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Return and volatility spillovers between energy and BRIC markets: Evidence from quantile connectedness

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ABSTRACT

Using the quantile connectedness approach for the median, lower, and upper quantiles, we examine the return and volatility connectedness between energy and BRIC markets from January 1, 2000, to July 9, 2021. We find that uncertain economic activity and intense periods characterize energy and BRIC market returns and volatility connectedness. A parallel return and volatility connectedness structure for upper and lower quantiles against the average quantile revealed different results. Time-varying features are substantiated between energy and BRIC markets; significant distress events, such as the Global Financial Crisis, European Debt Crisis, Shale Oil Revolution, and COVID-19 pandemic, intensified spillovers. We highlight diversification avenues for energy and BRIC markets given the periods of financial turmoil, with investors' concerns widely addressed by opt-in investment opportunities with lower risk and greater diversification. Our study has beneficial implications for policymakers, regulators, investors, and financial market constituents to redevelop their existing strategies to avoid financial losses.

1. Introduction

Sharp price movements in energy commodities have led to renewed interest in measuring return and volatility spillovers. The information transmission from energy commodities to other international stock markets is determined by examining volatilities more than returns (Alawi et al., 2022; Pham et al., 2020; Mensi et al., 2020; Sarwar et al., 2020). Return and volatility spillovers are imperative to policymakers, investors, and portfolio managers. Recurring, unexpected financial turmoil has motivated a focus on choosing those investment streams that offer greater diversification and provide hedging benefits (Tiwari et al., 2021; Huynh et al., 2020). Like other financial markets, energy commodities have suffered great return and volatility uncertainty (Goodell, 2020; Naeem et al., 2020a), which embarks severe risks and exposures to the investors. Energy commodities offer diverse returns and volatilities

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during macroeconomic shocks. Recent literature highlights the significant impact of energy commodities on the economy, as they are vital to various sectors (Balli et al., 2019; Albulescu et al., 2019; Naeem et al., 2020a, 2020b). The dynamics of energy commodities depend on interest rate disparities, downside inflationary pressures, and wealth transfer mechanisms across oil-importing and oil-exporting countries, bringing exchange rates fluctuations, ultimately manifesting oscillations in financial markets and numerous economic sectors (Ashraf and Goodell, 2021; Karim et al., 2022a, 2022b; Naeem and Karim, 2021; Broadstock et al., 2016).

Unlike developed economies, most developing economies are less diversified, with greater risk and higher dependence on energy commodities (Bouri et al., 2018). Emerging economies are more susceptible to energy price volatilities, as their growth is more rapid than developed economies due to complex production structures. Similarly, the price instabilities of energy commodities in emerging economies lead to volatility in export earnings, current account imbalances, foreign exchange reserves, and debt obligation difficulties in due course (Duan et al., 2021; Corbet et al., 2020; Bouri et al., 2018). BRIC (Brazil, Russia, India, and China) markets, in contrast to other emerging economies, are a central focus due to their profound role in global and regional economic development, which includes two leading importers (China and India) and a principal producer and exporter (Russia) of energy commodities (Huynh et al., 2020; Shahzad et al., 2021). BRIC represents a heterogeneous market group that attracts a large segment of capital inflows with greater investment destinations for global portfolio managers (Naeem et al., 2022c). Correspondingly, BRIC markets attract institutional investors holding energy commodities in their portfolios to portray a complete picture of interconnectedness between energy commodities and BRIC stocks to avoid substantial losses given uncertain market conditions (Fang and Egan, 2018; Liu et al., 2019; Shahzad et al., 2021; Feng et al., 2022).

In light of the above background, the current study contributes to the existing literature in multiple ways. First, the study empirically examines the quantile return and volatility connectedness of energy commodities and BRIC markets at the median, upper, and lower quantiles to quantify the connectedness structures and time-varying attributes. Second, methodologically, previous studies have employed the time-varying optimal copula (TVOC) approach to examine the extreme dependence between energy and BRIC markets (Shahzad et al., 2021), time-varying approach of Diebold and Yilmaz (2012) for configuring connectedness among energy markets and international financial markets (Elsayed et al., 2020; Tiwari et al., 2021; Karim and Naeem, 2021; Karim et al., 2022c, 2022d), Baba, Engle, Kraft and Kroner (BEKK-GARCH) technique to examine volatility between energy markets and Asian stocks (Sarwar et al., 2020), and dynamic condition correlation (DCC-GARCH) to measure uncertainty in energy markets (Naeem et al., 2022a, 2022b). However, evidence is lacking from studies employing the quantile connectedness approach to analyze the return and volatility connectedness of energy commodities and BRIC markets to highlight their diversification potential during normal and turbulent periods.

Third, this methodology allows us to capture extreme dependencies in return distribution tails not captured by the average connectivity method. In this case, the added value of our new methodology lies in its ability to capture connectivity in the upper and lower quantiles and thus the relative dependencies of the quantiles. Fourth, our quantile-based connectivity approach provides the first empirical evidence for other extreme spillovers between the upper and lower extreme quantiles, helping to explain tail risk dispersion in energy commodities and the BRIC. Moreover, the application of quantile connectedness for volatility spillovers implies that spillovers of energy markets and BRIC countries vary across extreme high, extreme low, and median volatilities, sufficiently explaining the risk transmission mechanism when economic conditions are not favorable (Bouri et al., 2020; Naeem et al., 2022a, 2021c; Huynh et al., 2022). Finally, we propose several practical implications of study findings for policymakers, BRIC markets, financial market participants, and investors to consider in portfolio diversification.

We find several variations in each quantile by employing the quantile connectedness for average, lower and upper quantiles to compute return and volatility connectedness. A common information transmission mechanism is observed in the NET directional return and volatility analysis. Economic uncertainty and unexpected events directly or indirectly affect energy commodities' connectedness and BRIC markets. The rolling window analysis revealed time-varying attributes, where market dependence varies for return and volatility spillovers. A parallel return and volatility dependency is manifested in the lower and upper quantiles, where an extreme event characterizes the return and volatility connectedness. However, the quantile connectedness for the median quantile showcased different connectedness from those of upper and lower quantiles. We also analyzed the dynamic return and volatility spillovers between the energy commodities and BRIC markets, which were affected by the different financial turmoil periods. The results show that the middle, lower, and upper quantile spillovers between the energy and BRIC markets have improved significantly, reaching levels unprecedented during the Global Financial Crisis (GFC), European Debt Crisis (EDC), Shale Oil Revolution (SOR), and COVID-19 outbreak. We stipulate useful implications for policymakers, regulatory authorities, portfolio managers, and investors to design an optimal portfolio that offers sufficient diversification and minimizes default risk.

The remainder of this research paper is arranged as follows: Section 2 presents a review of earlier empirical studies, Section 3 gives the methodology and data used in the paper, Section 4 describes empirical results, and Section 5 concludes the paper and provides policy implications.

2. Literature review

The last decade marked energy as a commodity market not only on the international level but also as an important financial tool to attract investors' attention. The existing literature mainly features the commodity aspects of energy markets. Yet they present themselves as a long-run potential and strategic stream of investment for international portfolio managers and investors (Mensi et al., 2021a, 2021b and 2021c). Lim and Lam (2014) report that investments in the energy sector of emerging economies grabbed increasing importance due to their sizable commercial value and for balancing the energy sectors. Most of the cross-market studies examining the connectedness of energy commodities and international stock markets highlight a common finding that there are intense spillovers during the economic downturns, resulting in lesser diversification potential for international investors. For instance, in prior studies, Zhang and Broadstock (2018) conducted a systematic analysis of international commodity markets and documented elevated codependence during crisis episodes. Gharib et al. (2021) configured that investment strategies like cross-hedging and cross-speculation are surmounted when there are high spillovers among energy commodities.

Further, Liu et al. (2021) examined tail risk spillovers in the oil–stock relationship by applying a quantile risk spillover approach. The authors found varied spillovers and network mechanisms following uneven economic circumstances, and asymmetric risk

Table 1
Summaries of Prior Studies.

No.	Author (s)	Method (s)	Sample Period	Findings
1.	Shahzad et al. (2021)	TVOC	2002–2019	Evidence shows the existence of multiple tail dependence regimes specifying that static or dynamic copulas do not fully characterize the extreme dependence between oil and BRIC markets. Conditional diversification benefits of investing in oil for BRIC stocks are substantiated.
2.	Lin and Su (2021)	TVP-VAR	2019–2020	There has been a dramatic increase in the connectedness of energy commodities following the COVID-19 period. However, some temporary changes in the connectedness model are also documented. The COVID-19 shock propagation system in energy commodities highlights financial panic risk.
3.	Geng et al. (2021)	Diebold and Yilmaz (2012)	2006–2019	Total information spillovers for global energy companies are very high for the volatility system. There is an asymmetric information transmission among energy companies confirming the significant contribution of bad news toward risk exposure than good news. New energy companies are net information transmitters playing a central role in the network.
4.	Naeem et al. (2020a)	DCC-GARCH	2007–2016	The systematic risk of energy markets is significantly affected during the Global Financial Crisis, shale oil revolution, and subperiods. The study reports the positive impact of energy markets uncertainty on US industries.
5.	Mensi et al. (2020)	Cross, Partial, and Multiple Wavelets	1999–2019	Intensified spillovers are formed during crisis periods, particularly during financial and oil crises. Gold and energy markets are net transmitters of spillovers, whereas the rest of the markets are net recipients irrespective of stock status. Significant comovement between energy markets and stock indices is observed.
6.	Tiwari et al. (2021)	Diebold and Yilmaz (2012)	2000–2017	Spillovers of energy markets are qualitatively similar, whereas total connectedness measured by rolling window analysis showcased time-varying, dynamic and volatile features in return and volatility connectedness across multiple stock markets.
7.	Elsayed et al. (2020)	Diebold and Yilmaz (2012)	2000–2018	Shocks of energy markets are exogenous, and the contribution of energy markets to financial markets is insignificant. A substantial impact on energy markets is exhibited with the segregated data of pre, during, and postcrisis episodes.
8.	Sarwar et al. (2020)	BEKK-GARCH	1997–2014	There are bidirectional volatility spillovers between energy markets and Asian stock markets. Interestingly, similar spillovers are reported before and after crisis periods. However, results vary across daily, weekly, and monthly frequencies.
9.	Chuliá et al. (2019)	Diebold and Yilmaz (2012) VAR	2008–2016	There are varying volatility spillovers in energy markets. There is higher integration among European markets, and natural gas may replace crude oil setting the global price benchmark for energy markets.
10.	Khalfaoui et al. (2019)	DCC and cDCC-GARCH	2010–2016	There is weaker evidence of interdependence between oil-importing and oil-exporting countries with international stock markets. The asymmetric volatility analysis indicates that negative shocks outweigh the positive shocks.
11.	Bouri et al. (2018)	Cross-Quantilogram	2008–2016	There is strong and consistent quantile predictability when the implied volatility of crude oil is low. However, there is no significant improvement in predictability when volatility is at a medium level.
12.	Fang and Egan (2018)	Generalized Pareto Distribution, Multinomial Logit	1997–2015	When comparing the contagion effects in various energy and stock markets, the weaker effect between the oil market and stock sectors is observed. During volatile periods, the existence of contagion weakens the diversification potential of oil concerning stocks.
13.	Ji et al. (2018)	Connectedness framework and Ensemble empirical mode decomposition (EEMD)	2000–2017	The magnitude and direction of spillovers between oil and gas returns vary across different time scales. Crude oil transmits spillovers to the US and UK natural gas markets, and total systemwide connectedness bears dynamic and volatile characteristics.
14.	Shahzad et al. (2018)	VAR for VAR and Cross-Quantilogram	1996–2016	There is both upside/downside risk propagation from oil to precious metals. Varied characteristics are reported to identify precious metals' safe haven potential for oil markets.
15.	Zhang (2017)	Diebold and Yilmaz (2012)		The contribution of energy market shocks to the international financial system is limited. However, the variations in the energy markets shocks can explain the financial system. There is an occasional contribution of energy markets to stock markets.

spillovers are reported in both tails than in the median quantile. Jena et al. (2021) investigated the spillovers of six major petroleum futures and assessed the level of connectedness in both bearish and bullish market states. The authors identified the leading role of Brent crude futures among all markets. Similarly, Khalfaoui et al. (2021) analyzed quantile coherency between energy and nonenergy commodities and reported low market dependence at different quantiles and frequencies. Saeed et al. (2021) worked on the extreme return spillovers of clean and dirty energy investments and documented profound return connectedness at left and right tails than in the mean. Concurrently, spillovers in the upper and lower tails are asymmetric and macroeconomic factors drive the return spillovers. Foglia and Angelini (2020) worked on the volatility connectedness of clean energy firms and crude oil following the COVID-19 pandemic and reported significant insights on portfolio management at the firm level.

