International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2023, 13(2), 231-239.

Assessing the Asymmetric Effect of Local Realized Exchange Rate Volatility and Implied Volatilities in Energy Market on Exchange Rate Returns in BRICS

Thobekile Qabhobho*

Department of Economics, Faculty of Business and Economic Sciences, Nelson Mandela University, Port Elizabeth, South Africa. *Email: thobekile.qabhobho@mandela.ac.za

Received: 08 October 2022 **Accepted:** 21 Febuary 2023 **DOI:** https://doi.org/10.32479/ijeep.13685

ABSTRACT

This paper investigates the leverage effect of local realised exchange rate volatility and implied volatilities in energy market on exchange rate returns in BRICS for the period May 07, 2012 to March 31, 2022, using the quantile regression technique. This paper reveals that oil implied volatility shocks (OVX changes) have a significant negative impact on Russian-U.S. Dollar exchange rate returns in all quantiles. When it comes to the Indian rupee and Chinese RMB returns/Dollar, the adverse effects of OVX are most apparent in both normal and booming market conditions. Although South Africa's currency rate returns are affected by both slump-and boom-market situations, Brazil also tends to be in higher quantiles. The implied volatility indices in the energy market have a substantial and considerable negative impact on the BRICS currencies, with the exception of China, where the effect is only noticeable in the upper extreme quantiles. The policy implications and suggestions are discussed.

Keywords: Asymmetric Effect, BRICS, Implied Volatilities in Energy Market, Currency Returns, Quantile Regression
JEL Classifications: G10, G15, G19, O13

1. INTRODUCTION

The analysis and application of macroeconomic policy are impacted by changes in energy prices (Jan van de Ven and Fouquet, 2017). There has been a growth of empirical studies looking at the connection between the energy price and exchange rate following multiple occurrences of global energy price shocks (Ding and Vo, 2012; Rickne, 2014; Liu et al., 2020; Bouazizi, et al., 2022). This is so because the exchange rate channel is primarily how shocks to the price of energy are transferred to the domestic economy (Liu, et al., 2020). As a result, the exchange rate is directly and almost instantly affected by changes in the price of energy commodities. Energy price variations, however, affect exporting and importing nations differently (Salisu, et al., 2021). The outcome may also be influenced by the level of openness, the currency rate's flexibility, the presence of policy buffers, and the degree of economic complexity in economies under investigation.

Like energy price fluctuations, the local historical realized volatility is discovered in some empirical research to be a significant factor in the future rates variation of exchange rate returns. Return volatility is crucial for assets whose future returns are unclear. Knowing and predicting volatility enables us to better manage financial risks, better understand how prices behave and evaluate financial derivatives, among other things. Therefore, it is expected that estimating, modelling, and forecasting volatility have garnered a lot of attention in the literature since the time variation in volatility has been widely accepted as a reality (e.g., Andersen and Bollerslev, 1998; Bollerslev, 1986; Corsi, 2009; Engle, 1982).

This study investigates the impact of implied volatility in the energy market (VEnergy), crude oil implied volatility (OVX), and local realized exchange rate volatility for each BRICS economy on exchange rate returns for BRICS nations.

The choice of BRICS countries is even more intriguing because these countries are significant for both energy production and consumption. The BRICS countries currently contribute 36.4 % of the world's primary energy, and by 2040, that percentage is expected to climb to 40–50 % (International Energy Agency [IEA], 2019). In actuality, the world's biggest and fastest-growing energy producers and consumers are all members of the BRICS. China and India are the world's top two and third-largest net consumers of crude oil, respectively, while Russia is the world's second-largest net exporter of crude 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) claims that in July 2005, China switched from a fixed exchange rate regime to a managed floating exchange rate regime, but the rouble has been freely trading since 2014 when Russia dropped a previous peg. Brazil and South Africa both implemented floating exchange rate systems in 1999 and 2000, whilst India's currency rate system transitioned from a fixed exchange rate regime to the current kind of freely determined exchange rate regime in 1993 (Jiang, 2019). The analysis of the relationship between energy prices and exchange rates in BRICS countries is crucial for investment and risk management as well as for the stability of the economy and financial system due to the differences in the degree of energy commodity dependence among BRIC nations and their various exchange rate regimes or currency interventions (Mahdavi and Zhou, 1997; Hu and Xiong, 2013; Turhan et al., 2014).

