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Exploring the Time-varying Connectedness and Contagion Effects among Exchange Rates of BRICS, Energy Commodities, and Volatilities

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ABSTRACT

This paper investigates the total and net directional connectedness of the energy market and currency market amid volatilities (local and international) in BRICS setting for the period May 7, 2012 to March 31, 2022. The Time-varying parameter Vector Autoregression connectedness approach is specifically employed. We reveal that the average value of the total connectedness index is 46.91%, for the specific network of energy commodities, currency rates, and volatilities. Also, from the averaged dynamic connectedness, the global energy commodity index demonstrated the most transmitter of shocks. Conversely, BRICS currency markets (except for Brazilian Rubble) and most implied energy volatilities and realised exchange rate volatilities were net receivers of shocks. Moreover, the total connectivity indices were observed to vary substantially with strong susceptibility to crisis periods, especially, the COVID-19 pandemic. We advocate that most volatilities were consistent net transmitters across time as indicated by the net directional connectedness. The findings imply that in a network of energy commodities, exchange rate, and volatilities, risk minimisation is enhanced to boost investors' confidence across time.

Keywords: Time-Varying, Heterogeneity, Volatility Spillover, Adaptive market hypothesis, Energy commodities
JEL Classifications: G10; G15; G19; O13

1. INTRODUCTION

Assessing the size and direction of the net transmission effects during economic crises can assist economic agents such as investors to make informed investment decisions and policymakers to formulate accurate policies to restore financial stability (Bouri, Cepni et al., 2021). This is particularly pertinent during disastrous events such as the COVID-19 pandemic, wherein global economic and financial instabilities intensify, unemployment rates worsen, and energy and financial markets are highly volatile. Events like COVID-19 have induced research interest in the directional volatility and return network connectedness of commodity and financial markets. Investigating these matters is necessary for formulating regulations, managing risk, and allocating assets.

For instance, investors may utilise the net volatility transmission information to hedge or diversify their portfolios (Troster et al., 2019). This article contributes to the existing literature that focuses on the impact of economic events (Baig et al., 2020; Baker et al., 2020; Haddad et al., 2020; Sharif et al., 2020) by investigating the time-varying return and volatility network connectedness of energy, currency returns and volatilities. Hence, we assess the degree to which the connectedness in these markets responds to the unprecedented devastating shocks such as the Eurozone crises, the peak of the Euromigrant, BREXIT, US-China trade tension, COVID-19 pandemic, among others, across time for effective policy and investment decisions.

This study has a particular interest in energy and currency markets because energy commodities are among the most tradable commodities in the global market and unavoidable inputs in the production process for goods and services, while exchange rates play a bigger role in international trade (Senadza & Diaba, 2018). Furthermore, studies such as Ji et al. (2019) suggest a strong link between exchange rates and investment returns, and energy prices. According to Antonakakis and Kizys (2015), the volatility in energy and exchange rates can spread across commodity markets and affect the competitiveness and stability of the country. Considering the connectedness between energy and the currency market, exchange rates are perceived to be more responsive since energy has more characteristics of marketisation than other commodities (Ma et al., 2019a; Ji et al., 2019b).

Additionally, the choice of BRICS countries in this paper rests on their significance in the world trade of energy commodities as documented in the BRICS Energy Research Cooperation Platform (ERCP) report (2020). According to this report, Russia is the third biggest producer and consumer of energy commodities after China and the United States of America, and its production and consumption of energy account for about 10% and 5% of the world, respectively. China reached about 460 million tons (10% year-on-year increase) in 2018, ranking in the first position in the world, while China's natural gas production reached 160.3 billion cubic meters (4.2% of the world's total increase), which pushed China to rank number 6 globally. India is the net importer and number three largest consumer of energy following the US and China. Brazil is the net exporter of energy resources and produced about 306.8 million toe of primary energy in 2018. Although South Africa is the net export of energy resources, supplying above 45 million tons of coal annually to the global markets, it is also the second-largest energy consumer in Africa. However, South Africa imports most of the natural gas and oil.

Considering sample countries' exchange rate policies as a significant factor that determines exchange rate behaviours, the IMF (2009) proclaims that the BRICS countries have implemented floating exchange rate regimes, with China and Russia using a controlled floating regime whereas Brazil, India, and South Africa employ a free-floating regime. Das (2019) asserts that in July 2005, China switched from a fixed exchange rate regime to a controlled flexible exchange rate regime. According to Jiang (2019), Brazil switched from a fixed exchange rate system to a flexible exchange rate regime as a result of the financial crisis and balance of payments imbalance that hurt the Brazilian economy. In 1993 after high levels of Rubble volatility against the US Dollar, Russia changed from a free-floating regime to a managed exchange rate regime in July 1995. After a decade of India suffering from current account deterioration, currency reserves depletion, exchange rate depreciation pressure, and widening trade deficit and external debt, the Indian government and the monetary authorities adopted a floating exchange regime in 1993 (Lu and Chai, 2011; Jiang, 2019). Russia is one of the BRICS members that has seen the most unstable economy. Early in 1998, Russia adopted a fixed exchange rate of 6.2 Roubles to 1 US Dollar to stabilize its domestic price levels. However, due to difficulties for Russia to maintain the exchange Rubble-US Dollar peg at the targeted level, the Russian government switched to managed exchange rate regime in September 1998. After the end of apartheid, South Africa changed from a dual exchange rate system to a managed floating exchange rate system in 1995. In 2000, managed exchange rate regime was changed to a free-floating regime. All BRICS countries have gone from a fixed exchange rate policy to a managed floating exchange rate regime, and the majority have advanced to a free-floating regime. A flexible exchange rate can withstand economic shocks, but in any regime, flexibility is typically accompanied by volatility. The BRICS economies themselves could experience economic instability as a result of the high volatility among connected economies (Rogoff, 1999). This addresses, in part, the need of examining shocks transmission among BRICS' exchange rate returns and volatilities across time.

The previous studies investigated the connectedness, volatility effects, and contagion across markets by applying models such as conditional correlation, GARCH/EGARCH (Ahmed et al., 2016), the autoregressive distributed lag (ARDL) (Villarreal-Samaniego, 2021), Granger-causality (Bal and Rath, 2015), the approach of Diebold and Yılmaz (2012; 2014), etc. The application of the wavelet approaches has also been well documented in prior studies (Agyei et al., 2022; Asafo-Adjei, Adam, Darkwa, 2021; Asafo-Adjei, Adam et al., 2022; Asafo-Adjei et al., 2020; Amoako et al., 2022; Boateng et al., 2022; Kyei et al., 2023; Owusu Junior et al., 2021, etc.). A plethora of studies have also been conducted using the entropy approach (Asafo-Adjei, Frimpong et al., 2022; Asafo-Adjei, Owusu Junior & Adam, 2021; Bossman et al., 2022; Bossman, 2021; Qabhobho et al., 2022, etc.).

Different from these studies, our empirical study employs the TVP-VAR approach to address the research objective which captures a time-varying variance-covariance structure and evolution in the data for several financial time series simultaneously to enhance the effective degree of integration. This is necessary to respond to the heterogeneity of the financial market, (Müller et al., 1993), adaptiveness (Lo, 2004) and competitiveness (Owusu Junior et al., 2021). Again, there is no need to change the rolling-window size or discard observations when computing dynamic measures of network connectivity because rolling-window analysis is not required and this model is less prone to outliers.