Meanwhile, Shahzad et al. (2021) investigated the extreme dependence between oil and BRIC markets and documented the justified application of the TVOC approach in lower and upper tails. Sarwar et al. (2020) analyzed volatility spillovers between oil and Asian stock markets and concluded bidirectional spillovers for the Karachi stock market and unidirectional spillovers for the Shanghai stock market. However, mixed evidence is reported by the Bombay stock market. Given these studies, a blend of existing literature presents interconnectedness between energy commodities and stock markets, but the findings are unequivocal. A summary of earlier empirical studies is reported in Table 1.

3. Methodology and data

This study investigates the quantile return and volatility connectedness between energy commodities and BRIC markets. For estimation purposes, the price series are converted into log first difference returns as follows:

$$R_t = \ln(P_t - P_{t-1}) \times 100 \tag{1}$$

3.1. Volatility estimation

By using a vector of return series $r_t = [r_{1,t}, ..., r_{n,t}]$, the following mean equation is estimated:

$$r_t = \mu_t + \gamma r_{t-1} + \varepsilon_t. \tag{2}$$

In Eq. (2), the vector of the constant term is denoted by μ, whereas $\varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]$ represents a vector of error terms. Then, the estimated conditional volatilities $h^2_{i,t}$ from the univariate GARCH (1,1) process are as follows:

$$h^2_{i,t} = \omega + \alpha \varepsilon^2_{i,t-1} + \beta h^2_{i,t-1} \tag{3}$$

In Eq. (3), $\omega > 0, \quad \alpha \geq 0, \quad and \quad \beta \geq 0, \quad and \quad \alpha + \beta < 1.$.

Since the prime objective of this study is to examine the quantile connectedness of energy markets and BRIC countries, therefore traditional GARCH process is applied to estimate the volatility. In the coming steps, the spillovers at the extreme low, extreme high, and median quantiles are measured, servicing the main objective of the study.

3.2. Quantile connectedness

Following Ando et al. (2022), it is possible to estimate the dependence of yt on xt in each quantile $\tau(\tau \in (0,1))$ on the conditional distribution of y_t/x_t (Koenker and Bassett, 1978). The following equation shows a VAR process with n-variable pth quantiles:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), \quad t = 1, ..., T \tag{4}$$

where y_t refers to the n-vector of the dependent variable at time t, $c(\tau)$ and $e_t(\tau)$ are n-vectors of the intercept or residue on the quantile τ, and $B_i(\tau)$ represents the lagging coefficient matrix on the quantile τ, with $i = 1,...,p$. $\widehat{B}_i(\tau)$ and $\widehat{c}(\tau)$ can be estimated by assuming that the remainder exceeds the population quantile limit $Q_\tau(e_t(\tau)|y_{t-1}, \ldots, y_{t-p}) = 0$. The τth conditional quantile of the answer population y can be expressed as follows:

$$Q_\tau(e_t(\tau)|y_{t-1}, \ldots, y_{t-p}) = c(\tau) + \sum_{i=1}^{p} \widehat{B}_i(\tau) y_{t-i} \tag{5}$$

Since every possible equation in (5) on the right contains the same variables, the regression structure of the estimation problem is independent at first glance, and equations estimate the above model based on the quantile regression equations (Cecchetti and Li, 2008).

3.3. Spillover indices based on Diebold–Yilmaz

Based on the framework developed by Diebold and Yilmaz (2012, 2014), it is possible to determine the spillover index in each quantile by outlining the quantile variation. For this reason, Eq. (4) is rewritten in terms of the moving average process of an infinite-order vector, as shown below:

$$y_t \quad = \quad \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau), \quad t \quad = \quad 1, \ldots, \quad T \tag{6}$$

With,

$$\mu(\tau) = \left(\quad I_n - \quad B_1(\tau) - \quad \cdots - \quad B_p(\tau) \right)^{-1} \quad c(\tau), \quad A_s(\tau)$$

$$= \left\{ \begin{array}{c} 0, s < 0 \\ I_n, s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \cdots + \quad B_p(\tau)A_{s-p}(\tau), \quad s \quad > \quad 0 \end{array} \right\}$$

where y_t is given by the remaining sum of e_t in each quantile τ.

When asked about Cholesky-factor ordering, the approaches of Koop et al. (1996) and Pesaran and Shin (1998) are invariant concerning the order of the variables. This is because the shocks for each variable are not orthogonal, and the total contribution of the variance to the forecast error is not always equal to 1. Therefore, for the forecasting horizon H, the following equation can be used to calculate the Generalized Forecast Error Decomposition of Variance (GFEVD) of a variable due to shocks from different variables:

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{jj}^{-1} \quad \sum_{h=0}^{H-1} \quad \left(e_i^{'} h_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \quad \left(e_i^{'} h_h \sum e_i\right)} \tag{7}$$

where $\theta_{ij}^{g}(\mathrm{H})$ is the contribution of the jth variable to the variance of the forecast error of the i-th variable on the H horizon, $\sum$ referring to the variation matrix of the error vector, σ_{jj} is the jth diagonal element of the Σ matrix, and e_{i} is a vector with a value of 1 for the i-th element and 0 otherwise.

In turn, every entry in the variance decomposition matrix is normalized in the following way:

$$\widetilde{\theta} ijg(H) = \frac{\theta ijg(H)}{\sum_{j=1}^{N} \theta ijg(H)} \tag{8}$$

The framework presented in Diebold and Yilmaz (2012, 2014) can be used to determine connectivity measures in the τth conditional quantile. It is based on a generalized decomposition of the error variance in quantile forecast. More precisely, the total connectivity index for the quantiles τ can be expressed as follows:

$$TCI \quad (\tau) = \frac{\sum_{i=1,}^{N} \quad \sum_{j=1, i \neq j}^{N} \omega ijh(\tau)}{\sum_{i=1,}^{N} \quad \sum_{j=1}^{N} \omega ijh(\tau)} \times 100 \tag{9}$$

Additionally, for quantiles τ, the directional spillover index of all indexes to index i (referred to as "TO") is given as follows:

$$S_{i\bullet}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \omega ijh(\tau)}{\sum_{j=1}^{N} \omega ijh(\tau)} \times 100 \tag{10}$$

In contrast, the directional spillover index from index i to all commodities/stock indexes (called "FROM") on the quantile τ can be expressed as follows:

$$S_{\bullet i}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \omega ijh(\tau)}{\sum_{j=1}^{N} \omega ijh(\tau)} \times 100 \tag{11}$$

Given Eqs. (10) and (11), it is possible to write the net spillover index (NS) for the quantiles τ as follows:

$$NSi(\tau) = \quad S_{\bullet i}(\tau) - \quad S_{i\bullet}(\tau) \tag{12}$$

Similarly, the pairwise spillover index is given in quantiles τ as follows:

$$Sij \quad = \quad \omega_{ji}^{h}(\tau) - \quad \omega_{ij}^{h}(\tau) \tag{13}$$

A VAR lag of 1 (based on Bayesian information criteria) was used to assess connectedness and the forecast error variance of the forward decomposition in 10 steps. A rolling window approach (e.g., Diebold and Yılmaz, 2014; Shahzad et al., 2018) was carried out to reflect variations in spillover measures.

3.4. Data

To study the return and volatility spillovers between the BRIC markets and energy commodities and to compare results during the GFC, the SOR, and COVID-19, we used the daily futures prices of selected energy assets traded around the world, namely WTI crude oil, Brent crude oil, gasoline, heating oil, gas oil, and natural gas. In addition, we consider the daily stock indexes of the BRIC countries, MSCI Brazil Index, MSCI Russia Index, MSCI India Index, and MSCI China Index, with returns being the first difference of the natural logarithms of each index multiplied by $100(r = ln(Pt/Pt - 1) \times 100)$ and where p represents the closing price. All relevant data is collected from the DataStream database, consisting of approximately 21 years of daily data, i.e., from 01/01/2000–07/08/2021. Moreover, we used commodities futures prices for energy markets, as emphasized by Ameur et al. (2021), who confirmed the dominant contribution of futures market prices in determining commodity prices. They also inferred changes in the commodity prices are first reflected in the futures markets, therefore, informed investors and speculators preferably focus on future market prices as they offer low costs and high-leverage effect. In addition, Ji et al. (2018) and Mensi et al. (2020) also employed future commodity and energy market prices in their studies.

4. Empirical findings

Table 2 contains descriptive statistics and unit root tests for the energy commodities and BRIC indices for the sample period. Looking at the nature of this statistic, we can assume that most of the selected returns in the BRIC markets have positive average daily returns compared to energy commodities during the sample period. Russia and HO returns were the lowest with an average of 0.001, followed by Brazil and Brent. Among the indices included in the sample India and China indices have the highest returns with an average value of 0.028 & 0.031. The standard deviations of BRIC markets are smaller than the energy commodities, implying that BRIC indices are relatively smooth moves compared to energy commodities. Jarque-Bera (JB) normality test shows that the series is not normally distributed (Jarque and Bera, 1980). The Augmented Dickey-Fuller (ADF) test also illustrates stationarity and confirms satisfactory modeling conditions.

Fig. 1 depicts the development of energy commodities and the BRIC index, where it can be observed that the average price development is identical between energy commodities (WTI, Brent, Gasoil and HO) and BRIC (Brazil and Russia). At the beginning of the sampling period, there were large fluctuations in the energy and BRIC markets, except for NG and China during the GFC. Gasoline, Brazil, and India appear to be the most volatile key price points to identify during the GFC, EDC, and SOR. Moreover, as expected, except for the price of NG, which rose significantly during the COVID-19 pandemic crisis. WTI, Brent, Gasoil, Gasoline, HO, Brazil, and Russia markets show a similar pattern. In addition, gasoline and India showed the largest average changes, while NG and China showed the smallest changes. In contrast, India and China show the biggest impact as blockades and other measures have significantly reduced demand in equity markets.

4.1. Quantile connectedness of return spillovers

The research methods and databases were comprehensively described in the previous section, so accordingly, the focus of this section is the research results. The quantile connectedness approach helps capture the evolution of the spillover index over time. Therefore, this article describes the return connectedness and network connectivity diagrams for conditional low, median, and high quantiles to determine the direction, intensity, and structure of information spillover of energy sources and the BRIC index (see Table 3 & Fig. 2).[2] Table 3.1 presents the approximate size of the correlation of estimated returns in the middle quantile and shows that Brent and HO receive and transfer the most return spillovers. Furthermore, the overall correlation index is 56.20%, reflecting the moderate strength of return spillovers in the study system of the 10 median indices.

Fig. 2a depicts bilateral binary connectivity in most of the 10 energy commodities, and the BRIC market shows poor connectivity

Table 2
Descriptive statistics and unit root test.

		Mean	Max	Min	SD	Skew	Kurt	JB	ADF
BRIC Countries	BRAZIL	0.006	0.166	−0.194	0.023	−0.579	12.576	1.6E+ 04***	−64.032***
	RUSSIA	0.001	0.240	−0.256	0.022	−0.514	19.189	4.5E+ 04***	−59.787***
	INDIA	0.028	0.195	−0.156	0.016	−0.216	14.258	2.2E+ 04***	−61.628***
	CHINA	0.031	0.140	−0.128	0.017	−0.066	10.384	9.4E+ 03***	−62.100***
Energy Commodities	WTI	0.013	0.320	−0.282	0.026	0.203	24.711	8.1E+ 04***	−48.035***
	BRENT	0.004	0.191	−0.280	0.023	−0.680	18.074	3.9E+ 04***	−65.364***
	GAS OIL	−0.001	0.137	−0.192	0.020	−0.121	10.232	9.0E+ 03***	−62.616***
	GASOLINE	0.004	0.224	−0.385	0.027	−1.198	27.012	1.0E+ 05***	−65.314***
	HEATING OIL	0.001	0.109	−0.200	0.021	−0.565	10.831	1.1E+ 04***	−65.915***
	NATURAL GAS	−0.017	0.268	−0.181	0.032	0.557	7.762	4.1E+ 03***	−67.219***

Note: This table provides the descriptive statistics for the Energy commodities and BRIC markets under study. BRAZIL, RUSSIA, INDIA, and CHINA refer to BRIC markets, while WTI, BRENT, GASOIL, GASOLINE, HEATING OIL, and NATURAL GAS refer to WTI crude oil, Brent crude oil, gasoline, heating oil, gas oil, natural gas, respectively. Max, Min, SD, Skew, Kurt, JB, and ADF represents Abbreviation, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis, Jarque-Bera, and Augmented Dicky-Fuller test, respectively.
*** Indicates significance at 1%.

[2] We use 200-day rolling window Lags = 1 based on SIC. Forecast horizon of 10 days. The methodology is explained briefly in the econometric modeling framework later in Section 3.

