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Spillovers and connectedness among BRICS stock markets, cryptocurrencies, and uncertainty: Evidence from the quantile vector autoregression network

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ABSTRACT

In this study we advance the understanding of the spillovers and connectedness network among conventional and Islamic BRICS stock markets, cryptos (Bitcoin, Ethereum, Litecoin) and various global uncertainties, using a quantile vector autoregression method and daily data covering the period October 8, 2016, to May 28, 2021. Further, the study uses a network and sensitivity analyses to assess the nexus, examines risk causes, and the transfer paths in these markets under bearish, normal, and bullish markets. The evidence offers major findings. First, the overall static and dynamic connectedness is very high and more intense at extreme events. Second, the network connectedness structure shows that the markets have played both roles: net transmitters and receivers of shocks under several market states. Finally, the sensitivity to quantiles analysis shows switching behavior of net transfer spillovers over the quantiles. This could be beneficial to investors aiming at optimizing hedging strategies. Policymakers should consider carefully the overall network connectedness in the market system and formulate appropriate policies to conceive stock market price sensitivity.

1. Introduction

Investors, policy makers and researchers have given the BRICS countries a prominent position in their decision making. Brazil, Russia, India, China and South Africa have distinguished themselves as economies with a fast economic growth and high potential promises among other countries in the world. As a group, these countries account for 40% of the global population, are expected to account for 41% of the world's stock market capitalization and are ranked among the world's largest and most influential countries in the 21st century (Hammoudeh et al., 2013). Brazil is the largest economy in Latin America, the second largest in the Americas tailing only the United States and is very rich in natural resources. Brazil was one of the fastest growing major economies in the globe after the global financial crisis. Russia has tremendous natural resources, particularly hydrocarbons, and is the global largest by total land. India is the largest democracy, the second most populous country in the world with a large, skilled workforce, and has become an important center of information technology service. China is the most populous and the second largest global economy which has been dumbed as

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the factory of the world. South Africa possesses a highly developed economy and an advanced infrastructure. It is one of the largest global exporters of platinum, gold and other natural resources.

The BRICS have steadily generated high average stock returns with relatively low correlations with those of the developed markets. Moreover, the BRICS returns are relatively more volatile than those of the developed markets. Further, Barry et al. (1998) indicate that some of today's emerging stock markets have become some of tomorrow's developed markets, which is expected to apply to the BRICS stock markets. Buchanan et al. (2011) demonstrate the significance of including the emerging market asset class in developed markets' portfolios as this empowers investors to realize higher risk-adjusted performance.

In order to meet our objectives, this empirical research attempts to revisit static and dynamic spillover connectedness among important emerging stock markets by forming a state-of-the-art information spillover connectedness network, using the widely known connectedness framework of Diebold et al. (2012). Since the BRICS have volatile stock markets that have also suffered during the COVID -19 pandemic as well as low corrections with other markets, it is interesting to discern their spillover connectedness with more volatility assets such as the cryptocurrencies. These currencies are making more inroads by different types of consumers and investors since they are not gold and nor fiat. They are however a brand-new technology which has already demonstrated its capability to essentially disrupt the global financial system. In addition, it will be remarkable to demonstrate how the connectedness is influenced by less volatile indicators such gold, the U.S. Treasury security market, and Islamic stock markets in their countries. On the other hand, it will be valuable to also understand the effects on their connections with more volatile gauges such as global uncertainty, U.S. equity VIX, oil ETF volatility and gold ETF volatility, in addition to the major cryptocurrencies: Bitcoin, Ethereum and Litecoin. Understanding those connectedness's should help investors in building better portfolios by reducing risk and policy makers in making sounder decisions. This study attempts to address the following questions: does the dynamic spillover connectedness among the BRICS stocks, cryptocurrency, and uncertainty switch over the time domain? Are the directional spillover connectedness and transfer pathways sensitive to the quantiles of the joint distribution and the frequency domain? Do uncertainties (captured by global economic VIX, gold, oil, and COVID-19 pandemic) affect both the conventional and Islamic BRICS stock markets?

To this end, the paper examines the spillover connectedness between the BRICS markets and those of the major cryptocurrencies and the other variables that are market stabilizers and movers as indicted earlier, by using the quantile VAR (QVAR) and the network analysis. These methods support a deeper analysis of connectedness since they cover all distributions of the BRICKS variables and their risk spillover paths. The quantile VAR connectedness is powerful tool to address the issues of interconnectedness, information spillovers, and risk transfer paths between the BRICS stock markets and cryptos. However, by combining a quantile-based measure of connectedness and the network visualization with the Diebold-Yilmaz method, we are able to analyze the network of shock transmission among the BRICS conventional and Islamic stocks, cryptos, and uncertainty under normal and extreme market events. We selected the network analysis to quantify the direction of spillovers among the 23 market indexes, including fourteen stocks (conventional and Islamic), three cryptos, and six uncertainties. This method is suitable for studying the spillover directions of many variables.

The findings show that connectedness of the markets is more profound and intense during extreme events. The markets have also functioned as net transformers and net receivers, depending on the states of the markets. The network connectedness analysis demonstrates that the strength of the net structure was very robust under bad news (the COVID-19 health crisis) and good news (the COVID-19 vaccine recovery) news.

The paper contributes to the literature on the BRICS in these ways. First, it investigates the spillovers and connectedness among the conventional and Islamic BRICS stock markets, cryptos and uncertainty under normal and extreme market events, conveying a profound understanding into the behavior of shock transmissions between these markets. Second, based on the network analysis of the spillover effects, we can distinguish the origin of risks, the intensity of spillovers, the transfer paths of the spillovers, and the center of the market system network. This may provide both investors and policymakers deeper insights into portfolio management and financial security. Third, with the help of the sensitivity to the quantile analysis, we identify the net transmissions and/or net receivers of the shock pattern of each market over a broad spectrum of quantiles. Therefore, to the best of our knowledge, this work is the first to identify and assess the net transfer pathways among the conventional and Islamic BRICS stock markets, different cryptos, and various uncertainties.

The remainder of the paper is organized as follows. Section 2 presents the review of the literature. Section 3 describes the methodology used in the paper. Section 4 discusses the findings and section 5 concludes and focuses on policy implications.

2. Review of literature

The recent financial and health crises have increased connectedness between financial markets and increased the influence of the variables related to economic and financial uncertainty on those markets. However, the markets that have harnessed less attention within this context in the literature are those of the BRICS countries. This paper pertains to two distinct works of literature. The first strand focuses on the financial markets of the BRICS to study their connectedness between themselves and with other developed and developing markets and well as the influence of uncertainty on their relationships.

Xu and Hamori (2012) investigate the dynamic linkages between the four BRIC countries (Brazil, Russia, India, and China) and the United States in the mean and variance of stock prices. The authors concentrate on the impact of the September 2008 US financial crisis on the dynamic linkages between these stock markets. The findings show that the international transmission of stock prices between the BRIC countries and the United States diminished in both the mean and variance due to the 2008–2009 US financial crisis. That study did not attempt to use the variety of the variables including different uncertainties that we used in our study. It was also published before COVID -19 hit the world's markets.

Sharma et al. (2019) show that 2008 global financial crisis (GFC) has changed permanently the correlations between the five BRICS and developed US and Europe stock markets. Most BRICS stock markets conditional correlation series show an upward long-term trend with the U.S and European developed stock markets. Their findings provide strong evidence that the reducing diversification benefits are a long-run and world-wide phenomenon, particularly after the GFC. This referenced study shares the drawbacks of the previous study, compared to our study.

Hammoudeh et al. (2013) investigate the relationships among the economic, financial and political country risk ratings of the five BRICS and relate those risk factors to their respective national stock markets in the presence of global stock and oil markets. It also explores the interrelationships among the national country financial risk ratings factors to determine the transmission of the risk spectrum among this group. The findings show that only the Chinese stock market is sensitive to all the factors. Financial risk ratings generally indicate more sensitivity than economic and political risk ratings, and political risk is sensitive to both financial and economic risk ratings. Brazil indicates special sensitivity to economic and financial risks, while Russia and China hold strong sensitivity to political risk. India shows special sensitivity to higher oil prices. The above study used the ARDL approach and was not able to avail the current advanced econometric methods. It also used risk ratings instead of more explicit variables related to uncertainties as we do in our study.

Ahmad et al. (2013) explore the financial contagion of GIPSI (Greece, Ireland, Portugal, Spain and Italy), USA, UK and Japan markets on BRIICS (Brazil, Russia, India, Indonesia, China, South Korea and South Africa) stock markets. The findings indicate that Ireland, Italy and Spain among the GIPSI countries seem to be the most contagious for BRIICKS markets compared to Greece, during the euro-zone crisis. The authors also show that Brazil, India, Russia, China and South Africa are strongly struck by the contagion shock during the eurozone crisis. In contrast, Indonesia and South Korea indicate only interdependence and not contagion. While our study focuses on the BRICS's conventional and Islamic markets, the previous study focused on the impacts of major stock markets on the BRIIC markets and did not examine the impact of different uncertainties on those markets. COVID -19 also did not exist at that time, and thus was not examined. It also shares other methodological drawbacks like the previous.

Mensi et al. (2014) examine the dependence structure between the stock markets of the BRICS countries and influential global factors. Using the quantile regression, the findings show that the BRICS markets display dependence with the global stock represented by the S&P index and the commodity markets (oil, and gold), as well as with changes in the U.S. stock market uncertainty (CBOE Volatility Index). They also show that the dependence structure is often asymmetric and impacted by the onset of the recent global financial crisis. However, the U.S. economic policy uncertainty has no effect on the BRICS stock markets. Our study uses more measures of uncertainties including the global economic uncertainty (VIX), infectious disease uncertainty, oil ETF volatility and gold ETF volatility.

Mensi et al. (2016) examine the spillover effect between the U.S. market and the five stock markets of the BRICS (Brazil, Russia, India, China and South Africa), and draws implications for portfolio risk modeling and forecasting. This paper gives consideration to periods before and after the recent global financial crisis (GFC). It employs ploys the bivariate DCC-FIAPARCH model, the modified ICSS algorithm and the Value-at-Risk (VaR) to capture volatility spillovers, detect potential structural breaks as well as assessing the portfolio market risks. For the U.S. and the BRICS daily spot market indices, the findings indicate strong evidence of asymmetry and long memory in the conditional volatility and significant dynamic correlations between them. Moreover, we find several sudden changes in these markets with a common break date centered on September 15, 2008, which corresponds to the Lehman Brothers collapse. The four BRICS Brazil, India, China and South Africa markets are strongly impacted by the 2008 GFC, supporting the hypothesis of recoupling (increasing linkages). However, the hypothesis of decoupling is supported for the Russian stock markets only. Our study gives more consideration to COVID-19 which did not exist when the previous study was conducted.

Mensi et al. (2017) investigate the spillover effects and portfolio diversification between the five BRICS and the four major developed stock markets USA, Europe, Japan and Asia, using the multivariate DECO-FIEGARCH model. The findings show a significant and asymmetric long memory process for both the BRICS and the developed markets. There is also a significant variability in the time-varying conditional correlations between those markets during bull and bear markets. The optimal portfolio weights analysis also demonstrates time-varying hedge ratios and hedging effectiveness. Finally, the findings underscore the strong evidence of the diversification benefits and downside risk reductions for the BRICS markets.

Bouri et al. (2018) examine the relationship between the predictive power of implied volatility in the commodity and major developed stock markets and the implied volatility in individual BRICS stock markets, using the newly developed Bayesian Graphical Structural Vector Autoregressive (BGSVAR) model of (Ahelegbey, 2016). They find evidence that the predictability of individual implied volatilities in BRICS is generally a function of both global and within the group stock market implied volatilities. Additionally, they find that the role of commodity market volatility is marginal, except for South Africa.

Wang et al. (2017) implement a multiscale correlation contagion statistic to test for the presence of stock market contagion during the global financial crisis (GFC) emanating from the Unite States to the other six G7 as well as the four BRIC countries. They find that cross-market correlations between the United States and the selected countries are conditional on the time scale. They show that the stock market contagion during the GFC is dependent on both the recipient country and the time scale.

Sharma et al. (2019) investigate the information linkages of domestic volatility indexes (VIX) for the equity market indices of the BRICS countries, using the multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) model. The findings confirm a strong intertemporal linkages between the sample VIX's. The return and volatility spillovers show a varying degree of connectedness of the BRICS VIX's across the period under study.

Olanipekun et al. (2019) examine the causal relationship between exchange market exposure and domestic and global economic policy uncertainty for the four BRIC countries Brazil, Russia, India, and China, using the bootstrap Granger. They find a cross dependency among those countries. The individual country analysis demonstrates that only China has a bidirectional causality, while

Russia has no causality. Moreover, the findings find a bidirectional relationship between the Russian and Indian foreign exchange exposure and domestic economic policy uncertainty, while this uncertainty variable does not matter for China.

Shi (2021) explores the connectedness among the five BRICS stock markets in time and frequency domains. The heterogeneous frequency responses to shocks are separated into five frequency bands, underscoring the differentiated linkages among those markets. The return spillovers dominated by high frequencies decline with the fall in frequencies, while the volatility spillovers dominated by low frequencies grow with the decline in frequencies. The Russian and Chinese markets play an important role in the return and volatility spillovers across the BRICS markets, respectively.

Zhu et al. (2021) study the impact of COVID and related factors on the stock markets of the five BRICS countries using log-linear Generalized Additive Model (GAM) models. Their exposure–response curves show that the number of daily new COVID-19 cases increases with the rise in the policy stringency index. There is a rapid surge in number of daily new COVID-19 cases when the policy stringency index ranged from 0 to 45. The number of infections climb slowly when this index ranges from 46 to 80, and decreased when it is above 80, after controlling for other potential confounders.

Ledwani et al. (2021) quantify the impact of COVID-19 on the major stock markets of G-7 nations verses the BRICS markets, using an event study methodology. They attempt to capture the effect of the systematic event in the form of Buy and Hold Abnormal Returns (*BHAR*) and Average Buy and Hold Abnormal Returns (*ABHAR*). They consider a 90-day observation window consisting of six sub-event windows after the COVID-19 news harms the world, and 120 days prior to the selected event date to estimate average expected returns. *BHAR* values in the four event windows are statistically significant, covering the stock markets from panic and nosedive to their correction and recovery. *ABHAR* values reported are significantly negative in the event window ranging from −0.15% to −38.43% for G-7 and − 0.06% to −37.12% for BRICS nations. Despite similar ABHAR trends, the BHAR values and correlation matrix exhibit a diverse reaction in BRICS nations compared to the highly synchronized reaction in the G-7 group of nations in the COVID period.

Karim et al. (2021) examine the relationship between oil and stock market returns of the and their BRICS behaviors at different investment horizons using the wavelet and MGARCH-DCC They find that the stock markets' return of Russia, Brazil, and South Africa are comparatively more correlated with oil price return across the investment horizons and more volatile particularly during the Covid-19 period. In contrast, the returns of stock markets of China and India are less correlated with the oil price return and less volatile. Moreover, the findings indicate that oil price return leads the BRICS' stock returns but both are positively correlated.

Malik et al. (2021) investigate the relationship between the five BRICS and the U.S. Stock markets prior and during the pandemic periods using the BEKK model. Those authors show that the BEKK model captures the volatility spillovers and exhibits a statistical significance for own past mean and volatility with both short- and long-run persistence effects. The own volatility spillovers are the highest for the US, China and Brazil compared to Russia and India. The authors find that the own volatility spillovers (Heatwave phenomenon) to be the highest for the United States, China and Brazil, compared to Russia and India. They also find that the highest and long-term spillover effect is between U.S. and Russia. Russia is the least vulnerable to outside shocks. Finally, the pairwise findings suggest that the BRIC countries stock indices exhibit volatility spillover due to the COVID-19 pandemic.

The second strand discusses the relationship between the BRICS stock markets and cryptocurrencies, including measures of uncertainty. Certain studies highlight the distinctive traits of cryptocurrencies. Wang et al. (2019) examine the likelihood of cryptocurrencies serving as a hedge or a safe haven for 30 global indexes from a dynamic viewpoint. This study establishes that bitcoin is not a hedge, but instead is a safe haven for some global indices at certain periods. The safe haven property is more apparent in developed markets as well as in groups with increased market size and liquidity. Ghabri et al. (2021) examine the dependence structure between Bitcoin and various financial assets through various multivariate GARCH-Type specifications. They discover a proof of a low time-variant correlation of liquidity innovations throughout the stipulated period. This result indicates that utilizing Bitcoin instead of conventional assets may be advantageous for spreading the liquidity risk.

Som and Kayal (2022) compare portfolios for ten different countries using the generalized simulated annealing optimization method. For the ten countries around the world, multiple portfolios comprised of various permutations and combinations of stocks, gold, and bitcoin are created. The analysis reports that Bitcoin should be part of the portfolio, possibly in a limited proportion, as it significantly enhances the returns and mitigates the potential costs. Leirvik (2022) examines the link between the returns of five important cryptocurrencies and the volatility of liquidity. This study finds that there is a substantial overall positive, but enormously time-variant, relationship between liquidity volatility and returns. The findings illustrate that investors in Bitcoin view liquidity as a lower risk than they do for other cryptocurrencies, which may be a consequence of its extensive adoption.

Some studies have explored the relationship between cryptocurrencies and the BRICS stock markets. Lahiani and Jlassi (2021) exhibit indications of mean and tail dependence between the BRICS stock market returns and leading cryptocurrencies through a newly formed nonlinear model-free tail dependence measure. Additionally, the study conducts a subsample analysis of the mean and tail dependence between cryptocurrency returns and stock market returns prior to and following the launch of the Bitcoin futures. The findings reveal that the explanatory accuracy of cryptocurrencies (stock markets) in forecasting stock market returns (cryptocurrency returns) is distinct in the two arising subperiods. Jeribi and Ghorbel (2021) utilize generalized autoregressive score (GAS) models to anticipate and quantify the risk of stock market indices and cryptocurrencies. The study reveals that in contrast to developed economies, Bitcoin does not serve as a hedge in the BRICS countries. Further, it is reported that only Bitcoin has a positive correlation with the Brazilian and South African stock markets.

Dahir et al. (2020) utilize an unique TVP-VAR (time-varying parameter vector autoregression) model and demonstrate that the volatility transmission of Bitcoin returns is not a major reason for market return shocks in Brazil, Russia, India, China, and South Africa (BRICS). The study reveals that the volatility transmission of Bitcoin returns contributes less to the information volatility of the equities market. Goodell et al. (2022) analyze the effects of BRICS regulatory measures on the volatility and returns of cryptocurrencies.

Through the usage of quantile regression, the study reveals that there are significant and inverse relationships between BRICS proclamations and Bitcoin volatility, especially at lower ranges of the return distribution. Contrarily, Ethereum (ETH), Ripple (XRP), and Litecoin (LTC) seem to react to volatility unevenly, implying a possible risk shielding a feature toward the conduct of Bitcoin (BTC). Additionally, the robustness checks reveal that the cryptocurrencies respond to BRICS pronouncements far more robustly than they do to the U.S. Fed's statements. This highlights clear associations between cryptocurrencies and the BRICS markets.

Shahzad et al. (2022) distinguish between the Bitcoin's weak and strong hedging capabilities, with adverse swings in the indexes of the BRICS stock markets. The cross-quantilogram framework's findings show that Bitcoin is weak hedge. Secondly, investigations using the recursive cross-quantilogram method imply that Bitcoin plays a time variant hedging role in different BRICS countries.

There is a wide consensus that uncertainties can contribute substantially to the explanation of volatility in asset prices. In this vein, the impact of uncertainties on cryptocurrencies has attracted the curiosity of researchers significantly. In studies that emphasize on the cryptocurrency market, the EPU index is identified to be a determinant in the price movements of cryptocurrencies, notably Bitcoin (Demir et al., 2018; Wang et al., 2019). Bouri et al. (2017) employ the quantile technique to investigate whether Bitcoin can hedge against global uncertainty, as gauged by the American stock market fear index (VIX). They discover that Bitcoin can act as a buffer against risk for investors with shorter investment horizons and during volatile market situations. Akyildirim et al. (2020) report that cryptocurrency markets become more volatile when investor concerns were significant. Their study employs the CBOE-traded VIX volatility index and the DAX-traded VSTOXX volatility index as indices of the risk in the American and European financial markets, correspondingly.

Lucey et al. (2022) develop the Cryptocurrency Uncertainty Index (UCRY) which considers the price and policy uncertainty for the most popular cryptocurrencies. The index does exhibit different moves taken in response to significant cryptocurrency-related events. The study indicates that this index may prove beneficial for upcoming research on the volatility of cryptocurrencies, risk diversification, and the transmission influence.