The literature specifies three basic channels which are energy demand and supply, terms of trade, portfolio, and wealth, as how the price of energy such as oil and coal is transmitted to the currency rate (Buetzer et al., 2016). Except for the United States, a change in the dollar exchange rate has an impact on the prices paid to oil producers and consumers, which has an impact on the supply and demand for this energy commodity (Backus and Crucini, 2000). Regarding the demand channel, it is important to remember that transactions are conducted in US dollars, which is the currency in which the price of an oil barrel is indicated. Thus, the price of a barrel, once it is converted into the local currency, determines the demand for oil in nations that import it. Changes in the exchange rate cause this pricing to fluctuate. Specifically, research shows a negative correlation between energy prices and currency rates, which is easily explained by the supply and demand dynamics in both markets. When taking into account changes on the oil supply side, a decline in the US dollar's value might lead to a decrease in oil supply and an increase in oil prices, allowing economies that export oil, like Brazil and Russia, to stabilize their export earnings. However, importing nations like India and South Africa may increase their demand for oil if the US dollar falls in value since the price of the commodity will drop relative to the local currency. However, in the case of a country like China that pegs its currency to the US dollar, a decline in the value of the US currency could lead to higher exports and a rise in oil demand (Fratzscher et al., 2014). According to empirical evidence, the interconnection of the energy and currency markets has had conflicting consequences. According to Coudert et al. (2008), short-term supply and demand are slightly elastic. Low price elasticity of supply causes prices to decline due to lower marginal production costs than sales prices and rises due to restrictions on the firm's productive capacity. The lack of oil replacements that can be quickly and easily exploited at low prices may be the cause of the demand being inelastic as well. As a result, long-term trends in oil demand and supply are primarily discernible. Supply is changing on this horizon since fresh investments may boost businesses' productive capacities. Additionally, if demand grows more elastic, other energy sources that can eventually replace oil can be created. In conclusion, a decline in the value of the dollar leads to long-term increases in oil demand and decreases in supply, which usually increase the gross price.

The terms of trade effects and the wealth effects are two separate channels through which a change in the price of oil might affect the exchange rate, according to some studies. Oil-producing and-consuming nations are impacted by the trading channel's parameters, although in varying degrees. Positive terms of trade shock can cause the "Dutch curse," which is characterized by growing non-tradable prices and an actual appreciation of the currency, in countries that export oil. However, if the non-tradable commodity continues to be a normal good, this effect should support the appreciation of the real exchange rate for the home country (Tokarick, 2008). Higher earnings and wages in the primary sector result in higher demand for non-tradable items, which raises prices. The real exchange rate then rises because of this increase.

The wealth impact, which occurs when an increase in oil prices moves wealth from economies that import oil to those that export it, is another significant way that energy variations affect currency markets. This influences the exchange rate of countries that import oil through portfolio imbalance (Kilian and Park, 2009; Buetzer et al., 2016; Bodenstein et al., 2011).

Inspired by these theoretical arguments, multiple studies have experimentally examined the predictive information quality of energy/oil prices for exchange rates using various approaches and for various periods (Chen and Chen, 2007; Chen et al., 2010; Ferraro et al., 2015; Beckmann et al., 2017). Depending on the methodology used, the sample size, and whether the nation is a net exporter or importer of oil, the results of these studies show a wide range of results. These studies can often be split into two categories based on their technique. The inferences made by the first group are based exclusively on the findings of the in-sample Granger-causality test. Some of these studies find a causation effect from oil prices to currency rates, implying that oil prices can be a predictor of exchange rates, whereas others find no causal relationship (Beckmann et al., 2017). The second group (Chen and Chen, 2007; Chen et al., 2010; Ferraro et al., 2015; Salisu et al.,

2019) takes a step further and adds out-of-sample forecasting to the in-sample test results for validation. For instance, in their investigation of the long-term correlation between real oil prices and exchange rates for the G7, Chen and Chen (2007) discovered that real oil prices have a strong forecasting capacity and that the accuracy of out-of-sample predictions increases with increasing time horizons. While Salisu et al (2019) found the opposite, Chen et al. (2010) discovered that although energy commodities prices Granger cause exchange rates in-sample, this link is not robust to out-of-sample data. When oil prices and the Canadian/US dollar exchange rate are analysed outside of samples, Ferraro et al. (2015) find that there is a minimal regular link between these two variables at the monthly and quarterly frequencies. The current study uses the entire data set without dividing it into estimation and validation data sets since its main objective is to analyse the asymmetric impact of realized exchange rate volatility and implied volatility on exchange rate returns.

