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Quantile dependencies across BRICS currency markets in time of crisis: Analysis of the Russia–Ukraine war

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ABSTRACT
This paper examines the spillovers across BRICS currency markets during the Russia–Ukraine war. We observe that the connectedness across the BRICS currency markets is stronger during than before the war and the average-based connectedness framework shows a moderate level of connectedness across the BRICS currencies. However, using a quantile approach, the level of connectedness across the currencies is much higher at both tails of the conditional distribution. Overall, the result shows that war in Ukraine affect the connectedness among the BRICS currency markets and are stronger during extreme positive and negative events such as the war, indicating that the application of the average-based framework of connectedness to BRICS currencies is inadequate and restrictive.

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1. Introduction

The ongoing war between Russia and Ukraine that started militarily on February 24, 2022, has generated serious concerns across different policy circles as the global economies are still in the process of recovering from the effect of the COVID-19 pandemic. Wars and other related acts/events pose risks that affect business cycles and constitute distortions in the financial markets (Caldara & Iacoviello, 2016). These risks are identified by monetary authorities and financial investors as significant determinants of financial market dynamics and investment decisions (Balcilar et al., 2018; Caldara & Iacoviello, 2019).

Geopolitical tensions, local and international conflicts, terrorist incidents, and various acts of war characterised by geopolitical risks have been shown to have negative macroeconomic consequences by increasing risk uncertainty in the policy and economic environment. As a result, disinvestment is increasing as economic activity is redirected from investment spending to government spending, prompting investors to 'play a waiting game' strategy until the macroeconomic environment stabilises (Balcilar et al., 2018; Caldara & Iacoviello, 2022). Geopolitical tensions have produced widespread evidence of negative consequences on the level of economic activities, investment, stock prices, capital inflows, and exchange rates (Gupta et al., 2019; Zaremba et al., 2022; Salisu et al., 2022).

The transmission mechanism between geopolitical tensions and exchange rate movements in terms of returns and volatility could theoretically occur through various channels. First, by changing the country's balance of trade dynamism, such as cutting down on international trade

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movements (Balcilar et al., 2018; Gupta et al., 2019); changing the expectations of market participants (Balcilar et al., 2017); and altering the flows of portfolio or international capital (Cheng & Chiu, 2018). War and conflict, especially between the warring parties, are never helpful for international trade. Currency is more vulnerable to the event as a result of financial sanctions. In this case, the isolation of Russia through economic sanctions places new restrictions on international trade, which will have an influence on market connections and increase currency volatility (Boubaker et al., 2022). In the event of an increase in war-related events, market participants and investors may alter the direction of their savings, which could have an impact on the exchange rates of the concerned countries and the entire world, particularly if these countries are major players in the global trade market.

Against this backdrop, the focus of this paper is to examine the extreme directional spillovers among Brazil, Russia, India, China and South Africa (BRICS) currency markets. Currency volatility is expected to rise dramatically as the BRICS economies gradually adopt a floating exchange rate regime and become more integrated into the global financial market. The extent and persistence of this volatility could lead to a crisis, affecting many key policy variables, including interest rates and return on investment, as well as posing a risk to export competitiveness, international investment portfolios, international reserves, debt payment currency value, and economic stability and growth. Russia as a member country is a major oil exporter, and any disruptions in its oil supply due to the conflict can lead to higher oil prices, which can have a ripple effect on the currency markets of other BRICS nations. For example, a rise in oil prices could strengthen the Brazilian real and South African rand, as both countries are net oil importers, while the Indian rupee and Chinese yuan could weaken, as they are net oil importers. Also, the conflict between Russia and Ukraine could also impact trade relations between the two countries, as well as with other BRICS nations. Any disruption in trade could negatively affect the currencies of the affected countries, especially if it leads to a decrease in demand for their exports. Hence, this uncertainty may pre-empt investors to flock to safe-haven assets, which could lead to a depreciation of the currencies of BRICS nations. Analysing the BRICS currency market in the face of the geopolitical tension between Russia and Ukraine is quite essential, as these countries[1] are among the top ten economies in the world based on the purchasing power parity. This trade bloc-BRICS- constitutes more than one-fourth of the land area across the globe, slightly less than half of the world's population and about one-sixth of the world's GDP (Mensi et al., 2014). In the same context, BRICS countries have garnered an appreciable increase in their trade surplus from US$369.8 billion in 2016 to US$436.9 billion in 2019. In addition, the foreign trade flows of these countries have largely improved with staggering growth in the Foreign Direct Investment (FDI) inflows and a massive improvement in the bloc's foreign exchange reserves (see, inter alia, Das & Roy, 2023). Understandably, given the financial dependence in the modern globalised world, the current and potential growth of the BRICS countries has important implications for the capitalisation of the international equity markets. All these aforementioned internalisations affect a country's exchange rates, with all member countries gradually transitioning to flexible exchange rate regimes. These currencies are largely integrated into the world's currency market, where a currency shock originating from a specific country is not idiosyncratic but can propagate to other currencies (Bekiros & Marcellino, 2013; Bouri et al., 2020). This could create a crisis in the financial market, affecting the dynamics of international portfolios investments, export competitiveness, change in international reserves and economic growth crises. A plethora of studies exists on the dynamic return and volatility spillovers in currency markets (Erdemlioglu et al., 2012; Narayan et al., 2009; Niyitegeka & Tewari, 2020; Das & Roy, 2023) and how the Russia–Ukraine war affect the financial markets (Boubaker et al., 2022; Abbassi et al., 2022; Umar et al., 2022; Pandey & Kumar, 2023; Boungou & Yati´e, 2022; Chortane & Pandey, 2022). However, the currency spillover among trade blocs in the event of a member country's crisis is unclear. The closet to our paper (see, Salisu et al., 2022; Das and Roy, 2023) focuses on BRICS but either considers the historical geopolitical risks in the case of Salisu et al.

(2022) or the comovement between the trade bloc and selected globally traded currencies in the world as in the Das and Roy (2023) study, with no emphasis on the Russia–Ukraine war.

