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Do Local and International Shocks Matter in the Interconnectedness amid Exchange Rates and Energy Commodities? Insights into BRICS Economies

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ABSTRACT

The study examined the interdependence structure among energy (brent, natural gas and petroleum) commodities returns, crude oil implied volatility, and exchange rate returns and volatilities in the context of BRICS across time and/or frequencies. The wavelet approaches (bi-wavelet, partial wavelet and wavelet multiple) were employed for the period from May 07, 2012, to March 31, 2021. It was revealed that co-movements between exchange rate returns and energy commodities were negative and significant at certain times and frequencies. In this case, causality emanated from exchange rate returns. Moreover, in most instances, implied volatilities strongly impacted the exchange rate and energy interconnectedness returns. We found strong integration levels among the financial time series with Petroleum having the most likelihood to lead or lag. Findings from the study imply that co-movements between exchange rate returns and energy commodities are heterogeneous and adaptive. Also, local shocks (exchange rate volatilities), have the greatest spillover effect between exchange rate returns and energy commodities relative to implied crude oil volatility. This is the first study that employs the wavelet approaches to investigate the conditional effects of local and external shock on the comovement between exchange rate returns and energy commodities' returns.

Keywords: Time and Frequency, Markets Inefficiencies, Realised Exchange Rate Volatility, Energy Commodities

JEL Classifications: G10, G15, G19, O13

1. INTRODUCTION

Energy price and Exchange rate volatilities pose challenges for policymakers as adverse movements in energy and currency markets usher in insinuations for businesses' production costs and profits, and employment levels of the country. The persistent volatility detected in the currency and energy markets creates instability which not only has negative effects on the macroeconomy through higher inflation rates (Miyajima, 2020), reduction in production performance (Mlambo, 2020), reduction in trade performance (Aye et al., 2015), reduction in consumption (Mukalayi, 2021) and investment incentives (Gigey and Nuru, 2021). However, the energy and currency volatilities further create volatility clustering, which makes these markets more

prone to volatility spillover effects or contagion to and/or from international financial markets (Niyitegeka and Tewari, 2020). Hence, providing the need to address the asymmetric impact of local and international shocks (Amoako et al., 2022).

This is especially the situation for emerging economies such as BRICS which are complex and rapidly have deeper integration into the world's economic turmoil. Some BRICS economies have a growing demand for energy because of a high rate of industrialisation in their economies as net importers of energy commodities, while others are net energy exporters, which makes all be susceptible to energy price shocks and exchange rate volatilities. The outbreak of the COVID-19 pandemic was met with the reduction of demand for internationally traded

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goods and a decline in oil prices. An unexpected response to this catastrophic economic event came from Saudi Arabia when it announced a considerable increase in its oil production, despite an anticipated decline in demand for oil. On the same day of the announcement, the WTI crude oil, one of the major oil pricing benchmarks dropped by 25%, and in the same year (2020) the three BRICS currencies depreciated on average by 21% against US dollar (Villarreal-Samaniego, 2021).

Because of global economic shocks such as the Global Financial Crisis of 2008/2009, COVID-19, the Russian-Ukraine War accompanied by global market instability, many economic agents have given attention to the dynamic association between energy commodities and currency markets. This is the case because energy commodities are the inevitable inputs in many production processes in the world economy, the exchange rates are the monetary link between the domestic and international economies and there is a general accepted strong link between energy and currency markets as established by Hamilton (1983).

With the emergency of globalisation, the use of the US. Dollar as an invoicing currency and with high volatility in energy prices and exchange rates, proper knowledge of the association between energy and foreign exchange rate market is required for market regulation. The degree and direction for shocks transmission associated with currency depreciation (appreciation) for exporting (importing) countries are dynamic, and further depend on the mechanisms that describe the volatility spillover between energy and currency markets as we describe in detail at the theoretical framework section. Although, it is highly probable that shocks are frequently associated with currency depreciation, where netexporting countries may be impacted than importing countries by increasing prices from the supply-side channel. The study probes to investigate the role of local and international shocks on the interconnectedness between the currency markets and energy commodities in BRICS' setting.

Prior studies have documented contradicting results of interdependence between energy and currency markets. The inconsistencies in the outcomes could be due to the following reasons. First, a plethora of studies on the nexus between exchange rate of each of the BRICS nations and energy commodities utilise methodologies that fail to account for time and frequency domain (Chandrarin et al., 2022; Sadraoui et al., 2021; Salisu et al., 2021a; Tiwari et al., 2019, etc.). For instance, the quantile coherency methods employed by Tiwari et al. (2019) to assess exchange rate and crude oil have a frequency perspective of short-, medium-, and long-terms as well as considered bearish, normal and bullish conditions. The specific calendar time dimension was entire missing. This makes it difficult to assess both heterogeneinity and adaptability dynamics of the markets for effective portfolio decisions. In a similar fashion, the cross-quantilogram approach used by Chandrarin et al. (2022), and the copula-MGARCH model technique employed by Sadraoui et al. (2021), and the predictive model by Salisu et al. (2021a) to investigate the energy-exchange nexus are no exception. Hence, it is difficult to interpret the outcome in the systemic crises era in comparison with several other periods within the sample period selection while still maintaining the frequency perspective.

The study by Amoako et al. (2022), which looked at the timing and frequency of co-movements between energy commodities and stock returns of BRICS nations, is the one that is most similar to ours. However, stock and exchange rate returns theoretically demonstrate bi-causality from the perspectives of both flow-oriented (Dornbusch and Fisher, 1980) and stock-oriented (Branson, 1983). In line with this, prior studies on the exchange rate and stock returns draw inconsistent conclusions (Kallianiotis, 2021; Salisu and Ndako, 2018, etc.), making it difficult to infer from prior studies, the behaviour of energy-stock nexus for energy-currency nexus. In this regard, application of a time-frequency approach to examine the nexus between exchange rate returns in the context of each of the BRICS countries and energy commodities' returns is nascent, fledgling and timely.

Second, the few studies that consider the time and frequency discussion of the energy-currency nexus do not consider the influence of a mutual interdependence on the nexus amid energy commodities and exchange rate (He et al., 2019; Zhu et al., 2022). Third, the conditional effects of both local and international shocks are rarely investigated in the energy and currency markets. Fourth, the degree of integration among energy, exchange rates and both local and international shocks simultaneously, with the quest of addressing the non-isolated operability of financial time series (Osei and Adam, 2020; Owusu Junior et al., 2021), is less captured by prior studies. It is against this backdrop that the current study seeks to examine the time and/or frequency domain of energy and currency markets amid local and international shocks.