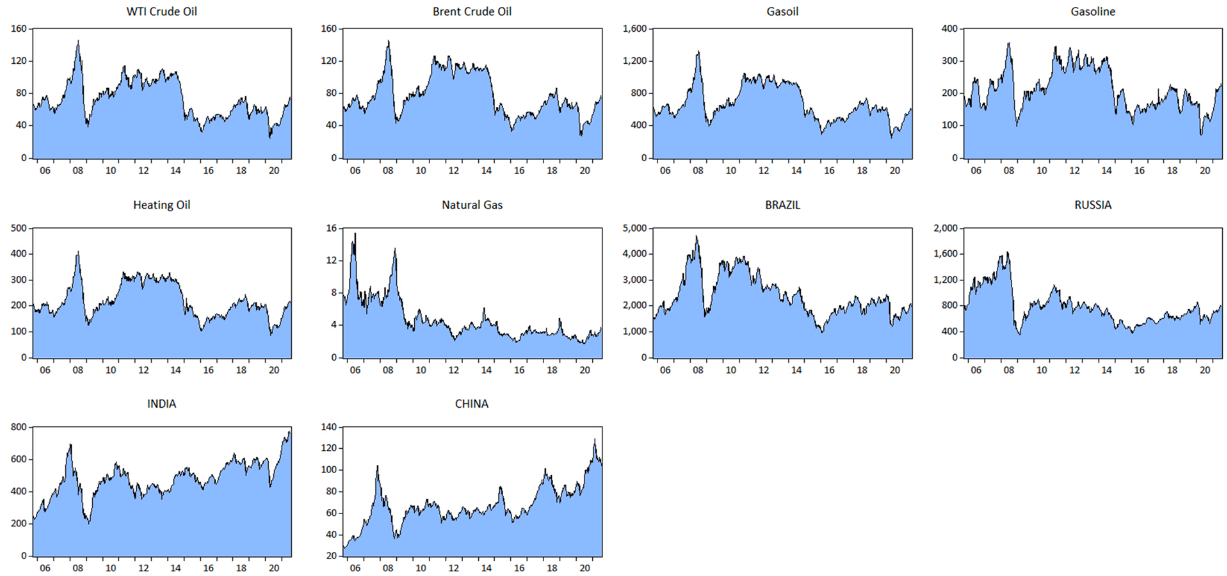

Fig. 1. Evolution of Energy commodities and BRIC indices from 09/30/2005–07/08/2021.

across the system. In particular, return spillovers are weak with NG and all BRIC, whereas they are comparatively more robust with Brent, Gasoil, Petroleum, WTI, and HO (Naeem et al., 2021b). China also has close ties with India and Brazil. There is a bidirectional spillover between Russia and Brazil and a moderate spillover between Brazil and Russia on all BRIC and other commodities. It also illustrates the degree of information spillover between the five net transmitters (energy commodities) and receivers (BRIC) and the intensity and direction of the information spillover. This indicates that when merged with energy resources, the BRIC market provides numerous opportunities for hedging and portfolio diversification.

Tables 3.2 and 3.3 show stronger mean connectivity measures concerning the lower and upper quantile connectivity measures. Therefore, TCI increased to 85.69% in the extreme lower quantile and 84.29% in the upper quantile, compared to 56.20% in the median, indicating that the return spillover was high in the left tail. Moving to the network diagram, Fig. 2b and c show the energy commodities spillover network and the BRIC market in the low and high quantiles, respectively. The spillover grid size in the lower quantile is relatively more significant than in the spillover with the high quantile. Except for NG, all energy commodities are more closely connected to other commodities in the low return state. These energy commodities dominate the spillover in the stable period. More specifically, Brent and WTI are more important, consistent with the work of Cui et al. (2021). In addition, energy commodities make the most considerable contribution to others, both in the lower and upper quantiles, indicating that they are at the heart of the spillover information network market. Compared to Fig. 2a network, pairwise spillover between India and China can be seen in the two quantiles (low and high) and Brazil and Russia only in the upper quantile. These figures demonstrate that the directional spillover effect is sensitive to the lower and upper quantile states. The spillover effect is more pronounced and focused on the BRIC and energy commodities in the lower quantile. Interestingly, energy products other than NG are the leading market among these indices, acting as information transmitters. A potential explanation for this is that this energy market can be regarded as the most efficient market among the sample indices. Consequently, other BRIC and NG markets must consider any positive or negative developments with the wider impacts.

Relationships in the lower and upper quantiles are stronger for energy commodities (excluding NG), India, and Russia. In contrast, energy commodities in the middle quantile appear to play a more stable role. Based on these results, it can be assumed that the energy market has a higher spillover when extreme price movements occur (Karim and Naeem, 2022; Pham et al.,2022; Naeem et al., 2022). The primary source of the spillover was Brent crude oil, which was also shared with Bhanja et al. (2021) results. In particular, these results complement previous studies that looked at the average model (Naeem et al., 2020b; Bhanja et al., 2021) and ignored the relationship between energy commodities and the BRIC index. Such a result is not surprising given the growing evidence of strong market connectivity under extreme conditions (Naeem et al., 2022a). Thus, the variation in the degree of connectedness between quantiles can be understood as a mode change process in which the conversion between intense negative news mode in the left tail and extreme positive news mode in the right tail alters as the number of shocks occurs.

4.2. Rolling-sample connectedness of return spillovers

In this section, a rolling analysis based on the VAR quantile was conducted to record the temporal variability in the inverse return spillovers of the conditional median and the upper and lower quantiles (see Fig. 3). A fixed window duration of 200 days and an approximate horizon of 10 steps were utilized.

Fig. 3a shows the total dynamic return connectedness of the system to the middle quantile. The middle quantile shows a

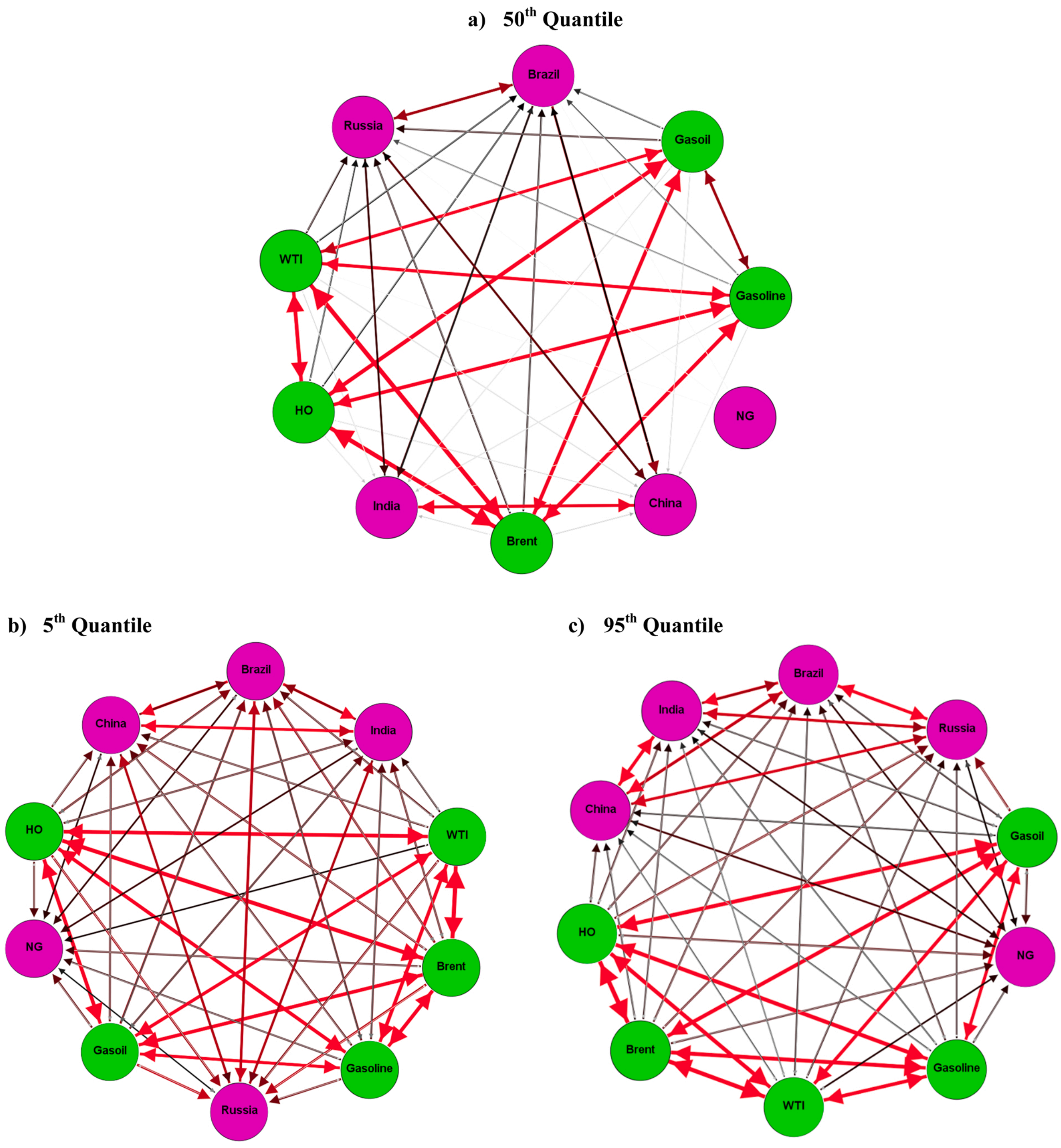

Fig. 2. Full-sample return connectedness networks between Energy Commodities and BRIC markets. Lags = 1 based on SIC. Forecast horizon of 10 days. Note: This network graph illustrates the degree of total connectedness in a system that consists of Energy Commodities and BRIC market returns over the full-sample period. Total connectedness is measured using the Diebold–Yilmaz framework. The node's size shows the magnitude of the contribution of each variable to system connectedness, while the color indicates the origin of connectedness. Node size signifies the extent of the spillover effect, and color specifies whether a market is a net transmitter (green) or recipient (pink) of spillovers. The forced directed layout algorithm sets the node location where the sum of the vectors sets the node route. Arrow width signifies the strength of the pairwise spillovers, and color specifies the strongest (red) to weakest (black) directions of spillovers.

connectedness index of returns exceeding 70. This fluctuates widely over time, indicating a moderate spillover effect on the energy market system and BRIC compared to the lower and upper quantiles (see Fig. 3b–c). This confirms the initial claim that significant volatility exists between the energy markets and the BRIC. The average connectivity index of the energy market system and the BRIC shows the different phases over time. Before 2009, it increased from 55 to 65, and subsequently, during the GFC, it sustained high volatility of approximately 64. Although the GFC caused a decline in manufacturing activity in the economy, resulting in lower energy

Table 3.1
50th Quantile Return Spillovers between energy commodities and BRIC markets.

	Brent	Gasoil	Gasoline	HO	NG	WTI	Brazil	China	India	Russia	From
Brent	28.42	14.16	15.41	21.04	0.04	20.76	0.05	0.01	0.05	0.06	71.58
Gasoil	18.82	33.74	11.46	20.60	0.03	15.19	0.06	0.03	0.01	0.05	66.26
Gasoline	19.35	10.46	35.54	18.23	0.07	16.20	0.05	0.01	0.04	0.06	64.46
HO	21.87	16.04	15.07	29.38	0.04	17.48	0.05	0.03	0.03	0.01	70.62
NG	0.12	0.09	0.14	0.13	98.68	0.20	0.20	0.11	0.14	0.20	17.27
WTI	23.03	12.55	14.27	18.64	0.05	31.35	0.04	0.01	0.03	0.03	72.15
Brazil	6.70	5.26	4.65	6.06	0.16	6.10	47.80	6.34	5.33	11.60	62.98
China	1.98	1.59	1.38	1.62	0.05	1.75	11.25	56.86	14.01	9.52	57.59
India	1.66	1.48	1.54	1.48	0.07	1.38	8.55	14.64	60.90	8.32	53.67
Russia	6.95	7.37	4.22	5.67	0.07	6.97	11.43	6.37	5.86	45.09	63.59
TO	100.46	16.04	68.14	93.47	0.58	86.02	31.68	27.56	25.51	29.83	**TCI**
NET	28.88	2.73	3.68	22.85	− 0.74	17.38	− 20.52	− 15.59	− 13.59	− 25.08	**56.20**

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying forecast error variance decomposition (FEVD) is based on a ten-dimension FIVAR of order 1, indicated by the AIC.

Table 3.2
5th Quantile Return Spillovers between energy commodities and BRIC markets.