In addition to energy-implied volatilities, the current study uses historical exchange rate volatilities to predict currency returns. This body of work has shown interest in the foreign currency market. According to Jorion (1995) and Xinzhong and Taylor (1995), implied volatility is preferable to realized volatility in terms of volatility modelling. However, Pong et al. (2004) asserted the exact opposite for a class of autoregressive fractionally integrated moving average models, contending that for forecasts up to 10 days in the future, using historical volatility led to more accurate forecasts due to the availability of high-frequency (high-precision) volatility estimators, which are not available for implied volatility. Furthermore, implied volatility still was not any better than historical volatility over longer forecast horizons. According to Covrig and Low (2003) and Busch et al. (2011) implied volatility is demonstrated to contain additional information on the realized volatility of the foreign exchange market. Covrig and Low (2003) only used a longer forecast horizon, ranging from 1 to 6 months, and discovered that implied volatility provides very precise predictions (better than realized volatility) for 1-month-ahead forecasts, but that as the forecast horizon gets longer, there are hardly any differences between the use of the two volatility measures.

Methodologically, this paper uses quantile regression estimations to look at the asymmetric impacts of locally realized and globally indicated volatilities on currency returns in the BRICS nations. The study's use of the QR approach would enable it to determine an accurate depiction of the interactions between the regressor and the regressand (Nusair and Al-Khasawneh, 2018). Further fluctuations in the coefficient estimates over the distribution of the explained variable, in this case, exchange rate returns, would be permitted using the QR. As suggested by Naifar (2016) and Nusair and Al-Khasawneh (2018), using QR allows for drawing inferences on the interaction between the two variables from a variety of quantiles, especially when making distinctions between market conditions. This contrasts with other techniques, which only present the average association between the variables. Furthermore, the QR method is reliable even in the presence of problems like skewness, non-normality, outliers in the data set, and heterogeneity within the regressand (Zhu et al., 2016). Additionally, according to Nusair and Al-Khasawneh (2018), the QR approach fully represents the relationship between the regressand and the regressor (s). This is produced by modelling the relationship between the regressor(s) and one or more specified quantiles of the regressand (Mensi et al., 2014).

2. METHODOLOGY

2.1. Model Specification

To examine the influence of realized exchange rate volatility and implied volatilities on the exchange rate of BRICS after controlling, a quantile regression technique was employed. The basic models specify the influence of OVX, VEnergy, and realized exchange rate volatility on the exchange rate of BRICS. The models employed in this study is

$$EXR_t = \beta_0(\theta) + \beta_1 EC_t(\theta) + \mu_t(\theta) \tag{1}$$

Where EXR_t denotes exchange rates at time t for each of the BRICS economies, EC_t represents each of the realized exchange rate volatility and implied volatilities at period t,θ is the θ^{th} quantile of the regressors, β represents parameters to be estimated at each quantile and μ_t is the error term at period t without a specific distribution form.

Erstwhile works such as Archer et al. (2022), Boateng, et al. (2021) Demir, et al. (2022), Barson et al. (2022), and Altunbaş and Thornton (2019) employed the Quantile Regression approach and has confirmed its usefulness over the Ordinary Least Square method. The Quantile Regression approach as popularized by Bassett and Koenker in the 1970s describes the conditional quantile of a response variable as a linear function of the explanatory variables instead of only the conditional mean of the regressand and as such estimates from quantile regression are more robust against outliers in the response measurement. Furthermore, quantile regression depicts in greater depth the influence of the independent variable on the regressand. That is, it richly describes and characterizes the data by portraying the impacts of the regressor on the explained variable across the gamut of the dependent variable. Generally, the quantile regression model is described by the equation as

$$Y_t(\theta \mid X) = \beta(\theta) X_t^{'} + \mu_t(\theta) \tag{2}$$

Where β^θ represents the vector of unknown parameters related to the θ^{th} quantile. The quantile regression minimizes $\Sigma_t\, \theta|\mu_t| + \Sigma_t\, (1-\theta)|\mu_t|$, thus the sum that offers the asymmetric penalties $\theta|\mu_t$ for underprediction and $(1-\theta)|\mu_t|$ for overprediction. To calculate the coefficient or the quantile estimator can be solved using the optimization problem stated as

