189	−0.121***	0.313*	33.94***
	(0.025)	(0.009)	(0.183)	(0.009)	(0.161)	(0.007)	(0.133)	(0.006)	(0.001)	(0.004)	
HIS	−0.021	−0.202	0.010	0.203*	0.029	−0.281	−0.038	0.181*	−0.132**	0.102	12.84*
	(0.183)	(0.171)	(0.312)	(0.211)	(0.432)	(0.193)	(0.111)	(0.009)	(0.002)	(0.212)	
JSE	−0.123	0.069	0.007	0.519*	0.021	0.132	−0.193**	0.026	−0.197**	0.718**	25.45**
	(0.471)	(0.206)	(0.254)	(0.005)	(0.132)	(0.338)	(0.004)	(0.116)	(0.011)	(0.004)	
90 % quantile											
Bovespa	−0.322**	0.214*	0.021	0.682**	0.031	−0.214*	−0.134	0.104	0.201**	0.539**	14.44*
	(0.021)	(0.009)	(0.541)	(0.003)	(0.539)	(0.016)	(0.213)	(0.247)	(0.008)	(0.011)	
RTS	−0.159	0.121	0.014	0.576**	0.061	−0.214	0.041	0.123	0.106	0.241	9.87
	(0.342)	(0.201)	(0.294)	(0.013)	(0.537)	(0.116)	(0.145)	(0.141)	(0.212)	(0.413)	
SENSEX	−0.149	0.203*	0.035	0.601*	0.013	−0.321*	0.111*	0.098	0.121*	0.213	11.42*
	(0.338)	(0.015)	(0.203)	(0.009)	(0.211)	(0.014)	(0.013)	(0.129)	(0.009)	(0.321)	
HIS	−0.231*	−0.152	0.012	0.544**	−0.009	−0.321	−0.006	0.112*	0.021	0.102	5.84
	(0.192)	(0.413)	(0.454)	(0.007)	(0.172)	(0.192)	(0.728)	(0.263)	(0.044)	(0.079)	
JSE	−0.132	0.117	0.008	0.598**	0.042	0.153	−0.032	0.029	0.117**	0.323**	18.32*
	(0.248)	(0.206)	(0.314)	(0.010)	(0.097)	(0.183)	(0.138)	(0.213)	(0.003)	(0.009)	
99 % quantile											
Bovespa	−0.182**	0.135*	0.014	0.694**	0.011	−0.143*	−0.083	0.103	0.111*	0.549**	20.23**
	(0.004)	(0.069)	(0.176)	(0.002)	(0.165)	(0.158)	(0.174)	(0.232)	(0.005)	(0.009)	
RTS	−0.121	0.121	0.009	0.599**	0.021	−0.101	0.065	0.160*	0.123*	0.261	16.56*
	(0.246)	(0.251)	(0.684)	(0.009)	(0.035)	(0.366)	(0.186)	(0.107)	(0.010)	(0.011)	
SENSEX	−0.204	0.172*	0.037	0.622*	0.051	−0.184*	0.021	0.117	0.121***	0.303*	23.79**
	(0.087	(0.011)	(0.293)	(0.004)	(0.521)	(0.011)	(0.103)	(0.076)	(0.001)	(0.004)	
HIS	−0.121	−0.182	0.002	0.573**	0.026	−0.153	0.041	0.251*	0.132*	0.132	15.56*
	(0.312)	(0.169)	(0.581)	(0.008)	(0.472)	(0.204)	(0.322)	(0.004)	(0.012)	(0.267)	
JSE	−0.142	0.071	0.006	0.618**	0.021	0.146	−0.165	0.035	0.147**	0.418**	25.32**
	(0.561)	(0.186)	(0.644)	(0.009)	(0.154)	(0.298)	(0.084)	(0.176)	(0.011)	(0.008)	

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 two sub-periods separated by the COVID-19 event outbreak. 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.

Table 4
Estimation results of the MVQM model during two subperiods. Subperiod I is defined as the stable period from January 3, 2015, to January 31, 2020, while Period II covers the turbulent period associated with the spread of the pandemic from February 1, 2020, to December 31, 2022. ***, **, 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**