Two studies closely related to our study that used the Time-varying Parameter Vector Autoregression (TVP-VAR) approach are Liu et al. (2020) and Singh et al. (2018) paid attention to the implied volatility of crude oil and developed countries' exchange rates. Different from this study, the current study focuses on the BRICS, which are emerging economies, and extends the data to cover the influence of the catastrophic event of the COVID-19 pandemic period, the period in which we have seen high instabilities in many commodities and financial markets. Additionally, the current study inculcates the spillover effects of realised volatilities from the exchange rate returns of BRICS in addition to the implied volatilities from the energy markets amid the energy commodities returns. This allows investigating whether local or international shocks matter in such a network of interconnectedness.

We discovered that the total connectedness index (TCI) for the particular network of energy commodities, currency rates, and volatilities had an average value of 46.91%. Additionally, the global energy commodity index showed to be the greatest shock transmitter based on the averaged dynamic interconnectivity. In contrast, the majority of implied energy volatility, the realized exchange rate volatility, and the BRICS currency markets (apart from the Brazilian Rubble) were net recipients of shocks. Also, it was observed that the overall connectivity indices changed dramatically throughout the study sample period, showing great sensitivity to crisis periods, particularly the COVID-19 pandemic.

The rest of this essay is structured as follows. We provide the data and lay out the empirical procedures used in the study in Section 2. In Section 3, we present the study's results and cover the pertinent justifications. The conclusion, policy implications, and suggestions are presented in Section 4.

2. METHODOLOGY

2.1. TVP-VAR

The TVP-VAR of Antonakakis et al. (2018) and Antonakakis et al. (2020) is specifically used in this work to address the time-varying connection among the financial assets. It integrates the work of Diebold and Yilmaz (2012) and Koop and Korobilis (2014) by incapacitating the burden of (a) losing precious observations, (b) arbitrarily rolling window size selection in most cases, and (c) sensitivity to outliers as indicated by Antonakakis et al. (2020). The TVP-VAR model of the lag length of order one indicated by the Bayesian information criterion (BIC) is estimated as

$$y_t = B_t y_{t,1} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0, r_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) \qquad v_t \mid \Omega_{t-1} \sim N(0, \rho_t) \tag{2}$$

Where y_t, y_{t-1} and ε_t are K × 1 dimension vector, but ε_t is of independent and identically distributed disturbance, and B_t and r_t denote K × K dimensional matrices. $vec(B_t)$ and v_t are $K^2 \times 1$ dimensional vectors while ρ_t is a $K^2 \times K^2$ dimensional matrix. Ω_{t-1} demonstrates all available information until t−1. This model makes it possible for all parameters B_t and the relationship across series to fluctuate with time. It is worthy of note also that the variance-covariance matrices (r_t, ρ_t) fluctuate over time. This has been proved by a plethora of studies that variance-covariance is time-varying regarding the heterogeneous nature of markets and their participants as well as investment risk in the context of financial markets.

Generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD), which are based on the time-varying coefficient and time-varying variance-covariance matrices retrieved from the TVP-VAR, were developed by Koop et al. (1996), Pesaran and Shin (1998), and Diebold and Yilmaz (2014). Therefore, using the Wold representation theorem, the TVP-VAR must be converted into its vector moving average (VMA) representation, as illustrated below:

$$y_t = \Phi'\left(\Upsilon_t\left(Z_{t-2} + \xi_{t-1}\right) + \xi_t\right) \tag{3}$$

$$= \Phi'(\Upsilon_t\left(Z_{t-3} + \xi_{t-2}\right) + \xi_{t-1}) + \xi_t) \tag{4}$$

$$\vdots \tag{5}$$

$$\Phi'(\Upsilon_t^{k-1} Z_{t-k-1} + \sum_{j=0}^{k} \Upsilon_t^j \xi_{t-j}) \tag{6}$$

Where y_t is a $m \times m$ dimensional matrix, ξ_t is $m \times m$ dimensional vector whereas Φ is an $m \times m$ dimensional matrix,

As k approaches ∞, taking the limit yields

$$y_t = \lim_{k\to\infty} \Phi'\left(\Upsilon_t^{k-1} Z_{t-k-1} + \sum_{j=0}^{k} \Upsilon_t^j \xi_{t-j}\right) = \sum_{j=0}^{\infty} \Phi' \Upsilon_t^j \xi_{t-j}, \tag{7}$$

following,

$$y_t = \sum_{j=0}^{\infty} \Phi' \Upsilon_t^j \Phi \tau_{t-j} \qquad \Lambda_{jt} = \Phi' \Upsilon_t^j \Phi \tag{8}$$

$$y_t = \sum_{j=0}^{\infty} \Lambda_{jt} \tau_{t-j} \tag{9}$$

Where an $m \times m$ dimensional matrix is Λ_{jt}.

The GIRFs($\Psi_{ij,t}^{g}(k)$) reflect all variables' responses to a shock in variable i. The differences between a K-step-ahead forecast where variable i is shocked and once where variable i is not shocked are computed because a non-structural model is used. The difference can be explained by the shock in variable i which can be estimated using the formula:

$$GIRF_t\left(K, \iota_{i,t}, I_{t-1}\right) = E(y_{t+k} \mid \tau_{i,t} = \iota_{i,t}, I_{t-1}) - E(y_{t+k} \mid I_{t-1}) \tag{10}$$

$$\Psi_{ij,t}^{g}(k) = \Sigma_{ii,t}^{-\frac{1}{2}} \Lambda_{k,t} \Sigma_t \tau_{i,t} \Sigma_{ii,t}^{-\frac{1}{2}} \iota_{i,t} \qquad \Sigma\, \iota_{i,t} = \Sigma_{ii,t}^{\frac{1}{2}} \tag{11}$$

$$\Psi_{i,t}^{g}(k) = \Sigma_{ii,t}^{-\frac{1}{2}} \Lambda_{k,t} \Sigma_t \tau_{i,t} \tag{12}$$

Where the forecast period is k, $\iota_{i,t}$ denotes the selection vector, with one at the $\iota_{i,t}$ location and zero elsewhere. After that, the $GFEVD(\hat{\Psi}_{ij,t}^{g}(k))$ is generated, which can be translated as the forecast error variance sharing one variable explained on others. The variance shares are then normalized so that each row equals 1, showing that all of the variables collectively account for all of the variation in the variable resulting from the I prediction error. This is worked out as follows:

$$\tilde{\Psi}_{ij,t}^{g}(k) = \sum_{t=1}^{k-1} \Psi_{ij,t}^{2,g} / \sum_{j=1}^{m} \sum_{t=1}^{k-1} \Psi_{ij,t}^{2,g} \tag{13}$$

With $\sum_{j=1}^{m} \tilde{\Psi}_{ij,t}^{g}(k) = 1$ and $\sum_{i,j=1}^{m} \tilde{\Psi}_{ij,t}^{g}(k) = m$