	Brent	Gasoil	Gasoline	HO	NG	WTI	Brazil	China	India	Russia	From
Brent	14.19	11.83	12.04	13.02	6.86	12.97	7.55	7.20	7.55	6.79	85.81
Gasoil	12.46	14.48	11.27	12.70	7.20	11.71	7.88	7.45	7.77	7.09	85.52
Gasoline	12.60	11.21	14.67	12.41	7.07	12.11	7.85	7.36	7.68	7.03	85.33
HO	13.10	12.16	11.92	14.17	7.05	12.27	7.67	7.31	7.51	6.84	85.83
NG	9.21	9.54	9.04	9.33	18.65	8.75	9.08	8.95	9.11	8.34	81.35
WTI	13.50	11.60	11.95	12.72	6.83	14.82	7.42	7.07	7.36	6.72	85.18
Brazil	10.08	9.89	9.65	9.87	7.53	9.46	13.46	9.73	9.96	10.36	86.54
China	9.75	9.53	9.46	9.49	7.74	9.23	10.86	12.71	10.94	10.29	87.29
India	9.64	9.55	9.37	9.49	7.54	9.01	11.00	10.54	13.56	10.29	86.44
Russia	10.34	10.45	9.67	10.09	7.61	9.80	10.53	9.40	9.72	12.39	87.61
TO	100.67	16.04	94.37	99.12	65.42	95.32	79.84	75.03	77.62	73.75	**TCI**
NET	14.87	10.23	9.04	13.29	− 15.92	10.13	− 6.7	− 12.26	− 8.82	− 13.86	**85.69**

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying FEVD is based on a ten-dimension FIVAR of order 1, indicated by the AIC.

Table 3.3
95th Quantile Return Spillovers between energy commodities and BRIC markets.

	Brent	Gasoil	Gasoline	HO	NG	WTI	Brazil	China	India	Russia	From
Brent	14.70	12.03	12.14	13.39	7.02	13.11	7.12	6.96	7.00	6.52	85.30
Gasoil	12.69	14.93	11.14	13.00	7.32	11.74	7.56	7.44	7.27	6.92	85.07
Gasoline	13.02	11.26	15.73	12.84	7.13	12.25	7.20	7.04	6.94	6.60	84.27
HO	13.23	12.31	11.89	14.64	7.22	12.33	7.29	7.25	7.12	6.72	85.36
NG	9.09	9.19	8.74	9.37	19.42	8.75	8.88	9.17	8.85	8.55	80.58
WTI	13.53	11.69	11.93	13.00	7.12	14.88	7.30	6.98	7.02	6.53	85.12
Brazil	9.13	8.79	8.88	9.28	7.74	8.69	16.04	10.34	10.06	11.06	83.96
China	8.55	8.59	8.28	8.96	8.19	8.12	11.24	15.85	11.62	10.60	84.15
India	8.70	8.64	8.37	9.03	8.13	8.07	10.89	11.59	16.05	10.54	83.95
Russia	9.27	9.71	8.67	9.59	7.87	8.78	11.32	10.04	9.90	14.83	85.17
TO	97.22	16.04	90.04	98.47	67.74	91.84	78.79	76.81	75.78	74.03	**TCI**
NET	11.92	7.13	5.78	13.11	− 12.84	6.72	− 5.17	− 7.34	− 8.16	− 11.14	**84.29**

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying FEVD is based on a ten-dimension FIVAR of order 1, indicated by the AIC.

demand, the degree of comovement of energy commodities increased due to the external financial crisis. Consequently, the average return spillover index also increased. In addition, the spread of the crisis in the euro area during the ESDC phase (2011–2012) caused a total of 72 spillover effects for the energy markets and the BRIC. On the other hand, the energy market and the BRIC experienced a decline in excess profits between 2013 and 2014, signifying a global economic recovery (Shahzad et al., 2017). From mid-2015, the spillover of total returns increased during the mid-point and lasted until the third quarter of 2016. It fluctuated around 75 at the end of the study period.

In contrast, the spread of the crisis on the global markets forced the total return spillovers of the lower and upper quantiles of energy and the BRIC index to be brought to its upper bounds (91 higher, 92 lower). This trend is likely attributable to the combination of a number of factors. For example, the March 2013 Financial Services Act, the impact of persistent European debt problems from several

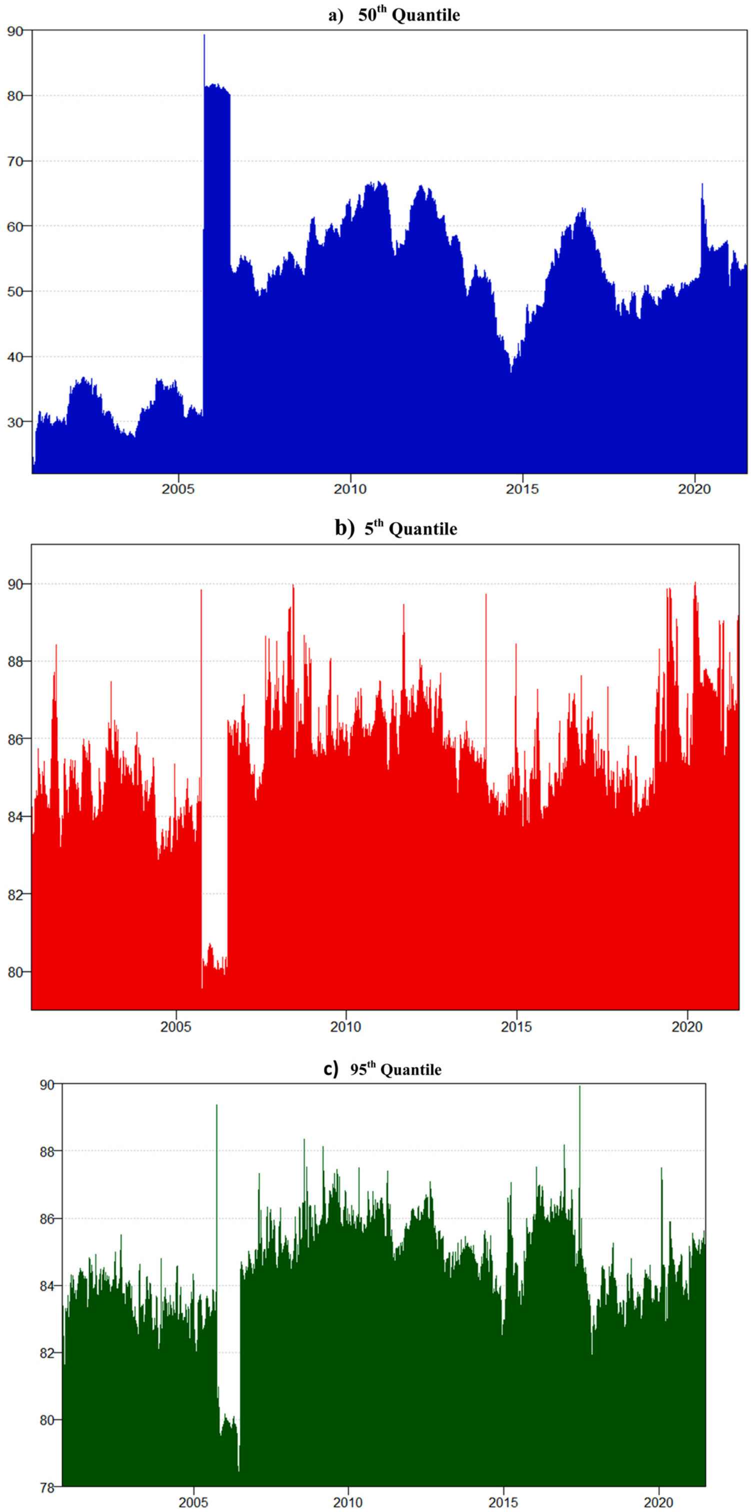

Fig. 3. Dynamic rolling window connectedness between Energy Commodities and BRIC market returns using 200-day rolling window Lags = 1 based on SIC. Forecast horizon of 10 days. The dashed black line represents the average connectedness.

member countries, including Spain, Italy, and Greece, growing concerns about China's economic slowdown in the first six months of 2012, increased unease about China's shadow financial institution and the problems encountered from Malaysian Airlines in 2014, the collapse of the Chinese financial markets in August 2015, and instability and political strikes in November 2016 (Ahmed and Elsayed, 2019). Total return spillovers for left and right quantiles decreased significantly in 2017, 2018, and up to mid-2019, which could explain the more significant benefits of diversifying this market during times of crisis (for example, the OPEC price reduction deal and the ongoing tensions between China and the US and the world of commerce) (Liow and Song, 2020). Following the onset of the COVID-19 pandemic in early 2020, the dynamic spillovers increased to a median, left tail, and right tail of approximately 23, 79, and 70, respectively. This is consistent with the interdependence and interlinked nature of financial markets (Morales and Andreosso-O′Callaghan, 2012) and how the interdependence of energy markets and the BRIC tends to increase in times of crisis. The ongoing global COVID-19 pandemic has had and likely will continue to have major economic ramifications. This includes changes in investor

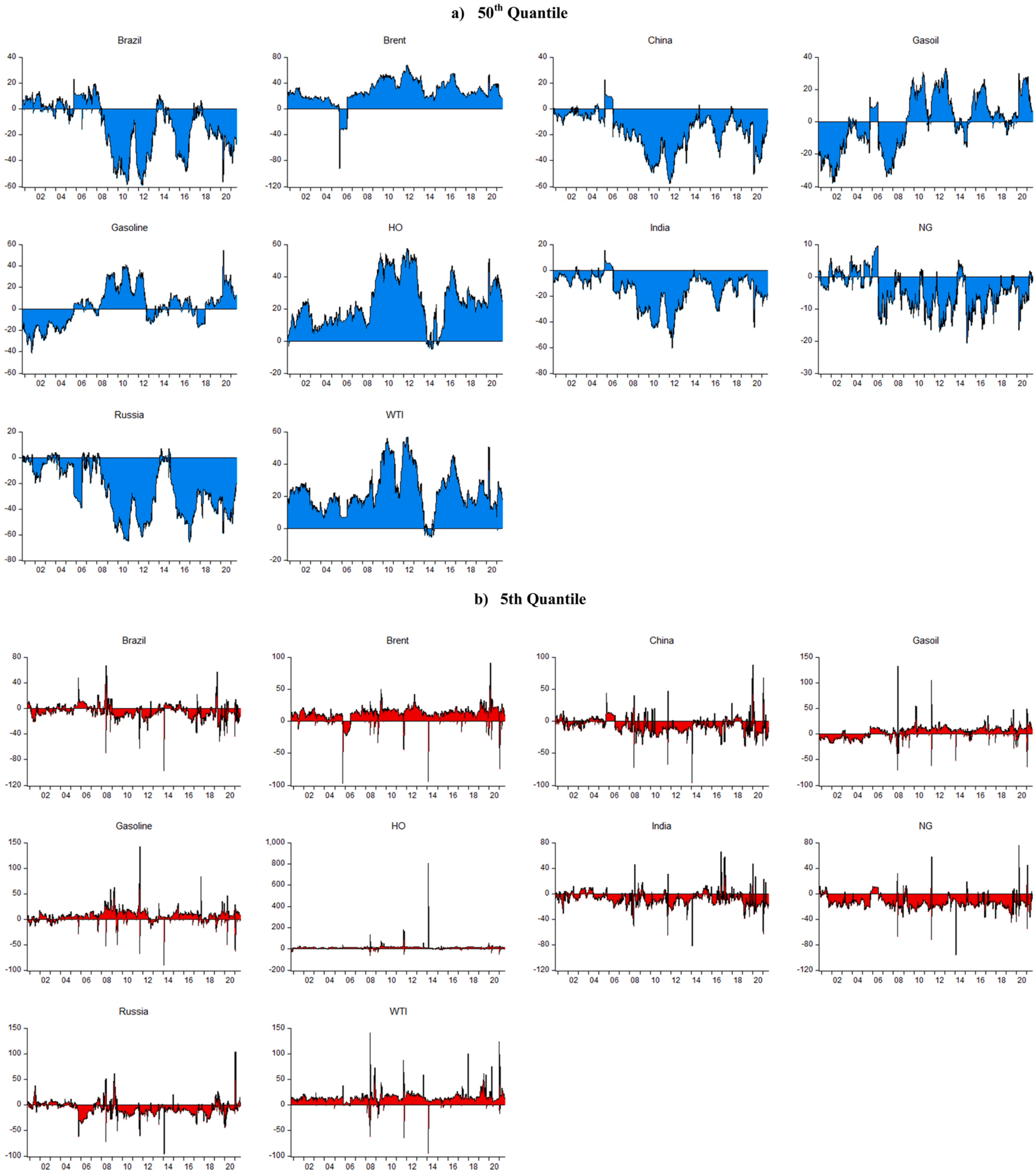

Fig. 4. Dynamic rolling window NET connectedness between the Energy Commodities and BRIC market returns using 200-day rolling window Lags = 1 based on SIC. Forecast horizon of 10 days.