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

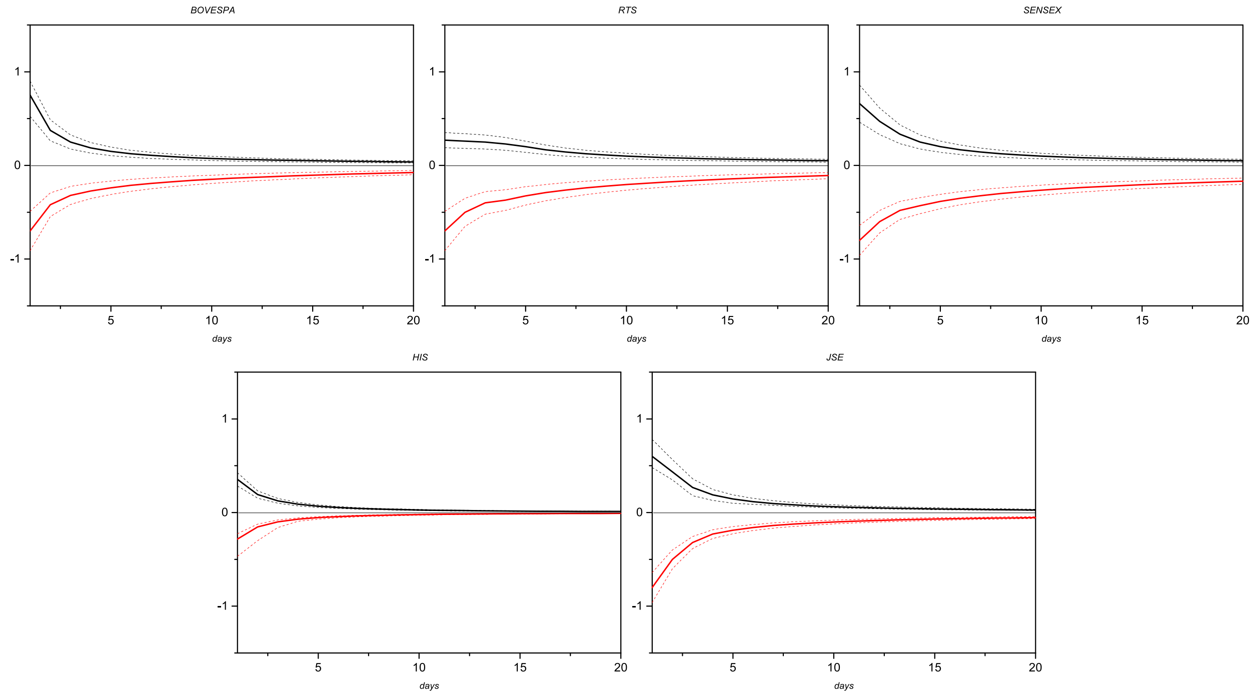

Fig. 1. Impulse-response functions of the BRICS market induced by a specific shock in the US market index over the whole sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals 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.)

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 asymmetric manner. Similar findings were reported by Kang et al. (2019). 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 two subsamples. The 2020 COVID-19 crisis is considered the most significant pandemic disaster in human history in a century, and has heavily impacted on global trade supply chains and international financial markets. During this period, the global stock market has not only experienced significant fluctuations but also exhibited a strong contagion effect. Consequently, the sample periods selected provide us with an ideal background to investigate the evolution of tail dependence during different market phases. We define Period I as the stable period covering January 3, 2015, to January 31, 2020, and Period II as the turbulent period associated with the spread of the pandemic, covering February 1, 2020, to December 31, 2022. 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 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