The second contribution of this paper is the application of quantile connectedness methods, developed by Ando et al. (2022), which extends the mean-based connectedness framework of Diebold and Yilmaz (D.Y., 2012, 2014) to analyse the spillovers of the BRICS currency markets. Following the Koenker and Bassett (1978) quantile regression approach, VAR models are fitted at the 5th and 95th percentiles to examine the network spillovers estimated at extreme asymmetric shocks (Bouri et al., 2020). In essence, the magnitude of the systemic shocks may differ from the average shocks, which may even be larger, thereby implying the possibility of heterogeneous effects around the magnitude horizons and distribution of the shocks (see, inter alia, Bouri et al., 2021; Mensi et al., 2021). This approach produces better results than focusing on only the middle quantile information through the mean-based techniques (see Pandey & Sehgal, 2018; Meng & Huang, 2019; Bouri et al., 2021). In the presence of frequent market turbulence, it becomes imperative to examine the connectedness among these markets putting different market conditions and time variation into consideration. We uncover the tail dependency structure of the spillovers in the BRICS exchange rate markets using a quantile-based approach to connectedness, which helps explain the tail risk propagation in the BRICS foreign exchange markets, an important issue that has been overlooked in previous literature (Salisu et al., 2022; Das & Roy, 2023, Pandey & Sehgal, 2018; Meng & Huang, 2019).

On the one hand, the quantile-based formulation of the proposed techniques helps capture the behaviour of the markets when the market tends to be normal or at the extremes. The analysis across the different market states is further vital in inferring mere risk transmission, contagion effects, and diversification advantages, all of which aid the effective management of portfolio risks (Mensi et al., 2021). On the other hand, incorporated into these approaches is the possibility of examining the relationship across different forecast horizons, which is another way to ensure optimal portfolio management, as investors will have the right knowledge of how the markets perform over time.

We compare returns and volatility connectedness between the BRICS foreign exchange markets using intra-day data on a 30-min frequency on the exchange rates of BRICS economies. The main results show no uniformity in the pattern of connectedness in the conditional distribution's left, middle, and right tail. We observe a similar structure at both the right and left tails of the conditional distribution but significantly dissimilar to the patterns observed at the middle quantile and the conditional mean. In essence, the network of connectedness for return shocks is more pronounced at the extreme tails than conditional mean or median.

The rest of the paper is organised as follows. Section 2 describes the methodology, while the data and preliminary analysis of the paper are presented in Section 3. Section 4 provides the empirical results, and Section 5 presents the conclusion and some policy implications.

2. Methodology

2.1. Quantile VAR model

The estimation of a quantile regression model shows the dependence of y_t on x_t at every quantile τ of the conditional distribution of y_t/x_t based on Koenker and Bassett (1978) framework. This framework can be defined as:

$$Q_\tau(y_t|x_t) = x_t\beta(\tau) \tag{1}$$

where Q_τ represents the τth conditional function of y_t; the quantile τ lies between 0 and 1; x_t is a vector of explanatory variables; and $\beta(\tau)$ determines the relationship between x_t and the τth conditional quantile of y_t. Specifically, $\beta(\tau)$ is the parameter vector estimated at the

τth conditional quantile τ via the expression:

$$\hat{\beta}(\tau) = \underset{\beta(\tau)}{argmin} \sum_{t=1}^{T} (\tau - 1_{\{y_t < x_t \beta(\tau)\}}) |y_t - x_t \beta(\tau)| \quad (2)$$

Accordingly, the n-variable quantile VAR process of pth order is:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), \qquad t = 1, \ldots\ldots, T \quad (3)$$

where y_t is the n-vector of dependent variables, $c(\tau)$ and $e_t(\tau)$ represent n-vector of constants and residuals at quantile τ respectively, and $B_i(\tau)$ is the matrix of lagged coefficients of the dependent variable at quantile τ, with $i = 1, \ldots\ldots, p$. $\hat{B}_i(\tau)$ and $\hat{c}(\tau)$ are estimated by assuming that the residuals conform to the population quantile restriction, $Q_\tau(e_t(\tau)|y_{t-1}, \ldots\ldots\ldots y_{t-p}) = 0$. The population τth conditional quantile response of y is given in equation (4). The latter can be estimated on an equation-by-equation at every quantile τ.

$$Q_\tau(y_t|y_{t-1}, \ldots\ldots\ldots y_{t-p}) = c(\tau) + \sum_{i=1}^{p} \hat{B}_i(\tau) y_{t-i} \quad (4)$$

2.2. Quantile connectedness analysis

In this study, we employ the quantile VAR approach, following Ando et al. (2022), which extends the spillover framework of Diebold and Yilmaz (2012; 2014), to examine the quantile transmission mechanism among BRICS currency markets. To compute the quantile spillover metrics, we present an infinite order vector moving average (MA) in a quantile vector autoregression QVAR(p), as shown below:

$$y_t = \mu(q) + \sum_{j}^{p} \Phi_j(q) y_{t-j} + u_t(q) = \mu(q) + \sum_{i=0}^{\infty} \Omega_i(q) u_{t-i} \quad (5)$$

Following Koop et al. (1996) and Pesaran and Shin (1998), the generalised forecast error variance decomposition (GFEVD), with a forecast horizon H, is specified as follows:

$$\Theta_{ij}^{g}(H) = \frac{\sum(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(q) \sum(q) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Omega_h(q) \sum(q) \Omega_h(q)' e_i\right)}, \quad (6)$$

where e_i represents a zero vector with unity at the i^{th} position. The normalisation of each element in the decomposition matrix is given as follows:

$$\tilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{k} \Theta_{ij}^{g}(H)} \text{ with } \sum_{j=1}^{k} \tilde{\Theta}_{ij}^{g} = 1 \text{ and } \sum_{i,j=1}^{k} \tilde{\Theta}_{ij}^{g}(H) = 1 \quad (7)$$