First, total directional connectivity TO others is defined as, where variable i communicates its shock to all other variables j as,

$$C^{g}_{i\rightarrow j,t}\left(k\right)=\sum_{i,j=1}^{m}\tilde{\Psi}^{g}_{ji,t}\left(k\right) \tag{14}$$

Second, the total directional connectedness FROM others, which is the shock variable i receives from variables j, is estimated by,

$$C^{g}_{i\leftarrow j,t}\left(k\right)=\sum_{j=1,i\neq j}^{m}\tilde{\Psi}^{g}_{ij,t}\left(k\right) \tag{15}$$

The NETtotal directional connectivity, which can be viewed as the influencing variable I has on the investigated network, is produced by subtracting the total directional connection TO others from the total directional connectedness FROM others. In addition, the influence index (II) is calculated according to Greenwood-Nimmo et al. (2015) as,

$$C^{g}_{i,t}=C^{g}_{i\rightarrow j,t}\left(k\right)-C^{g}_{i\leftarrow j,t}\left(k\right) \tag{16}$$

$$II_{i,t}=\frac{C^{g}_{i\rightarrow j,t}\left(k\right)-C^{g}_{i\leftarrow j,t}\left(k\right)}{C^{g}_{i\rightarrow j,t}\left(k\right)+C^{g}_{i\leftarrow j,t}\left(k\right)} \tag{17}$$

$$AII_{i,t}=\left|II_{i,t}\right| \tag{18}$$

If variable i has a positive NET total directional connectivity, it suggests that it influences the network more than it is influenced by it. If the NET total directional connectedness is negative, on the other hand, the network is driving variable i. The $II_{i,t}$ gives a measure that is normalized between 1 and +1 and can be understood in the same way. The NET total directional connectedness is further broken down to explore bidirectional interactions by computing the net pairwise directional connectedness (NPDC), the pairwise impact index (PII), and its absolute version (APII) as,

$$NPDC_{\mathbf{ij}}\left(K\right)=\tilde{\psi}_{jit}\left(K\right)-\tilde{\psi}_{ijt}\left(K\right) \tag{19}$$

$$PII_{ij}\left(K\right)=\frac{NPDC_{\mathbf{ij}}\left(K\right)}{\tilde{\psi}_{jit}\left(K\right)+\tilde{\psi}_{ijt}\left(K\right)} \tag{20}$$

$$APII_{ij}\left(K\right)=\left|PII_{ij}\left(K\right)\right| \tag{21}$$

The $NPDC$ determines whether variable i is driving or being driven by variable j, and the $PII_{ij}(K)$ standardizes the $NPDC_{ij}(K)$ to be between −1 and +1. The TCI is a tool for calculating market interconnectivity as shown,

$$C^{g}_{t}\left(k\right)=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\Psi}^{g}_{ij,t}\left(k\right)}{\sum_{i,j=1}^{m}\tilde{\Psi}^{g}_{ij,t}\left(k\right)}=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\Psi}^{g}_{ij,t}\left(k\right)}{m} \tag{22}$$

The fundamental issue with this metric is that determining what constitutes a high level of interconnection is subjective. It can be demonstrated using Monte Carlo simulations that the own variance shares are always bigger or equal to all cross-variance shares. This suggests that the TCI is located between $[0,\frac{m-1}{m}]$ and not [0,1], making interpretation problematic. To improve the TCI's interpretability, it needs to be tweaked slightly as,

$$C^{g}_{t}\left(k\right)=\left(\frac{m}{m-1}\right)\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\Psi}^{g}_{ij,t}\left(k\right)}{m} \tag{22}$$

$$=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\Psi}^{g}_{ij,t}\left(k\right)}{m-1} \tag{23}$$

$$0\leq C^{g}_{t}\left(k\right)\leq 1 \tag{24}$$

The pairwise connectedness index (PCI) measures the interconnectivity between two variables i and j as a decomposed form of the TCI.

$$C^{g}_{ijt}\left(k\right)=2\frac{\tilde{\Psi}^{g}_{ij,t}\left(k\right)+\tilde{\Psi}^{g}_{ji,t}\left(k\right)}{\tilde{\Psi}^{g}_{ii,t}\left(k\right)+\tilde{\Psi}^{g}_{ij,t}\left(k\right)+\tilde{\Psi}^{g}_{ji,t}\left(k\right)+\tilde{\Psi}^{g}_{jj,t}\left(k\right)} \tag{25}$$

$$0\leq C^{g}_{t}\left(k\right)\leq 1 \tag{26}$$

This metric, which runs from [0,1], depicts the degree of bilateral interconnectivity between variables i and j that are hidden by the TCI.

The credibility assumptions of the asymmetric shock and the financial assets are examined in this study utilizing the $APII$ and the PCI, respectively. The smaller the $APII$ and the higher the PCI, the more likely variables i and j are in the same OCA. Bootstrapping is used to calculate the average of each OCA measure and its confidence interval.

2.2. Data Sources and Description

The study's analyses, which cover the period from May 7, 2012 to March 31, 2021, take into account twelve important variables, including BRICS exchange rates, the price of energy commodities, and implied volatility in the energy markets. The data were combined to create this period so that the dates were consistent. However, the period is pertinent to show the effects of significant economic occurrences such as the COVID-19 epidemic, BREXIT, US-China trade tension, and Eurozone crisis. Exchange rate returns for the BRICS economies—Brazil (EXRB), Russia (EXRRU), India (EXRIND), China (EXRC), and South Africa (EXRSA)—are among the variables used. The local currency is measured as a percentage against the US Dollar for determining exchange rates. The energy commodity prices were also based on the Brent, Global Energy Commodity (GEnergy), Heating Oil (HOil), Natural Gas (Ngas), and Petroleum (Pet) futures markets. Due to their large market capitalization and important role in portfolio diversification with other financial assets, these commodities were chosen.

The indicated volatilities were picked to reveal global shock transmission. Particularly, the volatility in the energy markets (VEnergy) and the implied volatility of crude oil (OVX) were chosen as forward-looking proxies relevant to the energy markets but having a similar impact on other financial time series through contagion (Dutta et al., 2021; Boateng et al., 2021; Asafo-Adjei et al., 2022; Amoako et al., 2022). Additionally, we used the

GARCH approach to extract daily realised exchange rate volatility from the BRICS exchange rate returns. All of the financial time data, excluding the realised exchange rate volatilities, were obtained from investing.com.

3. EMPIRICAL RESULTS

3.1. Preliminary Statistics

Figure 1 illustrates plots of the price and returns of energy commodities, energy implied volatilities, and exchange rates of BRICS countries. All the energy commodities prices and returns are showing similar trends where the prices are downward moving. The figure shows a steep drop in prices in both BREXIT in 2016 and the COVID-19 pandemic in the 2020 turmoil periods, wherein the COVID-19 crisis period seemed to be more severe compared to the BREXIT period. During the COVID-19 crisis period, we notice extremely high implied volatilities. This implies that the energy implied volatilities are negatively related to the energy commodities in times of crises, and hence they may offer safe-haven benefits for inverters. Furthermore, BRICS currencies seemed to be depreciating against U. S. dollar as indicated by the upward trend. All the data returns show volatility clustering with excess shocks in the COVID-19 crisis period. Considering that both energy commodity BRICS currency markets are losing value at the same time that means the investor can diversify or hedge by combing the assets from these two markets.