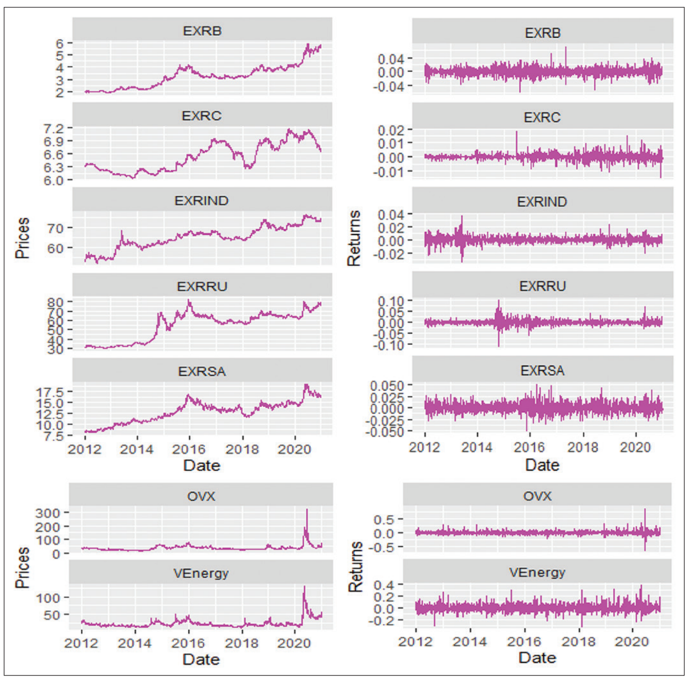
$$\min \sum\nolimits_{t\varepsilon\{Y_t \ge X_{t\theta}^{'}\}}^{n} \theta \,|Y_t - X_t^{'}\beta| + \sum\nolimits_{t\varepsilon\{Y_t < X_{t\theta}^{'}\}}^{n} (1-\theta)\,|Y_t - X_t^{'}\beta| \tag{3}$$

Where Y_t is the dependent variable and X_t is a K by 1 vector of regressors. The relationships between exchange rate and local volatility and international volatilities were examined across 19 different quantiles, thus from the 0.05th quantile to the 0.95th quantile. These quantiles were chosen to assess whether the variations in the commodities market conditions would have the same impact on exchange rate movements. Owing to this, three market conditions which include the slump market condition (lower quantiles; θ = 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35), normal or stable market condition (intermediate quantiles; θ = 0.40, 0.45, 0.50, 0.55, 0.60, 0.65) and the boom market condition (higher quantiles; θ = 0.70, 0.75, 0.80, 0.85, 0.90, 0.95) were utilised in this study.

2.2. Data Sources and Description

The study's analyses, which span the time period from May 7, 2012 to March 31, 2021, take into account BRICS exchange rates and implied volatility in the energy markets. In order to ensure that the dates were consistent, the data were combined to form this timeframe. However, the time period is relevant to demonstrate the effects of key economic events as the COVID-19 outbreak, BREXIT, US-China trade conflict, and Eurozone crisis. The variables included include exchange rate returns for the BRICS economies - Brazil (EXRB), Russia (EXRRU), India (EXRIND), China (EXRC), and South Africa (EXRSA). For the purpose of calculating exchange rates, the local currency is expressed as a percentage of the US Dollar. Since the current study employs a direct quote against the US Dollar, a rise in BRICS' exchange rate denotes depreciation of the domestic currencies. To identify the propagation of a worldwide shock, the stated volatilities were used. The implied volatility of crude oil (OVX) and the volatility in the energy markets (VEnergy) in particular were picked as contagion proxies that are significant to the energy markets but also have an impact on other financial time series (Dutta, et al., 2021; Boateng, et al., 2021; Frimpong et al., 2022; Amoako et al., 2022). Additionally, we took the daily realized exchange rate volatility that we had extracted from the BRICS exchange rate returns and used it as the local shock. Investing.com was used to gather all the financial time data, with the exception of the realized exchange rate volatilities.