We make four different contributions to the literature. First, we use the bi-wavelet technique, which previous research overlook, to look at the co-movements between energy commodities and exchange rate returns in the time and frequency domain. Second, the study investigates the influence of local and international shocks on the comovements between energy commodities and exchange rate returns across time and frequency using the partial wavelet approach. The partial wavelet approach allows assessing the extent to which shocks are transmitted from a third variable to the co-movements between other two variables (Agyei et al., 2022; Boateng et al., 2022; Asafo-Adjei et al., 2021; Owusu Junior et al., 2021, etc.). This enables investors to decipher the extent to which their investments could be hedged against shocks, and form a diversified portfolio or portfolio redeployment. It also gives policymakers the chance to fine-tune country-level policies to ensure economic stability. Third, we utilise both local and international shock transmitters that are relevant in the co-movements of energy and currency markets, and hence, make a recommendation to policymakers as well as investors. The shock transmitters employed in this study include; exchange rate volatility for each BRICS economy and crude oil implied volatility (OVX).

Fourth, we investigate the degree of integration among energy commodities, exchange rate returns, exchange rate volatilities and OVX simultaneously. This is particularly important because in the system of energy-currency connectedness, considering the role of

shock transmitters would give a clearer picture of the integration and address the nonisolated system of financial time series, but which prior studies ignore. We execute this with the wavelet multiple approach employed by extant literature on other financial assets (Asafo-Adjei et al., 2021; Asafo-Adjei et al., 2022; Boateng et al., 2022; Fernández-Macho, 2012; Tweneboah, 2019, etc.). The wavelet multiple approach can examine integration among more than two financial time series and warrants the discussion to be performed across frequencies.

Accordingly, the time and/or frequency investigations of this study enable the researchers to address the heterogeneity (Müller et al., 1993) and adaptiveness (Lo, 2004) that is replete in the energy and currency markets (Amoako et al., 2022; Asafo-Adjei et al., 2021; Salisu et al., 2021a; Zhu et al., 2022). Therefore, to the best of our knowledge, this is the first study that examines the leadlag relationships between energy commodities and exchange rate returns of BRICS amid local and international shocks from a time and/or frequency domain using wavelet approaches.

The remaining sections are arranged as follows. The theoretical framework and research methodology are next shown, section 4 has the study's results and discussion. We conclude the study in section 5 indicating recommendations, policy ad practical implications.

2. THEORETICAL FRAMEWORK

From a theoretical perspective, the three major mechanisms that describe the volatility transmission between energy and currency markets include the terms of trade channel, the portfolio and wealth channel, and the energy demand and supply channel (Buetzer et al., 2016). Intuitively, an increase in energy prices such as oil prices in the case of oil-importing countries negatively affects the trade balance and reduces the value of a domestic currency. As highlighted above, another important channel of energy fluctuations influence currency markets is through the wealth effect where the increase, for instance, in oil prices shifts the wealth from economies that import oil to those that export it, and this ultimately affects the exchange rate of oil-importing countries via portfolio imbalance.

Moreover, the literature documents that there is a negative relationship between energy prices and exchange rates, which is well explained through the demand and supply mechanism of both markets. Considering changes in the oil supply side, a decline in the value of the US dollar can result in a decline in oil supply and a rise in oil prices so that net-oil-exporting economies like Brazil and Russia can stabilise their export revenue. In this case, net-exporting countries are more protected. However, a decline in the value of the US dollar can result in a rise in demand for oil by net-importing economies such as India and South Africa as the commodity in question becomes cheaper in terms of the domestic currency. Hence, net-importers are less adversely impacted. Nevertheless, in the case of a country such as China that pegs its currency to the US dollar, a depreciation in the dollar might result in an oil demand increase owing to higher exports (Fratzscher et al., 2014). Accordingly, the degree and direction of shocks transmission associated with currency depreciation

(appreciation) for exporting (importing) countries are dynamic and depends on the mechanisms that describe the volatility spillover between energy and currency markets as we re-iterate as the terms of trade, the portfolio and wealth, and the energy demand and supply channels (Buetzer et al., 2016).

Due to our unique contribution to prior studies on the wider application of the wavelet approaches in the exchange rate-energy nexus, we develop the following research questions;

- 1. What is the comovements between exchange rate and energy commodities' returns across time and frequency?
- 2. What is the conditional influence of volatilities on the interrelationship between exchange rate and energy commodities' returns across time and frequency?
- 3. What is the degree of integration among exchange rate returns, energy commodities' returns and volatilities across investment horizons in a systemic crises era?
- 4. Does local or international shocks matter in the interconnectedness between exchange rate and energy commodities' returns across time and frequency?

3. MATERIALS AND METHODS

The study makes use of the wavelet approaches-bi-wavelet, partial wavelet and wavelet multiple. Hence, the employed methodologies are vital in addressing the nexus between exchange rate returns and energy commodities following a conditional influence of local and international shocks across time and frequency. Aside deciphering co-movements and conditional influence across time and frequency, the approach is relevant in assessing integration, interdependencies as well as lead-lag nexus among several variables in a system of exchange rate returns, energy commodities returns, exchange rate volatility and implied volatilities across investment horizons of short-, medium-, and long-terms. The procedure minimises issues of structural breaks, non-linearity, non-stationarity, non-normality with less consideration about the nature of the data before successful estimation.

With these said, techniques such as quantile coherency methods and the nonparametric conditional value-at-risk granger causality test, Diks and Wolski, Hiemstra and Jones and Diks and Panchenko utilised in the study of Tiwari et al. (2019) to assess exchange rate and crude oil fall short. Although, the study of Tiwari et al. (2019) revealed some of the relationships at intrinsic time dimension of short-, medium-, and long-terms as well as considered bearish, normal and bullish conditions, the specific calendar time perspective was entirely missing. Similarly, the cross-quantilogram approach used by Chandrarin et al. (2022), and the copula-MGARCH model technique utilised by Sadraoui et al. (2021) to investigate the energy-exchange nexus are no exception. Hence, it is difficult to interpret the outcome in the systemic crises era in comparison with several other periods within the sample period selection while maintaining the frequency perspective.

3.1. Bi-wavelet

In this study, the bi-wavelet technique is utilised to investigate the lead-lag relationship between the exchange rate of BRICS and energy commodities from a time and frequency perspective. Torrence and Compo (1998) define wavelet transformation coherence (WTC) as the squared value normalization of a cross-absolute spectrum to a single wavelet power spectrum. Equation 1 is the equation for the squared wavelet coefficient.

$$R_{p}^{2}(x,y) = \frac{\left| p(s^{-1}W_{xy}(\Omega,s)) \right|^{2}}{p(s^{-1}\left| W_{x}(\Omega,s) \right|^{2}) p(s^{-1}\left| W_{y}(\Omega,s) \right|^{2})}$$
(1)

Where ρ is a smoothing factor and the square difference ranges from 0 and 1. A number near to 1 indicates a strong connection, whereas a number close to 0 indicates a weak connection. The statistical significance of this nexus was tested using the Monte Carlo method (Torrence and Compo, 1998).