All energy commodity returns have negative means suggesting negative performance as presented in Table 1. On the other hand, the energy implied volatilities and exchange rate returns have positive means. Except for natural gas, all the energy commodities exhibit negative skewness indicating a high level of negative performance. Conversely, energy implied volatilities and exchange rate returns (except for Brazil) display positive skewness with the high possibility of positive performance. The kurtosis values are above three, indicating leptokurtic distributions. However, it is important to note an upward going trend of exchange rate prices means the depreciation in domestic currency; therefore, positive means imply negative performance. The time series is not regularly distributed, according to the Jarque-Bera (JB) Statistics. All data returns are stationary, as demonstrated by the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, according to the accepted unit root tests.

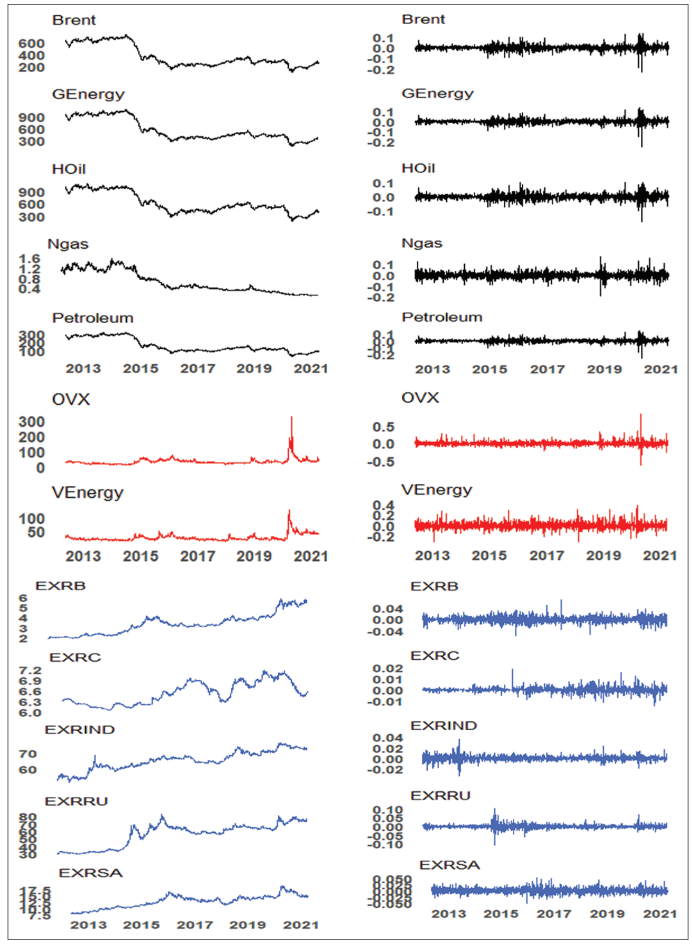
The correlation matrix in Table 2 depicts that most of the energy commodities are strongly positively associated with one another suggesting a high possibility of energy markets integration. Furthermore, the BRICS exchange rate returns are somewhat positively associated with one another, indicating some degree of similar trade relations. On the contrary, energy commodities are negatively correlated with energy implied volatilities and BRICS' exchange rate. This allows investors to diversify their portfolio. Correlation analysis measures the degree of linear association and thus does not imply causation.

3.2. Main Results

3.2.1. Averaged dynamic connectedness results

The findings on average dynamic connectedness are shown in Table 3. It is evident from Panel A that the specific network of

Figure 1: Time series plots of prices and returns



energy commodities, currency rates, and volatilities captures changes within the network to a higher extent given that the average value of the TCI is 46.91%. This suggests that around 46.91% of the forecast error variance in this network of sustainability stocks is a result of cross-market innovations. As a result, idiosyncratic impacts are responsible for around 53.09% of the system's forecast error variance. Reasonable data suggests that, in comparison to earlier studies, energy commodities, currency rates, and volatility tend to alter less significantly (Balcilar et al., 2021; Gabauer, 2021; Adekoya and Oliyide, 2021; Bouri, Lucey et al., 2021, etc.).

All energy commodities in Panel A (except natural gas) are net transmitters of shocks in the system, where global energy seemed to be the most important transmitter among energy commodities. BRICS currency markets (except Brazilian Rubble) are all net receivers of respective shocks. Moreover, both implied energy volatilities and realised exchange rate volatilities are net receivers of shocks. The net receives (negative shocks) can serve as a good hedge and safe haven for investments depending on the market condition. The most essential receivers include natural gas, OVX, and the Chinese RMB volatility, while the most important transmitters are brent, global energy, heating oil, and petroleum.

Concerning the commodities and implied volatilities in Panel B, the same is observed during severe economic events such as the

Table 1: Descriptive statistics

Data	Mean	Median	SD	Skewness	Kurtosis	JB Probability	ADF	KPSS
Energy commodities								
Brent	−0.0004	0.0005	0.0224	−0.6758	14.712	0.00	−31.01***	0.1162
GEnergy	−0.0005	0.0005	0.0208	−0.9215	19.8913	0.00	−31.22***	0.0827
HOil	−0.0004	0.0004	0.0198	−0.243	9.1655	0.00	−49.08***	0.0873
NGAS	−0.001	−0.001	0.0264	0.1174	6.9675	0.00	−48.83***	0.1164
Petroleum	−0.0005	0.0005	0.022191	−0.766	16.57319	0.00	−31.26***	0.0766
Energy volatilities								
VEnergy	0.0002	−0.00E4	0.0592	0.701	7.0651	0.00	−47.92***	0.0334
OVX	0.0002	−0.0036	0.0587	1.6427	33.61	0.00	−29.78***	0.0231
BRICS exchange rate								
EXRB	0.0005	0.0003	0.0105	−0.0129	5.6284	0.00	−49.56***	0.0671
EXRRU	0.0004	0.0004	0.0107	0.3832	16.4015	0.00	−46.02***	0.1581
EXRIND	0.0001	0.0000	0.0045	0.2862	10.8857	0.00	−36.59***	0.0730
EXRC	0.0000	0.0000	0.0021	0.3953	11.42	0.00	−47.19***	0.1539
EXRSA	0.0003	−0.0001	0.0101	0.2865	4.4456	0.00	−46.69***	0.1610

Notes: Asterisks ***, **, * respectively denote 1%, 5%, and 10% levels of significance. GEnergy: Global energy, HOil: Heating oil, NGAS: Natural gas, VEnergy: Volatility in the energy market, EXR: Exchange rate, EXRB: EXR Brazil, EXRRU: EXR Russia, EXRIND: EXR India, EXRC: EXR China, EXRSA: EXR South Africa, JB: Jarque-Bera, SD: Standard deviation, ADF: Augmented dickey-fuller, KPSS: Kwiatkowski-phillips-schmidt-shin, OVX: Crude oil implied volatility, BRICS: Brazil, Russia, India, China and South Africa