Following Diebold and Yilmaz (2012, 2014), the spillover measures based on GFEVD are expressed as follows:

$$TO_{j,t} = \sum_{i=1,\ i\neq j}^{k} \tilde{\Theta}^{g}_{ij,t}(H) \tag{8}$$

$$FROM_{j,t} = \sum_{i=1,\ i\neq j}^{k} \tilde{\Theta}^{g}_{ji,t}(H) \tag{9}$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \tag{10}$$

$$TCI_t = \frac{\sum_{i,j=1,\ i\neq j}^{k} \tilde{\Theta}^{g}_{ij}(H)}{k-1} \tag{11}$$

$$NPDC_{ij,t} = \tilde{\Theta}_{ij,t}(H) - \tilde{\Theta}_{ji,t}(H) \tag{12}$$

In the above equations, $TO_{j,t}$ represents the aggregate impact of a shock in variable j on all the other variables. $FROM_{j,t}$ illustrates the aggregated influence of all other variables on the variable. Further, $NET_{j,t}$ indicates the difference between 'TO' and 'FROM.' A positive value suggests a net transmission effect, whereas a negative value refers to a net reception effect from other markets. Moreover, TCI_t represents the average level of total connectedness. To get a better picture of the directional spillovers, we compute the net pairwise directional spillovers (*NPDC*, as shown in Eq. 12) to explain the bidirectional connectedness between the variables. If $NPDC_{ij,t} > 0$ ($NPDC_{ij,t} < 0$), it suggests that variable j is dominating (dominated by) variable i. The connectedness analyses are based on a VAR lag order of 1, chosen based on the Bayesian information criterion (BIC) and a forecast horizon of 10. We adopt a 200- day rolling window to estimate the dynamic connectedness at quantile. The sensitivity analysis involves a window length of 250 days and a forecast horizon of 5 and 10.

3. Data and preliminary analysis

We collect intra-day data on a 30-min frequency on the exchange rates of BRICS currencies, namely the Brazilian real (BRL_USD), Russian ruble (RUB_USD), Indian rupee (INR_USD), Chinese yuan (CHY_USD), and South African rand (ZAR_USD) with respect to the US dollar, downloaded from the Thomson Reuters DataStream. To compare the performance before and during the Russia–Ukraine war, we divide the entire sample into two. The first, the pre-war era, covers the period of September 15, 2021, to February 23, 2022, while the during-war era is from February 24, 2022, to August 4, 2022. To ensure uniformity and avoid unnecessary bias in the results, we use an equal number of days for the Pre and During war periods, and only periods when all assets are traded concurrently across the different regional exchanges are considered. Hence, it would help to control for potential confounding factors that could bias the results of the analysis, improve the robustness of the analysis and increase confidence in the results.

Table 1 presents the statistical description of the returns of the data. Compared to the Pre-War era, there are obvious changes in the values of the return series during the war. Skewness values show all series are positively skewed across the board in both periods except for the *ruble*, which is negatively skewed before the war. Kurtosis statistics also reveal all series are leptokurtic for both periods. It is not surprising that the Jarque-Bera test rejects the null hypothesis of normal distribution for all the return series following the reports of both the skewness and kurtosis statistics. Hence, it justifies the need to study extreme spillovers and consider any form of asymmetry in these spillovers. Notable standard deviation values, especially for the *ruble* (RUB_USD), also suggest increased volatility attributable to the conflict. Figure 1 also corroborates this assertion as evidence suggests stronger volatility clustering following the commencement of the war on February 24,

Table 1. Descriptive statistics.

	Pre-War Era:				
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**
Mean	−0.005	0.014	0.002	−0.002	0.007
Std. Dev.	0.334	0.317	0.108	0.063	0.303
Skewness	0.153*	−1.614***	1.061***	0.447***	0.175**
	(0.081)	(0.000)	(0.000)	(0.000)	(0.047)
Ex.Kurtosis	7.561***	27.444***	18.564***	37.803***	6.058***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	1844.114***	24594.081***	11244.989***	46053.950***	1186.065***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−10.959***	−12.321***	−8.401***	−12.375***	−10.948***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	14.848***	5.219	5.673	16.524***	2.01
	(0.006)	(0.473)	(0.409)	(0.002)	(0.937)
Q2(10)	2.849	0.44	21.493***	1.336	6.125
	(0.841)	(1.000)	(0.000)	(0.982)	(0.350)
ADF Stat.	−29.776***	−27.833***	−28.398***	−30.803***	−27.927***
P.P. Stat.	−30.934***	−27.833***	−28.392***	−30.967***	−27.927***
Obs.	773	773	773	773	773
During-War Era:					
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**
Mean	0.004	−0.023	0.003	0.005	0.007
Std. Dev.	0.317	2.094	0.091	0.097	0.261
Skewness	0.145**	0.467***	0.866***	2.128***	0.354***
	(0.030)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	4.623***	11.358***	18.318***	39.978***	9.186***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	1201.550***	7272.509***	18959.272***	90513.782***	4753.691***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−1.256	−4.997***	−2.739***	−12.748***	−4.316***
	(0.209)	(0.000)	(0.006)	(0.000)	(0.000)
Q(10)	7.561	85.435***	15.136***	4.866	5.574
	(0.203)	(0.000)	(0.005)	(0.527)	(0.423)
Q2(10)	26.456***	55.504***	5.245	3.268	11.268**
	((0.000)	(0.000)	(0.470)	(0.781)	(0.038)
ADF Stat.	−37.789***	−25.329***	−39.844***	−36.599***	−36.794***
P.P. Stat.	−37.808***	−50.126***	−39.821***	−36.599***	−36.799***
Obs.	1344	1344	1344	1344	1344

Note: Unit root tests are ADF Stat.= Augmented Dickey-Fuller Statistic and P.P. Stat.= Phillips Perron statistic. [a] indicates no constant and trend, [b] represents constant without deterministic trend; [c] is the model with constant and deterministic trend as exogenous lags are selected based on Schwarz info criteria. Probability values are presented in parentheses. The significance level is represented by the superscripts *, **, and *** for 10%, 5% and 1%, respectively.

2022. Thus, the war increased the return series' variability compared to the pre-war era. Thus, justifying the need for the comparative examination of risk transmission in both periods.

Interestingly, all return series are stationary according to the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP.) unit root tests. The Ljung-Box test also indicates evidence of serial correlation for some of the return series.

4. Empirical results

This section focuses on the results of return and volatility spillovers estimated within the mean-based VAR models and the quantile-based VAR models.