Figure 1: Time series plots of prices and returns



3. RESULTS

3.1. Preliminary Statistics

Figure 1 shows the implied volatility price and returns series for the energy markets and the currency rates of the BRICS. The implied volatilities were on the rise and, in a manner similar to how the COVID-19 crisis era did, they similarly shot to a peak. The upward trend in exchange rates suggests that the US dollar value of the BRICS currencies is declining. The high energy implied volatilities in 2016 (the BREXIT era) and 2020 (COVID-19 pandemic crisis) are associated with sharp declines in declines in the BRICS currency markets against the U.S. dollar. This implies that the energy implied volatilities are negatively affecting the BRICS currencies against U.S. Dollar in times of crisis, and hence they may offer safe-haven benefits for inverters. During the COVID-19 epidemic, all the return series were found to have volatility clustering with excessive shocks. The energy prices decline between 2012 and 2013 can be related to the Eurozone Crisis.

Table 1: Descriptive summary

	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB Prob.	ADF	KPSS
Exchange rate returns										
EXRB	0.0005	0.0003	0.0716	−0.0595	0.0105	−0.0129	5.6284	0.00	−49.56***	0.0671
EXRRU	0.0004	0.0004	0.1022	−0.1084	0.0107	0.3832	16.4015	0.00	−46.02***	0.1581
EXRIND	0.0001	0.0000	0.0369	−0.0332	0.0045	0.2862	10.8857	0.00	−36.59***	0.0730
EXRC	0.0000	0.0000	0.0184	−0.0145	0.0021	0.3953	11.42	0.00	−47.19***	0.1539
EXRSA	0.0003	−0.0001	0.0511	−0.0499	0.0101	0.2865	4.4456	0.00	−46.69***	0.1610
Exchange Rate Volatility										
EXRBVOL	0.0017	0.0012	0.0281	0.00040	0.0019	6.4715	61.6008	0.00	−10.33***	1.9297
EXRRUVOL	0.4929	0.2269	33.8193	0.0454	1.3012	15.6533	329.2845	0.00	−10.23***	0.2323
EXRINDVOL	0.0821	0.0680	1.4035	0.0636	0.0598	12.1188	204.7843	0.00	−7.83***	4.1218
EXRCVOL	0.0002	0.0002	0.0039	1.42E-05	0.0002	10.1091	153.9758	0.00	−38.98***	0.4449
EXRSAVOL	0.019195	0.016134	0.153275	0.005644	0.009579	6.405255	63.1367	0.00	−21.00***	1.7473
Energy Volatility										
VENERGY	0.0002	−0.004	0.3808	−0.3103	0.0592	0.701	7.0651	0.00	−47.92***	0.0334
OVX	0.0002	−0.0036	0.8577	−0.6222	0.0587	1.6427	33.61	0.00	−29.78***	0.0231

Asterisks ***, **, * represent 1%, 5%, and 10% level of significance

Table 1 shows that both the exchange rate returns and the implied energy volatility have positive means. Apart from Brazil, the implied energy volatility and currency rate returns exhibit positive skewness and a strong potential for positive performance. However, it is crucial to remember that an upward trend in exchange rate pricing indicates a decline in the value of the local currency; as a result, positive means signify poor performance. The Jarque-Bera (JB) Statistics reveal that the time series does not exhibit a regular distribution. All the return series are stationary, according to the results of the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

Table 2 displays the matrix of unconditional correlations between the study's variables. The results show that the variables exhibit weak and moderate correlation. The strong correlation signifies the presence of multicollinearity. Therefore, since the highest correlation between our variables is 0.49, we conclude that our results are free from the multicollinearity problem. The exchange rate returns within the BRICS economies are often somewhat positively correlated, indicating some degree of similarity in trade linkages. On the other hand, we discover a negative correlation between energy implied volatilities and exchange rate volatility in the BRICS. Depending on the state of the market, this enables investors to diversify, hedge, or seek safe haven.

Table 2: Pairwise correlations

Probability	EXRB	EXRRU	EXRIND	EXRC	EXRSA	EXRBVOL	EXRRUVOL	EXRINDVOL	EXRCVOL	EXRSAVOL	VENERGY	OVX
EXRB	1.00											
EXRRU	0.34***	1.00										
EXRIND	0.19***	0.24***	1.00									
EXRC	0.14***	0.17***	0.22***	1.00								
EXRSA	0.49***	0.42***	0.30***	0.24***	1.00							
EXRBVOL	−0.06***	−0.02	0.00	0.03	−0.01	1.00						
EXRRUVOL	0.01	0.04*	0.00	0.05**	0.02	0.08***	1.00					
EXRINDVOL	0.01	−0.01	−0.03	−0.01	−0.01	0.03	0.01	1.00				
EXRCVOL	−0.01	−0.04	0.02	0.03	−0.02	0.10***	0.04*	0.08***	1.00			
EXRSAVOL	−0.01	−0.04**	0.01	0.04*	−0.02	0.27***	0.13***	0.03	0.10***	1.00		
VENERGY	0.23***	0.38***	0.22***	0.11***	0.34***	−0.01	−0.02	−0.01	−0.02	−0.031	1	
OVX	0.13***	0.30***	0.17***	0.10***	0.20***	−0.07***	0.01	−0.01	−0.01	−0.04*	0.49**	1