The disturbances in the oscillation are shown by the WTC Phase difference in a certain period. Equation 2 considers the phase difference between x(t) and y(t).

$$\emptyset_{xy}\left(\Omega,s\right) = tan^{-1} \left(\frac{\Im\{S\left(s^{-1}W_{xy}\left(\Omega,s\right)\right)\}\}}{\Re\{S\left(s^{-1}W_{xy}\left(\Omega,s\right)\right)\}\}} \right)$$
(2)

In equation 2, the letters \Im and \Re stand for imaginary and real operators, respectively. The wavelet coherence map's phase pattern dimension draws attention to the wavelet coherence difference as a source of inspiration. To distinguish phase patterns, dimensional arrows are utilized.

Arrows pointing right and left, upward and downward, as well as up and down, are used to graphically represent the bi- wavelet. Right arrows pointing up and left arrows pointing down indicate the first variable, and vice versa for left arrows pointing up and right arrows pointing down. The relationship between the linked variables is demonstrated using a color scheme and a surface colour. Areas with a lot of co-movements are shown in red (warm), whereas those with less co-movements are shown in blue (cool) (Agyei et al., 2022; Asafo-Adjei et al., 2022). Outside of the sphere of influence, the results are unimportant (COI).

3.2. Partial Wavelet Coherence (PWC)

PWC is employed in the literature to limit the problem of "pure" correlation between time-series variables z(t) and to control the influence of a time series variable on the wavelet coherence between other two time series variables x(t) and x(t). As illustrated in equation 3, PWC is represented by a similar equation to partial correlation squared

$$R_p^2(x,y,z) = \frac{\left| R(x,y) - R(x,z) \cdot R(x,y) \cdot \right|^2}{[1 - R(x,z)]^2 [1 - R(y,z)]^2}$$
(3)

Where $R_p^2(x, y, z)$ is between 0 and 1. In the study, the letters x, y, and stand for the exchange rate, the return of energy commodities, and local and international shocks, respectively. For estimating, PWC employs Monte Carlo techniques.

3.3. Wavelet Multiple

We utilise the wavelet multiple approaches in this study to investigate the degree of integration among exchange rates, energy commodities and volatilities, simultaneously in a frequency domain. We are also able to detect the lead-lag relationship among the financial time series across investment horizons (short, medium-, and long-terms). Particularly, the wavelet multiple cross-correlations (WMCC) is utilised in this study. The WMCC has a property of determining the leading or lagging variables, as well as a potential lead or lag.

A nonlinear function of all $\frac{n(n-1)}{2}$ wavelet correlations of scale λ_j and a steady estimator of wavelet correlation from the MODWT is shown in equation 7

$$\tilde{\Omega}X(\lambda_{j}) = \left(1 - \frac{1}{\max diag} \tilde{P}_{j}^{-1}\right)^{\frac{1}{2}} = Corr(w_{ijt}, \ \hat{w}_{ijt})$$

$$= \frac{Cov(\tilde{w}_{ijt}, \ \hat{w}_{ijt})}{\left(Var(\tilde{w}_{ijt})Var(\hat{w}_{ijt})\right)^{1/2}}$$
(4)

Where w_{ij} is used to capitalize on $\Omega X(j)$ an \hat{w}_{ijt} represents the fitted values in the regression of w_{ij} on the outstanding wavelet coefficients at scale λ_j , \tilde{w}_{ij} : The regression of the equivalent set of regressors $\{\tilde{w}_{kj}, k \neq i\}$ optimize the R², as indicated by Fernández-Macho (2012).

Similarly, a reliable equation for the WMCC can be estimated as

$$\tilde{\Omega}X, \tau(\lambda_{j}) = Corr(w_{ijt}, \ \hat{w}_{ijt}) = \frac{Cov(\tilde{w}_{ijt}, \ \hat{\tilde{w}}_{ijt+\tau})}{\left(Var(\tilde{w}_{ijt})Var(\hat{\tilde{w}}_{ijt+\tau})\right)^{1/2}}$$
 (5)

A detailed presentation of the WMCC approach can be found in the studies of Fernández-Macho (2012), Owusu Junior et al. (2021), Boateng et al. (2022), Asafo-Adjei et al. (2022), Agyei et al. (2022).

3.4. Data Sources and Description

Analyses of the study consider eleven (9) key variables for exchange rate returns, energy commodities returns and crude oil implied volatility in the energy markets, and span from May 08, 2012 to February 22, 2023 with a total observation of 2,633. This period was obtained after merging the data to have common dates. Yet, the period is relevant to reveal the impact of serious economic events such as Eurozone crises, BREXIT, US-China trade tension, COVID-19 pandemic, the Russian-Ukraine war, among others. The variables employed include exchange rate returns for Brazil (EXRB), Russia (EXRRU), India (EXRIND), China (EXRC) and South Africa (EXRSA) forming the BRICS economies. The exchange rates are measured as a number of the local currency against the US Dollar. Also, Brent, Natural gas (Ngas) and Petroleum (Pet) futures markets were utilised for the energy commodity prices. These commodities were selected due

to their high market capitalisation and significant role in portfolio diversification with other financial assets (Dmytrów et al., 2021; Rehman and Vo, 2021, etc.).

To divulge international shock transmission, the CBOE Crude Oil Volatility (OVX) was selected as forward-looking proxy germane to the energy markets but also has an analogous impact on other financial time series through contagion (Amoako et al., 2022; Dutta et al., 2021). Additionally, we used the GARCH technique to extract the daily realised exchange rate volatility from the exchange rate returns and used it as the local shock. From investing.com, the financial time series were taken.

4. EMPIRICAL RESULTS

4.1. Preliminary Statistics

The price series of energy commodities, OVX and exchange rates are presented in Figure 1. All the energy commodities are seen to trend downwards demonstrating similar price behaviour. We notice a fall in commodities prices on three important severe economic occasions that is BREXIT in 2016, COVID-19 in 2020 and the heat of the Russia-Ukraine war. There is a higher likelihood for the commodities markets to return to normal from the heat of the pandemic but further mitigated by the Russia-Ukraine war. Moreover, the exchange rates trend upwards to suggest depreciation of the currency rates relative to the US \$ in the BRICS countries.