4.1. Conditional mean spillover

With the standard connectedness measures estimated at the conditional mean (as in the standard model of Diebold and Yilmaz (2014)), we analyse the spillover tables for both returns and volatility

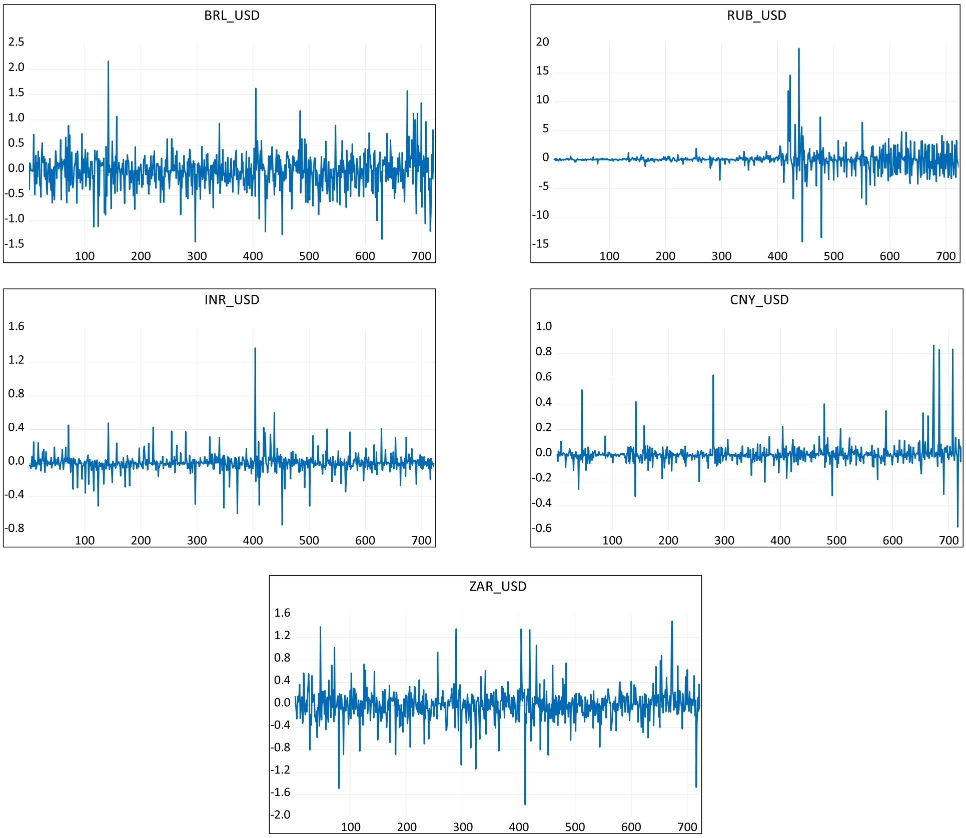

Figure 1. Trends in the returns of the assets.
Source: Compiled by the authors

of the BRICS foreign exchange markets (see Tables 2 and 3, respectively). Table 2 presents the returns spillovers computed for the *Pre-War* (Panel A) and *During-War* (Panel B) periods. Connectedness indices are computed for second order 5-variable VARs with 10-step-ahead forecasts

Table 2. Return spillovers in the mean VAR – based on the standard approach of Diebold and Yilmaz (2012, 2014).

Panel A: Pre-War Average Dynamic Connectedness						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	74.41	7.66	6.74	3.82	7.38	25.59
RUB_USD	7.28	70.98	5.99	1.76	13.99	29.02
INR_USD	6.61	6.26	72.25	5.21	9.67	27.75
CNY_USD	2.34	2.00	5.15	84.07	6.43	15.93
ZAR_USD	6.88	12.83	8.86	5.10	66.34	33.66
Contribution TO others	23.12	28.75	26.74	15.88	37.46	131.95
Contribution including own	97.52	99.73	98.99	99.96	103.80	
Net spillovers	−2.48	−0.27	−1.01	−0.04	3.80	TCI = 26.39
Panel B: During-War Average Dynamic Connectedness						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	80.64	1.10	5.04	4.02	9.19	19.36
RUB_USD	1.76	92.21	2.61	1.07	2.34	7.79
INR_USD	3.82	2.12	74.71	7.36	12.00	25.29
CNY_USD	1.75	0.80	7.37	70.83	19.26	29.17
ZAR_USD	5.99	1.31	10.64	17.56	64.51	35.49
Contribution TO others	13.31	5.33	25.66	30.01	42.79	117.10
Contribution including own	93.95	97.54	100.37	100.84	107.30	
Net spillovers	−6.05	−2.46	0.37	0.84	7.30	TCI = 23.42

Source: Compiled by the authors

Table 3. Volatility spillovers in the mean VAR – based on the standard approach of Diebold and Yilmaz (2012, 2014).

	BRL_USD	RUB_USD	INR_USD	CNY_USD	ZAR_USD	FROM others
Panel A: Pre-War Average Dynamic Connectedness						
BRL_USD	67.55	6.92	11.26	5.05	9.23	32.45
RUB_USD	5.65	60.57	15.88	7.69	10.20	39.43
INR_USD	8.89	13.73	52.33	8.83	16.23	47.67
CNY_USD	4.63	8.36	10.91	65.74	10.36	34.26
ZAR_USD	7.77	9.31	17.46	9.19	56.26	43.74
Contribution TO others	26.94	38.32	55.51	30.76	46.02	197.56
Contribution including own	94.49	98.89	107.84	96.50	102.28	
Net spillovers	−5.51	−1.11	7.84	−3.50	2.28	TCI = 39.51
Panel B: During-War Average Dynamic Connectedness						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	73.33	7.25	5.64	4.99	8.80	26.67
RUB_USD	7.20	82.45	3.83	2.69	3.83	17.55
INR_USD	4.52	3.68	67.23	12.12	12.45	32.77
CNY_USD	3.81	2.79	12.25	64.29	16.85	35.71
ZAR_USD	6.64	4.54	11.33	16.04	61.45	38.55
Contribution TO others	22.18	18.25	33.05	35.83	41.94	151.25
Contribution including own	95.51	100.71	100.28	100.12	103.39	
Net spillovers	−4.49	0.71	0.28	0.12	3.39	TCI = 30.25

Source: Compiled by the authors

for both periods. Starting with the Pre-War era, the TCI value of 26.39 indicates that, on average, 26.39% of the forecast error variance in one currency can be attributed to the innovations in all others. Furthermore, the net directional spillovers reveal a moderate spillover effect across the BRICS currency markets, with all significantly giving and receiving. Notably, the Dynamic Connectedness results show that on average, *Rand* (3.80) is the only net shock giver; implying that it gives more than it receives while *Brazilian real* (−2.48), *Rupee* (−1.01), *Ruble* (−0.27), and *Yuan* (−0.04) are net shock receivers, as they receive more than they transmit. Implying that the *Rand* shows the weakest vulnerability to idiosyncratic shocks from other currencies of the BRICS market, it is, therefore, suitable for investors willing to obtain their targeted returns through minimal risk exposure. *Russian Ruble* & *South African Rand*, *Indian Rupee* & *South African Rand*, and *Russian Ruble* & *Brazilian Real* show evidence supporting strong bi-directional relationships.