To our knowledge, we have not found research that deals with the magnitude and direction of shock spillovers between the BRICS stock (conventional and Islamic) and cryptocurrency markets simultaneously at both the time and frequency domains and employing the QVAR and network methodology. Further, the sensitivity to quantile analysis is conducted to deeply understand the spillover transfer pathways under the normal and unstable market scenarios. We have included different measures of uncertainties. The time was not also appropriate for other BRICS studies to account for the impact of infectious diseases like COVID on those markets. We take care of the new data in this paper. Furthermore, as far as we know, this study is among the first to investigate the sensitivity of net information spillover transmission structure of markets in the form of heatmaps throughout a broad spectrum of quantiles and frequency domain.

3. Data and methodology

3.1. Data description

The data are gathered for the conventional and Islamic BRICS stock markets from the Bloomberg terminal. Further, we have collected data for three Coinbase's including Ethereum (*ETH*), Litecoin (*LTC*), and Bitcoin (*BTC*) from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org). Additionally, the data for the uncertainty indexes include CBOE gold volatility (*GVZ*), crude oil *ETF* volatility (*OVX*), CBOE global volatility (*VIX*), Twitter usage (*TEU*), and infectious disease equity market volatility (*FDEMV*)[1] are sourced from different websites. *TEU* and *FDEMV* are sourced from www.policyuncertainty.com, while the other volatilities are sourced from the Bloomberg terminal. We have further collected data for the 1-year Treasury bill market rate (*TB1YR*) from https://fred.stlouisfed.org. The data sample covers the period from October 8, 2016 to May 28, 2021 according to availability of all the data series.

Table 1 describes the variables used in the study, while Table 2 reports the summary statistics for the return series. The compounded returns are obtained continuously following the formula: $R_t = (P_t - P_{t-1})/P_{t-1}$. To estimate the time and frequency connectedness, we have modeled the volatility series by a covariance stationary VAR(p). The absolute value of the return series is employed as a measure of volatility in this study.

Regarding Table 2, it is found that the BRICS stock market returns (conventional and Islamic), cryptos, the Treasury bill, and the infectious disease equity market volatility exhibit positive average returns, while the uncertainties demonstrate negative average returns, with the Twitter economic uncertainty yielding the lowest average return followed by the MSCI Islamic index return of South Africa. Further, it can be seen from Table 2 that Bitcoin *BTC* returns exhibit the highest volatility, followed by Brazilian *IBOV* stock returns and Ethereum returns. However, these markets are the riskiest, while the least risky markets are the conventional MSCI China and MSCI India. Regarding the skewness quantification, the return distributions are left thick tailed for the majority of the series, except *LTC* (Litecoin), *BTC* (Bitcoin), *FDEMV* (Infectious disease volatility), *TEU* (Twitter economic uncertainty), *VIX* (global economic uncertainty), and *OVX* (oil volatility) are positively skewed. The kurtosis values are greater than 3, thereby providing asymmetry in the distributions of the returns. Non-normality of the return distributions is shown with the Jarque-Bera statistics, which are significant at 1% level. The coefficients of Elliott-Rotenberg-Stock (ERS) unit root test demonstrate stationary return series. Both return and squared return series exhibit nonexistence of autocorrelation as indicated with the Ljung and Box test statistics of order 20.

[1] Infectious disease equity market volatility (*FDEMV*) encompasses occurrences related to E: economic, economy, and financial; M: stock market, equity, equities, and Standard and Poors; ID: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1.

Table 1
Variables' definitions and sources.

Variable	Abb.	Source
Ibovespa Brasil Sao Paulo Stock Exchange Index	IBOV	Bloomberg terminal
MSCI Brazil index	MXBR	Bloomberg terminal
MSCI Brazil Islamic index	MXBRI	Bloomberg terminal
MOEX Russia Index	MOEX	Bloomberg terminal
MSCI Russia index	MXRU	Bloomberg terminal
MSCI Russia Islamic index	MXRUI	Bloomberg terminal
S&P BSE SENSEX index	SENSEX	Bloomberg terminal
MSCI India index	MXIN	Bloomberg terminal
MSCI India Islamic index	MXINI	Bloomberg terminal
Shanghai Stock Exchange Composite index	SHCOPM	Bloomberg terminal
MSCI China index	MXCN	Bloomberg terminal
FTSE/JSE Africa All Share index	JALSH	Bloomberg terminal
MSCI South Africa index	MXSA	Bloomberg terminal
MSCI South Africa Islamic index	MXSAI	Bloomberg terminal
Coinbase Ethereum, U.S. Dollars	ETH	Federal Reserve Bank of St. Louis
Coinbase Litecoin, U.S. Dollars	LTC	Federal Reserve Bank of St. Louis
Coinbase Bitcoin, U.S. Dollars	BTC	Federal Reserve Bank of St. Louis
1-Year Treasury Bill Secondary Market Rate	TB1YR	Federal Reserve Bank of St. Louis
Infectious Disease Equity Market Volatility	FDEMV	Economic Policy Uncertainty
Twitter Economic Uncertainty	TEU	Economic Policy Uncertainty
CBOE Volatility Index	VIX	Bloomberg terminal
CBOE Gold ETF Volatility Index	GVZ	Bloomberg terminal
Crude Oil ETF Volatility Index	OVX	Bloomberg terminal

Fig.1 charts the dynamics of the fluctuation for the level series. Fig. 2 visualizes the heatmap of correlation between pairs of markets. The pairs *MXIN-SENSEX* (0.96), MXRU-MOEX (0.94), MXRU-MXRUI (0.90), and MXIN-MXBRI (0.87) exhibit the largest correlations, suggesting that MSCI Indian market and MSCI Russian market (conventional and Islamic) as well as the MSCI Indian market and the MSCI Islamic Brazilian market cannot be used for diversification purpose or hedging strategies. It can further be seen from the correlation heatmap that it is possible to diversify and hedge investment strategies by the use of several assets from the conventional, Islamic markets, Bitcoins, and uncertainties.

3.2. *Quantile vector autoregression method*

To measure the spillover connectedness of a market index variable U_t(dependent) on a market V_t (independent) at the τth quantile, where $\tau \in (0,1)$of the conditional distribution $U_t \mid V_t$, we use the quantile connectedness framework motivated by Ando et al. (2021).

A quantile vector autoregression (VAR) model of order p and dimension n can be written as follows:

$$U_t = \omega_0(\tau) + \sum_{j=1}^{p} \Theta_j(\tau) V_{t-j} + \upsilon_t(\tau) \tag{1}$$

where $U_t$is $n \times n$vector of dependent variables, p denotes the lag length, $\omega_0(\tau)$is the mean vector of order $n \times 1$ at the quantile τ, $\Theta_j(\tau)$is the matrix of quantile VAR coefficients of order $n \times n$, and $\upsilon_t(\tau)$refers to the residual terms at quantile τ.

The quantile moving-average illustration of Eq. (1) can be expressed based on the Wold theorem as follows.

$$U_t = \omega_0(\tau) + \sum_{j=1}^{p} \Theta_j(\tau) V_{t-j} + \upsilon_t(\tau) = \omega_0(\tau) + \sum_{m=0}^{\infty} \Psi_m(\tau) + \upsilon_{t-1} \tag{2}$$

Following Ando et al. (2022), the mean-based quantities of Diebold and Yilmaz (2012a, 2012b) are extended in order to compute several estimates of return connection among quantiles. The connectedness amount at each quantile $\tau$for an infinite order vector-moving average is defined in Jena et al. (2022) as below.

$$U_t = \omega_0(\tau) + \sum_{l=0}^{\infty} \Lambda_l(\tau) \delta_{t-l} \tag{3}$$

where

$$\omega_0(\tau) = \left(I_n + \Phi_1(\tau) + \cdots + \Phi_p(\tau)\right)^{-1} \gamma(\tau) \tag{4}$$

and

Table 2
Descriptive statistics for the return series.

Variable	Mean	Variance	Skewness	Prob.	Kurtosis	Prob.	JB	Prob.	ERS	Prob.	Q(20)	Prob.	$Q^2(20)$	Prob.
IBOV	8.556	904,220.4	−0.912***	0.000	11.406***	0.000	9239.617***	0.000	−6.122***	0.000	14.353	−0.151	32.938***	0.000
MXBR	1.048	6598.11	−0.776***	0.000	10.782***	0.000	8217.759***	0.000	−4.939***	0.000	19.054**	−0.026	29.308***	0.000
MXBRI	0.688	460.285	−1.084***	0.000	12.375***	0.000	10,931.458***	0.000	−5.641***	0.000	8.217	−0.702	38.054***	0.000
MOEX	0.031	1.293	−0.736***	0.000	3.740***	0.000	1118.827***	0.000	−6.684***	0.000	73.433***	0.000	227.057***	0.000
MXRU	0.607	393.992	−0.464***	0.000	3.855***	0.000	1088.546***	0.000	−7.078***	0.000	50.212***	0.000	206.069***	0.000
MXRUI	0.533	335.094	−0.082	−0.169	2.700***	0.000	506.643***	0.000	−9.210***	0.000	32.517***	0.000	119.518***	0.000
SENSEX	0.542	132.585	−0.320***	0.000	5.081***	0.000	1816.295***	0.000	−6.479***	0.000	63.212***	0.000	50.278***	0.000
MXIN	0.019	0.162	−0.343***	0.000	3.919***	0.000	1096.150***	0.000	−4.542***	0.000	66.782***	0.000	67.313***	0.000
MXINI	2.361	2526.82	−0.171***	−0.004	5.454***	0.000	2068.052***	0.000	−8.081***	0.000	58.227***	0.000	117.749***	0.000
SHCOMP	0.153	122.184	−0.639***	0.000	6.104***	0.000	2693.217***	0.000	−8.327***	0.000	52.921***	0.000	139.886***	0.000
MXCN	0.012	0.097	−0.312***	0.000	4.558***	0.000	1465.769***	0.000	−5.553***	0.000	69.099***	0.000	235.975***	0.000
JALSH	1.558	18,176.15	−0.476***	0.000	4.702***	0.000	1593.648***	0.000	−10.326***	0.000	45.321***	0.000	208.668***	0.000
MXSA	0.039	15.545	−0.447***	0.000	5.837***	0.000	2414.920***	0.000	−5.972***	0.000	51.365***	0.000	215.863***	0.000
MXSAI	−0.214	580.252	−1.195***	0.000	17.088***	0.000	20,615.790***	0.000	−17.704***	0.000	36.691***	0.000	35.500***	0.000
ETH	4.249	21,306.03	−1.233***	0.000	56.470***	0.000	221,246.470***	0.000	−17.864***	0.000	157.524***	0.000	979.507***	0.000
LTC	0.376	927.345	5.040***	0.000	126.531***	0.000	1,115,729.274***	0.000	−17.559***	0.000	74.089***	0.000	234.113***	0.000
BTC	63.413	4,550,597	0.460***	0.000	24.048***	0.000	40,106.163***	0.000	−16.209***	0.000	52.473***	0.000	589.011***	0.000
TB1YR	0.001	0.100	−8.833***	0.000	454.240***	0.000	14,310,267.899***	0.000	−26.766***	0.000	175.442***	0.000	154.292***	0.000
FDEMV	0.02	206.081	0.528***	0.000	12.647***	0.000	11,153.340***	0.000	−34.725***	0.000	430.521***	0.000	695.418***	0.000
TEU	−0.255	14,647.69	0.820***	0.000	18.233***	0.000	23,208.746***	0.000	−1.121	−0.263	273.544***	0.000	266.606***	0.000
VIX	−0.011	12.859	1.646***	0.000	21.293***	0.000	32,148.427***	0.000	−2.918***	−0.004	15.266	−0.111	295.331***	0.000
GVZ	−0.015	3.082	0.875***	0.000	7.471***	0.000	4077.089***	0.000	−5.039***	0.000	21.898***	−0.007	237.756***	0.000
OVX	−0.133	36.932	−1.064***	0.000	78.058***	0.000	422,255.418***	0.000	−9.385***	0.000	74.995***	0.000	601.874***	0.000

Note: This table displays the descriptive statistics for the return series (in percentage). JB is the Jarque-Bera test. Q-statistics: Q(20) and $Q^2(20)$ indicate the Ljung and Box test up to the 20th order. The Elliott, Rothenberg and Stock (ERS) is the unit root test for stationarity. *** and ** refer to the 1% and 5% significance levels, respectively.

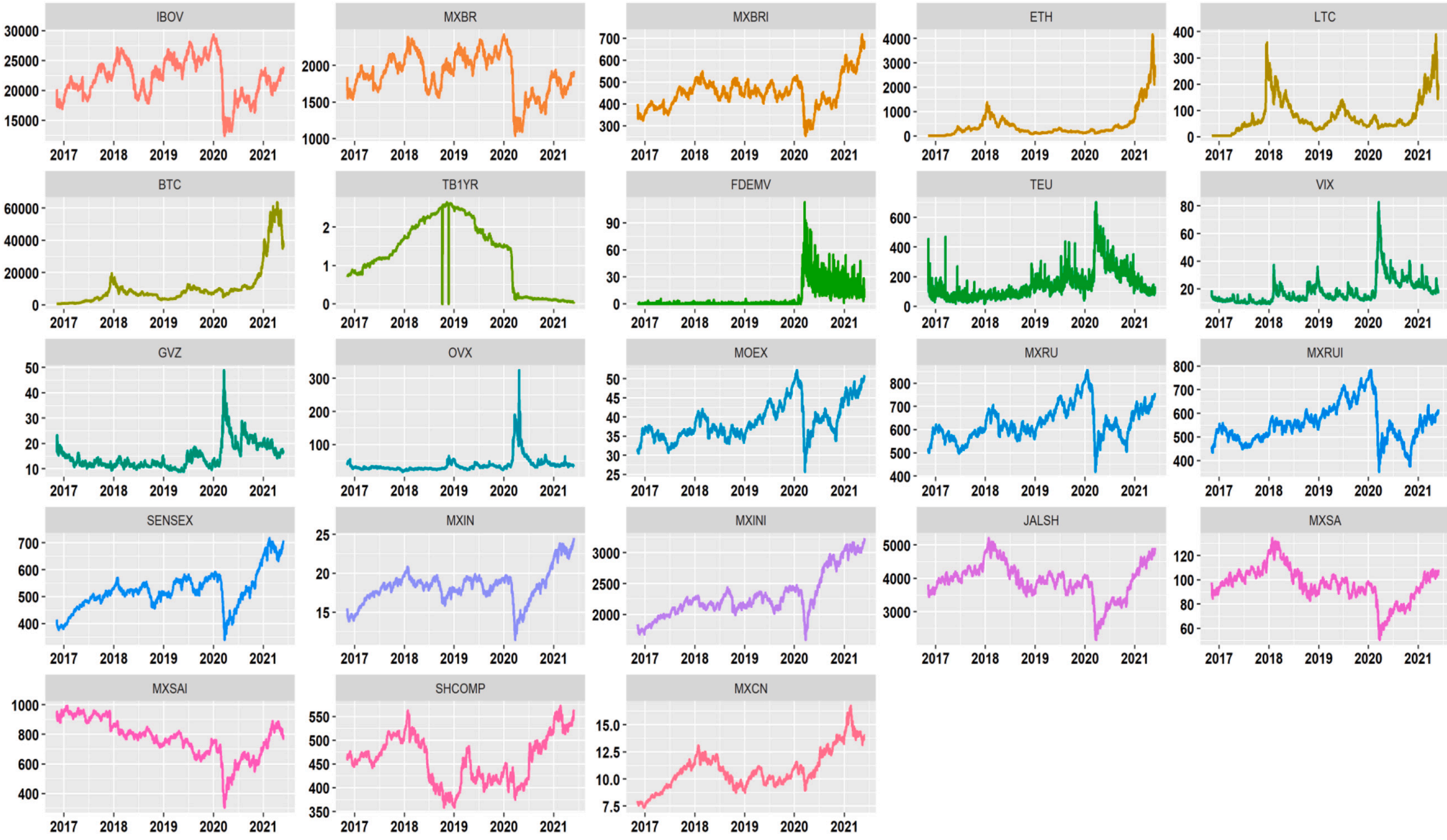

Fig. 1. Dynamics for the level time series.

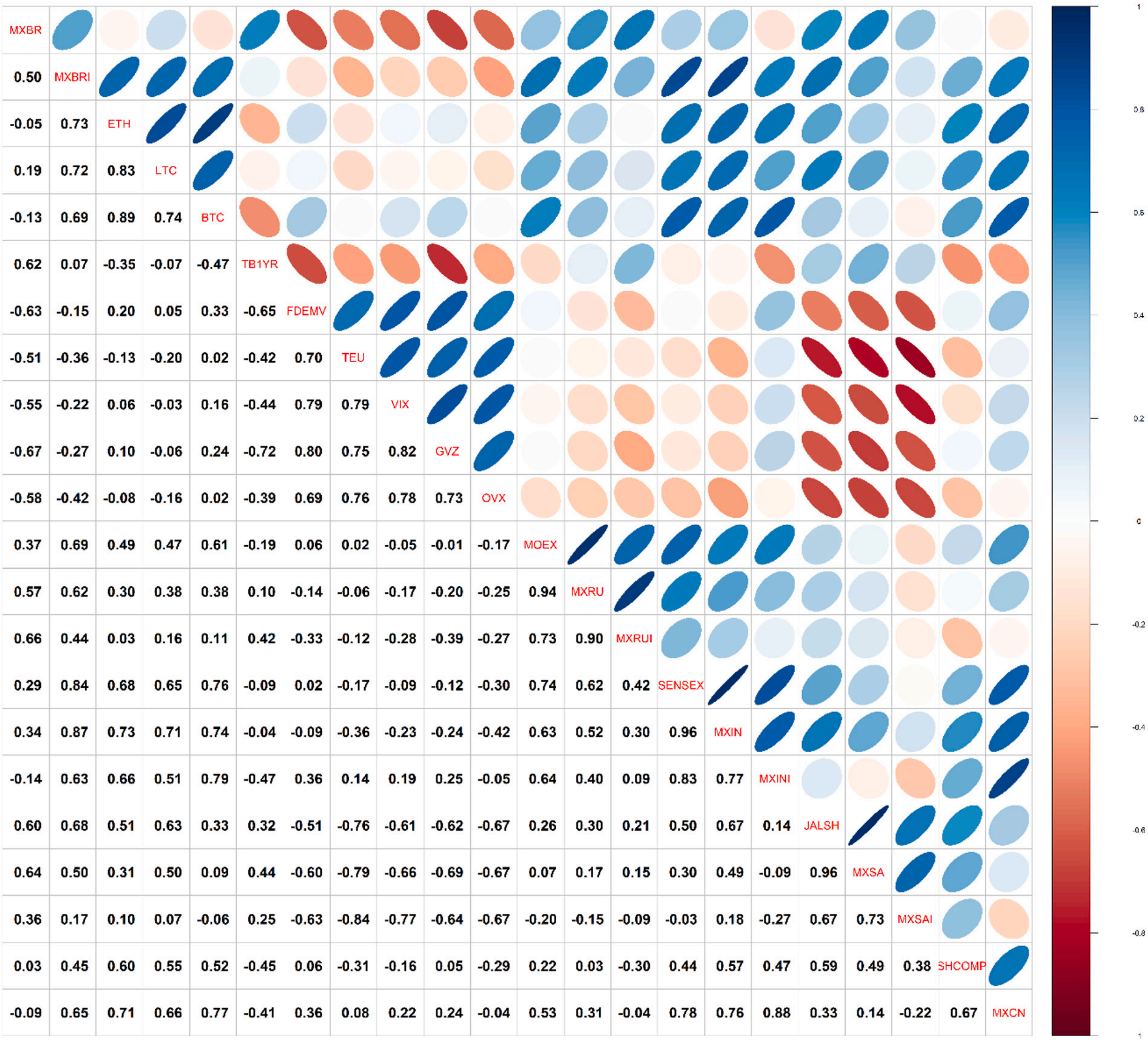

Fig. 2. Visualization of the correlation heatmap. The relative strength of the different colors is displayed in the colour bar where red (blue) refers to negative (positive) correlation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$\Lambda_l(\tau) = \begin{cases} 0, l < 0 \\ I_n, l = 0 \\ \Phi_1(\tau)\Lambda_{l-1} + \cdots + \Phi_p(\tau)\Lambda_{p-1,l} > 0 \end{cases} \tag{5}$$

In Eq. (3), the variable $U_t$is expressed with the sum of the error terms δ_{t-l}. In the next step, the H-variates ahead Generalized Forecast Error-Variance Decomposition (GFEVD) is calculated following Chatziantoniou et al. (2021) in order to display how a spread in market i influences market j

$$\kappa_{ij}^{g}(H) = \frac{\sigma(\tau)_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i^{'}h_h\sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i^{'}h_h\sum e_j\right)} \tag{6}$$

where $\kappa_{ij}^{g}(H)$refers to the jth market's contribution to the variance of the forecasting error of the ith market at horizon H. The matrix$\sum$denotes the variance matrix for the residual vector. The term $\sigma_{jj}(\tau)$indicates the jth diagonal component of the matrix $\sum$. The vector$e_i$designates a vector with value 1 at the ith component and 0 otherwise.