Asterisks ***, **, * represent 1%, 5%, and 10% level of significance

3.2. Main Results

3.2.1. Quantile regression estimates

Using quantile regression, this study investigates how implied volatility index in the energy market (VEnergy), implied volatility index in the price of crude oil (OVX), and local realized currency volatility shocks affect exchange rate returns in the BRICS. Based on equation (3), the study estimates the asymmetric relationships for the BRICS nations, and Table 3 displays the findings.

As highlighted above, if the current study does not pay close attention to the currency quote, the interpretation of the directional movements with exchange rates does not seem to offer diversification, hedging, or safe haven. Since the current analysis uses a direct quote against the US dollar, an increase in the BRICS exchange rate indicates a decline in the value of the local currencies. Therefore, a spike in indicated energy commodities volatilities and currency market returns that indicates positive comovements should be read carefully (Qureshi et al., 2018). Investors are less likely to diversify, hedge, or seek safe haven in this situation because they intrinsically mean the same positions. In this instance, the study more accurately explains negative correlations between the direct quotes of the BRICS exchange rate and energy prices, implying the positive effect is that an upsurge in the OVX and VEnergy would augment the U.S. Dollar and depreciate the BRICS currencies.

In terms of Table 3, oil implied volatility shocks (OVX changes) have a significant negative impact on Russian-U.S. Dollar exchange rate returns in all quantiles, implying that an increase in volatility shocks in the crude oil market results in a depreciation of the ruble against the US dollar. However, in the case of the Indian rupee and Chinese RMB returns, the OVX negative effect is largely seen as approaching the higher quantiles or the right-tailed thus, in

Table 3: Quantile regression estimates

Quantiles	OVX	VEnergy	EXRBVOL
Brazil			
0.05	0.01606*	0.02540***	−9.87542***
0.1	0.01107	0.03695***	−6.40817***
0.15	0.00574	0.03644***	−4.56160***
0.2	0.00867	0.03535***	−3.35951***
0.25	0.00624	0.03529***	−2.55879***
0.3	0.00841	0.03524***	−1.75265***
0.35	0.00580	0.03809***	−1.25803***
0.4	0.00360	0.04066***	−0.79303***
0.45	0.00705	0.03694***	−0.34626***
0.5	0.00645	0.03510***	−0.00079
0.55	0.00725	0.03230***	0.43350***
0.6	0.00743	0.03347***	0.96892***
0.65	0.01123	0.03225	1.41572***
0.7	0.01023*	0.03291***	2.19258***
0.75	0.01525**	0.03100***	2.91580***
0.8	0.01492**	0.02696***	4.20077***
0.85	0.015681	0.02931***	5.83610***
0.9	0.01728*	0.02406***	7.61429***
0.95	0.01540**	0.03309***	10.58114***

Russia			
Quantiles	**OVX**	**VEnergy**	**EXRRUVOL**
0.05	0.01312*	0.05580***	−0.03033*
0.1	0.01975***	0.04633***	−0.01862***
0.15	0.02070***	0.04596***	−0.01303***
0.2	0.02475***	0.04222***	−0.00873***
0.25	0.02525***	0.04190***	−0.00640***
0.3	0.02405***	0.04271***	−0.00421***
0.35	0.02333***	0.04211***	−0.00290***
0.4	0.02409***	0.04215***	−0.00176***
0.45	0.02447***	0.04153***	−0.00088
0.5	0.02350***	0.04302***	0.00058
0.55	0.02472***	0.04373***	0.00137***
0.6	0.02617***	0.04171***	0.00175**
0.65	0.02923***	0.03876***	0.00362***
0.7	0.02825***	0.03893***	0.00530***
0.75	0.02919***	0.03765***	0.00770***
0.8	0.02704***	0.03779***	0.01051***
0.85	0.03046***	0.03830***	0.01461***
0.9	0.02284***	0.04180***	0.02222***
0.95	0.02943***	0.04370***	0.03555***