However, TCI shrinks considerably during the war to 23.42%, probably due to the effect of the Russia–Ukraine war and the strong sanctions on Russia. As we see, the *Ruble* is least subject to return spillovers from other currencies, given that it has the largest proportion of returns explained by itself and contributes least to spillovers in other currencies. One of the factors that drive economic ties between the BRICS is the level of trade and investment. However, due to increased sanctions on Russia, the level of trade and investment between Russia and other BRICS countries is reduced, decreasing the overall connectedness between these markets. Furthermore, following increased uncertainty and geopolitical risk, investors' willingness is affected markets, leading to a decline in capital flows and increase market volatility, which also contributes to reduced overall connectedness between BRICS currency markets.

Indian Rupee and Chinese Yuan have now transformed into net receivers of shocks perhaps due to tight trade relations with Russia. The South African Rand remains the highest net transmitter of shocks during the war era; this can be attributed to the fact that it is essentially a commodity currency driven by the sale of gold which is often sought after for its haven properties during periods of crisis.

Comparing the results of the return spillovers with the volatility spillovers, we notice a significant elevation in the volatility TCIs for both periods. For instance, we record a pre-war volatility TCI of 39.51% compared to 26.39% for the return spillovers. By implication, on average, 39.51% of the volatility forecast error variance in one currency can be attributed to the innovations in all others in the BRICS foreign exchange market. Having higher Volatility TCI compared to Return TCI can be attributed to the fact that market shocks and volatility are often the primary drivers of connectedness among financial assets. During periods of high volatility, investors may seek to reduce their exposure to risk, leading to increased correlation among asset prices and a higher degree of connectedness among financial assets, as measured by Volatility TCI.

Similar to the results presented for the returns spillover (see Table 2), the *Russian Ruble's* contribution to volatility in other BRICS foreign exchange markets reduced significantly during the war, accounting for just 17.5% of volatility forecast error variance in the BRICS foreign exchange market, closely followed by the *Brazilian Real* with about 26.67%. This can be attributed to a decline in demand for emerging market currencies during times of geopolitical risk and uncertainty, reduced financial integration between Russia and other BRICS countries, and the potential implementation of stabilisation policies by the Russian government. Also, regarding volatility transmissions, the Indian rupee shows the weakest vulnerability to idiosyncratic shocks from other currencies of the BRICS foreign exchange market before the war, being the highest net giver, followed remotely by the Rand. However, during the war, the *Yuan* and the *Ruble* also became net transmitters of shocks, while the *Brazilian Real* remains a net shock receiver.Table 3

4.2. Quantile spillovers

We report the results of the returns (Table 4) and volatility (Table 5) spillovers within the BRICS foreign exchange market following a quantile connectedness approach for the *Pre-War* and *During-War* eras. First, we examine the results of the return spillovers presented in Table 4. The estimated connectedness measures at the conditional median (q = 0.5) based on quantile VAR models are reported in Panel A for both periods. There is evidence of high similarity with the connectedness measures estimated at the mean and reported in Table 2. Overall, the TCI for the *Pre-War* and *During War* reaches 26.04% and 21.50%, respectively, marginally lower than the conditional mean results for both periods. To this end, it is crucial to distinguish between the extreme return spillovers associated with negative shocks from those associated with positive shocks; we estimate the connectedness measures at the extreme lower and extreme upper tails.

First, it is clear from Table 4 that there are excess return spillovers in the tails relative to the mean and median. The TCI at the extreme lower quantile (q = 0.05) for the *Pre-War* and *During War* periods are 67.73% and 69.11%, respectively, whereas it is 67.06% and 68.90%, respectively, at the extreme upper quantile (q = 0.95). These values are higher compared to only 39.51% and 30.25% recorded for the *Pre-War* and *During War* periods, respectively, for the conditional mean. These results highlight the higher impact of extreme shocks on the system of return spillovers. Notably, the contributions to others and from others in both the left and right tails are much stronger than those for the mean or median. This is because extreme events can have a disproportionate impact on financial markets, leading to larger spillover effects at the upper and lower tails of the return distribution.

Furthermore, the net receivers and transmitters of spillovers differ from those shown in Table 2. For example, at the left tail of the conditional distribution, the net transmitters of return spillovers are the *Rand* and *Rupee*. Interestingly, the *Yuan* and *Ruble* remain net receivers while the *Rand* is a net transmitter of shocks across all quantile-based connectedness measures due to the fact that it is essentially a commodity currency driven by the sale of gold which is often sought after for its haven properties during periods of crisis. As expected, we also observe a stronger connectedness at the 5th quantile compared to other quantiles horizons, given that connections among markets are stronger under stress periods than in normal periods (e.g., Ang & Bekaert, 2002). However, the variation in the TCI between lower/upper quantiles and the middle quantile implies that the strength of connectedness rises with shock size for both extreme negative and extreme positive shocks. This result follows the findings of (Londono, 2019), which highlight the spillover of extreme events in both upper and lower quantiles.

On the other hand, compared to results obtained for the return spillovers, volatility spillover results (Table 5) reveal evidence of stronger connectedness among the BRICS foreign exchange market for both periods, especially considering the middle and upper quantiles. However, the

Table 4. Return spillovers in the quantile VAR.