The normalized variance decomposition matrix is expressed with the following formula:

Table 3
Spillover connectedness in the quantile VAR (at the 5th quantile) for the case of Brazil.

	IBOV	MXBR	MXBRI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
IBOV	12.75	11.59	10.4	8.07	7.57	7.71	6.52	7.38	7.49	6.78	7.48	6.26	87.25
MXBR	12.09	12.02	10.76	8.09	7.58	7.66	6.37	7.39	7.39	6.79	7.52	6.34	87.98
MXBRI	11.2	11.04	12.42	8.17	7.6	7.76	6.53	7.44	7.35	6.62	7.41	6.47	87.58
ETH	8.29	7.96	8.07	12.48	10.23	10.18	6.45	7.58	7.56	6.84	7.44	6.9	87.52
LTC	8.27	7.83	7.94	10.75	12.53	10.09	6.52	7.46	7.23	6.9	7.63	6.84	87.47
BTC	8.32	7.77	7.98	10.51	10.08	12.62	6.48	7.34	7.48	6.84	7.69	6.89	87.38
TB1YR	7.85	7.13	7.05	6.89	6.73	6.92	24.69	6.88	6.68	6.39	6.67	6.12	75.31
FDEMV	8.57	8.14	8.11	7.87	7.53	7.66	6.77	14.08	7.95	7.61	8.3	7.4	85.92
TEU	8.73	8.18	7.88	7.92	7.52	7.7	6.78	8.01	14.27	7.82	7.99	7.19	85.73
VIX	7.7	7.36	7.21	7.57	7.56	7.33	6.49	8.15	8.4	14.03	9.65	8.55	85.97
GVZ	8.27	7.66	7.61	7.92	7.79	7.87	6.46	8.02	8	9.08	13.07	8.26	86.93
OVX	8.15	7.56	7.6	8.03	7.67	7.76	6.58	8.16	7.99	8.67	8.81	13.02	86.98
TO others	97.45	92.22	90.62	91.8	87.84	88.65	71.95	83.81	83.51	80.34	86.59	77.23	1032.01
Inc. own	110.2	104.24	103.04	104.28	100.37	101.27	96.65	97.89	97.79	94.37	99.66	90.25	TCI = 86%
NET	10.2	4.24	3.04	4.28	0.37	1.27	−3.35	−2.11	−2.21	−5.63	−0.34	−9.75	

Notes. The findings are based on the quantile VAR specification with a lag length of order one (SIC) and a 10-step-ahead generalized forecast error variance decomposition. "FROM others" denotes the total spillover received by a specific index from all other indexes. "TO others" shows the total spillovers transmitted by a certain index to all other indexes. "NET" refers to the difference between "TO others" and "FROM others", in which a positive value indicates a net transmitter of information spillovers, while a negative value shows a net receipt of shock spillovers. "Inc. own" is the contribution including own.

Table 4
Spillover connectedness in the quantile VAR (at the 50th quantile) for the case of Brazil.

	IBOV	MXBR	MXBRI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
IBOV	36.86	30.97	20.31	0.57	0.49	0.42	1.33	0.25	0.36	5.49	1.13	1.84	63.14
MXBR	30.46	35.42	23.54	0.59	0.57	0.46	1.05	0.34	0.35	4.5	0.99	1.73	64.58
MXBRI	22.32	26.16	39.54	0.96	0.79	0.82	1.24	0.23	0.37	4.81	1.31	1.44	60.46
ETH	0.64	0.71	1.08	48.51	24.49	22.18	0.28	0.29	0.29	1	0.26	0.27	51.49
LTC	0.55	0.69	0.88	24.84	48.56	22.18	0.31	0.27	0.27	0.71	0.37	0.36	51.44
BTC	0.51	0.58	0.83	22.88	22.65	49.43	0.56	0.34	0.33	0.93	0.61	0.35	50.57
TB1YR	2.38	1.58	1.76	0.38	0.6	0.83	81.46	0.3	0.86	3.16	4.96	1.72	18.54
FDEMV	0.66	0.58	0.52	0.6	0.72	0.67	0.84	92.32	1.03	0.89	0.89	0.28	7.68
TEU	0.77	0.81	0.92	0.82	1.14	0.74	1.36	1.56	89.13	0.94	1.03	0.77	10.87
VIX	7.93	6.7	6.89	1.3	1.07	1.23	2.2	0.28	0.51	57.42	8.95	5.51	42.58
GVZ	2.05	1.87	2.13	0.39	0.61	0.88	5.41	0.7	0.48	10.73	69.28	5.48	30.72
OVX	3.55	3.32	2.84	0.53	0.48	0.67	2.09	0.44	0.62	6.85	5.76	72.85	27.15
TO others	71.82	73.97	61.7	53.89	53.6	51.08	16.68	5.01	5.47	40.02	26.26	19.73	479.23
Inc. own	108.68	109.39	101.24	102.4	102.16	100.51	98.14	97.32	94.6	97.44	95.54	92.58	TCI = 39.94%
NET	8.68	9.39	1.24	2.4	2.16	0.51	−1.86	−2.68	−5.4	−2.56	−4.46	−7.42	

Notes. See notes in Table 3.

Table 5
Spillover connectedness in the quantile VAR (at the 95th quantile) for the case of Brazil.

	IBOV	MXBR	MXBRI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
IBOV	11.95	11.34	10.29	8.32	7.84	7.64	6.29	7.73	7.89	6.44	7.57	6.71	88.05
MXBR	11.07	11.59	10.29	8.28	7.86	7.7	6.37	7.75	7.97	6.56	7.75	6.8	88.41
MXBRI	10.63	10.9	11.93	8.09	7.78	7.59	6.33	7.62	7.99	6.45	7.62	7.07	88.07
ETH	7.82	8.05	7.99	11.72	9.89	9.6	6.4	7.94	8	7.11	8.15	7.33	88.28
LTC	8.01	7.99	7.88	9.73	11.6	9.64	6.56	7.97	8.02	7.06	8.21	7.34	88.4
BTC	8.19	8.34	7.93	10	10.01	11.54	6.27	7.73	7.89	6.96	8.07	7.06	88.46
TB1YR	7.27	7.44	7.32	7.3	7.1	6.93	21.54	7.09	7.49	6.51	7.34	6.67	78.46
FDEMV	7.96	8.15	7.87	8.57	8.34	7.92	6.72	12.25	8.35	7.74	8.32	7.83	87.75
TEU	7.93	8.22	8.01	8.4	8.11	7.92	6.54	7.95	13.18	7.57	8.3	7.87	86.82
VIX	7.52	7.65	7.42	7.76	7.75	7.57	6.73	8.08	8.46	12.73	9.72	8.61	87.27
GVZ	7.76	7.91	7.69	8.21	8.18	7.89	6.43	8.03	8.24	8.87	12.49	8.3	87.51
OVX	7.66	7.8	7.58	8.23	8.1	8.08	6.47	8.12	8.66	8.38	9.14	11.78	88.22
TO others	91.82	93.77	90.26	92.89	90.96	88.49	71.12	86.02	88.95	79.64	90.19	81.58	1045.7
Inc. own	103.77	105.36	102.19	104.62	102.56	100.03	92.67	98.27	102.13	92.37	102.68	93.36	TCI = 87.14%
NET	3.77	5.36	2.19	4.62	2.56	0.03	−7.33	−1.73	2.13	−7.63	2.68	−6.64	

Notes. See notes in Table 3.

Table 6
Spillover connectedness in the quantile VAR (at the 5th quantile) for the case of Russia.

	MOEX	MXRU	MXRUI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
MOEX	12.6	11.77	11.16	7.98	7.63	7.67	7.12	7.11	7.29	5.99	7.11	6.59	87.4
MXRU	11.82	12.02	11.37	7.89	7.5	7.59	7.22	7.2	7.55	6.2	6.96	6.68	87.98
MXRUI	11.56	11.7	12.14	7.82	7.61	7.64	7.14	7.12	7.27	6.22	6.99	6.78	87.86
ETH	8.59	8.33	8.07	12.24	10.04	10.17	6.73	7.21	7.68	6.66	7.26	7.01	87.76
LTC	8.27	8.02	7.83	10.57	12.55	10.2	6.93	7.28	7.24	6.75	7.37	6.99	87.45
BTC	8.5	8.24	8.03	10.19	9.84	12.39	6.84	7.14	7.56	6.72	7.48	7.08	87.61
TB1YR	7.75	7.4	7.42	6.64	6.73	6.85	25.98	6.28	6.69	5.75	6.23	6.29	74.02
FDEMV	8.64	8.44	8.3	7.85	7.53	7.81	7.2	13.42	8.03	7.29	7.97	7.51	86.58
TEU	8.55	8.18	7.95	7.89	7.47	7.66	7.02	7.95	14.39	7.49	7.85	7.59	85.61
VIX	7.71	7.72	7.6	7.41	7.39	7.5	6.61	7.87	8.28	13.74	9.36	8.81	86.26
GVZ	8.25	7.98	7.82	7.86	7.85	8.09	6.78	7.64	7.92	8.65	12.56	8.61	87.44
OVX	8.05	7.98	7.86	7.88	7.6	7.84	6.81	7.78	7.84	8.23	8.83	13.31	86.69
TO others	97.71	95.77	93.4	90	87.19	89.01	76.41	80.58	83.33	75.95	83.41	79.94	1032.68
Inc. own	110.3	107.78	105.55	102.24	99.73	101.4	102.38	94	97.71	89.69	95.96	93.25	TCI = 86.06%
NET	10.3	7.78	5.55	2.24	−0.27	1.4	2.38	−6	−2.29	−10.31	−4.04	−6.75	

Notes. See notes in Table 3.

Table 7
Spillover connectedness in the quantile VAR (at the 50th quantile) for the case of Russia.

	MOEX	MXRU	MXRUI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
MOEX	34.87	29.22	24.07	0.78	0.44	0.64	1.23	0.15	0.27	4.77	1.43	2.11	65.13
MXRU	28.93	33.39	27.9	0.59	0.38	0.39	0.96	0.19	0.25	3.99	1.39	1.64	66.61
MXRUI	25.46	29.87	35.79	0.54	0.34	0.41	0.97	0.22	0.27	3.55	1.31	1.26	64.21
ETH	0.9	0.78	0.71	48.5	24.46	22.19	0.3	0.28	0.29	0.99	0.27	0.33	51.5
LTC	0.54	0.5	0.47	24.93	48.87	22.28	0.39	0.3	0.28	0.73	0.32	0.38	51.13
BTC	0.63	0.43	0.44	23	22.78	49.52	0.62	0.36	0.33	0.97	0.56	0.36	50.48
TB1YR	2.25	1.78	1.7	0.42	0.7	0.88	81.56	0.27	0.91	2.91	4.95	1.66	18.44
FDEMV	0.71	0.62	0.57	0.57	0.63	0.6	0.79	92.57	0.93	0.89	0.79	0.32	7.43
TEU	0.85	0.98	1.25	0.87	1.2	0.76	1.47	1.43	88.28	1.04	1.15	0.73	11.72
VIX	6.61	5.22	4.21	1.39	1.06	1.31	2.24	0.23	0.52	61.55	9.45	6.2	38.45
GVZ	2.51	2.39	2.17	0.4	0.53	0.8	5.35	0.61	0.52	10.72	68.43	5.57	31.57
OVX	4.15	2.91	1.81	0.64	0.52	0.7	2.02	0.48	0.62	7.21	6.11	72.83	27.17
TO others	73.54	74.73	65.3	54.14	53.04	50.96	16.35	4.51	5.21	37.78	27.72	20.55	483.83
Inc. own	108.41	108.12	101.09	102.64	101.91	100.48	97.91	97.08	93.48	99.33	96.15	93.38	TCI = 40.32%
NET	8.41	8.12	1.09	2.64	1.91	0.48	−2.09	−2.92	−6.52	−0.67	−3.85	−6.62	

Notes. See notes in Table 3.

Table 8
Spillover connectedness in the quantile VAR (at the 95th quantile) for the case of Russia.

	MOEX	MXRU	MXRUI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
MOEX	11.78	11.18	10.77	8.09	7.89	7.72	6.58	7.72	7.57	6.42	7.4	6.87	88.22
MXRU	10.92	11.56	11.15	8.05	7.9	7.69	6.51	7.69	7.52	6.62	7.49	6.91	88.44
MXRUI	10.38	11.06	11.78	8.02	7.83	7.7	6.53	7.76	7.51	6.79	7.52	7.12	88.22
ETH	8.09	8.08	8.13	11.51	9.87	9.61	6.28	8.01	7.79	7.27	7.99	7.36	88.49
LTC	7.96	8	8.07	9.96	11.76	9.94	6.63	7.81	7.76	6.98	7.88	7.26	88.24
BTC	8.17	7.96	8	9.91	10.08	11.79	6.52	7.79	7.72	7.02	7.82	7.22	88.21
TB1YR	7.23	7.27	7.4	7.09	7.01	7	23.43	6.94	6.84	6.36	6.96	6.48	76.57
FDEMV	8.02	8.09	8.19	8.49	8.22	8.05	6.61	12.28	8.28	7.67	8.14	7.96	87.72
TEU	7.93	8.06	8.11	8.32	8.05	8.04	6.68	8.05	12.82	7.76	8.17	8	87.18
VIX	7.77	7.96	8.14	7.69	7.87	7.76	6.76	8.07	8.19	11.9	9.3	8.56	88.1
GVZ	8.03	8.03	8.2	7.92	8.1	7.9	6.6	7.89	7.85	8.88	12.31	8.3	87.69
OVX	7.58	7.7	8.04	8.06	8.1	8.08	6.48	8.41	8.26	8.36	8.79	12.14	87.86
TO others	92.1	93.39	94.19	91.6	90.93	89.5	72.17	86.13	85.28	80.14	87.46	82.05	1044.94
Inc. own	103.88	104.94	105.97	103.11	102.69	101.29	95.59	98.41	98.1	92.04	99.77	94.19	TCI = 87.08%
NET	3.88	4.94	5.97	3.11	2.69	1.29	−4.41	−1.59	−1.9	−7.96	−0.23	−5.81	

Notes. See notes in Table 3.

Table 9
Spillover connectedness in the quantile VAR (at the 5th quantile) for the case of India.

	SENSEX	MXIN	MXINI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
SENSEX	12.82	12.53	10.91	7.68	7.26	7.53	6.33	7.14	7.45	6.6	7.29	6.44	87.18
MXIN	12.24	12.89	11.18	7.61	7.19	7.5	6.24	7.18	7.45	6.69	7.31	6.53	87.11
MXINI	11.02	11.54	13.11	7.64	7.24	7.63	6.29	7.26	7.52	6.61	7.41	6.74	86.89
ETH	8.04	8.16	7.81	12.79	10.49	10.42	6.36	7.34	7.78	6.63	7.32	6.85	87.21
LTC	7.76	7.88	7.63	10.99	12.94	10.65	6.45	7.2	7.55	6.71	7.49	6.75	87.06
BTC	7.88	8.01	7.78	10.8	10.31	13	6.42	7.12	7.64	6.56	7.66	6.82	87
TB1YR	7.22	7.36	7.05	6.83	6.96	7.15	25.03	6.5	7.04	6.06	6.62	6.19	74.97
FDEMV	8.09	8.21	7.93	7.92	7.52	7.87	6.88	14.37	8.19	7.39	8.21	7.43	85.63
TEU	7.89	8.23	8.12	7.96	7.7	7.86	6.74	7.87	14.54	7.56	8.13	7.38	85.46
VIX	7.77	8.06	7.87	7.3	7.24	7.25	6.32	7.98	8.27	13.8	9.48	8.67	86.2
GVZ	7.54	7.75	7.82	7.9	7.84	8.13	6.6	7.78	7.96	8.9	13.44	8.33	86.56
OVX	7.76	8.11	8.13	7.84	7.57	7.81	6.66	7.65	7.94	8.38	8.81	13.33	86.67
TO others	93.22	95.84	92.22	90.47	87.33	89.79	71.29	81.02	84.8	78.08	85.72	78.13	1027.93
Inc. own	106.04	108.73	105.34	103.26	100.27	102.8	96.32	95.39	99.34	91.88	99.16	91.46	TCI = 85.66%
NET	6.04	8.73	5.34	3.26	0.27	2.8	−3.68	−4.61	−0.66	−8.12	−0.84	−8.54	

Notes. See notes in Table 3.

Table 10
Spillover connectedness in the quantile VAR (at the 50th quantile) for the case of India.

	SENSEX	MXIN	MXINI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
SENSEX	37.38	34.1	19.16	0.5	0.33	0.5	1.3	0.22	0.28	2.8	1.98	1.44	62.62
MXIN	33.21	36.44	21.67	0.43	0.38	0.55	1.11	0.21	0.25	2.53	1.88	1.35	63.56
MXINI	22.43	26.34	43.09	0.5	0.36	0.58	1.1	0.29	0.19	2.46	1.68	0.97	56.91
ETH	0.53	0.47	0.5	48.98	24.71	22.42	0.29	0.28	0.28	0.99	0.27	0.29	51.02
LTC	0.42	0.43	0.26	25.1	49.1	22.41	0.35	0.27	0.28	0.7	0.33	0.35	50.9
BTC	0.33	0.41	0.49	23.08	22.88	49.61	0.61	0.34	0.32	0.97	0.58	0.37	50.39
TB1YR	1.24	1.24	1.17	0.44	0.65	0.86	83.22	0.35	0.88	3.03	5.24	1.68	16.78
FDEMV	0.45	0.52	0.61	0.62	0.65	0.59	0.86	92.72	1.03	0.84	0.75	0.36	7.28
TEU	0.58	0.57	0.5	0.92	1.22	0.85	1.39	1.61	89.36	1.06	1.07	0.87	10.64
VIX	2.53	2.51	1.91	1.53	1.18	1.42	2.72	0.31	0.67	67.94	10.5	6.79	32.06
GVZ	2.28	2.36	1.56	0.39	0.63	0.87	5.39	0.63	0.57	10.84	69.18	5.3	30.82
OVX	2.09	2.03	1.1	0.54	0.48	0.68	2.15	0.52	0.63	7.57	6	76.21	23.79
TO others	66.09	71	48.93	54.05	53.46	51.73	17.27	5.03	5.39	33.78	30.28	19.76	456.77
Inc. own	103.47	107.45	92.02	103.03	102.56	101.34	100.49	97.75	94.75	101.72	99.46	95.96	TCI = 38.06%
NET	3.47	7.45	−7.98	3.03	2.56	1.34	0.49	−2.25	−5.25	1.72	−0.54	−4.04	

Notes. See notes in Table 3.

Table 11
Spillover connectedness in the quantile VAR (at the 95th quantile) for the case of India.