Table 2: Unconditional correlation matrix

Probability	BRENT	GEnergy	HOil	NGAS	PET	EXRB	EXRRU	EXRC	EXRIND	EXRSA	VEnergy	OVX
Brent	1.00											
GEnergy	0.98***	1.00										
HOil	0.94***	0.93***	1.00									
NGAS	0.12***	0.23***	0.14***	1.00								
Petroleum	0.99***	0.99***	0.94***	0.13***	1.00							
EXRB	−0.19***	−0.19***	−0.21***	−0.06***	−0.20***	1.00						
EXRRU	−0.49***	−0.48***	−0.46***	−0.06***	−0.48***	0.34***	1.00					
EXRC	−0.12***	−0.12***	−0.12***	−0.01	−0.12***	0.14***	0.17***	1.00				
EXRIND	−0.10***	−0.11***	−0.11***	0.00	−0.11***	0.19***	0.24***	0.22***	1.00			
EXRSA	−0.24***	−0.23***	−0.23***	−0.02	−0.23***	0.49***	0.42***	0.24***	0.30***	1.00		
VEnergy	−0.41***	−0.39***	−0.37***	−0.03	−0.40***	0.23***	0.38***	0.11***	0.22***	0.34***	1.00	
OVX	−0.45***	−0.47***	−0.41***	−0.06***	−0.46***	0.13***	0.30***	0.10***	0.17***	0.20***	0.49***	1.00

Notes: Asterisks ***, **, * respectively denote 1%, 5%, and 10% levels of significance. GEnergy: Global energy, HOil: Heating oil, NGAS: Natural gas, VEnergy: Volatility in the energy market, EXR: Exchange rate, EXRB: EXR Brazil, EXRRU: EXR Russia, EXRIND: EXR India, EXRC: EXR China, EXRSA: EXR South Africa, JB: Jarque-Bera, SD: Standard deviation, ADF: Augmented dickey-fuller, KPSS: Kwiatkowski-phillips-schmidt-shin, OVX: Crude oil implied volatility, BRICS: Brazil, Russia, India, China and South Africa

Pre-Chinese crash, the Chinese crash, BREXIT, and the COVID-19 pandemic where all energy commodities (except natural gas which is a receiver in all turmoil periods) are net transmitters. On the other hand, both implied volatilities are net receivers of shocks. Slight changes can be spotted in the case of BRICS currencies and their volatilities. The Indian Rupee and the RMB are still showing hedge and safe haven abilities as all severe economic events are still inversely related to all other variables. The Brazil Real remained the net receiver of shocks in all turmoil economic events except for the Chinese crash. The South African Rand is a transmitter of shocks during the Chinese crash and pandemic declaration periods, while it remained a net receiver in other economic turmoil periods. Russian Rubble is a net receiver of shocks in the Pre-Chinese crash and a net transmitter in other economic turmoil events. The exchange rate volatilities are negatively related to other variables in the system, except during the pre-Chinese crash and Chinese crash periods in the case of EXRRUVOL and the COVID-19 declaration period in the case of EXRSAVOL.

Findings from the study imply that in a network of energy commodities, exchange rates, and volatilities, risk minimisation is possible. Hence, the spillover connectedness does not entirely depict massive integration and is likely to boost investors' confidence. Additionally, the spillover connectedness is influenced by economic events with several receivers of shocks to act as a safe haven (other than realised volatilities) or to hedge (realised volatilities) against excess shocks.

3.2.2. Dynamic total connectedness

It should be highlighted that average results are mostly required for purposes of summarising the underlying interdependence and do not efficiently assist the investigation of the linkages within a network of variables in consideration of significant economic events. Consequently, a dynamic approach analysis is necessary. For the analysis of the TCI's evolution and the presentation of how the significance of different variables within the network of study can change over time, a dynamic approach is required (for example, from a net transmitter to a net receiver or vice versa). Figure 2 shows the dynamic total connectedness results. Figure 2 shows the total connectivity index's intertemporal evolution (TCI).

Total connectivity indices are seen to vary significantly during the study sample period. The graph demonstrates higher TCI values in 2012 (during the eurozone crisis), 2015 (during the height of the euro migrants), and 2020 (during the COVID-19 pandemic), which reflect strong contagion between the financial time series of interest. The decrease in connection during the COVID-19 pandemic is consistent with the theories advanced by Asafo-

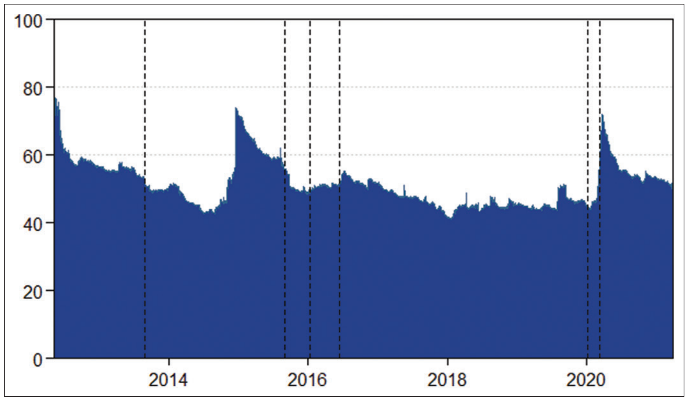
Table 3: Averaged dynamic connectedness approach