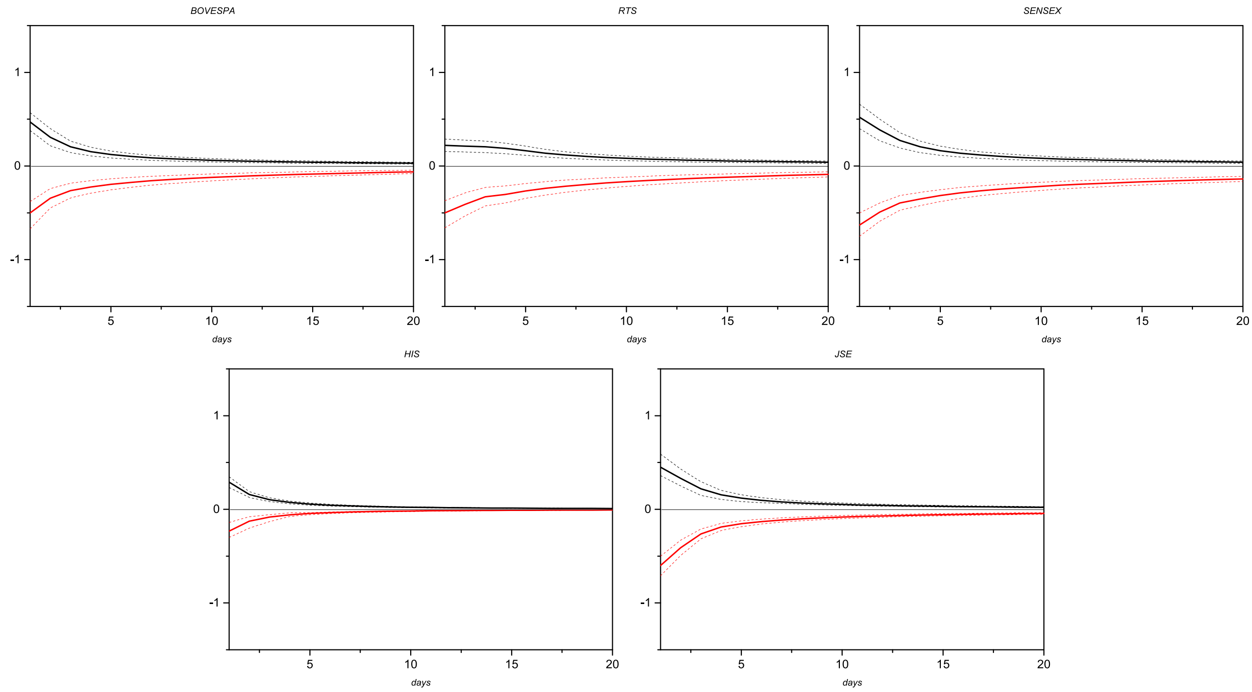

Fig. 2. Impulse-response functions of the BRICS market induced by a specific shock in the US market index during the first sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals 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.)

(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.

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 has 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

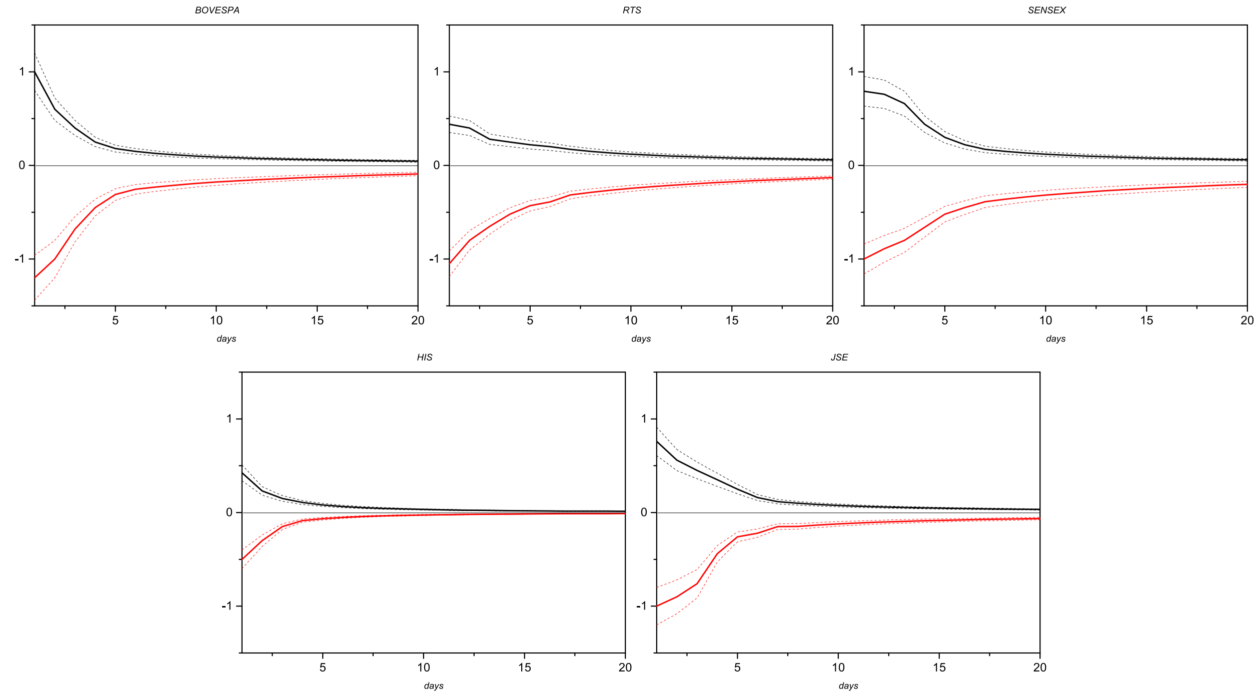

Fig. 3. Impulse-response functions of the BRICS market induced by a specific shock in the US market index during the second sample period. The black and red solid lines represent the responses at the 0.99 and 0.01 quantiles, respectively. The dotted lines represent their corresponding confidence intervals 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.)