	SENSEX	MXIN	MXINI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
SENSEX	11.52	11.26	9.94	7.71	7.59	7.84	6.45	7.83	7.47	7.4	7.66	7.32	88.48
MXIN	11.16	11.83	10.12	7.6	7.46	7.93	6.33	7.9	7.4	7.42	7.63	7.2	88.17
MXINI	10.01	10.37	11.6	7.76	7.57	7.64	6.46	8.28	7.68	7.44	7.67	7.49	88.4
ETH	8	8.05	7.78	11.66	9.96	10.17	6.4	7.92	7.72	7.26	7.91	7.19	88.34
LTC	7.84	7.88	7.67	10.1	11.32	9.97	6.68	7.98	7.73	7.16	7.99	7.69	88.68
BTC	8.03	8.04	7.58	9.82	9.63	12.09	6.42	7.88	7.48	7.39	8.19	7.43	87.91
TB1YR	7.27	7.25	7.02	7	6.79	7.09	23.75	7.02	6.93	6.43	6.77	6.67	76.25
FDEMV	8.22	8.22	7.97	8.2	7.75	8.14	6.48	12.56	8.14	8.21	8.15	7.95	87.44
TEU	7.9	8.03	7.96	8.08	7.72	8.12	6.52	8.42	12.89	7.98	8.27	8.13	87.11
VIX	7.87	8.02	7.89	7.66	7.56	7.88	6.53	8.35	8.19	12.18	9.22	8.65	87.82
GVZ	7.83	7.92	7.84	7.85	7.62	8.19	6.48	8.05	7.78	9.23	12.86	8.35	87.14
OVX	7.7	7.69	7.68	7.91	7.62	8.26	6.46	8.24	8.25	8.65	8.86	12.67	87.33
TO others	91.83	92.73	89.45	89.69	87.27	91.24	71.22	87.87	84.78	84.58	88.33	84.07	1043.07
Inc. own	103.35	104.56	101.05	101.34	98.59	103.33	94.97	100.43	97.67	96.77	101.18	96.74	TCI = 86.92%
NET	3.35	4.56	1.05	1.34	−1.41	3.33	−5.03	0.43	−2.33	−3.23	1.18	−3.26	

Notes. See notes in Table 3.

$$\widetilde{\kappa}_{ij}^{g}(H) = \frac{\kappa_{ij}^{g}(H)}{\sum_{j=1}^{k}\kappa_{ij}^{g}(H)} \tag{7}$$

GFEVD is used in the next step to quantify the degree of connectedness at each quantile. According to Diebold et al. (2012) the total spillover connectedness index at quantile τ, which assesses the overall spillover impact in the whole system, is calculated as follows:

$$TCI(\tau) = \frac{\sum_{i=1}^{k}\sum_{j=1,i\neq j}^{k}\widetilde{\kappa}_{ij}^{g}(\tau)}{\sum_{i=1}^{k}\sum_{j=1}^{k}\widetilde{\kappa}_{ij}^{g}(\tau)} \times 100 \tag{8}$$

To measure the spillover effect of market *i* from all other markets or the spillover effect from market *i* to all other markets at each quantile τ, the "FROM" and "TO" measures are identified. Thus, the τthdirectional spillover index "FROM" is given as follows:

$$FROM = \frac{\sum_{j=1,i\neq j}^{k}\widetilde{\kappa}_{ij}^{g}(\tau)}{\sum_{j=1}^{k}\widetilde{\kappa}_{ij}^{g}(\tau)} \times 100 \tag{9}$$

The τthdirectional spillover index "TO" is expressed as follows:

$$TO = \frac{\sum_{j=1,i\neq j}^{k}\widetilde{\kappa}_{ji}^{g}(\tau)}{\sum_{j=1}^{k}\widetilde{\kappa}_{ji}^{g}(\tau)} \times 100 \tag{10}$$

Given the τthquantile directional spillover index measures "FROM" and "TO", the τthnet spillover index "NET" is calculated as the difference between the "TO" and "FROM" measures.

$$NET(\tau) = TO - FROM \tag{11}$$

Finally, the τthnet pairwise directional spillover index can be defined as follows:

$$NPDC = S_{ij} = \widetilde{\kappa}_{ji}^{g}(\tau) - \widetilde{\kappa}_{ij}^{g}(\tau) \tag{12}$$

4. Empirical findings

4.1. Static connectedness analysis

The findings of the risk spillovers by using a quantile-based VAR for the BRICS countries represent the theme of this section. We estimate the connectedness measures of the asset volatilities based on the quantile-based VAR estimations with 10 days forecast horizon and 200-day rolling window. For each BRICS market, three tables are covered which provide the results for the bearish markets (5th quantile), normal markets (50th quantile), and bullish markets (95th quantile) for the joint distributions under the static settings. Tables 3-17 depict the risk spillover connectedness for the five selected markets covering extreme lower (5th), intermediate (50th), and extreme-upper (95th) quantiles. Taken together, the findings of our research reveal topical insights. Findings provide evidence of asymmetric risk spillover connection between the extreme lower and the extreme higher quantiles for all BRICS markets. There is evidence of severe risk spillover connectedness for both the bearish and bullish market states and a weak risk spillover transmission at the normal market state.

The results of the risk spillover connectedness in the quantile VAR at the 5th, 50th and 95th quantiles for the case of Brazil are presented through Tables 3, 4 and 5. The total connectedness index (TCI) ranges from 86% (in the 5th quantile) to 87.14% (in the 95th quantile) and 39.94% (in the 50th quantile). In the bearish market (in the 5th quantile), the contributions from (to) others range

Table 12
Spillover connectedness in the quantile VAR (at the 5th quantile) for the case of China.

	SHCOMP	MXCN	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
SHCOMP	15.42	12.15	8.35	8.2	8.5	7.45	8.23	8.11	7.83	8.22	7.55	84.58
MXCN	11.91	15.87	8.87	8.5	8.5	7.6	8.1	8.09	7.14	8.14	7.27	84.13
ETH	7.84	8.28	15.02	12.04	11.9	6.75	7.73	8.2	7.15	7.85	7.25	84.98
LTC	8.15	8.38	12.23	14.83	11.66	6.9	7.61	7.77	7.36	7.96	7.15	85.17
BTC	7.92	8.49	12.02	11.59	14.85	6.89	7.47	7.92	7.17	8.28	7.39	85.15
TB1YR	7.35	7.88	7.28	7.34	7.51	28.61	6.84	6.93	6.44	7.07	6.75	71.39
FDEMV	8.55	8.93	8.29	8.12	8.35	7.3	16.89	8.44	8.13	9.02	7.99	83.11
TEU	8.15	8.49	8.56	8.18	8.29	7.22	8.58	17.2	8.45	8.91	7.98	82.8
VIX	8.43	7.89	7.64	7.69	7.63	6.81	8.44	8.73	16.52	10.78	9.44	83.48
GVZ	8.14	8.02	8.35	8.3	8.53	6.97	8.27	8.25	10.19	15.8	9.19	84.2
OVX	8.04	8.33	8.33	8.09	8.25	7.4	8.29	8.39	9.26	9.69	15.92	84.08
TO others	84.48	86.81	89.91	88.06	89.13	71.29	79.55	80.84	79.13	85.92	77.94	913.08
Inc. own	99.9	102.69	104.93	102.89	103.98	99.91	96.44	98.04	95.65	101.72	93.86	TCI = 83.01%
NET	−0.1	2.69	4.93	2.89	3.98	−0.09	−3.56	−1.96	−4.35	1.72	−6.14	

Notes. See notes in Table 3.

Table 13
Spillover connectedness in the quantile VAR (at the 50th quantile) for the case of China.

	SHCOMP	MXCN	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
SHCOMP	65.59	23.77	1.35	1.79	1.26	0.95	0.36	0.28	1.9	1.41	1.34	34.41
MXCN	21.34	62.27	0.89	0.92	0.85	1.02	0.46	0.4	6.85	2.93	2.07	37.73
ETH	0.71	0.71	49.16	24.66	22.31	0.28	0.28	0.3	1.03	0.26	0.3	50.84
LTC	1.1	0.66	24.84	48.79	22.31	0.31	0.24	0.29	0.74	0.33	0.38	51.21
BTC	0.73	0.7	22.96	22.86	49.61	0.59	0.35	0.34	0.96	0.55	0.35	50.39
TB1YR	0.82	0.9	0.4	0.63	0.87	84.97	0.28	0.93	3.3	5.14	1.76	15.03
FDEMV	0.27	0.32	0.58	0.66	0.58	0.9	93.76	0.97	0.86	0.78	0.3	6.24
TEU	0.7	0.76	0.88	1.27	0.76	1.44	1.54	89.75	1.01	1.12	0.77	10.25
VIX	1.15	5.49	1.57	1.22	1.45	2.83	0.31	0.68	68.03	10.55	6.73	31.97
GVZ	1.22	2.85	0.41	0.62	0.81	5.42	0.6	0.54	11.28	70.69	5.59	29.31
OVX	1.14	2.04	0.6	0.51	0.71	2.14	0.47	0.62	7.68	6.12	77.98	22.02
TO others	29.18	38.21	54.48	55.13	51.91	15.88	4.87	5.35	35.61	29.2	19.59	339.39
Inc. own	94.77	100.47	103.64	103.93	101.52	100.85	98.63	95.11	103.64	99.88	97.57	TCI = 30.85%
NET	−5.23	0.47	3.64	3.93	1.52	0.85	−1.37	−4.89	3.64	−0.12	−2.43	

Notes. See notes in Table 3.

Table 14
Spillover connectedness in the quantile VAR (at the 95th quantile) for the case of China.

	SHCOMP	MXCN	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
SHCOMP	13.86	10.92	8.76	8.72	8.79	7.05	8.91	8.43	7.95	8.49	8.13	86.14
MXCN	10.92	13.99	8.7	8.9	8.56	7.01	9.11	8.66	7.65	8.58	7.92	86.01
ETH	8.12	8.53	13.64	11.57	10.95	6.59	8.82	8.34	7.64	8.34	7.46	86.36
LTC	8.36	8.48	11.33	13.67	11.05	6.81	8.7	8.33	7.42	8.38	7.49	86.33
BTC	8.35	8.69	11.22	11.36	13.5	6.65	8.61	8.13	7.4	8.48	7.62	86.5
TB1YR	7.14	7.64	7.73	7.52	7.67	26.77	7.44	7.42	6.52	7.29	6.87	73.23
FDEMV	8.33	8.38	9.21	8.96	8.7	6.84	15.19	8.88	8.35	8.82	8.35	84.81
TEU	8.33	8.68	8.76	8.78	8.77	6.72	8.9	15.07	8.38	9.05	8.55	84.93
VIX	8.28	7.94	8.03	8.35	8.25	6.69	8.98	8.79	14.66	10.52	9.51	85.34
GVZ	8.37	8.29	8.58	8.73	8.79	6.57	8.78	8.71	9.81	14.41	8.97	85.59
OVX	8.03	7.86	8.56	8.61	8.56	6.8	9.14	9.01	9.35	9.65	14.44	85.56
TO others	84.22	85.41	90.87	91.49	90.1	67.71	87.39	84.7	80.47	87.59	80.86	930.81
Inc. own	98.07	99.4	104.51	105.16	103.6	94.48	102.57	99.77	95.13	102.01	95.3	TCI = 84.62%
NET	−1.93	−0.6	4.51	5.16	3.6	−5.52	2.57	−0.23	−4.87	2.01	−4.7	84.62

Notes. See notes in Table 3.

between 75.31% (71.95%) and 87.98% (97.45%), while in the normal markets (in the 50th quantile), the contributions from (to) range from 7.68% (5.01%) to 64.58% (73.97%). In boom markets (95th quantile), the contributions from (to) others lie between 78.46% (71.12%) and 88.46% (93.77%).

The diagonal elements which reveal own contributions range from 24.69% (*TB1YR*) in the bearish markets to 21.5% (*TB1YR)* in the bullish market. Through the above-mentioned tables, it is found that under the bust market conditions, the highest transmitters and receivers of the spillovers are *IBOV* (97.45%) and *MXBR* (87.98%), whereas *TBIYR* is both the smallest transmitter and recipient of the spillover connectedness (71.95,75.31). Under the bullish market conditions, the largest transmitters and receivers of the spillovers are *MXBR* (93.77%) and *BTC* (88.46%). *TBIYR* is both the smallest transmitter and recipient of the spillover connectedness (71.12%,78.46%).

The results of the risk spillover connectedness in the quantile VAR at the 5th, 50th and 95th quantiles for the case of Russia are presented through Tables 6, 7 and 8. The total connectedness index (*TCI*) ranges from 86.06% (5th quantile) to 87.08% (95th quantile) and 40.32% (50th quantile). In the bust market (5th quantile), the contributions from (to) others range between 74.02% (75.95%) and 87.98% (97.71%), while in the normal markets (50th quantile), the contributions from (to) range from 7.43% (4.51%) to 66.61% (74.73%). In boom markets (95th quantile), the contributions from (to) others lie between 76.57% (72.17%) and 88.49% (94.19%).

The diagonal elements which reveal own connectedness range from 25.98% (*TB1YR*) in the bearish markets to 22.43% (*TB1YR*) in the bullish market. In addition, the above tables reveal that under the bust market conditions, the largest transmitters and receivers of the spillovers are *MOEX* (97.71%) and *MXRU* (87.98%). *VIX* (75.95) is the smallest transmitter and *TBIYR* (74.02) is the smallest recipient of the spillover connectedness. Whereas under the bullish market conditions, the largest transmitters and receivers of the spillovers are *MXRUI* (94.19%) and *ETH* (88.49%). *TBIYR* is both the smallest transmitter and the recipient of the spillover connectedness (72.17%,76.57%).

Tables 9, 10, and 11 show the results of the risk spillover connectedness in the quantile VAR at the 5th, 50th, and 95th quantiles for the case of India. The total connectedness index (*TCI*) ranges from 85.66% (5th quantile) to 86.92% (95th quantile) and 38.06% (50th quantile). Contributions from others oscillate from 74.97% (71.29%) to 87.21% (95.84%) in the bust market (5th quantile), while contributions from others range from 7.28% (5.03%) to 63.56% (71%) in normal markets (50th quantile). Contributions from others range from 76.25% (71.22%) to 88.68% (92.73%) in rising markets (95th quantile). The diagonal elements which manifest own

Table 15
Spillover connectedness in the quantile VAR (at the 5th quantile) for the case of South Africa.

	JALSH	MXSA	MXSAI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
JALSH	12.57	12.18	9.28	8	7.76	7.9	6.67	7.41	7.23	6.33	7.68	6.99	87.43
MXSA	12.32	12.78	9.43	7.95	7.67	7.88	6.46	7.41	7.19	6.34	7.57	7.01	87.22
MXSAI	10.2	10.12	12.3	7.88	7.68	7.89	6.95	7.47	7.37	6.94	7.77	7.41	87.7
ETH	8.6	8.57	7.8	12.06	10.03	10.2	6.46	7.25	7.41	6.83	7.55	7.25	87.94
LTC	8.47	8.23	7.75	10.63	12.39	10.36	6.49	7.19	6.99	6.87	7.58	7.05	87.61
BTC	8.61	8.4	7.69	10.25	10.04	12.48	6.44	7.21	7.31	6.7	7.7	7.17	87.52
TB1YR	7.69	7.35	7.2	6.82	6.79	7.04	25.37	6.23	6.41	6.1	6.49	6.51	74.63
FDEMV	8.9	8.69	7.95	7.47	7.29	7.71	7.08	14.14	7.61	7.46	8.16	7.53	85.86
TEU	8.32	8.11	7.83	7.83	7.38	7.69	6.87	7.82	14.52	7.73	8.16	7.73	85.48
VIX	7.88	7.72	7.77	7.53	7.36	7.5	6.73	7.8	7.94	13.4	9.47	8.91	86.6
GVZ	8.23	8.1	8.03	7.71	7.63	7.92	6.63	7.59	7.68	8.9	12.98	8.6	87.02
OVX	8.2	8.18	7.94	7.86	7.5	7.84	6.85	7.79	7.61	8.38	8.62	13.23	86.77
TO others	97.41	95.66	88.67	89.93	87.12	89.94	73.63	81.17	80.75	78.6	86.74	82.16	1031.78
Inc. own	109.98	108.44	100.97	101.99	99.51	102.41	99	95.31	95.26	92	99.72	95.39	TCI = 85.98%
NET	9.98	8.44	0.97	1.99	−0.49	2.41	−1	−4.69	−4.74	−8	−0.28	−4.61	

Notes. See notes in Table 3.

Table 16
Spillover connectedness in the quantile VAR (at the 50th quantile) for the case of South Africa.

	JALSH	MXSA	MXSAI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
JALSH	38.98	36.07	10.88	0.58	0.61	0.78	1.23	0.2	0.41	6.65	1.87	1.73	61.02
MXSA	36.81	39.84	10.78	0.5	0.53	0.62	1.07	0.28	0.46	5.77	1.95	1.37	60.16
MXSAI	16.28	15.72	58.29	0.43	0.51	0.8	1.21	0.6	0.62	2.74	1.54	1.27	41.71
ETH	0.6	0.47	0.32	49.08	24.73	22.47	0.29	0.28	0.27	0.97	0.25	0.28	50.92
LTC	0.66	0.55	0.31	24.89	48.84	22.46	0.34	0.3	0.27	0.71	0.32	0.33	51.16
BTC	0.81	0.65	0.74	22.96	22.8	49	0.58	0.34	0.3	0.9	0.59	0.32	51
TB1YR	1.74	1.61	1.23	0.42	0.7	0.88	82.4	0.34	0.82	3.07	5.03	1.76	17.6
FDEMV	0.64	0.67	0.88	0.6	0.67	0.59	0.76	92.22	0.99	0.88	0.79	0.3	7.78
TEU	1.07	1.13	1.01	0.83	1.14	0.68	1.29	1.54	88.6	0.96	1.01	0.75	11.4
VIX	8.66	6.94	2.38	1.33	1.01	1.24	2.35	0.27	0.56	60.12	9.35	5.78	39.88
GVZ	2.78	2.7	1.78	0.39	0.63	0.87	5.42	0.62	0.53	10.75	68.07	5.47	31.93
OVX	2.86	2.2	1.62	0.54	0.48	0.66	2.19	0.49	0.61	7.19	6.18	74.99	25.01
TO others	72.91	68.71	31.92	53.47	53.8	52.05	16.74	5.26	5.84	40.59	28.89	19.36	449.56
Inc. own	111.89	108.56	90.21	102.55	102.64	101.05	99.14	97.49	94.44	100.71	96.96	94.36	TCI = 37.46%
NET	11.89	8.56	−9.79	2.55	2.64	1.05	−0.86	−2.51	−5.56	0.71	−3.04	−5.64	

Notes. See notes in Table 3.

Table 17
Spillover connectedness in the quantile VAR (at the 95th quantile) for the case of South Africa.

	JALSH	MXSA	MXSAI	ETH	LTC	BTC	TB1YR	FDEMV	TEU	VIX	GVZ	OVX	FROM others
JALSH	11.72	11.56	9.57	8.05	7.88	7.9	6.39	7.82	7.55	6.78	7.63	7.15	88.28
MXSA	11.24	11.91	9.51	8.13	7.95	7.89	6.57	7.71	7.7	6.87	7.52	6.99	88.09
MXSAI	9.5	9.73	11.91	7.9	8.04	8	6.49	8.06	7.59	7.37	7.9	7.51	88.09
ETH	7.93	8.21	8.04	11.66	10.2	9.95	6.26	7.93	7.71	7.29	7.74	7.06	88.34
LTC	8.07	8.23	8	10.06	11.49	10.03	6.46	7.9	7.5	7.23	7.85	7.18	88.51
BTC	7.97	8.36	8.1	9.71	9.75	11.68	6.32	7.91	7.63	7.33	8.05	7.18	88.32
TB1YR	7.29	7.54	7.33	7.11	7.06	7.08	23.78	6.74	6.72	6.43	6.65	6.25	76.22
FDEMV	7.99	8.26	8.13	8.4	8.16	8.18	6.5	12.45	8.03	7.89	8.26	7.75	87.55
TEU	8.13	8.38	8.1	8.22	8.11	8.05	6.28	8.07	12.52	7.98	8.3	7.87	87.48
VIX	7.51	7.86	8.11	7.95	7.8	7.99	6.47	8.14	8.26	11.89	9.45	8.58	88.11
GVZ	7.81	8.15	8.01	8	8.1	8.06	6.36	7.95	7.99	9.15	12.24	8.16	87.76
OVX	7.57	7.93	7.85	7.84	7.98	8.09	6.37	8.41	8.26	8.67	8.91	12.13	87.87
TO others	91.03	94.21	90.75	91.36	91.04	91.22	70.47	86.65	84.95	83	88.28	81.67	1044.61
Inc. own	102.75	106.12	102.66	103.02	102.53	102.9	94.25	99.1	97.47	94.88	100.52	93.81	TCI = 87.05%
NET	2.75	6.12	2.66	3.02	2.53	2.9	−5.75	−0.9	−2.53	−5.12	0.52	−6.19	

connectedness range from 25.03% (*TB1YR*) in the bearish markets to 23.75% (*TB1YR*) in the bullish market. The above-mentioned tables also reveal, (at the 5th quantile), the largest transmitters and receivers of the spillovers are *MXIN* (95.84%) and *ETH* (87.21%). *TBIYR* is both the smallest transmitter and the recipient of the spillover connectedness (71.29%,74.97%). However, at the 95th quantile, the largest transmitters and receivers of the spillovers are *MXIN* (92.73%) and *LTC* (88.68%). *TBIYR* is both the smallest transmitter and the recipient of the spillover connectedness (71.22%, 76.25%).