India			
Quantiles	**OVX**	**VEnergy**	**EXRINDVOL**
0.05	0.00121	0.01379***	−0.07385***
0.1	0.00337*	0.01167***	−0.05269***
0.15	0.00241	0.01209***	−0.03980***
0.2	0.00206	0.01313***	−0.03217***
0.25	0.00357*	0.01236***	−0.02523***
0.3	0.00438**	0.01212***	−0.01939***
0.35	0.00520**	0.01207***	−0.01399***
0.4	0.00389*	0.01231***	−0.00960***
0.45	0.00424*	0.01247***	−0.00519***
0.5	0.00381*	0.01322***	−0.00010***
0.55	0.00267	0.01541***	0.00400***
0.6	0.00367*	0.01465***	0.00957***
0.65	0.00495*	0.01399***	0.01483***
0.7	0.00782**	0.01263***	0.02170***
0.75	0.01020***	0.01185***	0.02837***
0.8	0.01144***	0.01182***	0.03634***
0.85	0.01083***	0.01420***	0.04484***
0.90	0.00923***	0.01403***	0.06040***
0.95	0.01381***	0.01252**	0.08535***

(*Contd*...)

Table 3: (*Continued*)

China			
Quantiles	**OVX**	**VEnergy**	**EXRCVOL**
0.05	0.00028	0.00425	−15.15037
0.1	0.00129	0.00118	−9.61649
0.15	0.00059	0.00119	−6.97781
0.2	0.00078	0.00039	−5.11486
0.25	0.00077	0.00089	−3.84316
0.3	0.00143*	0.00094	−2.66802***
0.35	0.00146*	0.00070	−1.77321***
0.4	0.00136**	0.00058	−0.91633***
0.45	0.00118*	0.00048	−0.55763***
0.5	0.00065	0.00009	−0.02037
0.55	0.00137**	−0.00009	0.38993**
0.6	0.00199**	0.00013	1.15077***
0.65	0.00197**	0.00083	2.05403
0.7	0.00214**	0.00129*	2.67750***
0.75	0.00266**	0.00084	3.74438***
0.8	0.00179	0.00191	5.15596***
0.85	0.00376**	0.00284**	7.21780***
0.9	0.00615***	0.00407***	10.36360***
0.95	0.00804***	0.00786***	15.73393***

South Africa			
Quantiles	**OVX**	**VEnergy**	**EXRSAVOL**
0.05	0.01629***	0.04644***	−0.76251***
0.1	0.01324**	0.04541***	−0.58292
0.15	0.00907**	0.04794***	−0.44866***
0.2	0.00730	0.04744***	−0.36281***
0.25	0.00502	0.04987***	−0.27607***
0.3	0.00604	0.04974***	−0.21442***
0.35	0.00260	0.05053***	−0.16053***
0.4	0.00451	0.04945***	−0.11500***
0.45	0.00503	0.05258***	−0.06372***
0.5	0.00380	0.05467***	−0.02038
0.55	0.00702	0.05699***	0.03985***
0.6	0.00610	0.05403***	0.09876***
0.65	0.00751	0.05166***	0.15896***
0.7	0.01167*	0.05161***	0.21786***
0.75	0.00955	0.05070***	0.29913***
0.8	0.01458*	0.05047***	0.38313***
0.85	0.01598**	0.05280***	0.50856***
0.9	0.01077*	0.05569***	0.65507***
0.95	0.01176	0.05834***	0.86559***

That OVX and *VEnergy* represent implied volatility shocks from the crude oil index and the energy market implied volatility, respectively. Also, ***, ** and * represent 1%, 5% and 10% significance level

the normal market condition and the booming market condition. While the OVX effect in Brazil is mostly in higher quantiles, South African exchange rate returns are affected by slump market conditions and boom market conditions.

The implied volatility in the energy market appeared to have a high and significant negative effect on the BRICS currencies, as increases in energy market volatility are associated with depreciation in these currencies' returns against the US dollar, with the exception of China, where the significant negative effect is only visible in the upper extreme quantiles (0.7, 0.85, 0.9, and 0.95). These findings are consistent with those of Qabhobho et al. (2020), who claim that, in practice, financial markets have a substantial negative association between returns and volatility. As a result, high volatility typically results in negative returns rather than positive returns. The leverage effect is used to describe this asymmetries connection.