c) 95th Quantile

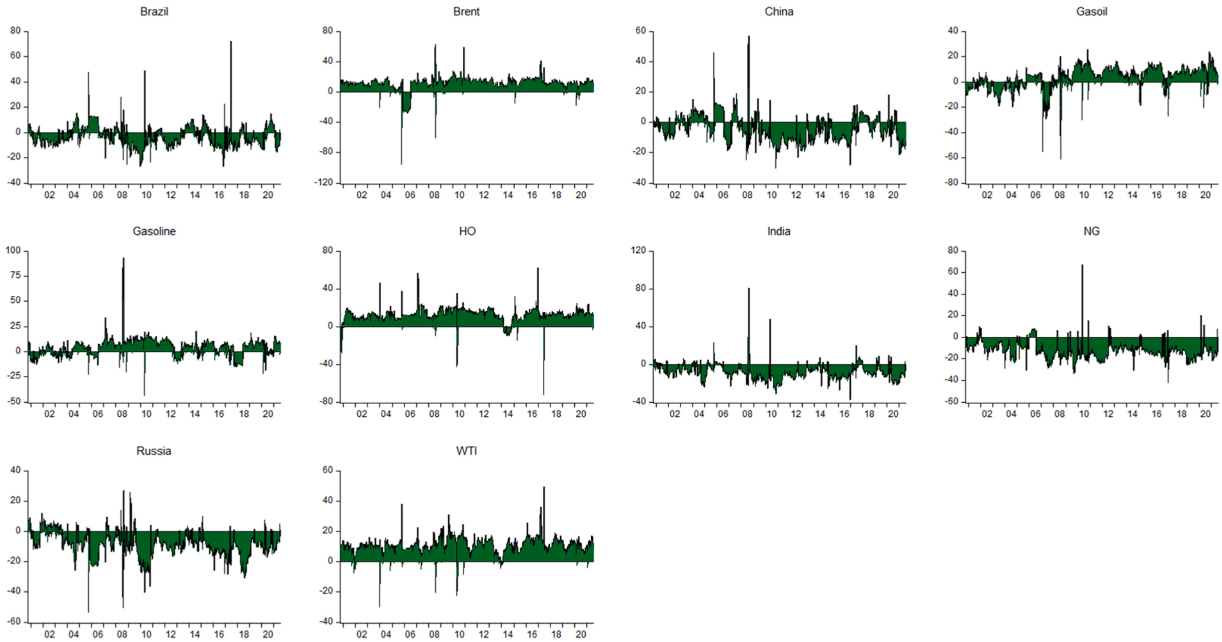

Fig. 4. (*continued*).

sentiment and decisions, and consequently, prices of energy commodities and the BRIC markets have been significantly impacted.

The spike in the dynamic total connectedness index in the conditional median, right, and left quantiles is primarily associated with environmental changes in the energy market and the BRIC. In particular, the total spillover across various quantiles in the energy commodities and BRIC systems was relatively stable in phase II (2008–2010) compared to phase III (2011–2020), mainly due to the variability of commodity prices across different stages. In particular, the highest points of return spillovers were from 2011 to 2015 and in 2020, which corresponds to the major events of the EDC and the COVID-19 pandemic. Such shocks exacerbate the spillover between the energy commodities and BRIC indices (but not all indexes), thereby reducing the potential for investment diversification.

4.3. Net directional return connectedness in the quantile VAR

Next, the connectedness of time variation of net returns at the middle (50th quantile), left (5th quantile), and right (95th quantile) were examined, as shown in Fig. 4a–c. The return net spillover is measured by obtaining the difference between the "TO others" and "FROM Others" directed spillovers. Using the net return spillover index, one can easily distinguish the net transmitter and net receiver of the quantile return spillovers. In general, the dynamic spillover in net returns is reciprocal and asymmetric, as it swings in the positive or negative direction with varying magnitudes (Kang and Yoon, 2019, 2020).

WTI, Brent, Gasoil, Gasoline, and HO act as net transmitters of the average return spillovers in the middle quantile. The remaining energy commodity, which is NG and BRIC, is the net recipient of the spillover. This result is in line with Luo and Ji (2018), namely that the energy commodity market acts as a network transmitter and transfers higher spillover risk to agricultural commodities in China. Guhathakurta et al. (2020) also reported that the WTI market transfers significant return spillovers on agricultural commodities and metals. Dynamic spillover in net returns on Brent, WTI, and HO increased sharply during the fall in GFC, ESDC, and oil prices, which indicates that major crises significantly increase net return spillovers. Negative sentiment enveloped the market during the GFC, and further return spillovers were driven by investors' herd mentality and irrational trading behaviors. However, the role of the individual market changes dramatically in a short period. This conclusion attests to the time-specific ramifications of the directional return spillovers across the BRIC market and energy commodity returns. Another important point is that the dynamic spillover in the net return spillovers of WTI and Brent oil shows a significant improvement following the decline in oil prices in 2020, during the COVID-19 pandemic. Overall, for the median quantiles, the energy commodities are the net shock transmitter for most samples for all other BRIC indices. This signifies that energy commodities, except NG, impact other markets for most of the sampling period.

Fig. 4b depicts the lower quantile spillovers, which differ markedly from the average and high spillovers. This illustrates that under both conditions, for extreme occurrences, the network spillover patterns will vary for the whole duration, which is attributable to the lack of a separate transmitter or receiver of net returns. For instance, after the bankruptcy of Lehman Brothers (September 15, 2008), gains in net return spillovers have expanded in a negative or positive direction, and their magnitude has changed frequently during the recent financial crisis. Additionally, BRIC and energy markets became spillover transmitters, and China and NG were recipients of net spillovers between late 2008 and early 2010. However, between late 2014 and 2016, NG was a net return transmitter, coinciding with a sharp decline in crude oil prices. In 2018 and 2019, developments in net return connectedness for Brent, WTI, gasoline, HO, Brazil, and Russia were stimulated by rising negative interest rates, divergent market valuations, and the subsequent collapse and recovery of commodity prices.

Fig. 4c illustrates the upper quantile spillovers, with Brent, WTI, Brazil, and China demonstrating unexpectedly higher degrees, while Gasoline, Gasoil, HO, NG, India, and Russia models fluctuate between highs and lows. These results lead to closer integration of energy commodities and the BRIC market in terms of uncertainty; however, there is some ambiguity regarding the transmission of Gasoil, Gasoline, Brazil, and India as found in the middle of the sample (between April 2013 and January 2014). This can be explained by the decline in global inflation (meaning the value of gold falls as a hedge against higher prices) and the weakening of gold as a safe haven, restoring confidence in the US dollar. While Brent, WTI, Brazil, and China continued to provide shocks for all energy and BRIC indexes after late 2010 (which can be viewed as a factor in growth and profitability pursuit), Gasoline and HO moved from receiver to transmitter of return spillovers to other markets, both then and in late 2019 during the outbreak of the COVID-19 pandemic.

Fig. 4a–c show that the network spillover signal does not change over time. These findings provide insight into the specific time spillover effects of the BRIC and energy markets.

4.4. Quantile connectedness of volatility spillovers

Volatility is the most crucial concept in the financial discipline and is synonymous with risk management. Therefore, uncovering the volatility relationships between energy and BRIC indices help market participants and academic researchers to draw meaningful conclusions about the overall risk dynamics in the financial system. For example, the second-moment spread of the distribution of returns between energy and BRIC markets can be used to understand how shocks due to instability in one asset or market can predict volatility in another asset or market. In addition, the identity and role of exogenous factors that can influence the dynamics of the variability relationship are essential. Therefore, Tables 4.1–4.3 & Fig. 5a–c show the quantile spillover index between the energy commodities and the BRIC indices volatilities in the lower, middle, and upper tail. The quantile volatility spillovers correspond to the quantile return spillovers (see Tables 4.1–4.3 & Fig. 2a–c). This means that network connectedness, assessed based on the average return/volatility conditions, does not reflect the level of connectivity associated with significant positive or negative shocks. This is largely in accord with the existing literature (e.g., Betz et al., 2016; Baumöhl, 2019; Bouri et al., 2020), which draws attention to tail-based dependencies for meticulous surveillance and regulatory oversight.

The estimated degree of volatility connectedness in the middle quantiles is presented in Table 4.1. The results are consistent with the range of returns (Table 3.1), although the overall variance of each index concerning the volatility connectedness at the median examination has decreased significantly. The average impact of one index on all others in the system is moderate, as indicated by the TCI level (36.30%). Additionally, Fig. 5a shows network connectedness with volatility under conditions of average volatility. It also shows the extent of information spillover for the three transmitters and seven network receivers and the intensity and direction of information spillovers between them. A complete sample of the average volatility network shows that Brent, Gasoil, and HO transfer substantial volatility to all other energy indices except BRIC and are essential players in energy market connectedness (Yip et al., 2017). Furthermore, Brent and HO are bidirectional transmitters and receivers, followed by Brent and Gasoil. China and Russia exhibit moderate bilateral volatility spillovers. A key element is a thin arrow that connects the energy commodities and BRIC indices. The significance of this is that it demonstrates the low volatility spillovers between these markets.

Regarding the measure of volatility connectedness assessed at the lower quantile, Table 4.2 shows a moderate increase in spillover across the indices compared to spillover alone, especially for NG (35.48%) and Brazil (38.83%). There was also a slight increase in the TCI (44.71%) above the mean value (TCI = 36.30%). The results show that the connectedness between the volatility of the energy index and the BRIC is higher on the left than the median but not as strong on the return spillovers of this index. Regarding the estimated connectedness measure of volatility in the upper quantile, Table 4.3 shows that the cross-index spillover is much higher than that estimated in the median and left-tailed. In addition, the TCI index level is 85.93%, indicating that the average impact that one index has on all other indices in the system of volatility is high in the right tail. The emergence of renewable energy sources and clean

Table 4.1
50th Quantile Volatility Spillovers between energy commodities and BRIC markets.

	Brent	Gasoil	Gasoline	HO	NG	WTI	Brazil	China	India	Russia	From
Brent	71.51	8.92	4.59	9.79	1.12	1.69	0.70	0.15	0.98	0.56	28.49
Gasoil	9.37	71.01	5.05	13.55	0.13	0.37	0.12	0.18	0.07	0.15	28.99
Gasoline	5.49	5.73	80.85	4.89	0.52	0.66	0.44	0.19	0.98	0.25	19.15
HO	9.64	12.90	4.24	70.44	0.68	0.78	0.47	0.09	0.15	0.62	29.56
NG	0.33	0.08	0.10	0.15	38.22	18.00	22.36	0.04	7.75	12.97	61.78
WTI	0.81	0.26	0.26	0.24	21.33	44.88	19.02	0.10	4.67	8.43	55.12
Brazil	0.25	0.09	0.17	0.15	25.02	18.15	42.42	0.11	5.56	8.10	57.58
China	0.20	0.25	0.23	0.12	0.14	0.27	0.27	98.15	0.17	0.20	1.85
India	0.49	0.05	0.18	0.08	12.98	6.37	8.21	0.09	63.88	7.68	36.12
Russia	0.19	0.12	0.06	0.24	18.60	9.38	9.14	0.04	6.60	55.62	44.38
TO	26.76	16.04	14.86	29.21	80.51	55.67	60.74	0.99	26.93	38.95	**TCI**
NET	− 1.73	− 0.59	− 4.3	− 0.35	18.73	0.55	3.16	− 0.85	− 9.19	− 5.42	**36.30**

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying FEVD is based on a ten-dimension FIVAR of order 1, indicated by the AIC.

Table 4.2
5th Quantile Volatility Spillovers between energy commodities and BRIC markets.

	Brent	Gasoil	Gasoline	HO	NG	WTI	Brazil	China	India	Russia	From
Brent	57.35	11.86	7.76	11.81	1.91	3.22	1.67	0.62	2.04	1.77	42.65
Gasoil	12.22	59.11	8.02	15.20	0.93	1.38	1.04	0.68	0.60	0.82	40.89
Gasoline	9.05	9.08	66.88	6.99	1.03	2.03	1.46	0.74	1.83	0.90	33.12
HO	12.32	15.38	6.25	59.80	1.21	1.35	1.25	0.41	0.58	1.45	40.20
NG	1.18	0.56	0.55	0.72	35.48	17.60	21.56	0.24	8.54	13.58	64.52
WTI	2.25	0.94	1.22	0.90	19.87	40.05	19.13	0.59	5.65	9.42	59.95
Brazil	1.13	0.69	0.85	0.81	23.60	18.55	38.83	0.58	6.61	8.36	61.17
China	0.99	1.05	1.02	0.63	0.62	1.34	1.37	91.77	0.63	0.58	8.23
India	1.98	0.56	1.52	0.54	13.37	7.83	9.46	0.38	55.57	8.78	44.43
Russia	1.48	0.67	0.65	1.17	18.40	11.31	10.35	0.30	7.60	48.08	51.92
TO	42.60	16.04	27.83	38.78	80.93	64.62	67.29	4.54	34.07	45.66	**TCI**
NET	− 0.06	− 0.12	− 5.28	− 1.43	16.41	4.67	6.12	− 3.69	− 10.36	− 6.26	**44.71**

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying FEVD is based on a ten-dimension FIVAR of order 1, indicated by the AIC.