Tables 12, 13, and 14 display the results of the risk spillover connectedness in the quantile VAR at the 5th, 50th, and 95th quantiles for the case of China. The total connectedness index (*TCI*) ranges from 83.01% (5th quantile) to 84.62% (95th quantile) and 30.85% (50th quantile). In the bearish market (5th quantile), the contributions from (to) others fluctuate between 71.39% (71.29%) and 85.17% (89.91%), while in normal markets (50th quantile), the contributions from (to) range from 6.24% (4.87%) to 50.84% (55.13%). In boom markets (95th quantile), the contributions from (to) others lie between 73.23% (67.71%) and 86.39% (91.49%). The diagonal elements which exhibit own connectedness range from 28.61% (*TB1YR*) in the bearish markets to 26.77% (*TB1YR*) in the bullish market. Further the above-mentioned tables, manifest that (at the 5th quantile) he largest transmitters and receivers of the spillovers are *ETH* (89.91%) and *LTC* (85.17%). *TBIYR* is both the smallest transmitter and recipient of the spillover connectedness (71.29%, 71.39%). Whereas at the 95th quantile, the largest transmitters and receivers of the spillovers are *LTC* (91.49%) and *ETH* (86.36%).

The findings of the risk spillover connectedness in the quantile VAR at the 5th, 50th, and 95th quantiles for the case of South Africa are shown in Tables 15, 16, and 17. The total connectedness index (*TCI*) lies from 85.98% (the 5th quantile) to 87.05% (the 95th quantile) and 37.46% (the 50th quantile). In declining market (the 5th quantile), the contributions from (to) others fluctuate between 74.63% (73.63%) and 87.94% (97.41%), while in the normal markets (the 50th quantile), the contributions from (to) span from 7.78% (5.26%) to 61.02% (72.91%). In rising markets (the 95th quantile), the contributions from (to) others spell between 76.22% (70.47%) and 88.51% (94.21%).

The diagonal elements, which show own connectedness, range from 25. 37% (*TB1YR*) in the bearish markets to 23.78% (*TB1YR*) in the bullish market. In addition, the above-mentioned tables disclose that the largest transmitters and receivers of the spillovers are *JALSH* (97.41%) and *ETH* (87.94%). *TBIYR* is both the smallest transmitter and recipient of the spillover connectedness (73.63%, 74.63%).

In sum, our results reveal evidence of asymmetric risk spillover connectedness among BRICS markets at the extreme lower and extreme upper quantiles than during times of calm. Furthermore, there is changing spillover patterns for the selected markets under the three market conditions. In all the three market conditions, the results reveal that the conventional stock markets, MSCI stock indexes and MSCI Islamic indexes, are the dominant transmitters in the case of Brazil, Russia, India and South Africa, except China. Conventional stock markets are the leading transmitter of spillovers under the bust markets (the 5th quantile). Whereas MSCI stock indexes are the dominant transmitters (recipients) of spillovers under the normal (the 50th quantile) and the bullish markets (95th quantile).

Table 18 covers the Total connectedness index (*TCI*) of the BRICS markets in the three market conditions. It is found that the Total Connectedness Index (*TCI*) ranges from 83.01% (China) to 86.06% (Russia) in the bust markets (the 5th quantile), and spans from 84.62%(China) to 87.14%(Brazil) in the boom markets (the 95th quantile), whereas the TCI stretch from 30.85% (China) to 40.32% (Russia) in the normal markets (the 50th quantile). Covering all the five markets, we found that the largest own connectedness in bearish market is *TBIYR* (28.61%) and in bullish market is *TB1YR* (26.77%) in China.

Table 19 encapsulates the following information, namely, most contributor FROM others (least contributor FROM others) and most contributor TO others (the least contributor TO others). Taking into consideration all the five markets, in declining markets, the largest transmitter of spillovers is *MOEX* (MOEX Russia Index) (97.71%) and largest receivers of spillovers are *MXRU* (MSCI Russia index) (87.98%) and *MXBR* (MSCI Brazil index) (87.98%). In rising markets, the largest transmitter of spillovers is *MXSA* (MSCI South Africa index) (94.21%) and the largest receiver of spillover is *LTC* in *S*outh Africa (88.51%). In declining markets, smallest transmitter and recipient of the spillovers, is *VIX* (75.95%) in Russia, and *TB1YR* (75%) in Brazil. Whereas in the bullish markets, the smallest transmitter is *TB1YR* (72.17%) in Russia and *the* smallest receiver is *TB1YR* (78.46%) in Brazil. Moreover, *TB1YR* is the least transmitter and recipient, under declining and rising market conditions. Further, infectious disease equity market volatility is revealed as least transmitter and recipient under normal conditions in all BRICS markets. Further, the selected cryptocurrencies are the leading recipients in bust markets (5th quantile) and bullish markets (95th quantile).

Thus, investors and portfolio managers must assess their risks in the extreme upper and lower ranges because this information can help them optimize their asset allocation and risk mitigation strategies. In line, studies reveal that market spillovers are greater during bearish and bullish than during times of calm. As a result, the conditional mean system of connection cannot reflect the degree of spillovers during extreme negative and severe upward market conditions (Ang and Bekaert, 2002; Betz et al., 2016). Our study corroborates that spillovers are more intense during times of distress is a great addition to earlier research (Ahmad, 2017).

Table 18
Total connectedness index (TCI).

	5th quantile	50th quantile	95th quantile
Brazil	86%	39.94%	87.14%
Russia	86.06%	40.32%	87.08%
India	85.66%	38.06%	86.92%
China	83.01%	30.85%	84.62%
South Africa	85.98%	37.46%	87.05%

Table 19
Summary findings displayed in Tables 3-17.

Country	Brazil	Russia	India	China	South Africa
Bearish market (5th quantile)					
Most contributor FROM others	MXBR	MXRU	ETH	LTC	ETH
Least contributor FROM others	TB1YR	TB1YR	TB1YR	TB1YR	TB1YR
Most contributor TO others	IBOV	MOEX	MXIN	ETH	JALSH
Least contributor TO others	TB1YR	VIX	TB1YR	TB1YR	TB1YR
Normal market (50th quantile)					
Most contributor FROM others	MXBR	MXRU	MXIN	LTC	JALSH
Least contributor FROM others	FDEMV	FDEMV	FDEMV	FDEMV	FDEMV
Most contributor TO others	MXBR	MXRU	MXIN	LTC	JALSH
Least contributor TO others	FDEMV	FDEMV	FDEMV	FDEMV	FDEMV
Bullish market (95th quantile)					
Most contributor FROM others	BTC	ETH	LTC	ETH	LTC
Least contributor FROM others	TB1YR	TB1YR	TB1YR	TB1YR	TB1YR
Most contributor TO others	MXBR	MXRUI	MXIN	LTC	MXSA
Least contributor TO others	TB1YR	TB1YR	TB1YR	TB1YR	TB1YR

4.2. Network connectedness analysis

The network connectedness between different market indexes in the system is presented in network diagrams. However, each diagram reports the net spillover transfer structure among these markets. We visualize in the networks the net pairwise directional connectedness of risk spillovers over time and at several market conditions: bearish, normal, and bullish market states. The direction of the net spillovers from market *i* to market *j* is indicated by the direction of the arrow between two nodes, while the intensity of the magnitude of spillovers is given by the size of the arrow, where thick arrows show a strong net spillover effect, and vice versa.

The findings are displayed in Figs. 3-7. Each figure contains three network diagrams for the bearish (the 5th quantile), normal (the 50th quantile), and bullish (the 95th quantile) markets, respectively. These findings emphasize the following major ways: according to the network diagrams, the net spillover transmission mechanism in the BRICS follows a similar pattern in terms of the strength of the net spillover effects, having a high-risk spillover transfer for both the bearish and bullish market states, and a weak risk spillover transmission at the normal market state.

(i) Brazil

As for the Brazilian case, we can see in Fig. 3 at bearish market *LTC* (Litecoin), *BTC* (Bitcoin), *TB1YR* (Treasury bill rate), and *MXBRI* (MSCI Brazil Islamic index) act as strong shock transmitters, while *OVX* (oil volatility) and *VIX* (equity volatility index) act as strong net receivers of shocks. Furthermore, under the normal market condition (50th quantile), *VIX* appears to be strong net receiver of shocks from *MXBRI* (MSCI Brazil Islamic index), *MXBR* (MSCI Brazil index), *IBOV* (Sao Paulo Stock Exchange), and *GVZ* (gold volatility). The majority of other market indexes act as weak net transmitters/receivers of shocks. Accordingly, the net spillover connectedness is weaker during the periods of normal market conditions.

Likewise, contrary to the net spillover connectedness at the middle quantile (the 50th quantile), the net spillover connectedness at the extreme upper quantile (95th quantile) is stronger. At bullish market, the intensity of net shock transfer between the markets is more pronounced as given by the thicker arrows. Furthermore, we show that *OVX* (oil volatility) is the highest net shock receiver from all other markets. Interestingly, *FDEMV* (infectious disease volatility) and *TB1YR* (Treasury bill rate) are greater net shock transmitters to *OVX* (oil volatility), which indicates that infectious disease equity market volatility and the Treasury bill rate remain a key origin of shocks for oil volatility. As compared to both bearish and normal market states, the net spillover connectedness under the bullish market state in Brazil is found to be important and more markets became strong net shock transmitters/receivers.

A plausible explanation of the strong and weak net spillover connectedness among the market indexes at various market scenarios is that investors carry out a “risk-on risk-off” strategies (Maitra et al., 2021).

(ii) Russia

As for the Russian case, the network diagrams charted in Fig. 4 exhibit weak system-wide net connectedness between variables as shown by the thin arrows for all quantiles of the joint distribution. The exception was registered at the upper quantile (95th quantile) for the variables *BTC* (Bitcoin), *TB1YR* (Treasury bill rate), *TEU* (Twitter uncertainty), and *GVZ* (gold volatility). It is clear from the network diagram related to the 95th quantile that Bitcoin (*BTC*) acts as net shock transmitter to both Twitter usage and gold volatility, while *TB1YR* (Treasury bill rate) appears as net shock receiver from *GVZ* (gold volatility). We further found that under bearish and bullish market scenarios, the pattern of the network connectedness was more complex than under normal market state. These findings are consistent with Bouri et al. (2020).

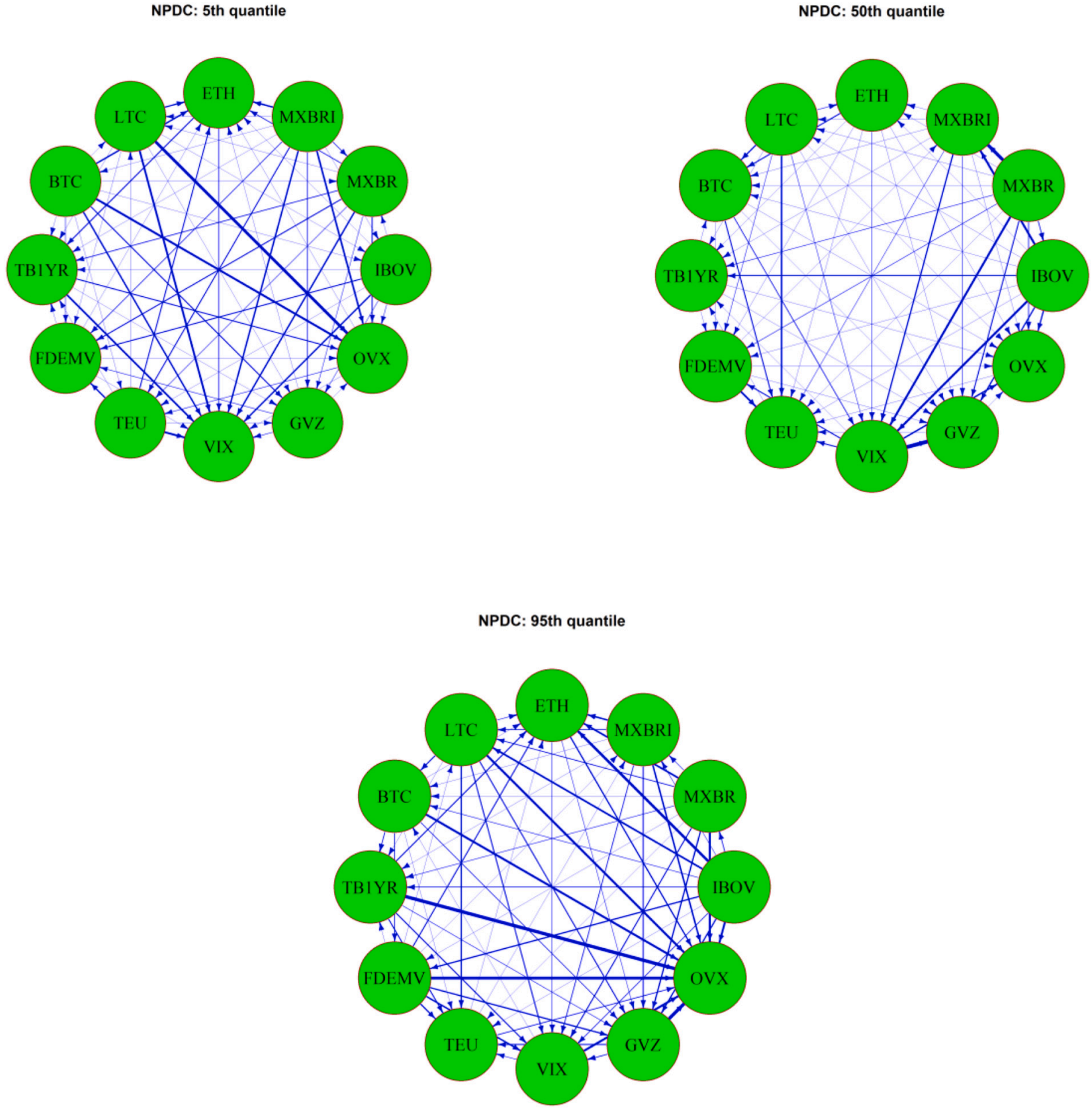

Fig. 3. Net pairwise directional connectedness (the Brazil case). Notes. The figure portrays the network diagram of the net pairwise directional spillovers among all possible couples. The findings are based on three quantiles of the joint distribution: the 5th (extreme negative co-movement), the 50th (stable co-movement), and the 95th (extreme positive co-movement). The strength of the connectedness between the markets is given with the edge thickness. The thicker the edge is, the stronger the connectedness network is.

(iii) *India*

Fig. 5 visualizes the network diagrams for the net spillover connectedness based on the *Indian* case. As can be seen in Fig. 5, the extreme lower and extreme upper quantiles demonstrate a close similar behavior of the net spillover connectedness in terms of directions and intensities of shocks. Obviously, *BTC* (Bitcoin) is the largest net transmitter of shocks to the *VIX* (volatility index), *FDEMV* (infectious disease volatility), and *GVZ* (gold volatility) markets. Therefore, *BTC* (Bitcoin) provides strong risk spillover on the gold volatility, infectious disease volatility, and volatility index under positive and negative market events. On the other hand, under normal market circumstances, the markets *MXIN* (MSCI India), *MXINI* (MSCI Islamic India), *SENSEX* (Indian stock index), and *TEU* are the major net transmitters/receivers of shock spillovers.

Overall, a closer look at the network diagrams for the Indian case pointed a strong and complex net transfer mechanism among

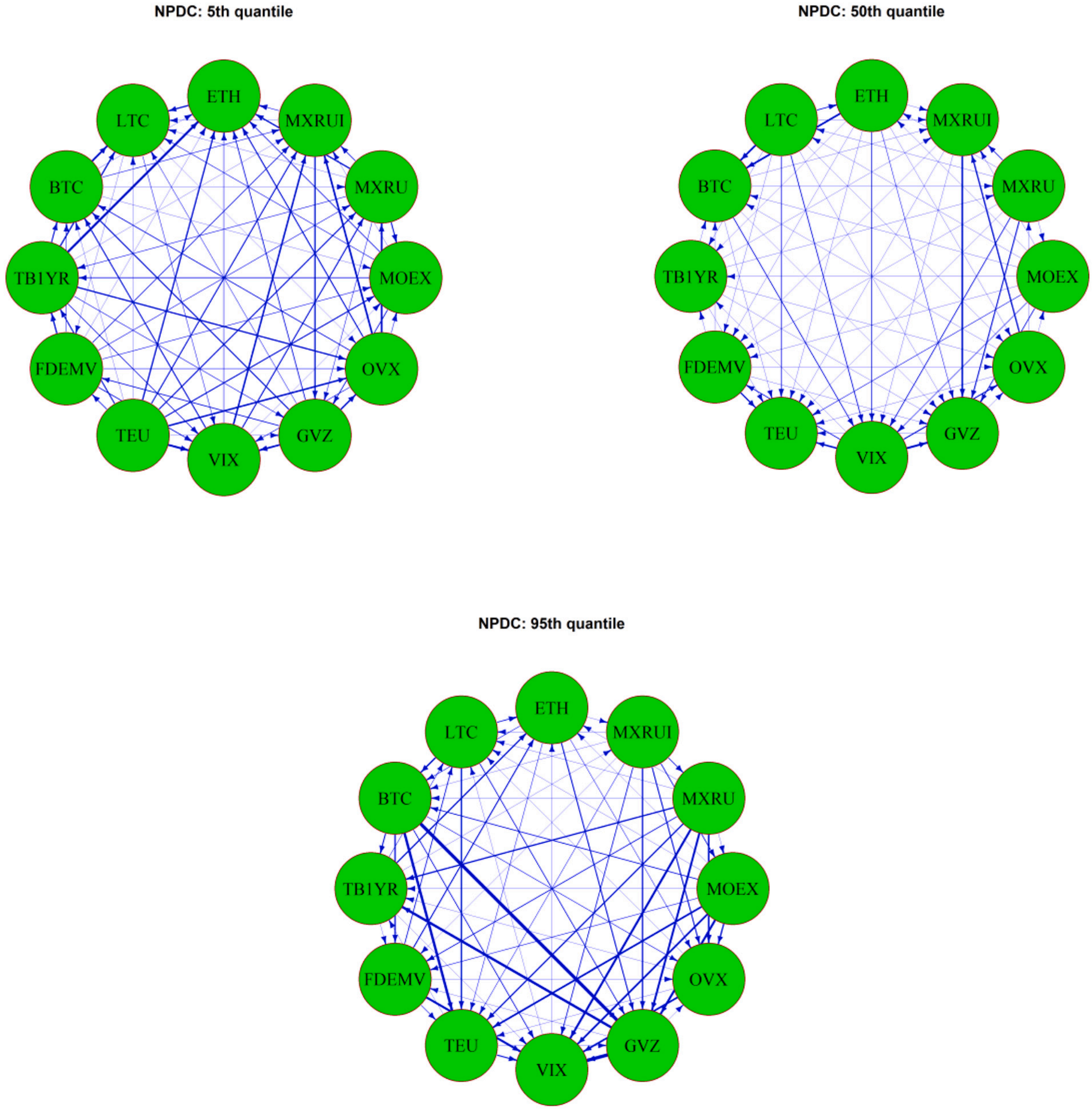

Fig. 4. Net pairwise directional connectedness (the Russia case). Notes. See notes under Fig. 3.

variables at bearish and bullish market states, and weak net spillover connectedness pattern at normal market condition.

(iv) *China*

Fig. 6 reports the findings of normal, bearish, and bullish market scenarios based on China case. Notably, it can be seen that the net spillover connectedness was more pronounced under bearish and bullish market states. At the bearish market state, we can observe an active role provided by *LTC* (Litecoin) as per net shock transmission to *VIX* and *FDEMV* (infectious disease volatility). This transfer role of shocks became inactive at bullish market state. Furthermore, *BTC* (Bitcoin) strongly receives shocks from *GVZ* (gold volatility) under bearish market state, while it greatly transmits shocks to *GVZ* under bullish market state. It is also worth pointing with regard to network diagram at the 50th quantile, that *MXCN* (MSCI China market index) and *GVZ* (gold volatility) are the largest net receivers of shocks from *VIX*.