	Brent	GEnergy	HOil	Ngas	OVX	Petroleum	VEnergy	EXRB	EXRIND	EXRC	EXRRU	EXRSA	EXRBVOL	EXRRUVOL	EXRINDVOL	EXRCVOL	EXRSAVOL	FROM others
Panel A																		
Brent	21.54	20.69	19.4	0.57	4.68	21.19	3.7	0.83	0.56	0.66	4.47	0.9	0.11	0.12	0.27	0.21	0.08	78.46
GEnergy	20.5	21.4	19.29	1.54	4.68	20.85	3.63	0.89	0.55	0.63	4.36	0.89	0.12	0.11	0.3	0.18	0.1	78.6
HOil	20.39	20.47	22.67	0.68	4.27	20.78	3.12	0.82	0.56	0.65	3.96	0.8	0.13	0.14	0.28	0.19	0.09	77.33
NGAS	2.16	5.79	2.43	78.83	1.44	2.25	1.25	0.64	0.41	0.52	0.65	0.65	0.48	0.4	0.71	0.65	0.73	21.17
OVX	8.48	8.5	7.29	0.45	43.29	8.64	11.59	1.27	1.36	0.76	4.71	1.88	0.54	0.34	0.33	0.28	0.31	56.71
Petroleum	21.03	20.87	19.61	0.57	4.74	21.38	3.64	0.87	0.53	0.61	4.46	0.89	0.12	0.12	0.27	0.19	0.09	78.62
VEnergy	7.14	7	5.69	0.49	11.19	7.07	42.35	2.57	2.41	1.07	6.58	4.3	0.47	0.21	0.43	0.53	0.49	57.65
EXRB	2.27	2.42	2.13	0.54	1.65	2.39	3.65	53.97	4.14	2.46	8.68	12.86	1	0.21	0.55	0.54	0.53	46.03
EXRIND	2.15	1.95	2.22	0.34	1.8	2.05	3.28	4.72	58.55	6.29	3.85	8.35	1.01	0.61	1.18	0.71	0.94	41.45
EXRC	1.71	1.66	1.62	0.78	1.12	1.63	1.59	3.31	7.44	63.62	4.1	7.37	0.52	0.46	0.64	2.01	0.42	36.38
EXRRU	7.22	7.15	5.97	0.33	4.22	7.28	5.9	6.09	2.36	2.76	38.48	9.76	0.28	1.32	0.43	0.24	0.22	61.52
EXRSA	1.94	1.89	1.56	0.39	2.05	1.87	5.34	11.68	6.68	4.89	11.96	47.93	0.19	0.28	0.43	0.57	0.34	52.07
EXRBVOL	0.4	0.4	0.38	0.35	0.78	0.41	0.84	3.05	1.54	0.78	0.92	1	73.91	3.51	4.72	0.81	6.2	26.09
EXRRUVOL	0.51	0.47	0.55	0.42	0.59	0.53	0.32	0.35	0.44	0.61	3.68	0.46	3.17	81.78	3.19	0.78	2.14	18.22
EXRINDVOL	0.49	0.49	0.58	0.43	0.65	0.5	0.67	1.09	2.12	1.07	1.23	1.13	4.97	4.53	75.35	2.93	1.76	24.65
EXRCVOL	0.55	0.53	0.52	0.52	0.67	0.51	0.93	0.86	2.84	4.65	0.62	1.26	0.76	0.52	3.59	79.6	1.07	20.4
EXRSAVOL	0.35	0.37	0.38	0.63	0.4	0.37	0.6	1.02	1.26	0.94	0.71	2.92	6.55	3.22	1.51	0.98	77.81	22.19
To others	97.31	100.65	89.63	9.05	44.92	98.31	50.06	40.05	35.19	29.35	64.94	55.39	20.43	16.1	18.83	11.81	15.52	797.54
NET	18.85	22.05	12.31	−12.12	−11.8	19.69	−7.59	−5.99	−6.26	−7.03	3.43	3.33	−5.66	−2.12	−5.82	−8.59	−6.67	46.91
NPDC	2	0	3	14	6	1	5	8	10	11	4	7	13	12	14	13	13	
Panel B																		
PreChinese crash	19.4	24.5	12.8	−20.5	−14.6	23.8	−12.4	−21.6	−29.3	−28.0	−4.4	−16.0	−70.4	296.5	−29.4	−71.4	−59.3	
Chinese crash	15.7	23.0	10.8	−14.8	−8.7	19.6	−10.3	0.7	−14.3	−11.1	2.7	3.1	−29.8	92.3	−11.5	−38.8	−28.6	
BREXIT	19.4	25.5	16.6	−19.2	−17.5	20.1	−2.1	−11.6	−9.0	−1.2	−1.1	−7.1	−8.3	−5.8	−17.7	−4.5	23.6	
COVID-19 detection	25.6	30.5	20.0	−16.7	−18.9	26.0	−1.2	−12.4	−14.3	−16.6	6.6	−8.5	−4.5	−4.4	−9.5	−8.6	7.0	
Pandemic declaration	18.9	22.0	12.3	−12.1	−11.8	19.7	−7.6	−6.0	−6.3	−7.0	3.4	3.3	−5.7	−2.1	−5.8	−8.6	−6.7	

GEnergy: Global energy, HOil: Heating oil, NGAS: Natural gas, VEnergy: Volatility in the energy market, EXR: Exchange rate, EXRB: EXR Brazil, EXRRU: EXR Russia, EXRIND: EXR India, EXRC: EXR China, EXRSA: EXR South Africa, NPDC: Net pairwise directional connectedness, EXRBVOL: Realised EXR volatility Brazil, EXRRUVOL: Realised EXR volatility Russia, EXRINDVOL: Realised EXR volatility India, EXRCVOL: Realised EXR volatility China, EXRSAVOL: Realised EXR volatility South Africa, OVX: Crude oil implied volatility, BRICS: Brazil, Russia, India, China and South Africa, BREXIT: British Exit, NET: Net spillover

Adjei et al. (2022) and others regarding the delayed volatility of market competitiveness and exogenous shocks. This affirms the idea that portfolio risk was most likely to be reduced for investors who put off investing or kept their investments for an extended period of time. The connection index reached its peak in 2012, slightly below the 80% mark and as low as 42%. The study by Balcilar et al. (2021) shows how commodity markets were more interconnected throughout the eurozone crisis.

Figure 2: Dynamic total connectedness



Figures 3 and 4 present the transmission of shocks from all other variables in the system to an individual variable and the transmission from a specific variable to all other underlying variables. The findings show that all energy commodities, except for natural gas, are highly integrated and transmit more or less the same amount of shocks to all other variables included in the study, where on average transmit about just above 80%. The less integration of natural gas amid other financial time series is profound in prior studies (Sensoy et al., 2015; Zhang et al., 2020; Gong et al., 2021).

However, they all seemed to be receiving less than they transmit. Russian exchange rate returns seemed to be transmitting the most shocks to all other underlying variables with an average of about 80% followed by the South African Rand, with an average of about 60%. Both Russian and South African exchange rate returns