Table 4.3
95th Quantile Volatility Spillovers between energy commodities and BRIC markets.

	Brent	Gasoil	Gasoline	HO	NG	WTI	Brazil	China	India	Russia	From
Brent	10.62	8.84	9.46	8.33	12.04	13.62	12.31	2.90	9.98	11.90	89.38
Gasoil	10.84	9.15	9.78	8.60	11.72	13.41	12.08	2.95	9.81	11.66	90.85
Gasoline	10.61	8.81	9.49	8.32	11.99	13.61	12.29	2.97	10.01	11.89	90.51
HO	10.40	8.54	9.25	8.15	12.28	13.80	12.50	2.94	10.09	12.05	91.85
NG	10.03	8.11	8.81	7.71	12.73	14.09	12.82	2.96	10.34	12.39	87.27
WTI	9.86	7.89	8.63	7.52	12.97	14.23	13.00	3.01	10.44	12.46	85.77
Brazil	9.81	7.85	8.62	7.55	12.92	14.25	13.00	3.04	10.44	12.50	87.00
China	8.92	12.00	8.05	8.17	4.07	5.20	5.93	40.59	3.85	3.21	59.41
India	10.06	8.07	8.76	7.68	12.78	14.13	12.84	2.91	10.37	12.40	89.63
Russia	9.99	8.03	8.75	7.64	12.83	14.13	12.87	2.92	10.43	12.40	87.60
TO	90.53	16.04	80.13	71.51	103.60	116.22	106.64	26.61	85.41	100.47	**TCI**
NET	1.15	− 12.7	− 10.38	− 20.35	16.33	30.45	19.64	− 32.8	− 4.22	12.87	**85.93**

Note: Quantile Spillover indices are calculated from variance decomposition based on 10-step-ahead forecasts. The underlying FEVD is based on a ten-dimension FIVAR of order 1, indicated by the AIC.

technologies as transmitters is comparable to recent research findings (Ferrer et al., 2018; Nasreen et al., 2020; Yahya et al., 2021).

In addition, Fig. 5b shows the volatility spillovers during low volatility conditions of the Energy and BRIC indices, where the volatility spillover is noticeably more prominent than during the average volatility spillovers. These results illustrate the more significant influence of extreme shocks on the systems' volatility spillovers. Contributions to and from others must be much more critical under low volatility conditions than under conditions of average volatility. By comparison, the median volatility spillovers (Fig. 5a) are more straightforward than the higher volatility condition (Fig. 5c), a connectivity network with volatility indicating significantly higher levels of connectedness across the system. An important aspect is that in this market, except NG, all energy commodities are the prevailing commodity indices and function as transmitters of information. A possible reason for this is that the energy commodities and the BRIC indices are considered the most efficient of the sample indices. Therefore, it is essential to consider the broader potential impact of positive and negative developments in the NG and BRIC markets.

In summary, the relationship between energy commodities and the BRIC markets is more robust with the average volatility conditions in Brent, Gasoil, and HO. In contrast, the BRIC markets are less associated with energy commodities. This suggests that the BRIC markets are less connected than the energy commodity markets, potentially allowing international investors to diversify. They can invest in a combination of energy and BRIC markets and hedge the risk of dramatic price fluctuations in financial markets. Another perspective shows that volatility spillovers and connectivity volatility analysis can support investors' decisions about risk-on and risk-off strategies. For example, negative volatility, which leads to a stronger correlation with volatility, indicates a greater link between declining or intense market conditions (Antonakakis et al., 2018).

4.5. Rolling-sample connectedness of volatility spillovers

Similar to the analysis of return on total spillover effects (Fig. 3a–c), a dynamic approach continued to be applied to understand the time-varying behavior of the volatility spillover effect between the upper/lower quantile and the middle quantiles, as shown in Fig. 6a–c. Up to this point, signs of disparities in the volatility spillovers across the lower, middle, and upper quantiles have been identified (see Fig. 5a–c). This indicates that the connectivity network estimated by the conditional median quantiles does not reflect the degree of connectivity associated with significant negative or positive shocks. This is somewhat in line with previous research (e.g., Betz et al., 2016; Bouri et al., 2021; Mensi et al., 2021a, 2021b and 2021c), exploring the meaning of tail-based dependencies on the

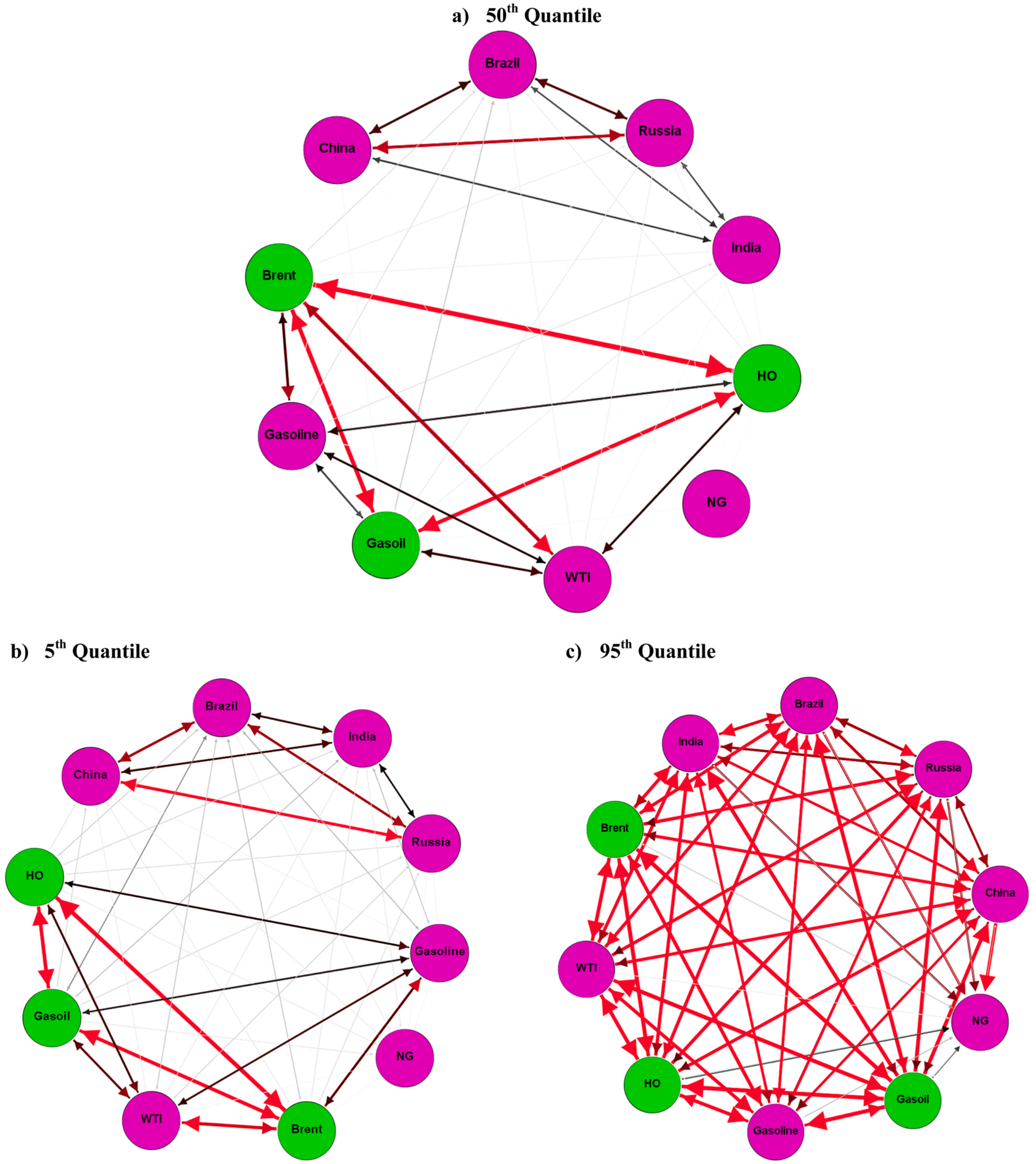

Fig. 5. Full-sample volatility connectedness networks between Energy Commodities and BRIC markets. Lags = 1 based on SIC. Forecast horizon of 10 days. Note: Please refer to Fig. 2.

dimensions of prudential regulation and oversight mechanisms.

Fig. 6a–c show that the total volatility spillover indices for the three quantiles show similar movements and cyclical magnitudes over the sampling period. Starting from lower values of approximately 40 (median), 57 (left tail), and 90 (right tail), the spillover volatility index increased in the third quarter of 2007 during the mortgage substrate crisis. The second spike in the index spillover was caused by the previously mentioned Lehman Brothers bankruptcy in September 2008, which shows the strong influence of GFC on the upper and lower quantiles compared to the average spillovers. The default of Lehman Brothers became the starting point for GFCs global expansion for 2007–2009, and both lower and higher values of total volatility spillovers were maintained through the first phase

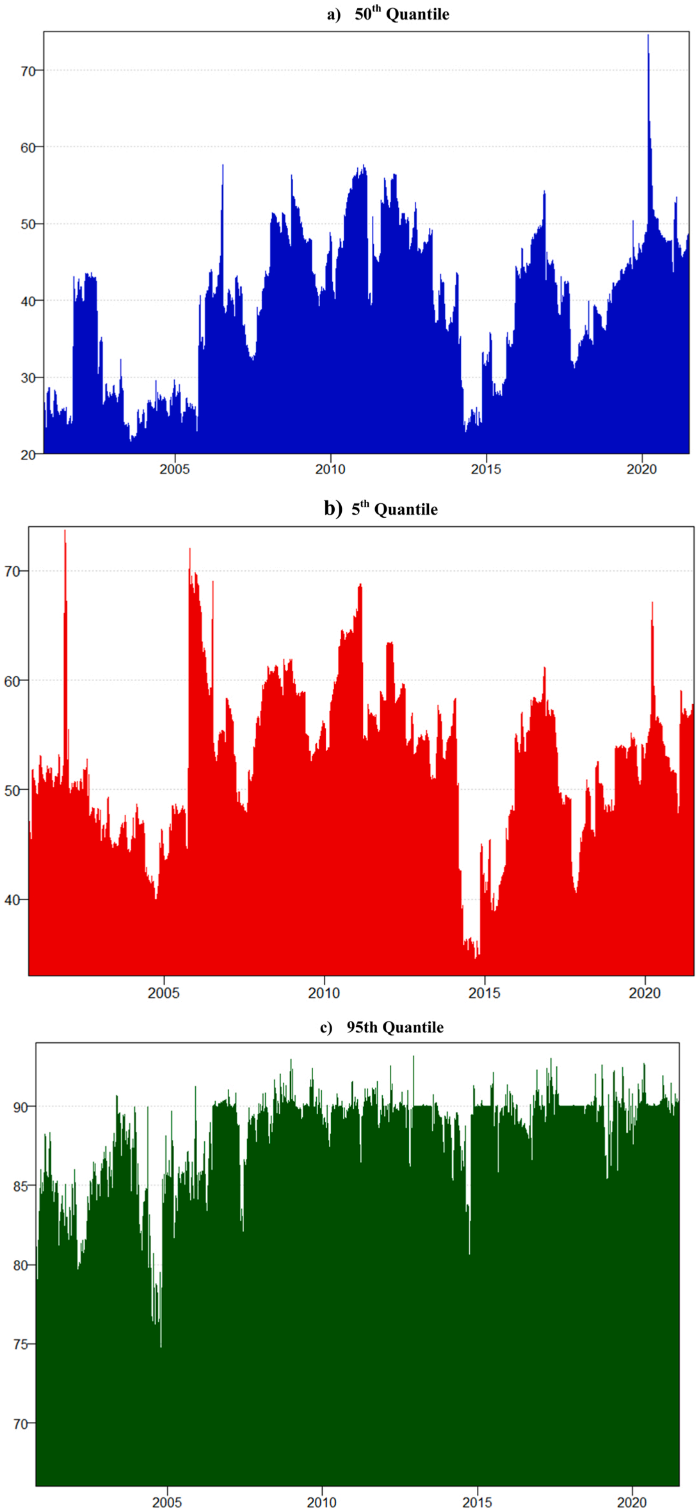

Fig. 6. Dynamic rolling window connectedness between Energy Commodities and BRIC market volatilities using 200-day rolling window Lags = 1 based on SIC. Forecast horizon of 10 days. The dashed black line represents the average connectedness.