In general, one can say that the role played by a market index is switching according to the market conditions. Sometimes one market plays an active role under given market event, while under other time periods it plays an inactive role under another market

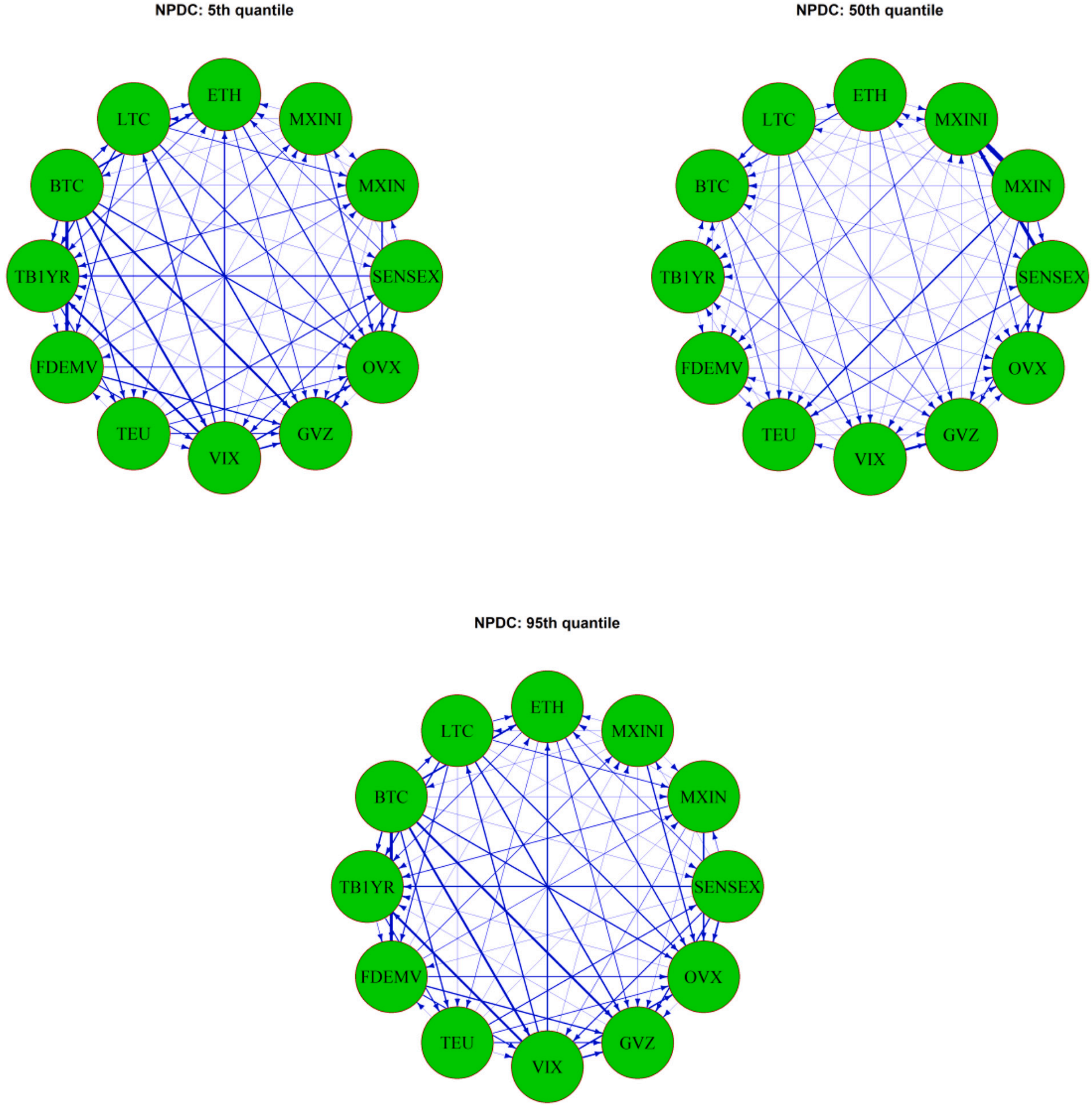

Fig. 5. Net pairwise directional connectedness (the India case). Notes. See notes in Fig. 3.

circumstance.

(v) *South Africa*

The findings of net spillover connectedness related to the South African case are visualized in the network diagram displayed in Fig. 7. We notice that *MXSAI* (MSCI Islamic South Africa), *MXSA* (MSCI South Africa), and *TEU* remain the largest net transmitters of shocks to *VIX* under bearish market scenarios. This significant role disappeared at normal market state. Furthermore, except *MXSAI-JALSH*, *MXSAI-MXSA*, and *VIX-GVZ* market pairs, the other market indexes under concern are weakly net connected at middle quantile, suggesting weak net shock transfer structure among the majority of markets under normal market states. On the other hand, the net spillover connectedness between markets is more active at the bullish market condition, in comparison to bearish and normal scenarios.

To summarize the net spillover connectedness over BRICS markets, it is important to point out that *VIX* (global volatility index), *OVX* (oil volatility), *GVZ* (gold volatility), cryptos (*BTC*, *ETH*, *LTC*), as well as conventional and Islamic indexes are the most active net

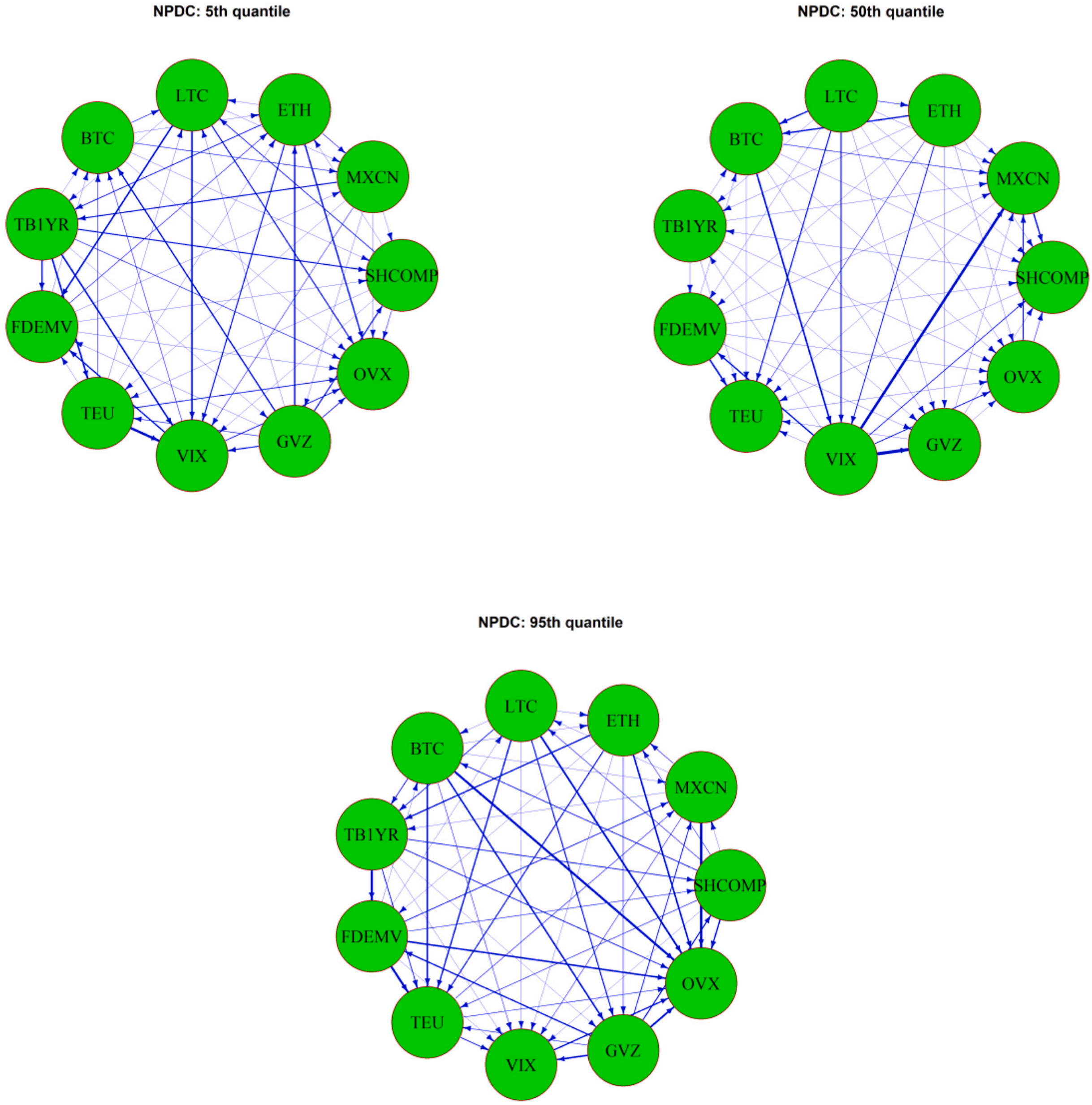

Fig. 6. Net pairwise directional connectedness (the China case). Notes. See notes in Fig. 3.

shock transmitters/receivers throughout market states. Additionally, bearish and bullish market scenarios demonstrate more a denser net shock transfer structure over time for BRICS economies. Finally, as *VIX*, *OVX*, and *GVZ* reflect investor sentiments, an extreme event (positive or negative) in these indicators, such as an increase (decrease) in these volatility indexes signifies that investors have raised fear of the conventional and Islamic BRICS stock markets, and this fear leads to increase volatility shocks (Su, 2020).

4.3. Sensitivity analysis

In this subsection, we examine an overall picture of the total dynamic connectedness among BRICS economies. We investigate the sensitivity of the total dynamic connectedness to the quantiles of the joint distribution. The findings are mapped in heatmap graphs.

Regarding the heatmap, strong total dynamic connectedness among all market indexes is reflected by warmer shades, while colder shades reflect weak connectedness. Fig. 8 depicts the findings related to each BRICS countries. According to these findings, we highlight a very great total spillover connectedness at both the upper (above the 80th quantile) and lower (below the 20th quantile) quantiles for all BRICS systems, indicating a symmetric total spillover effect. For the interval 20th–80th quantiles, the total

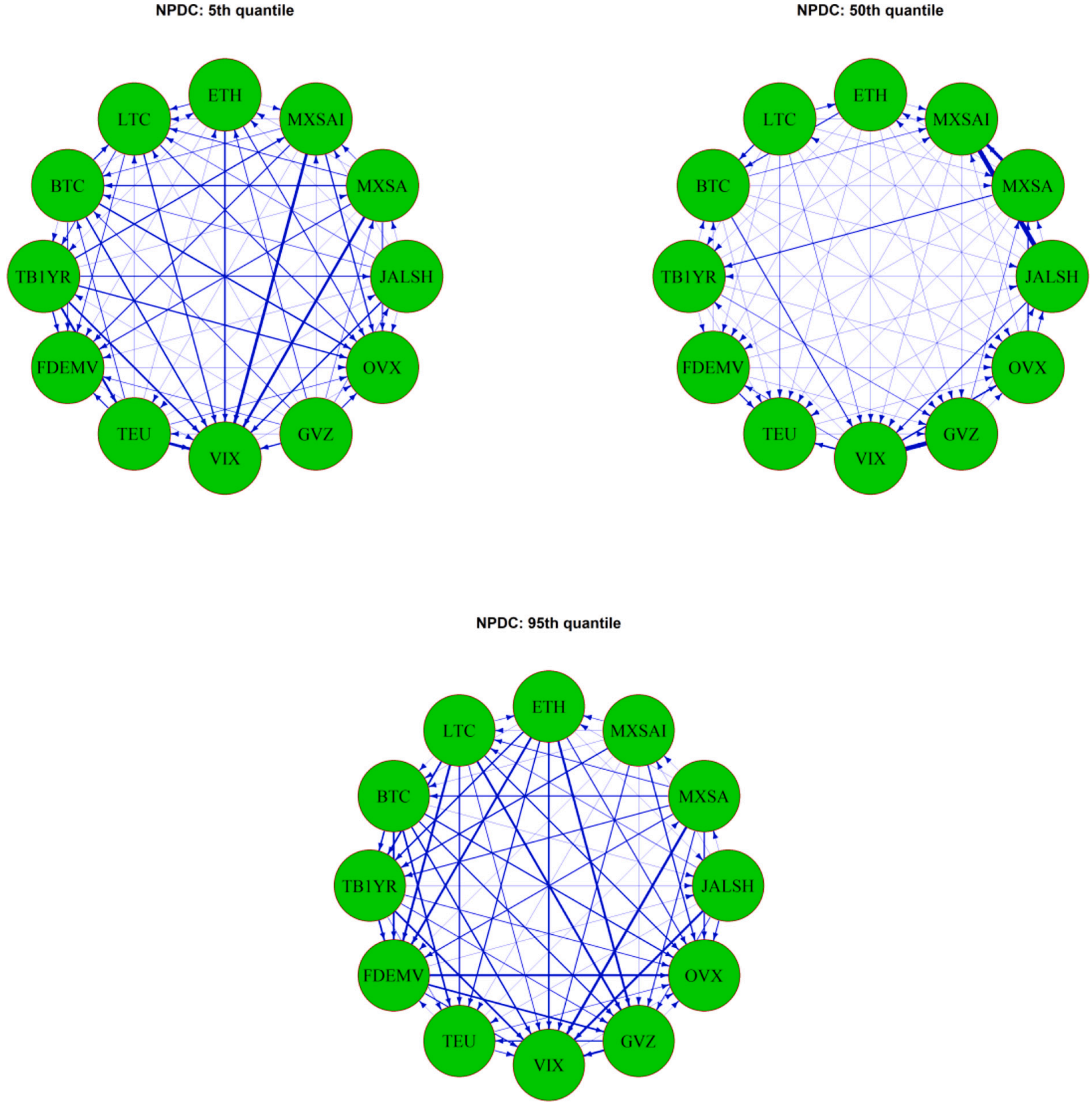

Fig. 7. Net pairwise directional connectedness (the South Africa case). Notes. See notes in Fig.3.

connectedness is very weak, which is shown by the colder shades in the middle of each heatmap.

To deeply explore the net directional spillover connectedness across a wide range of quantiles (sequence of quantiles is used with a 5% iteration as follows, $q = 0.05, 0.10, 0.15, \ldots, 0.90, 0.95$), and to show whether each market index is sensitive to quantiles, we present the sensitivity findings in heatmap forms. The findings are charted in Figs. 9-13. The net transmitter behavior of shocks is denoted by the warmer shades (red), while the net receiver pattern is distinguished by the colder shades (blue). We summarize our major findings as follows:

First, with reference to Brazil case, IBOV (Sao Paulo Stock Exchange Index), *MXBR* (MSCI Brazil index), *LTC*, *BTC*, and *ETH* cryptos are dominant net transmitters of shocks to all other markets, while *OVX* (oil volatility), *TEU* (Twitter uncertainty), *VIX* (equity volatility index), and *FDEMV* (infectious disease volatility) are net receivers of shocks from all other variables. Another interesting finding that can be revealed is that *MXBRI* (MSCI Brazilian Islamic index) is a net transmitter of shock information to all others during the entire period, except for the first half of 2019, when it acts mainly as net receiver from all other markets. For the GVZ (gold volatility), it appears as a net transmitter of shocks to all others in the beginning of the study period and switches to a net receiver from all others during the rest of the period. This changing pattern maybe due to the COVID-19 pandemic effect on gold volatility.

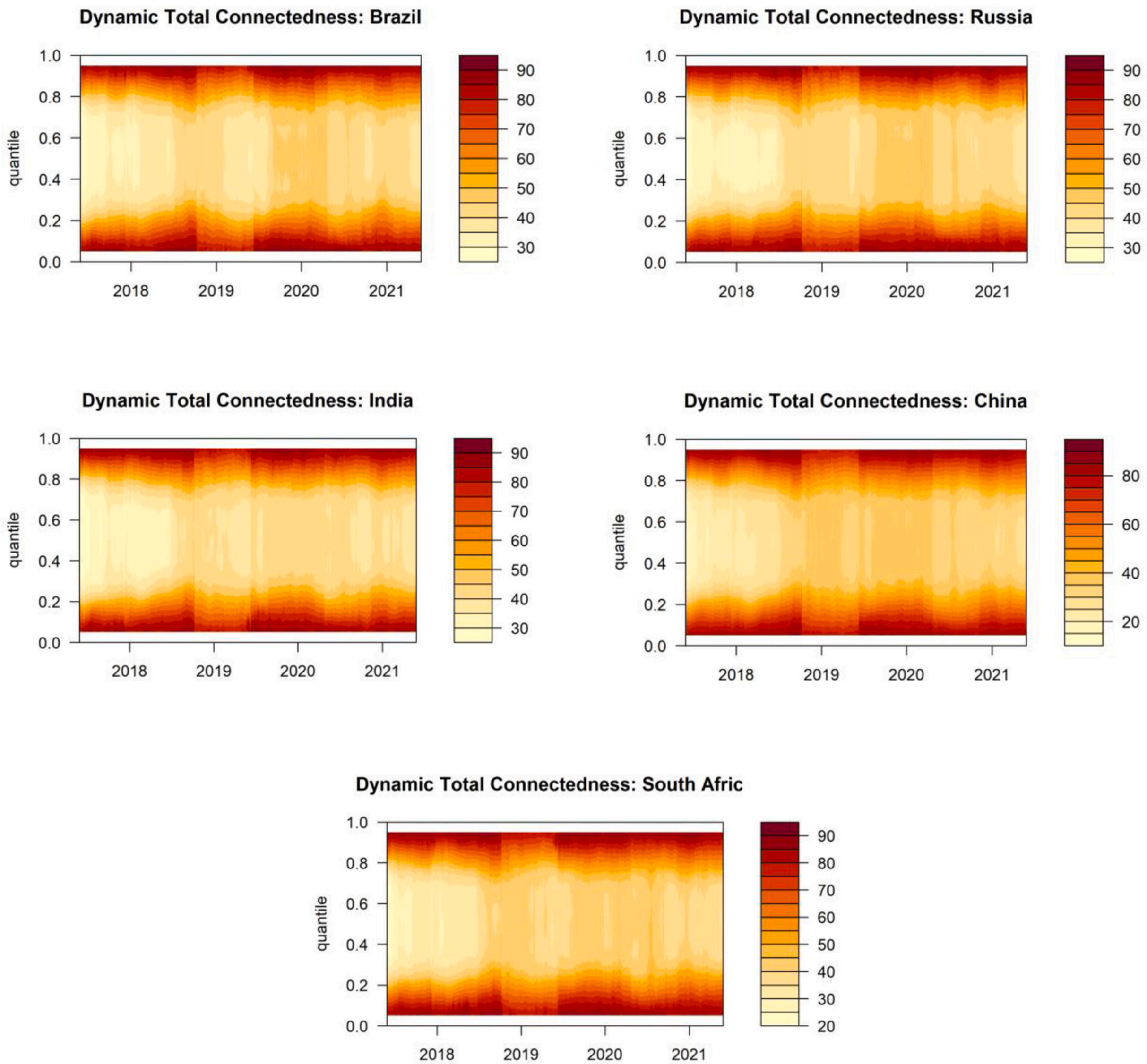

Fig. 8. The overall spillover connectedness. Notes. The findings are based on a quantile VAR model with a lag length of order 1 (SIC), a forecast horizon of 10 steps, and a 200-day rolling window. A sequence of quantiles is used with the 5% iteration as follows, $q = 0.05, 0.10, 0.15, \ldots, 0.90, 0.95$.

Second, with regard to Russia case (Fig.10), except *MXRU* (MSCI Russia index) and *MOEX* (Russia stock) market indexes, all other markets have played both roles (net transmitter/receiver of shocks to/from all others) over time. For instance, *MXRUI* (MSCI Islamic Russia index) acts as a net receiver of shocks from all others at the middle quantiles and for the period 2018–2019, while it appears as a net transmitter of shocks to all others at all market quantiles for the period 2020–2021. In addition, cryptos (BTC, LTC, ETH) assume to have a time-varying net connectedness pattern over quantiles.

Third, as for India (Fig.11), all market indexes except the *MXCN* (MSCI Chinese index) have played both roles of net spillovers. It is noteworthy that *SENSEX* (Indian stock) moved to a net transmitter to all others for the period 2018 to the end of sample period. Furthermore, with regard to TEU (Twitter uncertainty), the net receiver pattern is dominant for the entire period at the quantile interval below 90% and above 10%, while at very extreme upper and extreme lower quantiles, *TEU* (Twitter uncertainty) acts mainly as net shock transmitter to all others.

Fourth, as for China (Fig. 12), we observe an heterogenous net dynamic spillover mechanism for all variables, as indicated by the existence of both warmer and colder shades in each heatmap. It is noteworthy that market indexes are very sensitive to market events. Thus, market indexes switch from one net shock behavior to another in the Chinese market system according to market circumstances.