A glance at Table 1 provides that all the commodities returns have negative means indicating negative performance with a negative skewness highlighting a high degree of more negative performance. The OVX and exchange rate returns have positive

Figure 1: Time series plots of price

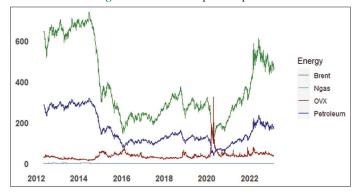


Table 1: Descriptive statistics

Variable Mean SD **KPSS Skewness** Kurtosis J_B Tsav -0.0001-0.722413.0488 $2.741^{\overline{a[29]}}$ Brent 0.0227 11,307.2800a 0.267 1746.6150a Ngas -0.00090.0307 -0.17406.9748 0.080 $5.598^{b[1]}$ 2.772a[29] Petroleum -0.00020.0226 -0.794414.4907 14,762.3000a 0.215 OVX 0.0597 $7.116^{a[8]}$ 0.0001 1.7317 31.6934 91,639.9700a 0.017 **EXRB** 0.0004 0.0105 0.0247 5.2839 572.5131a 0.097 $2.244^{c[2]}$ $5.640^{a[33]}$ **EXRRU** 0.0003 0.0135 2.4879 50.2621 247,772.8000° 0.101 $4.061^{a[15]}$ **EXRIND** 0.00020.0043 0.2964 11.1332 7295.6560a 0.049 $2.165^{a[15]}$ 0.2229 **EXRC** 0.00000.00235131.8920a 9.8249 0.083 $0.252^{[0]}$ **EXRSA** 0.0003 0.0100 0.2577 4.3094 217.2518a 0.097

Letters a, b and c represent 1%, 5%, and 10% level of significance. Values in parentheses indicate number of orders. SD: Standard deviation, JB: Jarque-Bera, KPSS: Kwiatkowski-Phillips-Schmidt-Shin

skewness with a high potential for greater positive performance. Nonetheless, all the kurtosis values show leptokurtic distributions. In this regard, all the returns series are found to be not normally distributed as shown by the Jarque-Bera (JB) Statistic. The outcome from the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test provides that all the returns series are stationary. However, the returns series are observable to exhibit nonlinearity from the Tsay test with a null hypothesis of linearity.

4.2. Results

4.2.1. Time and frequency domain

The time and frequency perspective analyses of BRICS' exchange rate and energy commodities amid volatilities are presented here in Figures 2-6. The bi-wavelet outputs are shown in the first column of the Figures whereas the partial wavelet outputs are presented in the remaining columns for each Figure. Through the bi-wavelet, we can reveal the degree of interconnectedness between each of the BRICS' exchange rates and energy commodities across time and frequency to reveal markets inefficiencies. On the other hand, the partial influence of a common interdependence (volatilities in exchange rate and OVX) between each of the exchange rates and energy commodities are ascertained with the aid of the partial wavelet.

As noted from prior studies, right-pointing arrows depict positive nexus suggesting movement in the same direction. This signifies financial market integration with a minimal tendency for portfolio diversification. On the other hand, left-pointing arrows are preferred for diversification purposes. Specifically, when the left-pointing arrows occur in significant economic events or crises, they suggest the degree to which one variable can act as a safe haven for the other. At normal market events, left-pointing arrows may be an indication of a hedge. The first variable leads when the arrows point either to the right upwards or left downwards, otherwise, the second variable leads.

However, the above interpretation on the directional movements with exchange rate offering either diversification, hedge or safe haven does not hold if we do not place particular attention to the quote of the currency. Since the current study employs a direct quote against the US\$, a rise in exchange rate denotes depreciation of the domestic currencies. Accordingly, a rise in the currency markets and a fall in the energy commodities indicating negative co-movements should be interpreted with care (Qureshi et al., 2018). Since they intrinsically mean the same positions in the eyes

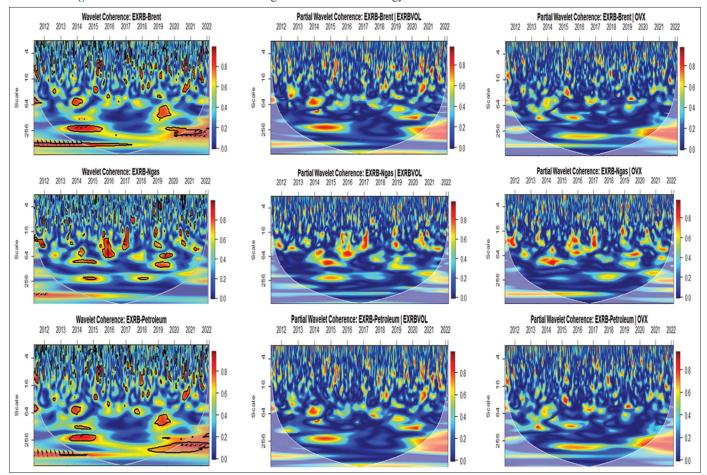


Figure 2: Co-movements between exchange rate of Brazil and energy commodities amid local and international shocks

of investors, it is less likely to diversify, hedge or seeks safe haven in this scenario. In this case, the study rather interprets negative co-movements between direct quotes of the exchange rate and energy commodities as high integration dwindling diversification potentials.

The colour pallet within the cone of influence (COI) signifies either part with major interactions (for warm/red colour) or weak interactions (cool/blue colour). Hence, contagion, which the study adopts the definition of increased interactions after the onset of a shock is realised in periods of warm colour right after the initiation of a significant economic event. Following the study of Agyei et al. (2022), Table 2 presents the interpretation of the wavelet scales.

Figures 2-6 show the bi-wavelet and partial wavelet approaches respectively for the nexus between exchange rate returns and energy commodities returns, and the influence of local and international volatilities. It can be noticed that the co-movements between exchange rates and energy commodities are negative as shown in Figures 2-6. This suggests that exchange rate and energy commodities move in different direction to indicate that an increase in one variable results in a decrease in the other variable. However, put differently, a rise in currency (depreciation) and a fall in the energy markets are not worthwhile for diversification potentials. Therefore, exchange rate returns and energy commodities cannot offer diversification, hedge or safe haven benefits depending on the economic event or situation. This outcome concurs with the

study of Amoako et al. (2022) who investigated the nexus between stock returns of BRICS and energy commodities using the same estimation technique and found positive co-movements. Here, the directional co-movements look different but connote similar meanings. We advocate that exchange rate and stock returns fundamentals react similarly with energy commodities shocks. We confirm earlier studies on stock returns and exchange rate dynamics in BRICS to move similarly (Salisu et al., 2021b; Zhu et al., 2022, etc.) with some degree of inferences.