PANEL A: QUANTILE VAR (MEDIAN Q = 0.5)						
Pre-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	75.37	7.62	6.86	2.76	7.39	24.63
RUB_USD	7.29	71.24	5.96	1.79	13.72	28.76
INR_USD	6.69	6.03	72.82	4.93	9.54	27.18
CNY_USD	2.58	1.89	5.35	83.89	6.29	16.11
ZAR_USD	6.87	12.83	8.76	5.03	66.51	33.49
Contribution TO others	23.43	28.36	26.94	14.51	36.94	130.18
Contribution including own	98.80	99.60	99.75	98.40	103.45	
Net spillovers	−1.20	−0.40	−0.25	−1.60	3.45	TCI = 26.04
During-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	85.61	0.52	4.03	1.98	7.86	14.39
RUB_USD	0.67	95.24	2.09	0.70	1.30	4.76
INR_USD	3.47	1.84	75.55	7.36	11.78	24.45
CNY_USD	1.71	0.61	7.12	71.37	19.19	28.63
ZAR_USD	5.94	1.25	10.42	17.66	64.73	35.27
Contribution TO others	11.80	4.22	23.66	27.69	40.13	107.49
Contribution including own	97.40	99.47	99.21	99.06	104.86	
Net spillovers	−2.60	−0.53	−0.79	−0.94	4.86	TCI = 21.50
PANEL B: QUANTILE VAR (LOWER QUANTILE Q = 0.05)						
Pre-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	32.83	18.04	16.04	14.19	18.90	67.17
RUB_USD	17.97	31.12	15.96	13.77	21.18	68.88
INR_USD	16.36	15.94	32.57	15.76	19.36	67.43
CNY_USD	15.16	14.08	16.48	35.48	18.79	64.52
ZAR_USD	17.59	19.49	17.51	16.07	29.34	70.66
Contribution TO others	67.08	67.56	65.99	59.79	78.24	338.66
Contribution including own	99.91	98.68	98.56	95.28	107.58	
Net spillovers	−0.09	-1.32	-1.44	-4.72	7.58	TCI = 67.73
During-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	30.90	16.70	17.23	16.05	19.12	69.10
RUB_USD	17.83	33.37	16.76	15.68	16.37	66.63
INR_USD	17.02	16.16	30.31	17.05	19.46	69.69
CNY_USD	15.27	15.38	17.53	31.19	20.64	68.81
ZAR_USD	18.11	15.36	18.30	19.56	28.67	71.33
Contribution TO others	68.22	63.61	69.81	68.34	75.59	345.57
Contribution including own	99.12	96.97	100.12	99.53	104.26	
Net spillovers	−0.88	−3.03	0.12	−0.47	4.26	TCI = 69.11
PANEL C: QUANTILE VAR (UPPER QUANTILE Q = 0.95)						
Pre-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	31.85	17.83	17.27	14.30	18.74	68.15
RUB_USD	18.31	33.47	16.23	12.05	19.94	66.53
INR_USD	17.35	15.92	32.52	15.42	18.79	67.48
CNY_USD	15.50	13.06	17.16	36.05	18.23	63.95
ZAR_USD	17.99	18.37	17.82	15.02	30.80	69.20
Contribution TO others	69.15	65.19	68.48	56.79	75.70	335.31
Contribution including own	101.00	98.66	101.00	92.84	106.50	
Net spillovers	1.00	−1.34	1.00	−7.16	6.50	TCI = 67.06
During-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	29.71	16.50	17.78	16.45	19.57	70.29
RUB_USD	17.62	34.52	16.32	15.33	16.21	65.48
INR_USD	17.68	15.12	30.99	17.02	19.19	69.01
CNY_USD	15.90	14.91	17.07	31.00	21.12	69.00
ZAR_USD	18.05	14.38	18.36	19.95	29.26	70.74
Contribution TO others	69.25	60.91	69.53	68.75	76.08	344.52
Contribution including own	98.96	95.43	100.52	99.75	105.34	
Net spillovers	−1.04	−4.57	0.52	−0.25	5.34	TCI = 68.90

Source: Compiled by the authors

Table 5. Volatility spillovers in the quantile VAR.

PANEL A: QUANTILE VAR (MEDIAN Q = 0.5)						
Pre-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	62.50	8.04	12.73	6.39	10.35	37.50
RUB_USD	6.80	56.08	16.96	8.99	11.17	43.92
INR_USD	9.89	14.81	48.38	10.22	16.70	51.62
CNY_USD	6.12	9.70	12.51	60.08	11.59	39.92
ZAR_USD	8.63	10.55	18.08	10.23	52.51	47.49
Contribution TO others	31.44	43.09	60.29	35.83	49.81	220.46
Contribution including own	93.94	99.17	108.66	95.91	102.32	
Net spillovers	−6.06	−0.83	8.66	−4.09	2.32	TCI = 44.09
During-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	74.39	7.16	5.39	4.89	8.17	25.61
RUB_USD	7.55	78.44	4.77	3.56	5.68	21.56
INR_USD	5.60	4.30	62.82	13.61	13.68	37.18
CNY_USD	4.17	3.28	13.46	61.19	17.90	38.81
ZAR_USD	6.69	4.66	12.58	17.15	58.92	41.08
Contribution TO others	24.00	19.40	36.20	39.21	45.43	164.25
Contribution including own	98.38	97.84	99.02	100.40	104.35	
Net spillovers	−1.62	−2.16	−0.98	0.40	4.35	TCI = 32.85
PANEL B: QUANTILE VAR (LOWER QUANTILE Q = 0.05)						
Pre-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	43.30	13.35	15.79	10.36	17.20	56.70
RUB_USD	12.76	41.58	18.05	11.58	16.03	58.42
INR_USD	14.02	16.66	38.34	12.12	18.87	61.66
CNY_USD	11.17	12.80	14.49	46.25	15.29	53.75
ZAR_USD	15.28	14.81	18.89	12.71	38.31	61.69
Contribution TO others	53.23	57.61	67.22	46.77	67.40	292.23
Contribution including own	96.53	99.19	105.55	93.03	105.71	
Net spillovers	−3.47	−0.81	5.55	−6.97	5.71	TCI = 58.45
During-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	50.32	13.06	11.93	9.87	14.82	49.68
RUB_USD	13.58	52.27	11.19	9.41	13.55	47.73
INR_USD	10.43	9.51	44.15	17.21	18.70	55.85
CNY_USD	8.79	8.12	17.40	44.39	21.30	55.61
ZAR_USD	12.07	10.66	17.27	19.45	40.55	59.45
Contribution TO others	44.86	41.35	57.79	55.94	68.37	268.32
Contribution including own	95.19	93.62	101.94	100.33	108.92	
Net spillovers	−4.81	−6.38	1.94	0.33	8.92	TCI = 53.66
PANEL C: QUANTILE VAR (UPPER QUANTILE Q = 0.95)						
Pre-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	24.11	17.09	18.52	18.43	21.85	75.89
RUB_USD	18.05	23.02	19.10	17.42	22.42	76.98
INR_USD	19.16	17.50	24.87	16.00	22.46	75.13
CNY_USD	17.74	17.44	18.08	26.15	20.59	73.85
ZAR_USD	19.24	17.38	19.08	17.10	27.20	72.80
Contribution TO others	74.19	69.41	74.78	68.96	87.32	374.66
Contribution including own	98.30	92.42	99.65	95.10	114.52	
Net spillovers	−1.70	−7.58	−0.35	−4.90	14.52	TCI = 74.93
During-War						
	BRL_USD	**RUB_USD**	**INR_USD**	**CNY_USD**	**ZAR_USD**	**FROM others**
BRL_USD	25.94	20.91	18.93	15.69	18.54	74.06
RUB_USD	22.35	24.19	19.33	16.12	18.01	75.81
INR_USD	22.20	20.12	21.84	16.85	18.99	78.16
CNY_USD	20.45	20.81	19.79	19.69	19.26	80.31
ZAR_USD	22.69	20.68	19.07	16.94	20.63	79.37
Contribution TO others	87.69	82.51	77.11	65.59	74.80	387.71
Contribution including own	113.63	106.70	98.95	85.28	95.43	
Net spillovers	13.63	6.70	−1.05	−14.72	−4.57	TCI = 77.54