Fifth, as for South Africa (Fig.13), a similar pattern (in terms of the double net connectedness role) is found as that for China case, except *JALSH* (FTSE/JSE Africa All Share index) and *MXSA* (MSCI South Africa index) are net transmitters of shocks to all other

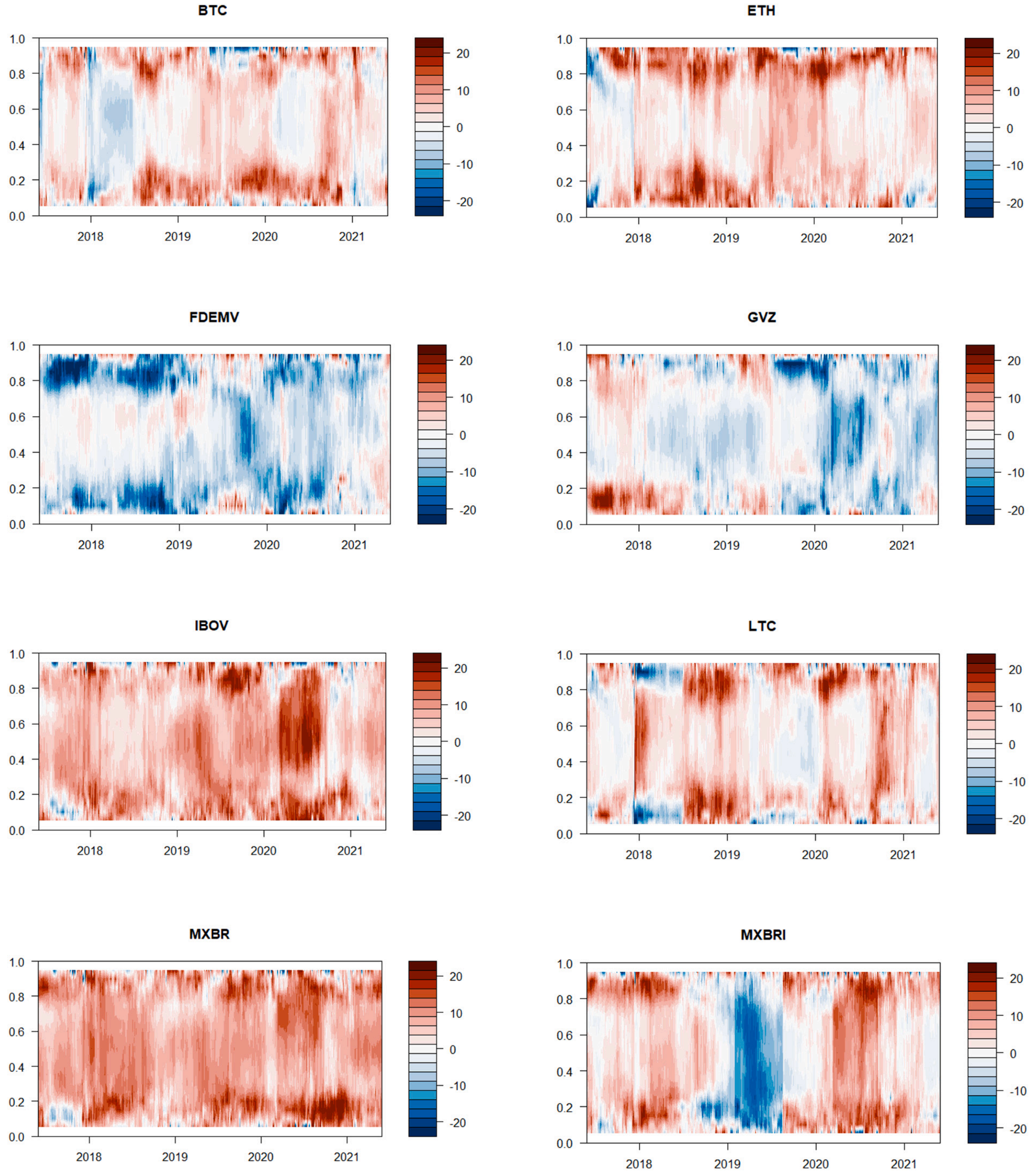

Fig. 9. Net spillovers connectedness of individual markets (the Brazil case). Notes. The heatmap shows the net transmitting/receiving pattern of each market. The colors span from deep blue (net receipt of risk) to deep red (net transmitter of risk). The vertical axis denotes the quantile levels (from the 5th to 95th quantiles). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

markets. Around 2019 and for below 20% quantiles, these two markets are net receivers of shocks from all other markets.

In sum, in the aftermath of several economic, financial, political, and health crises, our findings reveal an heterogenous behavior of the variables used in the study. However, all market indexes have played both roles (net receivers and net transmitters of spillovers) in the quantile VAR systems.

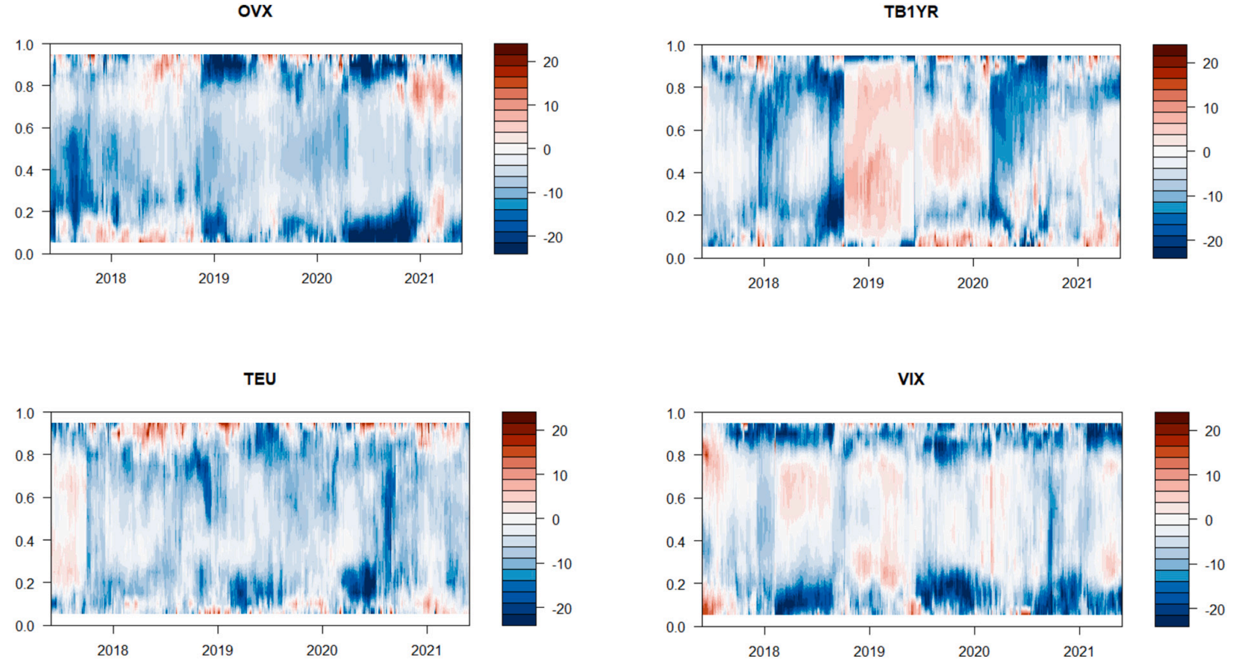

Fig. 9. (*continued*).

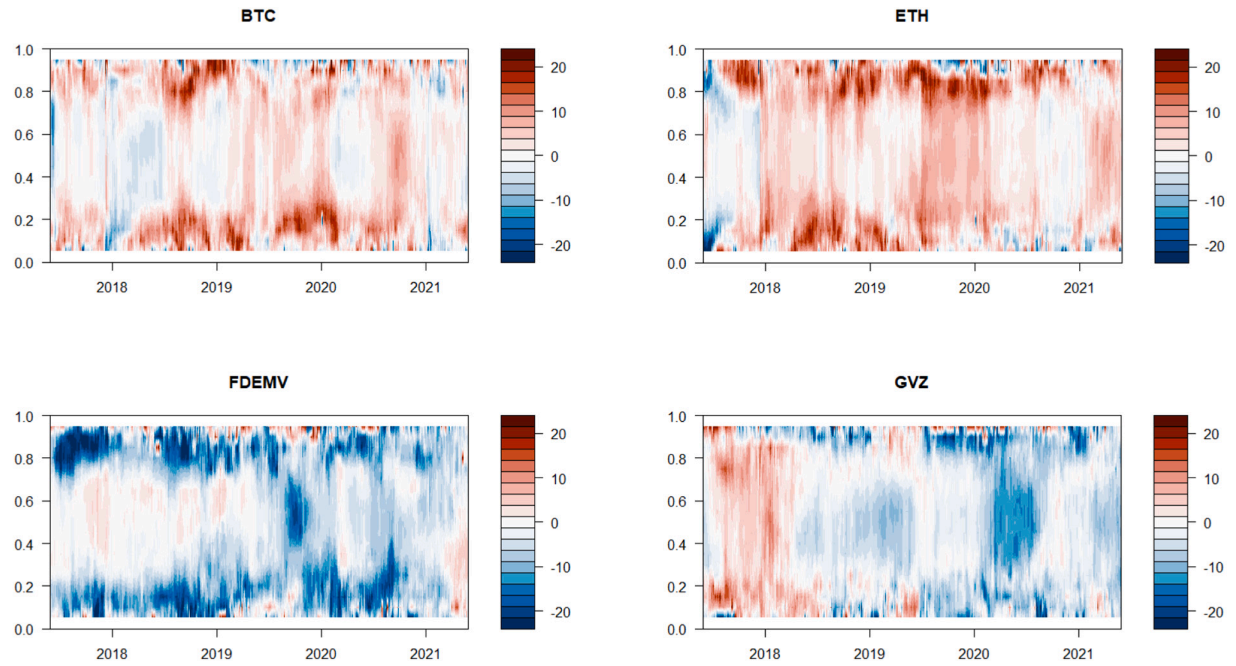

Fig. 10. Net spillovers connectedness of individual markets (the Russia case). Notes. See notes in Fig. 9.

4.4. Robustness checking

To further test the sensitivity of our findings to the choice of the lengths of the windows and the forecasting horizons, we have changed the rolling window period to various lengths, i.e., 150, 260, and 300 days, and the forecast horizon to 20 and 30 days in the re-estimation. The obtained findings are approximately similar to that found in the first analysis, which indicates that our findings are robust. Due to the voluminous size of the paper and many of the obtained findings, all results are available upon request from the

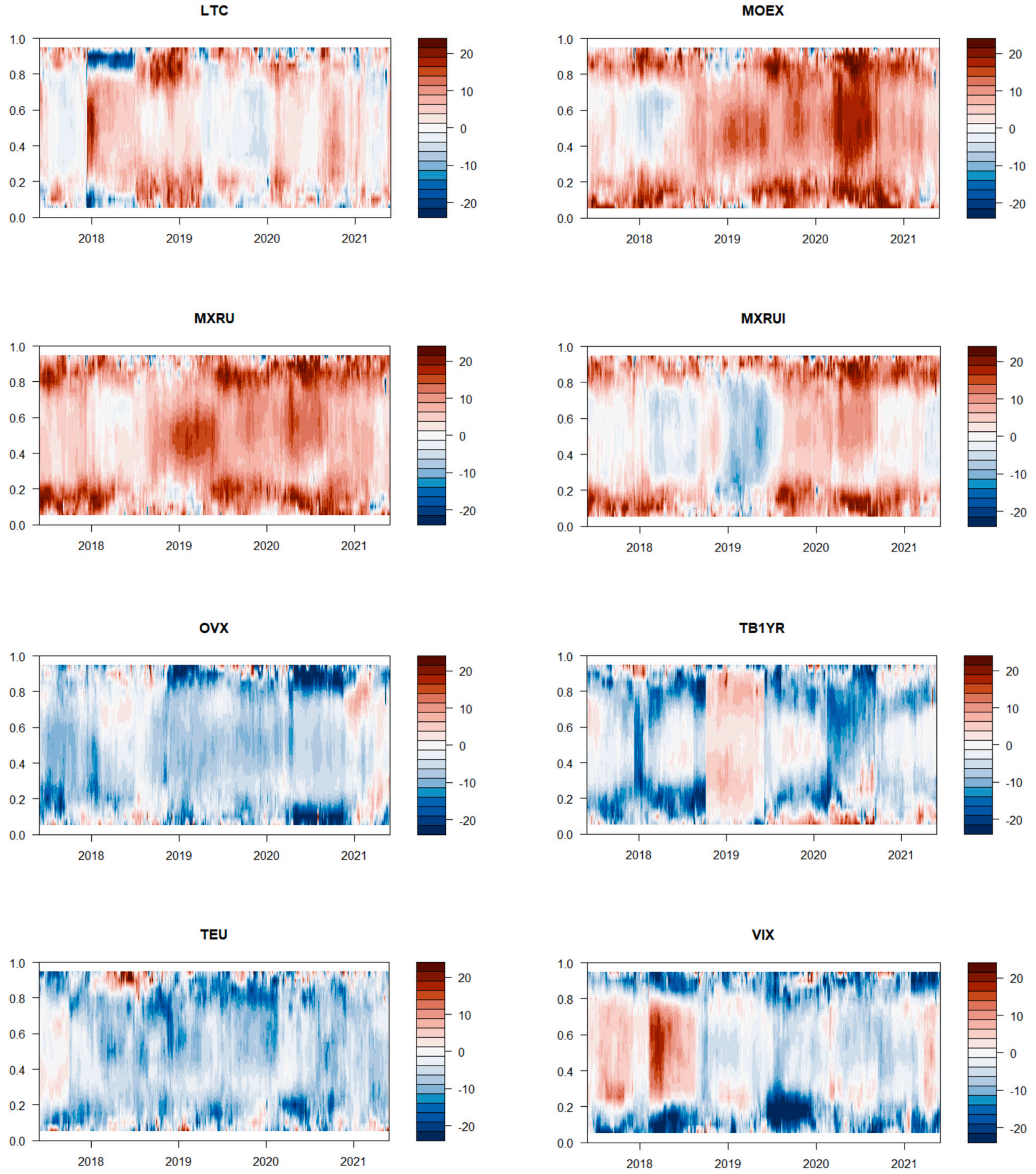

Fig. 10. (*continued*).

authors.

5. Conclusion and implications

5.1. Key findings

This empirical study attempts to explore the spillovers and connectedness among BRICS markets by combining the DY method (Diebold et al., 2012; Diebold and Yilmaz, 2012b) and the quantile VAR framework. We have used the conventional and Islamic BRICS

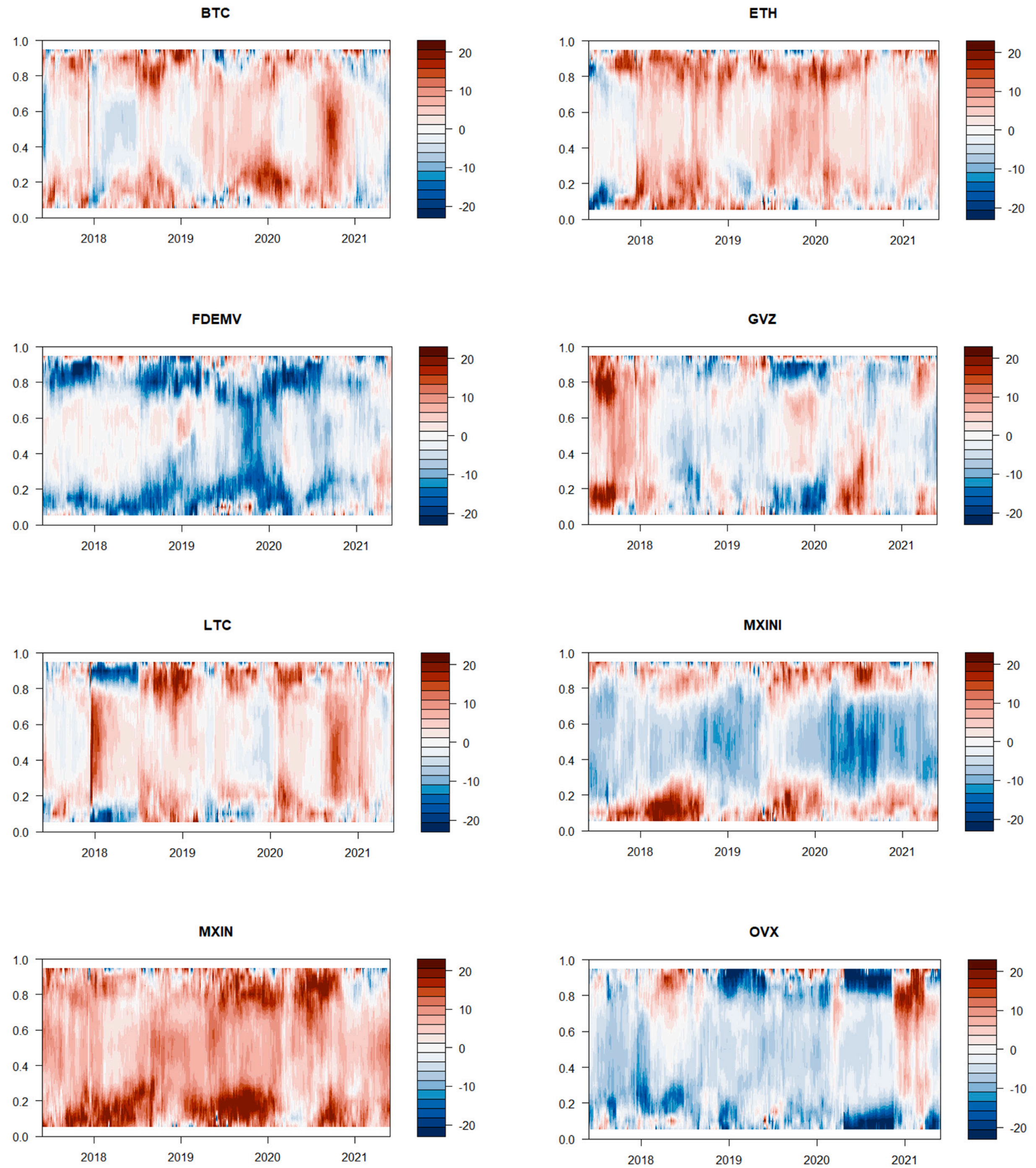

Fig. 11. Net spillovers connectedness of individual markets (the India case). Notes. See notes in Fig. 9.

stock markets, cryptos: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Treasury bill index, as well as different global uncertainties including the Twitter usage (TEU), global volatility index (VIX), oil ETF volatility (OVX), and gold ETF volatility (GVZ). Recently, and in particular during the last years (COVID-19 pandemic period), conventional and Islamic stock market volatilities and their spillovers impacts through various markets have played an important role for investors, market participants, and policymakers to better predict and control stock market risks. However, the use of the novel volatility spillover methods enables us to capture the potency and direction of shocks between conventional and Islamic stock markets, and uncertainty during several market scenarios. We also examined the time-varying features of shock transmission by employing a rolling-window technique. Furthermore, we presented a complex

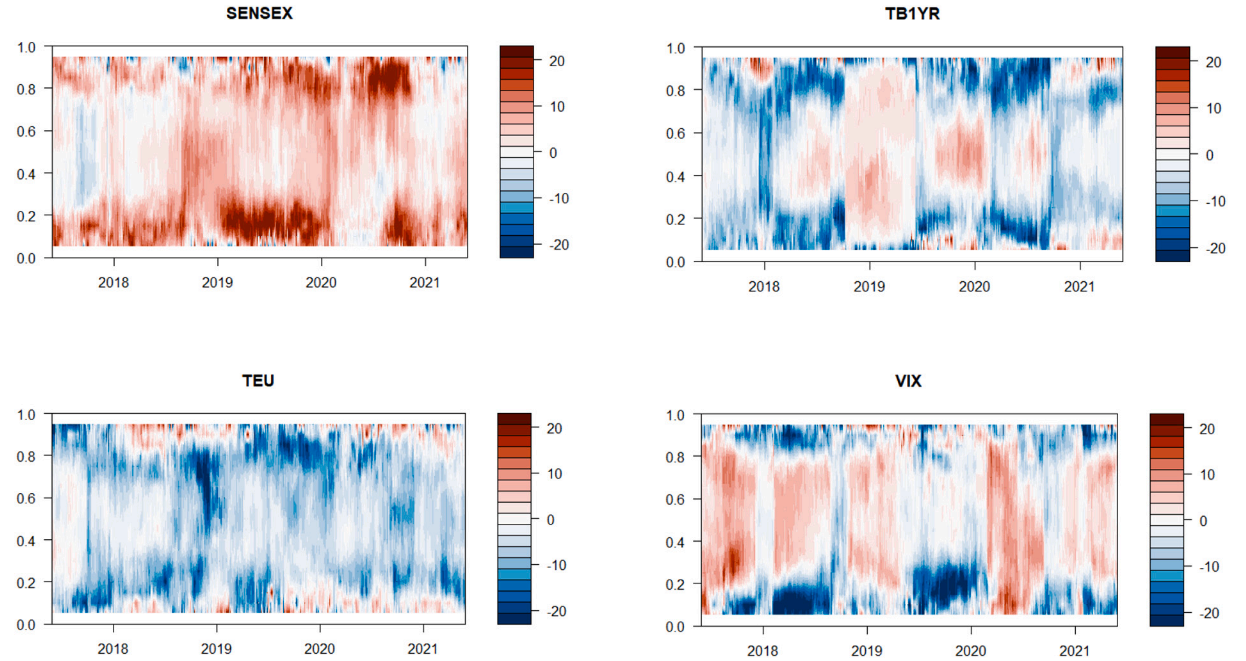

Fig. 11. (*continued*).