Nonetheless, it seems surprising for both net-importers and netexporters to respond similarly based on directional comovements. Hence, there should have been a trade-off in how net-exporters and net-importers react to the exchange rate-energy nexus. It goes to reason that the terms of trade as well as the portfolio and wealth channels are not consistent in this study where net-importers are expected to be largely adversely impacted during adverse movements in energy prices depicting a clear trade-off. However, we take cognisance from the energy demand and supply channels. This is further supported by the fact that significant directional comovements do not occur at the same time and frequency revealing heterogeneous as well as dynamic susceptibilities of exchange rate to energy shocks. In this sense, at a point of specific lead or lag across time and frequency in net-importer(s) does not exactly match lead-lag relationship with net-exporter(s) as can be confirmed from Figures 2-6. Although, BRICS nations rapidly have deeper integration into the world's economic turmoil and are

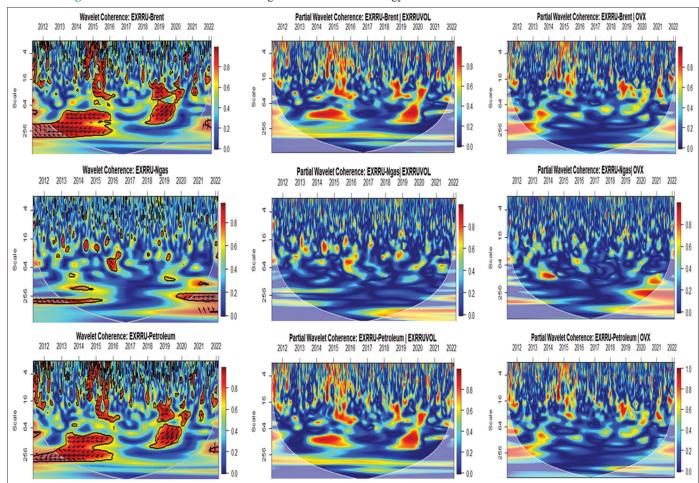


Figure 3: Co-movements between exchange rate of Russia and energy commodities amid local and international shocks

vulnerable to energy price shocks and exchange rate volatilities, their similar directional response slightly differ across time and frequency.

Accordingly, it is intuitive to suggest that both net-exporters and net-importers could have same directional effects but occurs at moderately different times and frequency following the demand and supply channels. The outcome is expected where on the supply side a decline in the value of the US dollar plunges supply for an eventual upsurge in oil price for stabilisation of revenue in Brazil and Russia as net-exporters. For a time-variant system where mismatches can be mitigated through a shift in demand, a decline in the value of the US dollar can result in a rise in demand for oil by net-importing economies such as India and South Africa as the commodity in question becomes cheaper in terms of the domestic currency. Also, in the case of China that pegs its currency to the US dollar, a depreciation in the dollar might result in an oil demand surge owing to higher exports (Fratzscher et al., 2014). In this regard, net-importers are less adversely impacted. Sequel to the aforesaid, we advocate that being net-importer or net-exporter of oil does not necessarily arouse a trade-off in the directional comovements between exchange rate-energy nexus due to a slight difference in the response regarding the specific time and frequency such comovements occur.

To determine the specific direction of causality in this study, the left upward or downward arrows are utilised. For Figure 2, co-movements with exchange rate returns of Brazil are mostly left downwards pointing arrows except for Ngas which shows left upwards. The left downwards pointing arrows imply that the exchange rate returns of Brazil drive most energy commodities, but a few time and frequencies. The causality from the exchange rate returns of Brazil to the energy commodities indicates that an increase in the exchange rate of Brazil (depreciation against the US \$) drives energy commodities to fall. This can be found in the medium-, and long-terms between 2013 and 2017 as well as beyond 2019. This is not surprising because the depreciation of the Brazilian real makes it expensive to import some energy commodities, thereby dwindling demand for the energy commodities. Despite being one of the top fifteen producers of crude, Brazil continues to import petroleum products to satisfy its growing domestic demand, make up for its fuel price subsidies, and compensate for its underinvestment in the refining industry. Hence, a fall in demand for energy commodities could result in a reduction in their prices.

The left upward co-movements with natural gas in Figure 2 indicate that in times of rising prices of natural gas, it would lead to a fall in the Brazilian real (appreciation against the US\$). Hence, international investors who want to benefit from such a market buy early to take advantage of rising prices and sell them when the prices have reached their peak. An increase in demand for the natural gas commodity would lead to an appreciation

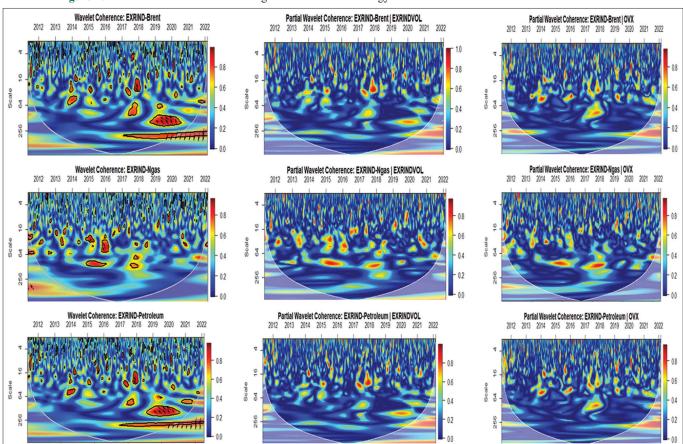
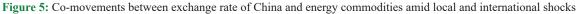
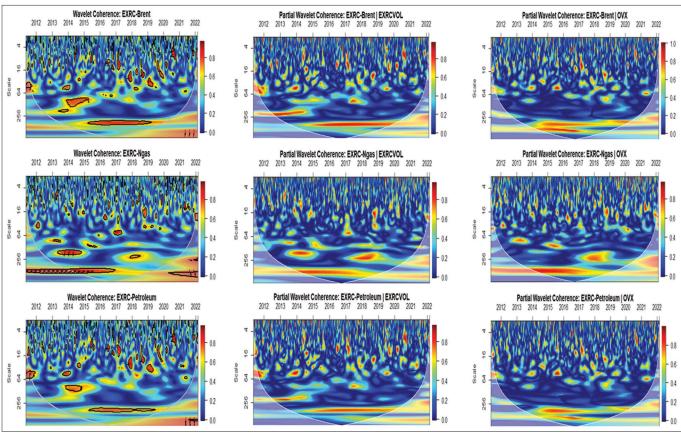


Figure 4: Co-movements between exchange rate of India and energy commodities amid local and international shocks





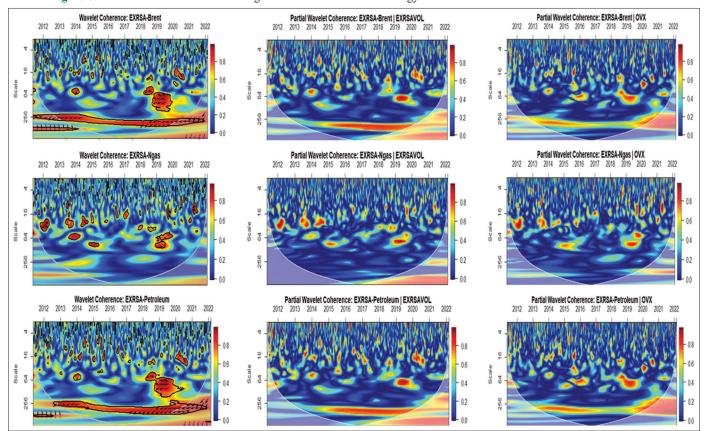


Figure 6: Co-movements between exchange rate of South Africa and energy commodities amid local and international shocks