(2009–2011) of the ESDC. More specifically, during the samples' first phase, the magnitude of the average volatility spillover was lower than that of the very low and very high-volatility spillovers. This result is in accord with expectations, as the sample period encompassed both the event and the nonevent occurrences (Andrada-Félix et al., 2018). Conversely, there was a significant decrease in spillover volatility for the middle, lower, and upper quantiles in 2017 and 2018. This can be understood as the recovery of the world economy in times of crisis; for example, OPEC price reduction agreements and ongoing trade tensions between the United States and China (BenSaïda et al., 2019; Liow and Song, 2020). According to the behavior of the total return spillover indices for various quantiles (see Fig. 3a–c), they experienced significant spikes of circa 75–90 during the outbreak of the COVID-19 pandemic.

Thus, the conclusion is reached that certain financial incidents, namely the GFC, the SOR, and the impact of the COVID-19 pandemic, exacerbated the spread of instability to both energy commodities and BRIC markets. Several studies have found similar results in the stock market (Diebold and Yilmaz, 2012; Yarovaya et al., 2016) between oil and stock markets (Husain et al., 2019;

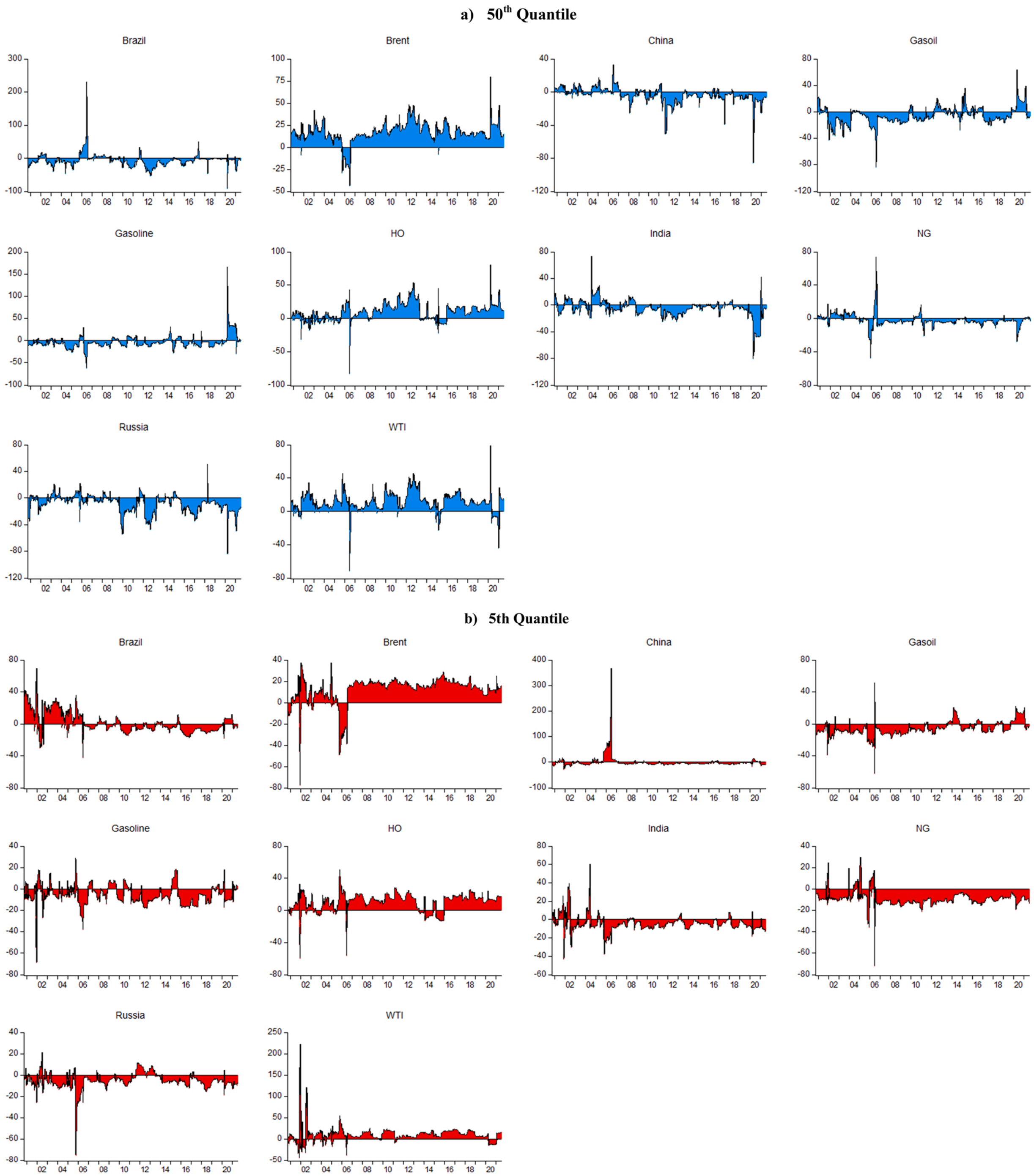

Fig. 7. Dynamic rolling window NET connectedness between the Energy Commodities and BRIC market volatilities using 200-day rolling window Lags = 1 based on SIC. Forecast horizon of 10 days.

c) 95[th] Quantile

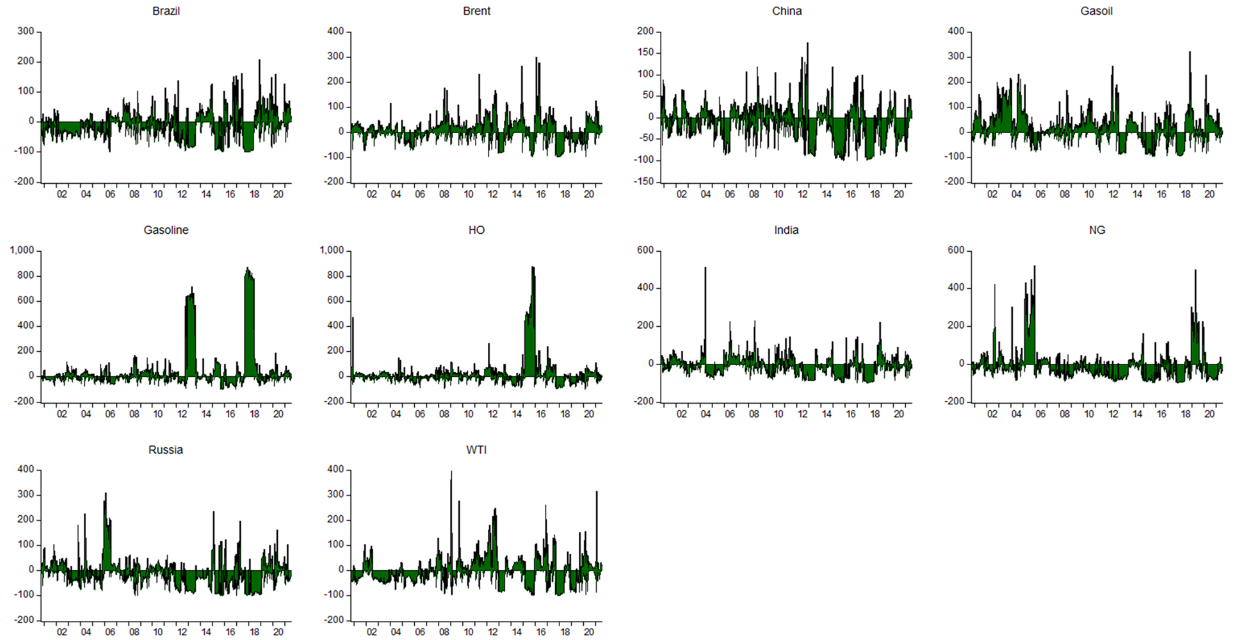

Fig. 7. (*continued*).

Gomez-Gonzalez et al., 2020), and between commodity and currency markets (Antonakakis and Kizys, 2015; Balli et al., 2019, 2021c).

4.6. Net directional volatility connectedness in the quantile VAR

Data on each market's volatility contribution to the overall system is obtained from net directional connectedness. Fig. 7 illustrates the relationship of rolling net volatility connectedness at the predicted levels of the three volatility conditions (i.e., average, extremely low, and extremely high).

The estimated net volatility spillover on the conditional median, the lower tail, and the upper tail is presented in Fig. 7a–c, respectively. Based on the spillover model, three groups of BRIC and energy commodities are observed in Fig. 7a: the first, including Brent, WTI, and HO, shows positive net spillovers (i.e., net volatility transmitters) for almost the entire sample period; the second is markets that are net recipients of spillovers, such as NG, Brazil, China, and India; and the third is markets that are sometimes net negative spillovers and sometimes net recipients of volatility spillovers. Hence, if the past model emphasized by average network connectedness is ongoing, both investors and regulators must monitor the three transmitters. More interestingly, after recent financial events such as the COVID-19 pandemic, net spillovers skyrocketed in negative and positive directions, and the number of net spillovers increased. All energy commodities, except NG, are spillover transmitters (indicating the flight to quality effect in financial incidents), and the BRIC markets are the spillover recipients.

However, for extreme events (i.e., in both quantiles), the net volatility spillover pattern is very different because there is no clear transmitter or receiver of net volatility for the entire period. Fig. 7b and c show that most energy commodities are net transmitters in some periods and net recipients in the BRIC markets. Therefore, investors and politicians should constantly monitor the dynamic spillover of net shocks due to volatility in the BRIC and energy commodities during extreme events.

The above results provide new insights into the spread of shocks due to extreme instability in the energy commodities and the BRIC markets. Fig. 7a–c depict fluctuations in the net volatility spillover index over time for each energy commodity and BRIC index and emphasize that spillover volatility in financial transactions often changes between the middle, lower, and upper quantiles.

4.7. Robustness tests

To look at the sensitivity of our results, we used an alternative Hstep-ahead forecast error variance decompositions and an opportunity M-day rolling window. Fig. A1–A2 from the appendix explores robustness examinations for assessments of 150 and 250 days with rolling windows with forecast horizons of 5 and 10 days. Across all subcharts, the spillover index seems to have a comparable pattern, indicating that the entire spillover scheme isn't always sensitive to widow length or forecast horizons. Similar opportunity values have also been typical as robustness checks in numerous previous research (Diebold and Yilmaz, 2009, 2012, 2014; Chau and Deesomsak, 2014; Antonakakis and Kizys, 2015; Greenwood-Nimmo et al., 2016; Kang et al., 2017; Ando et al., 2018; Billah et al., 2022).

4.8. Impact of the GFC

The three subsequent sections investigate the evolution of energy commodities and the BRIC transfer to individual indices during the GFC, SOR, and COVID-19 pandemic and examine the global economic impact. Spillovers of return and volatility between the energy commodities and BRIC markets are shown in Tables A1 and A2 to examine the possible heterogeneous effects of the GFC on these indices. It illustrates that the relationship between return and volatility spillovers varies in the middle, lower, and upper quantiles; as markets become increasingly dependent on high/low quantiles, their relative importance for shock transmission changes dramatically.

Table A1.1 presents return connectedness between the energy and BRIC markets in the middle quantile. More specifically, the connectedness index shows that Brent, Gasoline, HO, and WTI are net spillover transmitters for all energy commodities except for Gasoil and NG. Moreover, most of the connections are in the energy source, i.e., Brent, Gasoil, Gasoline, HO, and WTI. The most robust two-way connection is between Brent and WTI. In addition, the exclusion of BRIC from other energy commodities demonstrates their safe haven properties. In contrast, except NG, all energy commodities are net spillover transmitters between the lower and upper quantiles (see Tables A1.2 & A1.3). Brent is associated with WTI, Gasoline, HO, and China in the 5th quantile in the group and is also linked with Brazil in the upper quantile (see Tables A1.2 & A1.3). Several interrelationships between China and India between the lower and upper quantiles of the BRIC market were also noted. One possible reason is that uncertainty about future energy prices increased during the GFC period, exacerbating the spillover effect. A low relationship between energy commodities and the BRIC markets was observed, intuitively indicating their nature as a safe haven. In addition, TCIs in the middle, lower, and upper (56.37%, 86.05%, and 85.29%) quantiles were similar to those reported across the period (Table 3), indicating that the highlighted spillovers of the return are stable to the system during GFC.