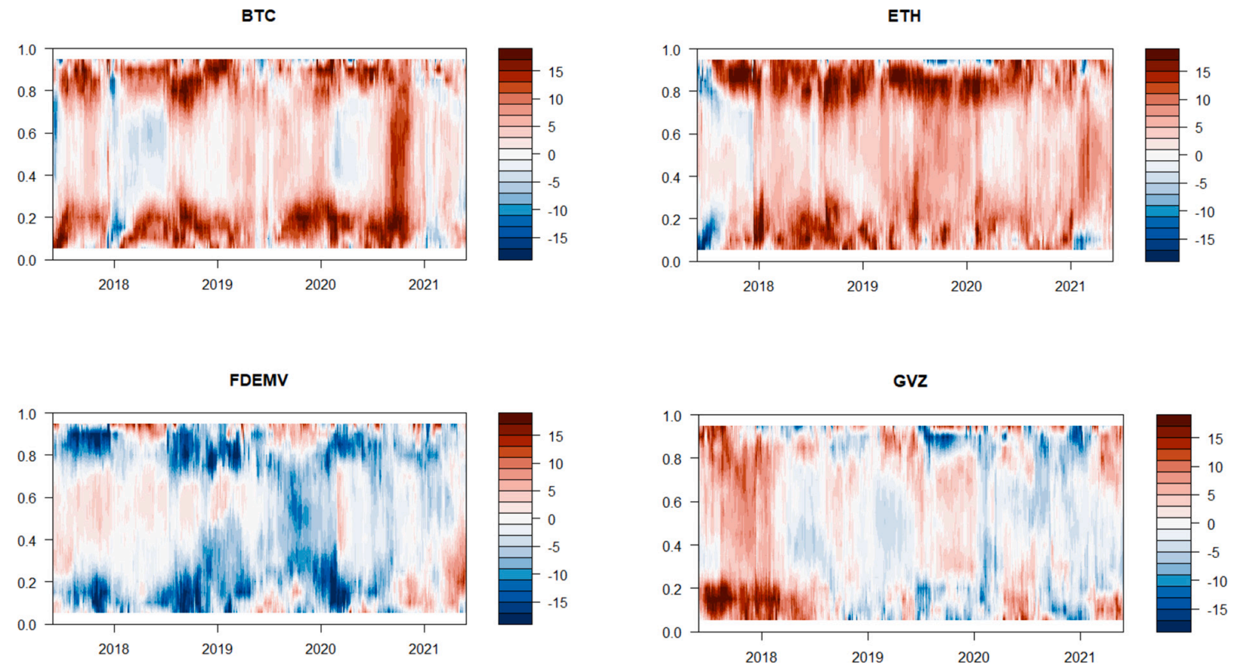

Fig. 12. Net spillovers connectedness of individual markets (the China case). Notes. See notes in Fig. 9.

network of net directional spillovers between markets. Finally, we provided novel insights about the sensitivity to a broad spectrum of quantiles for each market under concern.

The main findings of this work revealed the following interesting directions: first, regarding the static connectedness analysis, we found that volatility spillovers effects from and to others are significantly, greatly and more pronounced at extreme lower and extreme upper quantiles for all BRICS market systems, indicating that the transmission/receipt of shocks from (to) others were propagated more under the bearish and bullish market states. Therefore, this finding may suggest that extreme negative and extreme positive events

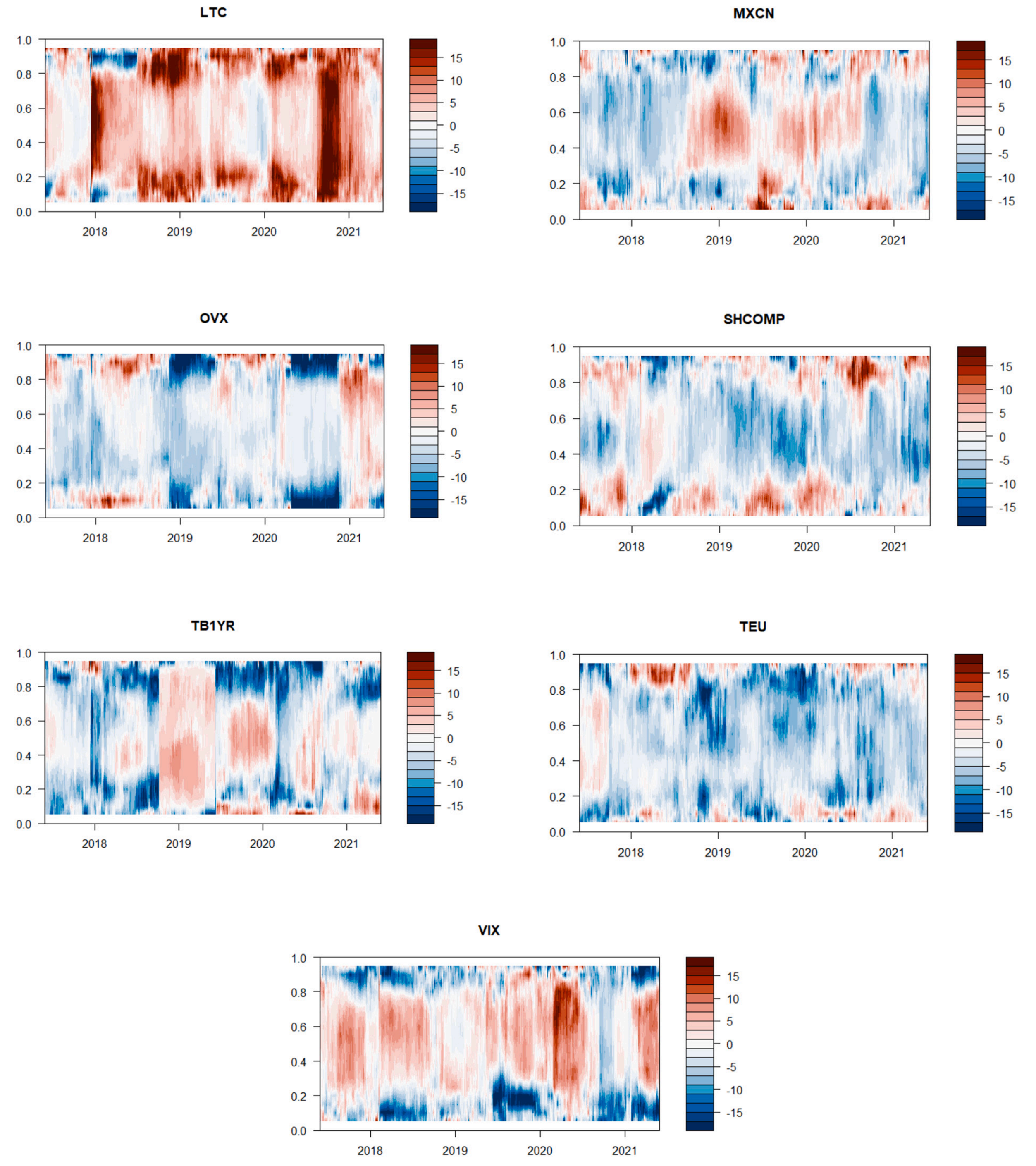

Fig. 12. (*continued*).

have led to strong shock transfer between markets, in particular at stress periods.

Second, regarding network connectedness framework, it is noteworthy that most of BRICS markets in the network connectedness system have played both roles: net transmitters and net receivers of information spillovers according to market conditions. Furthermore, the network connectedness analysis shows that the strength of net structure was very strong under bad (COVID-19 health crisis) and good (COVID-19 vaccine recovery) news. One may conclude that static and dynamic findings support the switching spillovers and connectedness pattern among BRICS stock market systems over both time and quantiles of the joint distributions. Additionally, the empirical evidence confirmed that network connectedness among markets is intensified under bearish and bullish market events compared to the stable market states. Recent evidence suggests that network connectedness and spillover transmission mechanism

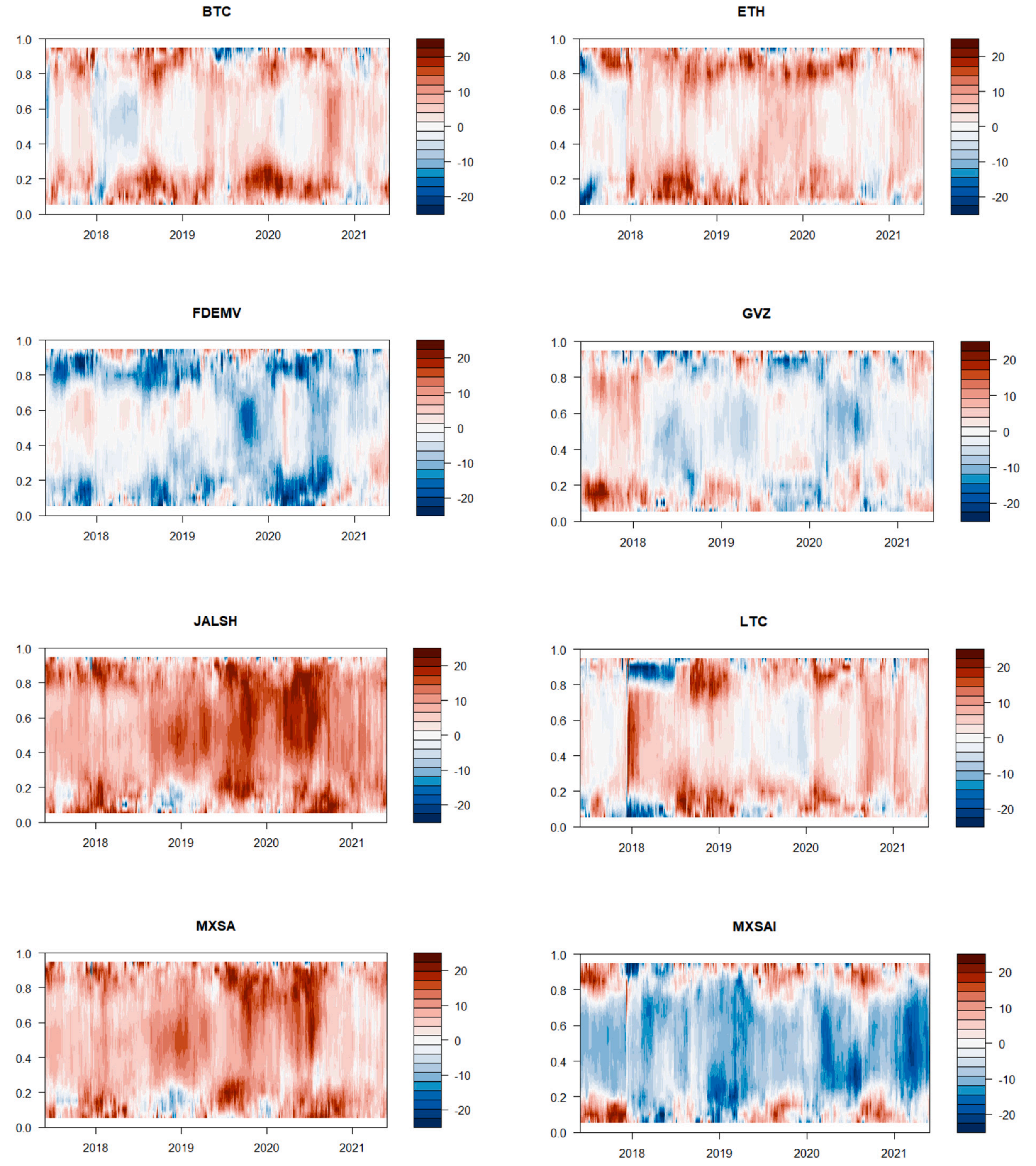

Fig. 13. Net spillovers connectedness of individual markets (the South Africa case). Notes. See notes in Fig. 9.

between markets highly connected at extreme market events (Bouri et al., 2021; Bouri et al., 2020; Mensi et al., 2021; Jiang and Chen, 2022; Umar et al., 2022).

Third, regarding sensitivity to quantile technique, overall, the evidence highlighted novel insights in stock market volatility and BRICS literature. Interestingly, at most network connectedness systems, conventional and Islamic BRICS stock markets, cryptos, and uncertainties have played time-varying role over quantiles, i.e., at a given time period and for a quantile range, one market has appeared as net transmitter of shocks to all others, while under another time period, it acted as net receiver of shocks from all other

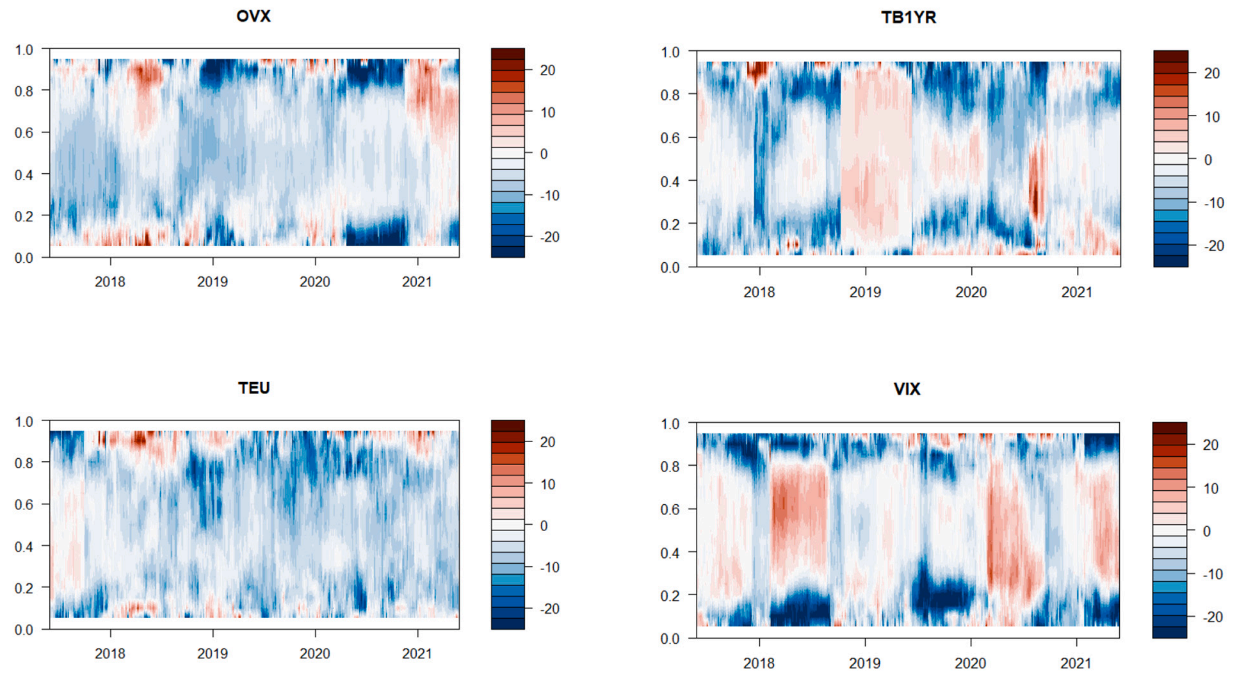

Fig. 13. (*continued*).

markets.

5.2. Implications

This empirical research extended the literature on finance by proposing sensitivity to quantile analysis that can be considered as a novel channel for academic researchers, investors, hedgers, and policymakers to deeply understand the transmission pathway of risk among the BRICS markets, as well as discerning the strength of connectedness over conventional, Islamic, cryptos markets, and uncertainty shocks. This research emphasized the extent of volatility spillovers between markets, which earlier studies have either investigated via the BRICS economies or not at all. Gaining a primary knowledge of the dynamics of spillovers and connectedness between the BRICS stocks (conventional and Islamic), cryptos, and uncertainties is vital for finance-based research, and this empirical work may accordingly be useful as the basis for future research on the dynamics of the network dependence between the markets. Furthermore, our research contributes to the existing strand of literature that exerts the quantile and volatility theory to the novel topic of sensitivity to quantile framework. By examining net transfer role of each market, this work demonstrated that sensitivity to quantile tool was able to deeply describing the dynamics of net spillovers across the BRICS economies.

This study also shed light on the network connectedness among BRICS stocks, cryptos, and uncertainty, as well as the direction and potency of risk transfer between markets. This research does not only favor BRICS investors and market operators who are looking for optimal portfolio allocation and appropriate hedging strategies, but also benefit investors around the whole world as well as policymakers. However, this study further provides crucial practical implications for both investors and policymakers.

First, in terms of investors and financial market participants, according to the dynamic connectedness analysis, owing to the weak connection of conventional and Islamic stock markets with cryptos and uncertainties under stable market states, conventional and Islamic stocks contribute a safe haven refuge to price fluctuation in BRICS markets. Accordingly, in order to obtain profits from portfolio diversification, it is recommended combining Islamic or conventional stocks with cryptos, oil volatility and gold volatility. On the other hand, at extreme events and particularly under extreme positive circumstances, due to higher interdependency between BRICS market systems, investors and financial market participants should take further caution when constructing their portfolios. For instance, for investors who are interested in Chinese stocks, it is advisable including more cryptos in their portfolios for greater diversification profits when market is bearish. While for investors who are interested in South African stock market, they can generate higher diversification profits by incorporating Islamic stocks, cryptos, Twitter and gold uncertainties in their portfolios when market is bullish.

This study further advocates that all investors and market participants should thoroughly account for cross-market spillovers transfer paths when predicting the BRICS stock market risks. Practically, the shock spillover impacts shift via several market states, thereby investors in BRICS markets should take into consideration the effect of different market scenarios of economic uncertainty on net spillover connectedness when adopting stock market risk management strategies.

Second, this study also offers crucial implications for policymakers interested in the BRICS economies. Despite that the BRICS countries are highly interactive with the whole world, the findings revealed how regulators and policing be expanded to adopt policies assisting sustainable economic growth. Regulators in BRICS countries should consider the overall network connectedness in the market systems. Owing to higher net transfer of shocks between markets under unstable market events, policymakers should formulate appropriate policies to conceive stock market price sensitivity. Another takeaway is that BRICS authorities should master the spillover connectedness and risk transfer intensity between conventional, Islamic stock markets, cryptos, and uncertainties, and also develop efficient policy initiatives to track abnormal status in these markets under the involvement of extreme occurrences.

A future avenue of research can be the implementation of the quantile cross-spectral method of Baruník and Kley (2019) and the time-frequency connectedness of Baruník and Křehlík (2018). Another interesting avenue for future directions can be the use of vector wavelet coherence recently developed by Oygur and Unal (2020) to address the combined effect of several indicators on the conventional and Islamic BRICS stock markets. In addition, the investigation of the relevance of the COVID-19 vaccine-related news to the network connectedness system could be another avenue for future studies. We hope that our study will support other scholars to address these topics in the future directions.

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CRediT authorship contribution statement

Rabeh Khalfaoui: Conceptualization, Software, Supervision, Formal analysis, Visualization, Data curation, Validation, Writing – original draft, Writing – review & editing. **Shawkat Hammoudeh:** Conceptualization, Supervision, Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Mohd Ziaur Rehman:** Conceptualization, Formal analysis, Data curation, Writing – review & editing.

Data availability

Data will be made available on request.

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