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 shows the results of the PIRF analysis during Period II, identified as the market turbulent period. Consistent with the findings 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 COVID-19 event has significantly increased the spillover of extreme risk from the US market to BRICS markets.

In conclusion, the above 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).

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.

Table 5
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

5.4. 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 5 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 31, 2022 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-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.

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.

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.

Data availability

Data will be made available on request.

References

Abduraimova, K. (2022). Contagion and tail risk in complex financial networks. *Journal of Banking & Finance, 143*, Article 106560.
Aboura, S., & Chevallier, J. (2018). Tail risk and the return-volatility relation. *Research in International Business and Finance, 46*, 16–29.
Abuzayed, B., & Al-Fayoumi, N. (2021). Risk spillover from crude oil prices to GCC stock market returns: New evidence during the COVID-19 outbreak. *The North American Journal of Economics and Finance, 58*, Article 101476.
Ahmad, W., Sehgal, S., & Bhanumurthy, N. R. (2013). Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling, 33*, 209–225.
Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2021). Financial contagion during COVID–19 crisis. *Finance Research Letters, 38*, Article 101604.

Bello, J., Guo, J., & Newaz, M. K. (2022). Financial contagion effects of major crises in African stock markets. *International Review of Financial Analysis, 82*, Article 102128.
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.
Brazys, J., Duyvesteyn, J., & Martens, M. (2015, June). Macroeconomic news and price discovery in international bond markets. European Financial Management Association 2015 Annual Meetings, Amsterdam, 2015.
Calvo, S. G., & Reinhart, C. (1996). Capital flows to Latin America: is there evidence of contagion effects? Available at SSRN 636120.
Cao, Y. (2022). Extreme risk spillovers across financial markets under different crises. *Economic Modelling, 116*, Article 106026.
Celık, S. (2012). The more contagion effect on emerging markets: The evidence of DCC-GARCH model. *Economic Modelling, 29*(5), 1946–1959.
Chevallier, J. (2020). COVID-19 pandemic and financial contagion. *Journal of Risk and Financial Management, 13*(12), 309.
Chevallier, J., Nguyen, D. K., Siverskog, J., & Uddin, G. S. (2018). Market integration and financial linkages among stock markets in Pacific Basin countries. *Journal of Empirical Finance, 46*, 77–92.
Chuliá, H., Guillén, M., & Uribe, J. M. (2017). Spillovers from the United States to Latin American and G7 stock markets: A VAR quantile analysis. *Emerging Markets Review, 31*, 32–46.
Dai, Y., & Harris, R. D. (2023). Average tail risk and aggregate stock returns. *Journal of International Financial Markets, Institutions and Money, 82*, Article 101699.
Das, S., Demirer, R., Gupta, R., & Mangisa, S. (2019). The effect of global crises on stock market correlations: Evidence from scalar regressions via functional data analysis. *Structural Change and Economic Dynamics, 50*, 132–147.
Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis, 30*, 46–56.
Ehrmann, M., Fratzscher, M., & Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: Measuring international financial transmission. *Journal of Applied Econometrics, 26*(6), 948–974.
Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of business & economic statistics, 22*(4), 367–381.
Fenech, J. P., & Vosgha, H. (2019). Oil price and Gulf Corporation Council stock indices: New evidence from time-varying copula models. *Economic Modelling, 77*, 81–91.
Fong, T. P. W., Li, K. F., & Fu, J. (2018). Accounting for sovereign tail risk in emerging economies: The role of global and domestic risk factors. *Emerging Markets Review, 34*, 98–110.
Forbes, K. J., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovements. *The journal of Finance, 57*(5), 2223–2261.
Georgoutsos, D., & Moratis, G. (2017). Bank-sovereign contagion in the Eurozone: A panel VAR Approach. *Journal of International Financial Markets, Institutions and Money, 48*, 146–159.
Gourieroux, C., & Lu, Y. (2019). Least impulse response estimator for stress test exercises. *Journal of Banking & Finance, 103*, 62–77.
Hanif, W., Mensi, W., & Vo, X. V. (2021). Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors. *Finance Research Letters, 40*, Article 101922.