Table 2: Interpretation of time-scales and frequencies

Frequency	Scale	Meaning	Horizon
W_{i1}	2-4	Intraweek	Short-term
w _{i2}	4–8	Weekly	
W _{i3}	8-16	Fortnightly	
W _{i4}	16-32	Monthly	Medium-term
W _{i5}	32-64	Monthly to quarterly	
W _{i6}	64–128	Quarterly to biannual	
W _{i7}	128-256	Biannual to annual	Long-term

of the Brazilian real (a fall in the currency which in this study, appreciation against the US \$). For investors of the Brazilian real, diversification benefits are minimal with fluctuations in most energy commodities especially, during 2013 and beyond 2019 marking the peak of the Eurozone crisis and COVID-19 pandemic respectively. On the other hand, it is better to diversify or hedge against external shocks in the Brazilian real using the energy commodities with the insignificant sections.

Also, for Figure 3, co-movements between exchange rate returns of Russia and energy commodities (except for Ngas) are the strongest across time (2012 to 2021) and frequencies (short-, medium-, and long-terms). This is because Russia is among the major energy commodities exporters, and fluctuations in energy commodities could have a significant impact on most economic fundamentals both locally and globally (Wu and Chen, 2017). We find a mixture of both left upwards and downwards arrows suggesting a bi-directional causality between exchange rate returns of Russia and energy commodities (except for Ngas). There is not

much to say about Ngas relative to the other energy products which account for a significant portion of Russia's export. It is better to diversify with Ngas and Russian Rouble.

For Figures 4 and 5, there are weak co-movements between exchange rates of India and China with the energy commodities to connote diversification potentials. India and China are considered net importers of energy products, but India is among the top five exporters of refined oil products whereas China is among the top twenty. However, fluctuations in both exchange rate returns and energy commodities are less captured by each other. This could be due to limited financial openness within China and India relative to their counterparts (Asafo-Adjei et al., 2022). Particularly for Figure 4, we notice that left-pointing arrows are mostly upward suggesting that a rise in energy commodities drives the Indian Rupees downwards (appreciation). There is no specific causality in the case of China in Figure 5.

Moreover, we notice the driving effects of the South African Rand on the energy commodities in medium-term beyond 2019 and long-term between 2012 and 2021. Hence, a rise in the South African Rand (depreciation) leads to a fall in energy commodities returns. This is similar to the case of Brazil, hence, implying that the depreciation of the South African Rand makes it expensive to import energy products for further refinery, but the impact of the significant co-movements is not much as compared to Russia. Hence, as South Africa is considered a net exporter of refined energy commodities, it is also a net importer of raw energy commodities.

From the greater impact of volatilities, it can be seen that exchange rate volatility in India has a stronger impact on the interconnectedness. The crude oil volatility has a stronger impact on the nexus between the exchange rate and energy returns for countries like Russia and Brazil, and possibly South Africa and China. It could be seen that at most times, crude oil implied volatility is germane in the interconnectedness between exchange rate returns and energy returns relative to local shocks. Hence, policymakers in BRICS must fine-tune policies on the exchange rate at relevant times and frequencies in order that exchange rate shocks are not escalated to harm macroeconomic environment fundamentals in the context of BRICS nations. It is also relevant to promote international trade and investment within the energy markets due to the stronger connections at certain time and investment horizons.

4.2.2. Frequency-dependent

The wavelet multiple cross-correlations (WMCC) are presented in Figure 7 and Table 3. The scales in Figure 7's y-axis represent the same concepts as in the bi-wavelet scenario. The x-axis, however, shows the length of the series' lag, following Agyei et al. (2022). Twelve days each for the positive and negative lags in this situation. At the corresponding scales, localizations at positive lag indicate lagging variables while those at negative lag indicate leading variables. There is no lead or lag at the localization zero-lag.

The dashed lines inside the dotted lines represent the localization, which displays the highest values in the linear combination of all variables at the wavelet scales (at all lags). The variable that can either lead or lag the other variables is the one that is listed on a scale. It suggests that when all the variables are integrated linearly at that scale, it has the highest value among all the variables at all the other scales. The WMCC has an impact on the economy because it shows how interrelated the variables are and selects the most crucial variable at a specific wavelet scale to serve as a leading (first mover to respond to shocks) or trailing (last variable to respond to shocks after the other variables) variable. Depending on how closely the other variables are related, the leading or trailing variable is influenced by the most important variable at a certain wavelet scale. Estimates are presented in Panels (Panels A, B, C and D) for four samples needed to decipher the impact of systemic crises which the current study considers the COVID-19 Pandemic and the 2022 Russian-Ukraine War.

When it comes to having the ability to either lead or lag behind other variables in terms of how they react to shocks, Figure 7's energy potential stands out for all samples. As shown, petroleum and possibly Brent reflect the dynamics of energy commodities which are deemed to be highly connected in a system of BRICS' exchange rate returns and volatilities. This emphasizes the argument made by Abramova and Fituni (2014) and supported by Amoako et al. (2022), according to which the BRICS economies'

Figure 7: Wavelet multiple cross-correlations among exchange rate of BRICS, energy commodities, local and international volatilities

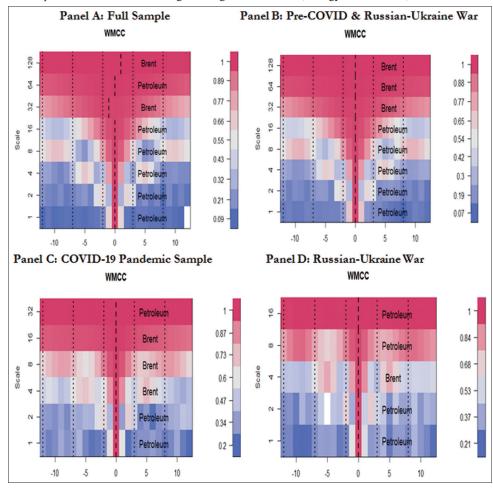


Table 3: Wavelet multiple cross-correlations coefficients among the network of exchange rate, energy commodities and volatilities for full sample and systemic crises era

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The COVID-19 sub-sample was chosen based on its declaration as a matter of Public Health Emergency of International Concern by WHO. We take insight on the initial date of the War from the study by Umar et al. (2022)

shared resource wealth is one of the factors driving their economies to cooperate in order to spur financial development and transform them into resource powers. This is not surprising because the energy market is an important investment for the BRICS economies with a greater tendency for the economies' fundamentals to be influenced by the energy market.