Figure 3: Total directional connectedness to others

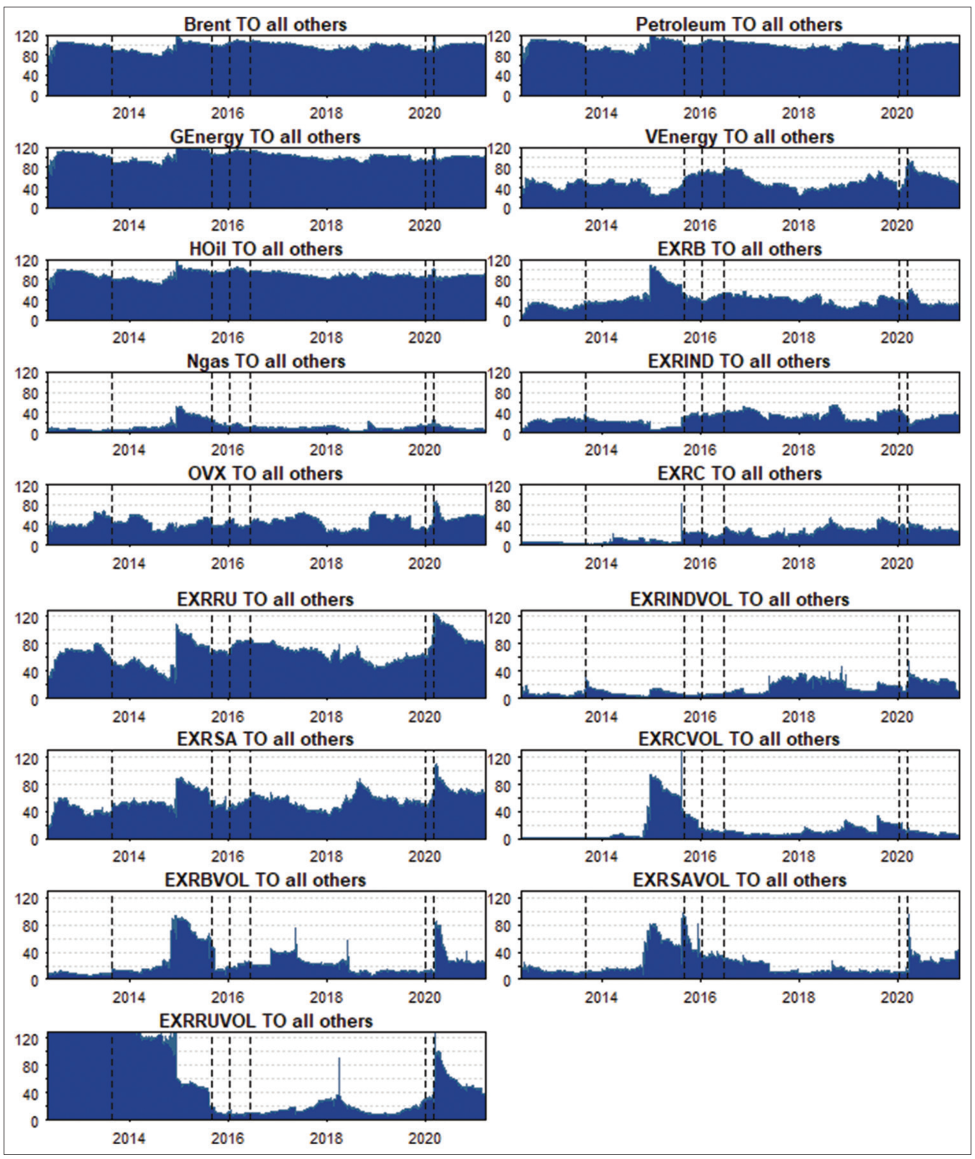
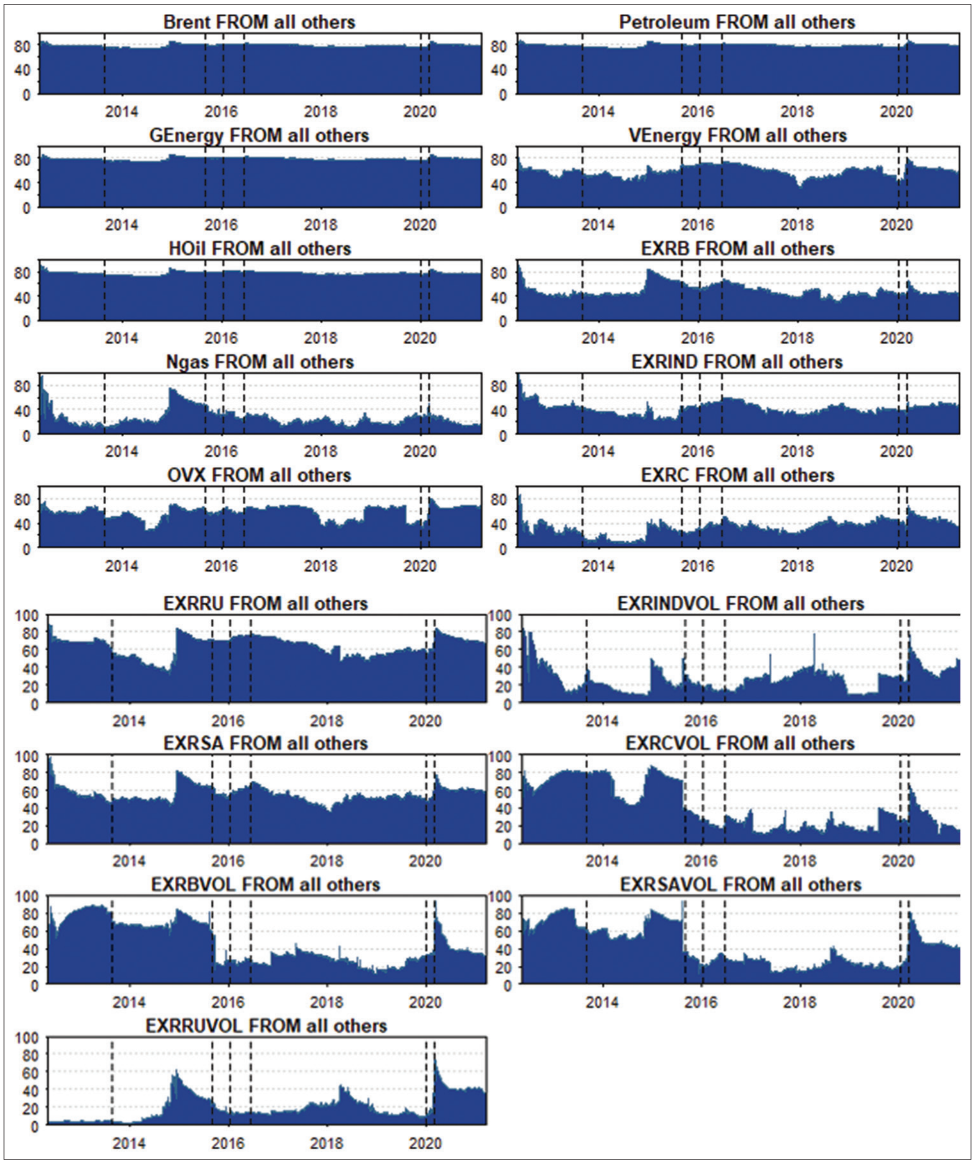