Hartmann, P., Straetmans, S., & Vries, C. D. (2004). Asset market linkages in crisis periods. *Review of Economics and Statistics, 86*(1), 313–326.
Kang, S. H., Uddin, G. S., Troster, V., & Yoon, S. M. (2019). Directional spillover effects between ASEAN and world stock markets. *Journal of Multinational Financial Management, 52*, Article 100592.
Kaul, A., & Kayacetin, N. V. (2017). Flight-to-quality, economic fundamentals, and stock returns. *Journal of Banking & Finance, 80*, 162–175.
Koenker, R., & Bassett, G., Jr (1978). Regression quantiles. *Econometrica: journal of the Econometric Society*, 33–50.
Koulakiotis, A., Babalos, V., & Papasyriopoulos, N. (2015). Liquidity matters after all: Asymmetric news and stock market volatility before and after the global financial crisis. *Economics Letters, 127*, 58–60.
Lashkaripour, M. (2023). ESG tail risk: The Covid-19 market crash analysis. *Finance Research Letters, 53*, Article 103598.
Lee, D. J., Kim, T. H., & Mizen, P. (2021). Impulse response analysis in conditional quantile models with an application to monetary policy. *Journal of Economic Dynamics and Control, 127*, Article 104102.
Luchtenberg, K. F., & Vu, Q. V. (2015). The 2008 financial crisis: Stock market contagion and its determinants. *Research in International Business and Finance, 33*, 178–203.
Mollah, S., Quoreshi, A. S., & Zafirov, G. (2016). Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money, 41*, 151–167.
Nasri, B. R., & Rémillard, B. N. (2019). Copula-based dynamic models for multivariate time series. *Journal of Multivariate Analysis, 172*, 107–121.
Ning, C. (2010). Dependence structure between the equity market and the foreign exchange market–a copula approach. *Journal of International Money and Finance, 29*(5), 743–759.
Niţoi, M., & Pochea, M. M. (2020). Time-varying dependence in European equity markets: A contagion and investor sentiment driven analysis. *Economic Modelling, 86*, 133–147.
Pearl, J. (2012). The causal foundations of structural equation modeling. *Handbook of structural equation modeling*, 68–91.
Pericoli, M., & Sbracia, M. (2003). A primer on financial contagion. *Journal of economic surveys, 17*(4), 571–608.
Perras, P., & Wagner, N. (2020). Pricing equity-bond covariance risk: Between flight-to-quality and fear-of-missing-out. *Journal of Economic Dynamics and Control, 121*, Article 104009.
Salisu, A. A., Pierdzioch, C., Gupta, R., & Gabauer, D. (2022). Forecasting stock-market tail risk and connectedness in advanced economies over a century: The role of gold-to-silver and gold-to-platinum price ratios. *International Review of Financial Analysis, 83*, Article 102300.
Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1–48.
Stoja, E., Polanski, A., Nguyen, L. H., & Pereverzin, A. (2023). Does systematic tail risk matter? Journal of International Financial Markets. *Institutions and Money, 82*, Article 101698.
Tiwari, A. K., Raheem, I. D., & Kang, S. H. (2019). Time-varying dynamic conditional correlation between stock and cryptocurrency markets using the copula-ADCC-EGARCH model. *Physica A: Statistical Mechanics and its Applications, 535*, Article 122295.
Uddin, G. S., Yahya, M., Goswami, G. G., Lucey, B., & Ahmed, A. (2022). Stock market contagion during the COVID-19 pandemic in emerging economies. *International review of economics & finance, 79*, 302–309.
Wang, Y. C., Wang, C. W., & Huang, C. H. (2015). The impact of unconventional monetary policy on the tail risks of stock markets between US and Japan. *International Review of Financial Analysis, 41*, 41–51.
Wen, D., Wang, G. J., Ma, C., & Wang, Y. (2019). Risk spillovers between oil and stock markets: A VAR for VaR analysis. *Energy Economics, 80*, 524–535.
White, H., Kim, T. H., & Manganelli, S. (2015). VAR for VaR: Measuring tail dependence using multivariate regression quantiles. *Journal of Econometrics, 187*(1), 169–188.
Ye, W. Y., Luo, K. B., & Liu, X. Q. (2017). Time-varying quantile association regression model with applications to financial contagion and VaR. *European Journal of Operational Research, 256*(3), 1015–1028.
Yousaf, I., Pham, L., & Goodell, J. W. (2023). Interconnectedness between healthcare tokens and healthcare stocks: Evidence from a quantile VAR approach. *International Review of Economics & Finance, 86*, 271–283.
Yu, L., Zha, R., Stafylas, D., He, K., & Liu, J. (2020). Dependences and volatility spillovers between the oil and stock markets: New evidence from the copula and VAR-BEKK-GARCH models. *International Review of Financial Analysis, 68*, Article 101280.
Yuan, Y., Wang, H., & Jin, X. (2022). Pandemic-driven financial contagion and investor behavior: Evidence from the COVID-19. *International Review of Financial Analysis, 83*, Article 102315.