Noting the impact of systemic crises era, Brent has the potential to lead or lag in the medium-, and long-terms for the pre-crises period but lags only in the long-term for the full sample. Conversely, petroleum has the tendency to lead or lag in the long-term for the two crises episodes. Accordingly, the crises seem to be driving estimates in the full sample with the impact of the War mitigating the presence of Brent crude oil and further arousing a decoupling effect relative to the pandemic in our system as depicted by Table 3. We conclude that the Russian-Ukraine War has had a protracted impact on the dynamics of financial markets (Umar et al., 2022) due to Russia's substantial contribution to global energy production which was unfortunately jeopardised during the War. This is not surprising because in the wake of the War, global oil prices skyrocketed beyond \$120 per barrel due to expectations from a cut in global supplied from Russia. This was as a result of the behavioral intentions of investors as irrational which alter across investment horizons rendering the energy markets to be heterogeneous. Nonetheless, growth in global economies and a reduction in demand have led to a sharp decline in global oil prices.

5. CONCLUSION

The BRICS economies have shown massive improvement in their macroeconomic fundamentals over the years with consistent growth in their energy consumption coupled with their role in net export and imports of energy commodities. As local and international shocks are relevant for economies around the world, we investigate the impact of realised exchange rate volatilities from each of the BRICS nations as well as implied volatilities in the energy commodities. We focused on the statistical features of exchange rate returns and energy commodities amid the realised local and implied international volatilities noting their chaotic behaviour across time and frequency. To achieve this purpose, the wavelet techniques (bi-wavelet, partial wavelet and wavelet multiple) were employed to further observe the impact of systemic crises episodes.

We found negative significant co-movements between exchange rate returns and energy commodities at certain times and frequencies revealing markets inefficiencies. This mostly occurred in the medium-, and long-terms. At most times, we found unidirectional causality from the exchange rate returns to the energy commodities. Hence, depreciation of exchange rate (rise in the currency) results in a fall in most energy commodities returns. Specifically, co-movements with the Russian Rouble were the strongest with a bi-directional causality, followed by the South African Rand and the Brazilian real. The exchange rate returns of China and India recorded the least persisting co-movements with energy commodities implying that investors have a greater opportunity for diversification.

Also, significant co-movements found during 2013 and beyond 2019 marking the peak of the Eurozone crisis and COVID-19 pandemic respectively highlight contagion effects in both markets. Generally, both local and international volatilities seemed to have an impact on the co-movements between BRICS' exchange rate returns and energy commodities as shown by the partial wavelet approach. However, international shocks, implied volatility in the crude market, was found to have a larger conditional effect. Moreover, in some instances, volatilities in the exchange rate strongly influenced the exchange rate returns and energy interconnectedness. Furthermore, we found a strong degree of integration among the variables with petroleum having the most potential to lead or lag. This is followed by Brent analogously with the potential to lead or lag. Hence, energy commodities are critical to the exchange rate fundamentals of BRICS economies.

Findings from the study imply that co-movements between exchange rate returns and energy commodities are heterogeneous and adaptive. The weak co-movements between exchange rate returns (China and India) and energy commodities imply that diversification opportunities are more crucial for exchange rates in China and India relative to Russia, South Africa and Brazil. Our findings also support the existence of substantial international

shock spillover between exchange rate returns and energy commodities. International shock (crude oil implied volatility), has the greatest spillover effect between exchange rate returns and energy commodities relative to realised exchange rate in the setting of BRICS countries. It must be noted that for portfolio diversification, hedge or safe haven opportunities, implied volatility is crucial amid energy-currency portfolio.

Considering the stronger co-movements at specific time and frequency in the bivariate case, we claim that exchange rates and the energy commodities in the framework of BRICS are strongly integrated only at intrinsic times of short-, medium-, and long-terms. The substantial integration in this perspective explicates that exchange rates and energy commodities are frequency-dependent but time and frequency specific. Also, whereas time-frequency domain revealed contagion effects for some crises episodes, we dominantly found decoupling effects during the systemic crises era for the frequency perspective.

It is recommended that policymakers in BRICS countries fine-tune policies on the exchange rate at relevant times and frequencies to restore them to appropriate levels while promoting international trade and investment within the energy markets. Also, investors of exchange rate markets in BRICS economies and energy commodities should diversify, hedge or seek safe haven opportunities from implied volatilities depending on the economic situation. For a more enhanced portfolio decision, it is better to consider exchange rate in China and India in a portfolio of energy commodities.

The study was limited to investigations conducted at time and/frequency domain. Hence, the Cross-quantilogram approach can be applied by future researchers who seek to explore market situations of bearish, normal and bullish outcomes for these time series data (Han et al., 2016; Husain et al., 2022; Samargandi and Sohag, 2022; Uddin et al., 2019). The market conditions can be observed at varying episodes of crises by way of splitting the data and verified through tests for structural breaks.

6. FUNDING

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REFERENCES

- Agyei, S.K., Adam, A.M., Bossman, A., Asiamah, O., Owusu Junior, P., Asafo-Adjei, R., Asafo-Adjei, E. (2022), Does volatility in cryptocurrencies drive the interconnectedness between the cryptocurrencies market? Insights from wavelets. Cogent Economics and Finance, 10(1), 2061682.
- Amoako, G.K., Asafo-Adjei, E., Mintah Oware, K. Adam, A.M. (2022), Do volatilities matter in the interconnectedness between world energy commodities and stock markets of BRICS? Discrete Dynamics in Nature and Society, 2022, 1030567.
- Asafo-Adjei, E., Adam, A.M., Adu-Asare Idun, A., Ametepi, P.Y. (2022), Dynamic interdependence of systematic risks in emerging markets