Figure 4: Total directional connectedness from others



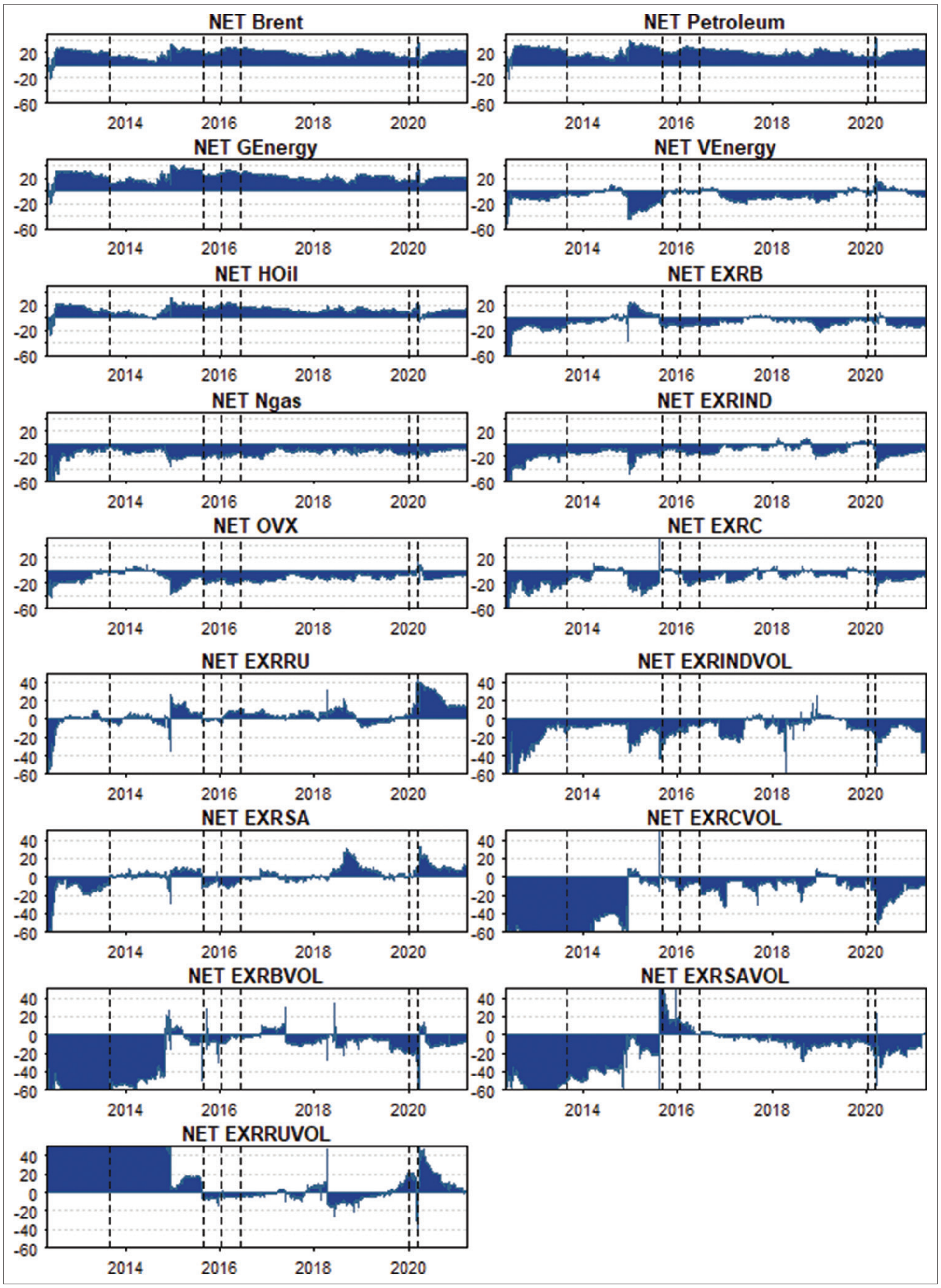
receive almost equal to what they transmit. China seems to be the least transmitter of shocks to other variables. There seemed to be relatively high currency volatility transmission between 2015 and 2016 from Brazil, China, and South Africa to all other variables in the system, while Russian exchange rate volatility transmission to other variables heightened tween 2012 and 15. The Indian currency market seems to be transmitting minimal shocks. Most realised currency volatilities (EXRBVOL, EXRCVOL, and EXRSAVOL) seemed to be receiving relatively higher shocks from all other variables. Hence, can be used as a proxy for assessing external shocks transmission in BRICS' macroeconomic fundamentals for policy decisions in the discussion of energy commodities.

3.2.3. Net total directional connectedness

In this subsection, we examine net connectedness results in Figure 5. The subsequent analysis categorises variables into net transmitting and net receiving roles. Different from the categorisation the study provided in section 3.2.1. above, the dynamic framework in this section can identify the switch between the two roles (net transmitting and net receiving). This means any variable can shift roles within the network from net transmitter to net receiver of shocks in the system over time. As highlighted above the positive values represent the net transmission role, while negative values represent the net receiving role. Considering the net connectedness findings, we observe that four energy commodities (brent, global energy, heat oil, and petroleum) are persistent net transmitters of shocks, while natural gas is the persistent net receiver of shocks as found by Sensoy et al. (2015), Zhang et al. (2020) and Gong et al. (2021).

It is revealed that both implied energy volatilities are the consistent net receivers, implying that they are good hedgers and safe havens for investors across time having in mind the economic events. This is in line with a plethora of studies on implied volatilities (Liu et al., 2020; Boateng et al., 2021; Ding et al., 2021; Owusu Junior et al., 2021; Ahmad et al., 2021; Amoako et al., 2022; Asafo-Adjei et al., 2022, etc.). To some extent, the same can be argued for Brazilian Real, Chinese RMB, and Indian Rupee and

Figure 5: Net connectedness



their volatilities (EXRBVO, EXRINDVOL, and EXRCVOL).

We further note that most of the time, EXRRUVOL, is a net transporter. However, the opposite is noticed in the case of EXRSAVOL, where it is a net receiver throughout the period except in 2016. Regarding results generated using the TVP-VAR model, it can be concluded that brent, global energy, heat oil, and petroleum are indeed net transmitters of shocks, while it can be confirmed that natural gas, OVX, VEnergy, Indian currency returns, and Chinese currency returns are net receivers of shocks in the system. It can be further concluded that all exchange rate volatilities, except for EXRRUVOL, are on average net receivers of shocks. The heterogeneous (Müller et al., 1993) and adaptive (Lo, 2004) dynamics of the energy commodities, exchange rate, and volatilities are in line with the study of Chen et al. (2022).

4. CONCLUSION AND POLICY IMPLICATIONS

In this study, we looked at the interactions and dynamic interconnectedness between energy commodities, the BRICS countries' exchange rates, and (local and global) volatility over time. In this way, the research goal was accomplished using the TVP-VAR connectedness approach of Antonakakis et al. (2020). The evaluation of the time-varying connections between energy commodities and the exchange rate of BRICS amid volatility is the study's original contribution to earlier work (both local and international shocks). This was executed to contribute to the fact that financial time series operate in a non-isolated system (Osei and Adam, 2020; Asafo-Adjei et al., 2022; Asafo-Adjei et al., 2021; Bossman et al., 2022).

The findings obtained from this study were in three folds. First, it was found that the average value of the TCI is 46.91%, for the specific network of energy commodities, currency rates, and volatilities. Also, from the averaged dynamic connectedness, the energy commodities (except for natural gas) were net transmitters of shocks in the system, with the global energy commodity index demonstrating the most important transmitter. Conversely, BRICS currency markets (except for Brazilian Rubble) were net receivers of shocks. Additionally, we found both implied energy volatilities and realised exchange rate volatilities to be net receivers of shocks. Second, the total connectivity indices were seen to vary significantly during the study sample period. Third, the net directional connectedness technique revealed that most volatilities were consistent net transmitters throughout time when switching between net transmitting and net receiving.

We advocate that the spillover connectedness is influenced by economic events with several receivers of shocks to act as a safe haven (other than realised volatilities) or to hedge (realised volatilities) against excess shocks. Nonetheless, the COVID-19 pandemic revealed the most spillover of connectedness as found by prior studies (Ahmad et al., 2021; Bouri et al., 2021; Adekoya and Oliyide, 2021; Asafo-Adjei et al., 2021; Amoako et al., 2022, etc.). The study's outcomes imply that in a network of energy commodities, exchange rate and volatilities, risk minimisation is possible rather than massive integration. Investors are most likely to boost their confidence across time.

It is recommended that realised volatilities from BRICS countries should be used as a proxy for assessing external shocks transmission in BRICS' macroeconomic fundamentals for policy decisions in the discussion of energy commodities. Investors are advisable to diversify, hedge or seek safe haven opportunities from implied volatilities in the energy commodities while taking note of the realised exchange rate volatilities.

5. CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

6. DATA AVAILABILITY STATEMENT

The data used to support this study is available upon request.

7. FUNDING

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