Under conditions of median volatility in Table A2.1, instead of a one-sided influence, the most robust reciprocal relationships can be found between Brent and Gasoil, Brent and WTI, and Brent and HO, with the first direction having a strong influence. There are moderate two-way relationships between China and Russia and between China and Brazil. Regarding volatility, the weakest correspondence was identified between energy commodities and the BRIC markets, with the link between NG and all other markets being particularly poor. From this, it can be concluded that these assets react to various extreme events and can be viewed as effective diversification tools. However, when volatility is low, the conditions indicate a different situation in which the mutual volatility relationship between most assets is relatively stronger. The linkage between energy commodities from other markets increases during low volatility conditions; a moderate gap between energy commodities and the BRIC market is still observed. The increase in connectivity with volatility noted in Table A2.2 is primarily generated by Brent, Gasoline, HO, and WTI, where the other volatility indices are net receivers of volatility. This could reflect increasing public debt concerns in some euro area countries due to high government deficits, rapidly rising sovereign debt ratios, and growing contingent liabilities from bank guarantees, which form the basis for a repeat of the financial crisis. Under the high-volatility conditions in Table A2.3, the main drivers of volatility are Brent, Gasoline, Gasoil, HO, WTI, and China. Furthermore, except for NG, energy commodities display the greatest volatility connection with other commodities, while BRIC was found to have the least effect on energy commodities. Furthermore, the TCI for the middle quantile reaches 45.22%. In the upper quantile, the intensity of reconnectivity (Table A2.3) is comparable to that estimated during the GFC in the lower quantile (Table A2.2). The state of volatility connectedness showed a higher correlation of volatility followed by low- and high-volatility conditions during the GFC.

In short, global transmission mechanisms are relatively more important for a single asset and had a much greater impact during the GFC. In contrast, there was a moderate connectedness in return and volatility spillovers between the energy commodities and the BRIC markets during the GFC, which could be interpreted as an instrument for international investors to diversify their portfolios more effectively. Moreover, policymakers benefit from a good understanding of the risk spillovers between energy and BRIC markets, since recognition of the volatility spillover connectedness can help them in taking appropriate and effective measures to safeguard stock markets from contagion during extreme and normal conditions, which is missing from previous studies (Naeem et al., 2020a; Bhanja et al., 2021; Bagheri et al., 2021; Zhang et al., 2021).

4.9. Impact of the SOR

The SOR is a renowned economic event with lasting consequences. To better understand it, Tables A3 and A4 show the impact of SOR on the returns and volatility spillovers of various BRIC markets and energy commodities between the middle, lower, and upper quantiles. According to Tables A3 and A4, the spillover was lower during the SOR period than during the GFC or COVID-19 pandemic. The low SOR connectivity indicates moderate returns and fluctuations due to the spillover between the energy market and the BRIC. Despite the varied intensity, the reciprocal changes between the energy commodity and the BRIC markets are significant (see Table A3). In contrast, the weakest transmission between these markets is observed (see Table A4).

Table A3.1 shows that Brazil, Russia, India, and NG are among the net shock recipients, while other energy markets play an essential role in shock transmission. It also shows a weak relationship between the energy market and BRIC (Brent, Gasoil, Gasoline, HO, and WTI, with BRIC and NG) and a relatively strong relationship for the others. Additionally, the graphical visualization of the lower quantiles in Table A3.2 shows a similar scenario to the lower quantile of the GFC (see Table A1), where nearly all assets are highly bidirectional. Energy commodities have the highest return connectedness on the BRIC relationship, followed by China to Brazil and India and Russia to China. The upper quantiles show some other interesting results in Table A3.3. In this scenario, there is a strong mutual influence between Brent, Gasoil, Petrol, HO, and WTI. The weakest are transmissions between BRIC and energy commodities and NG and other energies. Overall, TCI at the median reaches 51.05% during the SOR versus 56.20% during the full period, whereas at the lower and upper tails, it is 85.19% & 85.57% during the SOR versus 85.69% & 84.29% during the full period.

Table A4.1 illustrates the middle quantile index of volatility connectedness, showing poor connectivity across the system. The spillover volatility in Brazil, Russia, India, China, and NG is weak, while it is relatively more robust for Brent, Gasoil, Gasoline, and HO. The index of volatility connectedness has greater complexity in both the upper and lower quantiles (shown in Tables A4.2 and A4.3, respectively) than in the middle quantile (Table A4.1). Furthermore, they are slightly higher than those estimated at the upper quantile during the full period (Table 4.3). This indicates significantly greater connectivity across the system during the extreme condition (e.g., the SOR).

These results suggest that energy commodities and BRIC indices are more vulnerable to risk in times of crisis (low volatility); negative spillovers signify those uninformed traders dominate the entire system, and bad spillovers tend to be more contagious (BenSaïda, 2019). During the SOR, the spillover of returns in this asset market was higher in the upper quantile than in the middle and lower quantiles throughout the sample period. However, during the SOR, the spillover volatility demonstrated the opposite result. These findings suggest that shocks most likely drive the return connectedness between energy commodities and the BRIC market in the lower quantile. At the same time, financial events have a more significant impact in highly volatile conditions in the volatility spillovers. These results confirm that financial markets absorb information quickly and that a week (defined as a higher frequency) is sufficient time to transfer shocks from one asset to another (Naeem et al., 2021a).

4.10. Impact of the COVID-19 pandemic

To assess the impact of external shocks such as the COVID-19 pandemic, Tables A5 and A6 develop the relationship between returns and volatility spillovers between different energy commodities and the BRIC markets for three other quantiles (middle, lower, and upper). An investigation into the COVID-19 pandemic plan revealed some interesting aspects. The results show that the TCI for the mean quantile is 51.41%, indicating that nearly half of the total variance in the forecast errors for the 10 indices under normal conditions is due to excessive shocks in energy markets and the BRIC markets; On the other hand, under extreme conditions (lower tail and upper tail), TCI is 85.25% and 82.25%, respectively.

As shown in Table A5.1 (50th quantile), the return spillovers present intense reciprocal spillovers between Brent, Gasoil, Gasoline, HO, and WTI; however, the strongest spillover transmitters were found to be from WTI to Brent/HO, with HO having a relatively weaker impact on the WTI energy market. Interestingly, the NG and BRIC markets have at least a bidirectional connectedness with the return of the energy commodity markets. This indicates that when combined with the NG and BRIC indices during crises, the energy commodities markets provide copious opportunities to diversify hedging and portfolios. Table A5.2 shows the right tail return spillovers where the reciprocal transmission of the spillovers between the energy resource and the BRIC indices are significant. There are minimal transmissions from the NG market to the BRIC markets with low return conditions. Finally, the upper quantile (see Table A5.3) demonstrates a significant spillover of returns between energy commodities and the BRIC markets. While there is a two-way relationship between these markets, connectivity varies widely. These results may be consistent with the decline in global economic activity following the COVID-19 pandemic. This resulted in declining energy commodity markets and BRIC markets, responding to extreme price movements related to the COVID-19 public health emergency (Bissoondoyal-Bheenick et al., 2020; Yarovaya et al., 2020; Naeem et al., 2021b).

Table A6 shows the volatility of the connectedness between the energy commodities and BRIC markets during the COVID-19 pandemic in the middle, lower, and upper quantiles. As markets become increasingly dependent on the lower/upper quantiles, their relative importance for shock transmission changes dramatically. Table A6.1 shows strong volatility connectedness between some energy markets (Brent, Gasoil, Gasoline, and HO) and comparatively weak relationships for other markets, including the BRIC markets. Moreover, the lower quantile (see Table A6.2) shows high-volatility spillover transfers between the energy markets and the BRIC. In contrast, the WTI and NG markets have relatively lower spillovers transfer to the BRIC markets. Nonetheless, in Table A6.3, volatility transmission in the upper quantile increased significantly, while more moderate shocks prevailed across BRIC markets. Therefore, BRIC indices have insignificant connectedness to energy markets which are good choices for portfolio managers to hedge risks. Moreover, this finding shows that the dynamics of all volatility spillover indices react quickly to external shocks, according to previous results in the existing literature (e.g., Antonakakis et al., 2019; Ji et al., 2019; Bagheri et al., 2021; Zhang et al., 2021).

An examination of Tables A5 & A6 leads to several clear conclusions. First, the energy commodity markets show significant changes in time-varying transmission patterns. More specifically, during the COVID-19 pandemic, there was a decline in BRIC spillovers transmission to the energy commodities markets. Ahmad et al. (2018) suggested that international investors can use BRIC as a hedge and safe haven in times of uncertainty. Second, Table A5 shows that Brent and WTI transmit shocks and thus control the spillovers after the coronavirus outbreak. These results are consistent with the findings of Bhanja et al. (2021), who pointed out that the number of confirmed coronavirus cases, the general negative sentiment reported by the media, limited mobility, and government measures to restrict freedom of movement and business are strongly linked to the volatility of the crude oil market.

Similarly, the volatility spillovers (see Table A6) of energy commodities on the other BRIC indices appear minor for most of the sample period. Examination of the pairwise spillovers revealed that energy commodities dominate the BRIC indices as energy futures fall into the negative, thereby generating panic in the market. In addition, the limited mobility and lack of industrial activity due to the explosion have significantly reduced demand in the energy commodity markets, causing prices to fall as fears of a global recession grow. These results may be consistent with the decline in global economic activity following the COVID-19 pandemic. Therefore, the connectedness of both spillovers of returns and the volatilities between the middle, lower, and upper quantiles during the COVID-19 pandemic is complex.

Overall, the findings of this study can provide investors with valuable information to help them develop adequate portfolio diversification and risk management strategies. For example, portfolio managers can calculate optimal hedge ratios and weights to create a well-diversified portfolio while also considering the quantile connectivity framework between asset classes. In addition, the quantile connectedness indices show significant variability over the sample period and asset classes, indicating that portfolio managers need to adjust their hedging positions dynamically. Our study adds to the existing literature on BRIC (Naeem et al., 2020a; Bhanja et al., 2021; Bagheri et al., 2021; Zhang et al., 2021), which has considered so far mean-based return or volatility spillovers. Importantly, these studies disregarded how BRIC stock indices comove with other energy indices under normal and extreme market conditions (e.g., the GFC, SOR, & COVID-19 outbreak).

5. Conclusion

Due to the financialization of commodity markets and the globalization of financial markets, international stock and commodity markets have recently become more integrated. These developments in global asset markets have made hedging difficult and thus diminished the benefits of diversification. On the other hand, it is essential for asset allocation and portfolio risk management to understand the direction of returns and the volatility spillovers between energy commodities and the behavior of developing countries such as BRIC markets.

This study focuses on the commodity energy markets and the BRIC to highlight the quantile connectedness of the middle, lower and upper quantiles of both returns and the volatility spillovers of increasing stress levels in international financial markets. We considered energy commodities (Brent, Gasoil, Petrol, NG, and WTI) and the BRIC index to accomplish our objectives. Therefore, daily data from October 1, 2005, to July 9, 2021, covers many financial shocks and events, including the GFC, EDC, SOR, and most recent global pandemic, COVID-19, that have had an impact on global economic problems.

In this paper, quantile-based measurements are used to generate conditions for low, average, and high returns and volatility, and the main results show different levels of connectedness in the middle (50th), lower (5th), and upper (95th) quantiles. In addition, when analyzing net directional return and volatility connectedness, our results show general information (i.e., news about economic fundamentals and unforeseen events) that directly or indirectly affects uncertainty about the future development of the market segments under study. The results of the rolling analysis show that the degree of dependence of return and volatility spillovers differ over time. Interestingly, the inversion dependency of the lower quantile return/volatility spillover runs primarily parallel to the inversion dependency of the upper quantile. Hence, an extreme negative event was associated with increased stabilization of lower return/volatility condition's connectedness, combined with a concomitant increase in high-return/volatility conditions destabilizing connectedness. In addition, the spillover structure differs in the high and low quantiles compared to the middle quantile, suggesting that the development of a tail dependency structure is included when connectedness measures are estimated at the conditional mean. Therefore, quantile-based connectedness measures are recommended as a natural extension of the widely used average-based connectivity model. We also analyze dynamic returns and volatility spillovers between energy commodities and the BRIC markets affected by various financial shocks. The results show that the spillovers of the middle, lower, and upper quantiles between the Energy and BRIC markets have increased significantly and have reached unprecedented levels during the GFC, EDC, SOR, and COVID-19 outbreak. From a portfolio risk manager's perspective, our results have practical implications suggesting that understanding the dynamics of returns and volatility spillovers between energy commodities and the BRIC indices can provide an effective risk hedging model and diversification strategy in the risk phase that includes transmitter and receiver information about financial assets.

By understanding the direction and intensity of the middle, lower, and upper quantiles and the impact of spillovers sign and size on system connectedness, regulators can implement policy tools and oversight mechanisms to more effectively control the potential antagonistic effects of spillovers in the market. In this way, quantile connectedness measures can be used within the framework of careful regulatory and monitoring mechanisms to avoid possible destabilizing effects during extreme returns and volatility spillovers between energy commodities and BRIC markets.

CRediT authorship contribution statement

Mabruk Billah: Writing – original draft, Writing – review & editing, Methodology, Software, Formal analysis, Visualization. **Sitara Karim:** Writing – original draft, Writing – review & editing, Methodology. **Muhammad Abubakr Naeem:** Conceptualization, Writing – review & editing, Methodology, Software, Formal analysis, Visualization, Funding acquisition. **Samuel A. Vigne:** Writing – review & editing, Supervision, Project administration.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ribaf.2022.101680.

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