- economies: A recursive-based frequency-domain approach. Discrete Dynamics in Nature and Society, 2022, 1139869.
- Asafo-Adjei, E., Boateng, E., Isshaq, Z., Idun, A.A.A., Owusu Junior, P., Adam, A.M. (2021), Financial sector and economic growth amid external uncertainty shocks: Insights into emerging economies. PLoS One, 16(11), e0259303.
- Aye, G., Gupta, R., Moyo, P., Pillay, N. (2015), The impact of exchange rate uncertainty on exports in South Africa. Journal of International Commerce, Economics and Policy, 6(1), 1-14.
- Boateng, E., Asafo-Adjei, E., Addison, A., Quaicoe, S., Yusuf, M.A., Adam, A.M. (2022), Interconnectedness among commodities, the real sector of Ghana and external shocks. Resources Policy, 75, 102511.
- Branson, W.H. (1983), A Model of Exchange-Rate Determination with Policy Reaction: Evidence from Monthly Data. Cambridge: National Bureau of Economic Research, Inc.
- Buetzer, S, Habib, M.M., Stracca, L. (2016), Global exchange rate configurations: Do oil shocks matter? IMF Economic Review, 64(3), 443-470.
- Chandrarin, G., Sohag, K., Cahyaningsih, D.S., Yuniawan, D., Herdhayinta, H. (2022), The response of exchange rate to coal price, palm oil price, and inflation in Indonesia: Tail dependence analysis. Resources Policy, 77, 102750.
- Dmytrów, K., Landmesser, J., Bieszk-Stolorz, B. (2021), The connections between COVID-19 and the energy commodities prices: Evidence through the Dynamic Time Warping method. Energies, 14(13), 4024.
- Dornbusch, R., Fischer, S. (1980), Exchange rates and the current account. The American Economic Review, 70(5), 960-971.
- Dutta, A., Bouri, E., Roubaud, D. (2021), Modelling the volatility of crude oil returns: Jumps and volatility forecasts. International Journal of Finance and Economics, 26(1), 889-897.
- Fernández-Macho, J. (2012), Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets. Physica A: Statistical Mechanics and Its Applications, 391(4), 1097-1104.
- Fratzscher, M., Schneider, D., Van Robays, I. (2014), Oil Prices, Exchange Rates and Asset Prices. ECB Working Paper, No. 1689, European Central Bank (ECB).
- Gigey, H., Nuru, N. (2021), Exchange rate uncertainty effects on domestic investment in South Africa. Margin-the Journal of Applied Economic Research, 15(3), 338-352.
- Hamilton, J.D. (1983), Oil and the macroeconomy since World War II. Journal of Political Economy, 91(2), 228-248.
- Han, H., Linton, O., Oka, T., Whang, Y.J. (2016), The cross-quantilogram: Measuring quantile dependence and testing directional predictability between time series. Journal of Econometrics, 193 (1), 251-270.
- He, Y., Nakajima, T., Hamori, S. (2019), Connectedness between natural gas price and BRICS exchange rates: Evidence from time and frequency domains. Energies, 12(20), 3970.
- Husain, S., Sohag, K., Wu, Y. (2022), The response of green energy and technology investment to climate policy uncertainty: An application of twin transitions strategy. Technology in Society, 71, 102132.
- Kallianiotis, I.N. (2021), Exchange rate determination: The portfoliobalance approach. Journal of Applied Finance and Banking, 11(1), 19-40.
- Lo, A.W. (2004), The adaptive markets hypothesis. The Journal of Portfolio Management, 30(5), 15-29.
- Miyajima, K. (2020), Exchange rate volatility and pass-through to inflation in South Africa. African Development Review, 32(3), 404-418.
- Mukalayi, N. (2021), Does Exchange Rate Volatility Reduce South African Domestic Consumption? SA-TIED Working Paper, No. 160.
- Müller, U.A., Dacorogna, M.M., Davé, R.D., Pictet, O.V., Olsen, R.B., Ward, J.R. (1993), Fractals and Intrinsic Time: A Challenge to Econometricians. Unpublished manuscript. Zürich: Olsen and Associates, p130.

- Niyitegeka, O., Tewari, D. (2020), Volatility spillovers between the European and South African foreign exchange markets. Cogent Economics and Finance, 8(1), e174308.
- Osei, P.M., Adam, A.M. (2020), Quantifying the information flow between Ghana stock market index and its constituents using transfer entropy. Mathematical Problems in Engineering, 2020, 6183421.
- Owusu Junior, P., Adam, A.M., Asafo-Adjei, E., Boateng, E., Hamidu, Z., Awotwe, E. (2021), Time-frequency domain analysis of investor fear and expectations in stock markets of BRIC economies. Heliyon, 7(10), e08211.
- Qureshi, S., Rehman, I.U., Qureshi, F. (2018), Does gold act as a safe haven against exchange rate fluctuations? The case of Pakistan rupee. Journal of Policy Modeling, 40(4), 685-708.
- Rehman, M.U., Vo, X.V. (2021), Energy commodities, precious metals and industrial metal markets: A nexus across different investment horizons and market conditions. Resources Policy, 70, 101843.
- Sadraoui, T., Regaieg, R., Abdelghani, S., Moussa, W., Mgadmi, N. (2021), The dependence and risk spillover between energy market and BRICS stock markets: A copula-MGARCH model approach. Global Business Review, 2021, 09721509211049123.
- Salisu, A.A., Cuñado, J., Isah, K., Gupta, R. (2021a), Oil price and exchange rate behaviour of the BRICS. Emerging Markets Finance and Trade, 57(7), 2042-2051.
- Salisu, A.A., Cuñado, J., Isah, K., Gupta, R. (2021b), Stock markets and exchange rate behavior of the BRICS. Journal of Forecasting, 40(8), 1581-1595.
- Salisu, A.A., Ndako, U.B. (2018), Modelling stock price-exchange rate nexus in OECD countries: A new perspective. Economic Modelling, 74, 105-123.

- Samargandi, N., Sohag, K. (2022), Oil price shocks to foreign assets and liabilities in Saudi Arabia under pegged exchange rate. Mathematics, 10(24), 4752.
- Tiwari, A.K., Trabelsi, N., Alqahtani, F., Bachmeier, L. (2019), Modelling systemic risk and dependence structure between the prices of crude oil and exchange rates in BRICS economies: Evidence using quantile coherency and NGCoVaR approaches. Energy Economics, 81, 1011-1028.
- Torrence, C., Compo, G.P. (1998), A practical guide to wavelet analysis. Bulletin of the American Meteorological Society, 79(1), 61-78.
- Tweneboah, G. (2019), Dynamic interdependence of industrial metal price returns: evidence from wavelet multiple correlation. Physica A: Statistical Mechanics and Its Applications, 527, 121153.
- Uddin, G.S., Rahman, M.L., Hedström, A. and Ahmed, A. (2019), Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes. Energy Economics, 80, 743-759.
- Umar, Z., Bossman, A., Choi, S.Y., Vo, X.V. (2022), Are short stocks susceptible to geopolitical shocks? Time-Frequency evidence from the Russian-Ukrainian conflict. Finance Research Letters, 2022, 103388.
- Villarreal-Samaniego, D. (2021), The dynamics of oil prices, COVID-19, and exchange rates in five emerging economies in the atypical first quarter of 2020. Estudios Gerenciales, 37(158), 17-27.
- Wu, X.F., Chen, G.Q. (2017), Global primary energy use associated with production, consumption and international trade. Energy Policy, 111, 85-94.
- Zhu, H., Yu, D., Hau, L., Wu, H., Ye, F. (2022), Time-frequency effect of crude oil and exchange rates on stock markets in BRICS countries: Evidence from wavelet quantile regression analysis. The North American Journal of Economics and Finance, 2022, 101708.