Source: Compiled by the authors

Ruble's vulnerability weakens at the upper quantile during the war. Counter-sanction measures, potential implementation of stabilisation policies by the Russian government, reduced selling pressure from market participants during extreme events, and the influence of other factors that affect the demand for the Ruble during periods of heightened geopolitical risk and uncertainty may explain these results. For instance, the United States and the European Union imposed economic sanctions on Russia in response to its annexation of Crimea and involvement in the conflict in Ukraine. These sanctions included restrictions on trade and investment, as well as asset freezes and travel bans on individuals and entities involved in the conflict. The impact of these sanctions on the Russian economy and financial markets led to increased volatility and spillover effects to other emerging market currencies, including those of the BRICS countries. Russia responded to these sanctions by implementing counter-sanctions on several countries, including bans on imports of certain goods and restrictions on travel and financial transactions. These counter-sanctions further contributed to the volatility spillover effects, as they disrupted global supply chains and trade flows, leading to increased uncertainty and risk aversion among investors.

Figure 2 and 3 present the network visualisation of pairwise spillovers at the middle, lower and upper quantiles among the five (5) BRICS currencies based on Tables 4 and 5, respectively. Generally, the network of return connectedness at the middle quantile shows a weak system-wide connectedness for both returns and volatility spillovers during the pre and during-war periods. At the upper and lower quantile, the network of return connectedness is more complex than in the middle quantile, reflecting a much stronger system-wide connectedness. The graphical visualisation

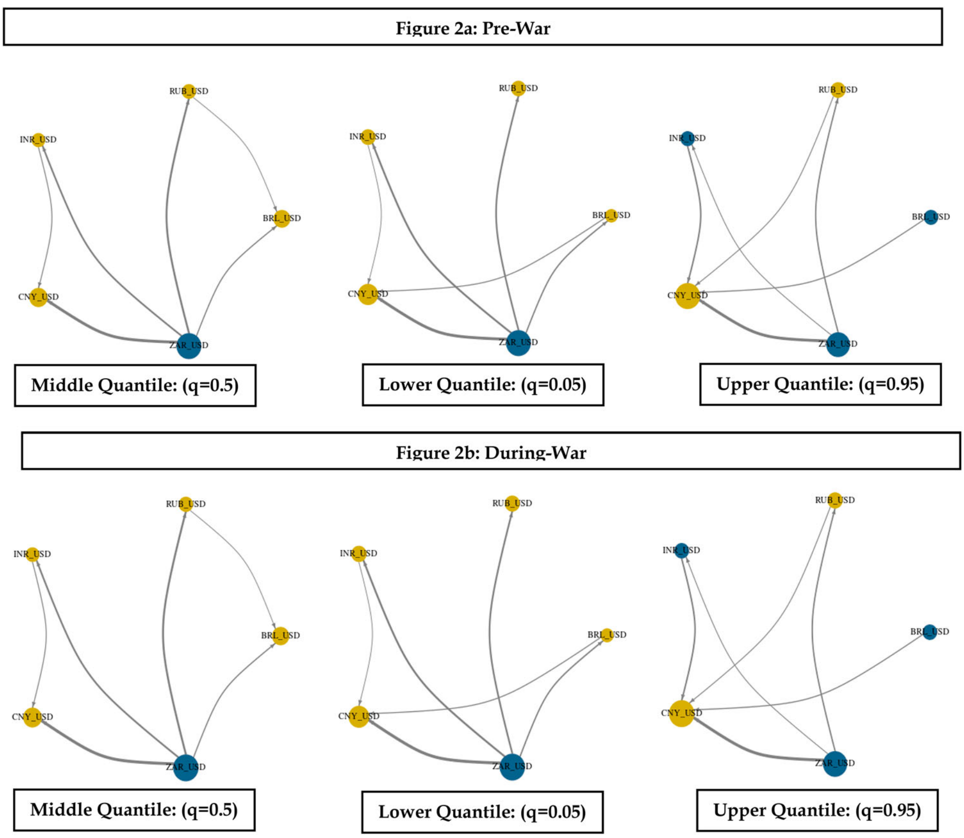

Figure 2. Network of Return Spillovers among BRICS currencies.
Source: Compiled by the author
Note: Blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents the weighted average net total directional connectedness

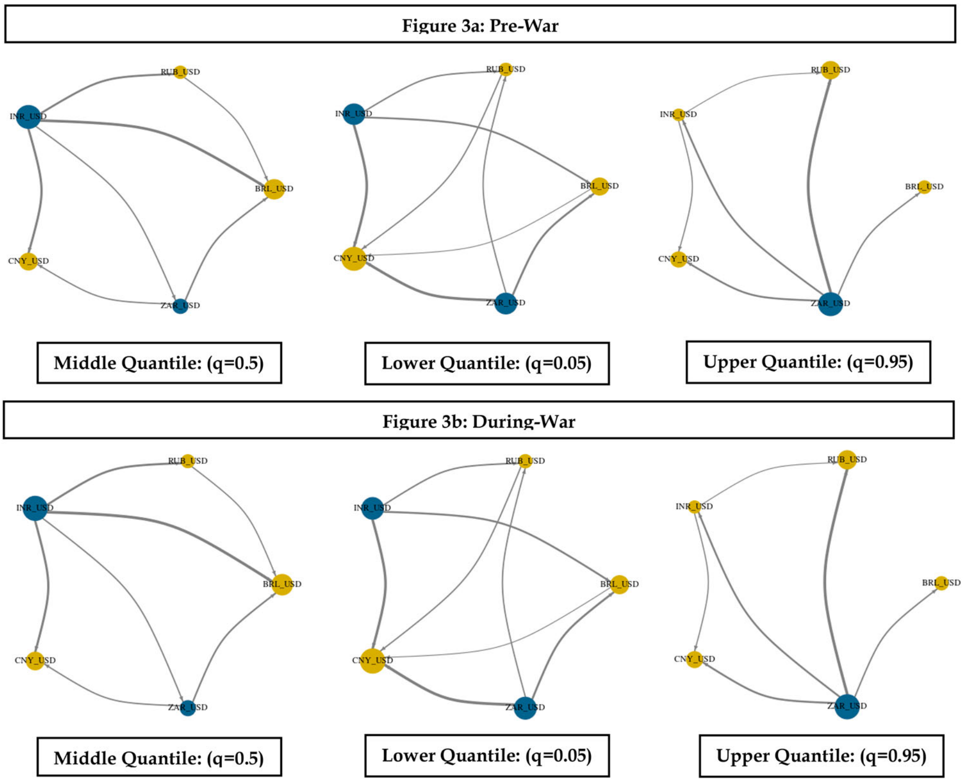

Figure 3. Network of volatility spillovers among BRICS currencies.
Note: Blue (yellow) nodes illustrate the net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. The size of nodes represents the weighted average net total directional connectedness

of pairwise return spillovers is consistent with the results in Tables 4 and 5. Our findings show that there is stronger connectedness at the lower quantile than other quantiles for the returns spillovers. In contrast, volatility connectedness is strongest at the upper quantile.

We can infer the following from our findings. First, at extreme events that justify the use of the QVAR, during war connectedness is significantly higher than pre-war period across the returns and volatility spillovers at lower and higher quantiles. This result corroborates the advantages of the quantile-based connectedness framework in measuring extreme events to produce a greater connectedness index at both left and right tails of the conditional distribution relative to the average-based estimator of the Diebold and Yilmaz (2012, 2014) framework. Above all, our results show that the return and volatility connectedness across the BRICS exchange currency markets are stronger during extreme negative and extreme positive events. This suggests that the Diebold and Yilmaz (2012, 2014) framework of connectedness is too restrictive and inadequate, especially when considering a geopolitical tension/an extreme event like the Russia–Ukraine War. The connectedness index for the returns and volatility spillovers for the average-based approach shows that Pre-War connectedness is higher than during the war, albeit too close to make a call.

4.3. Sensitivity analysis

To validate our analysis, we conduct sensitivity analyses of our quantile spillover analysis by considering an alternative daily rolling window and forecast horizon. So far, our analysis has been centred on using a window length of 200 days and a forecast horizon of 10. This section considers the robustness tests for the 250-day rolling window estimates with a forecast horizon of 5 days. The analysis is done to characterise the behaviour of the conditional lower, median, and upper quantiles relative to our previous window length of 200 days. The results[2] show no significant difference in the pattern of the return spillover index as estimates are robust to the rolling window and forecast horizon selection. Notably, there is evidence of substantial dependence in the tails. Hence, the network of connectedness estimated at the conditional median does not show the degree of connectedness associated with extreme shocks. Our results are not sensitive to the size of the window and the selection of the forecast horizon.

5. Conclusion

This paper extends the mean-based VAR connectedness framework of Diebold and Yilmaz (2012, 2014) to the quantile connectedness framework to distinguish the system of connectedness at low, middle and high quantiles of the conditional distribution, comparing the Pre-War and during War periods. We compare returns and volatility connectedness between the BRICS foreign exchange markets using intra-day data on a 30-min frequency on the exchange rates of BRICS economies. The main results show no uniformity in the pattern of connectedness in the conditional distribution's left, middle, and right tail of the conditional distribution. We observe a similar structure at both the right and left tails of the conditional distribution but significantly dissimilar to the patterns observed at the middle quantile and the conditional mean. In essence, the network of connectedness for return shocks is more pronounced at the extreme tails than conditional mean or median.

Our findings show a stronger connectedness at the lower quantile than other quantiles considering the return spillovers. In comparison, volatility connectedness is strongest at the upper quantile, suggesting that extreme adverse events are connected to an increase in stabilising lower-tail dependence coupled with a concurrent upsurge in destabilising upper-tail dependence. The evidence of the extreme return and volatility shocks on the right and left tails provides concrete justification for tail dependencies within the system of connectedness in the BRICS foreign exchange markets. Therefore, monitoring and regulatory efforts should pay more attention to extreme events rather than average shock events only, as failure to do so may lead to formulating and implementing ineffective policies aimed at stabilising the foreign exchange market during turbulent periods.

From a policy perspective, stronger volatility connectedness at the upper quantile in the BRICS currency market indicates the need for policymakers to prepare for extreme events that can significantly impact currency values. In light of the ongoing Russia–Ukraine War, political tensions and market uncertainties could increase volatility in the BRICS countries' currencies. Therefore, policymakers must implement measures to mitigate such events' impact. Additionally, heightened interdependence during times of extreme stress means that policymakers in the BRICS countries must coordinate their responses to prevent widespread contagion effects. Investors should also be cautious, diversify their portfolios and develop strategies to manage risks associated with high volatility connectedness during periods of market stress. Overall, policymakers and investors should be prepared to manage the risks associated with high volatility connectedness to prevent significant impacts on currency values.

Notes

1. The International Monetary Fund (IMF, October 2019) report shows that four out of the BRICS countries are among the top ten countries in the world based on the purchasing power parity adjusted in terms of the nominal Gross Domestic Product (GDP).
2. Available on request from the authors.

Disclosure statement

No potential conflict of interest was reported by the authors.

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