Furthermore, the effect of local realised exchange rate volatility on exchange rate returns is significant and negative in all lower quantiles for all BRICS countries except China, where only four quantiles (0.3, 0.35, 0.4, and 0.45) have negative estimates.

3.2.2. Non-parametric granger-quantile-causality tests

By establishing causality by employing the non-parametric Granger-quantile-causality approach, we follow Balcilar et al. (2016) to evaluate the robustness of the results. Unlike the basic Granger test, which only looks at the median, the nonparametric causality-in-quantiles analysis considers all quantiles in the distribution (Jena et al., 2019). Consequently, this approach might show how causality operates in both low and high exchange rate returns.

Figure 2 displays the results graphically. Figure 2 depicts the quantile causality tests between mean daily data for the BRICS exchange rate returns and implied volatilities in the energy market and local realized exchange rate volatility. The test statistics are displayed (vertically axis) in each plot against the corresponding quantiles (horizontally axis). At the 5% level of significance, the horizontal solid line has a critical value (CV) of 1.96. The null hypothesis in this situation states that a change in implied (OVX and VEnergy) and local realized exchange rate volatilities do not Granger cause a change in exchange rate returns in BRICS. For instance, the null hypothesis-that OVX does not Granger-cause exchange rate returns-is rejected (P < 0.05) spanning the quantile ranges of 0.2-0.55 in the causality test for OVX to the EXRB; 0.2-0.70 for EXRRU; 0.25-0.70 for EXRIND; and between 0.30 and 0.65 for EXRSA. Brazil, Russia, India, and South Africa are notable nations. The null hypothesis-that VEnergy does not Granger-cause exchange rate returns-is rejected (P < 0.05) for the quantile ranges of 0.25-0.65 in the causality test for VEnergy to the EXRB; 0.20-0.70 for EXRRU; 0.20-0.70 for EXRIND; and between 0.25-0.70 for EXRSA. Brazil, Russia, India, and South Africa are notable nations again in the case of VEnergy. Lastly, the null hypothesis-that local realized exchange rate volatility does not Granger-cause exchange rate returns-is rejected (P < 0.05) covering the quantile ranges of 0.78-0.80 in the causality test for local realized exchange rate volatility to the EXRB; and between 0.40-0.55 for EXRC. Only Brazil and China are notable nations in the case of local historical exchange rate volatility spillover.

The findings also highlight the causative role played by volatility indices in BRICS, particularly implied volatility in the energy market (VEnergy), whose impetus is stronger at the lower quantiles and reduces at the top tails of the distribution. As a result, the current study uncovers striking similarities and

Figure 2: Plots of causality-in-mean tests results

draws the conclusion that our results hold up well to a quantile regression method that takes into consideration the relationship's non-linearities.

4. CONCLUSION AND POLICY RECOMMENDATIONS

This study employed the quantile regression technique to examine the leverage effect of local realised exchange rate volatility and implied volatilities in energy market on exchange rate returns in BRICS, in which the Crude Oil Volatility Index (OVX) and the Energy Market Volatility Index (EMV/VEnergy) are used to proxy implied volatility in energy commodity market. The findings showed that Russian-U.S. exchange rate returns are significantly harmed by shocks to oil implied volatility (OVX movements) across all quantiles. In the case of the Indian rupee and Chinese RMB returns/Dollar, the OVX negative effect is primarily noticeable in the normal market condition and the booming rate returns are impacted market condition. Brazil also tends to be in higher quantiles, but South Africa's exchange rate returns are impacted in both slump-and boom-market conditions. With the exception of China, where the significant negative effect is only visible in the upper extreme quantiles, the implied volatility indices in the energy market have a high and significant negative impact on the BRICS currencies. Furthermore, for all BRICS nations except China, where only four quantiles (0.3, 0.35, 0.4, and 0.45) have negative estimates, the impact of local realised exchange rate volatility on exchange rate returns is considerable and negative in all lower quantiles.

The results partially confirm the hypothesis that exchange rate returns are determined by past exchange rate volatility and oil/energy price fluctuations. It is advised that local realised volatility be utilized to forecast the returns of the exchange rate. Our results also imply that implied volatility indices in the energy market can be used as a proxy for evaluating the transmission of global shocks in the macroeconomic fundamentals of the BRICS for policy decisions in the discussion of exchange rate behaviours, in line with the significance of energy commodities in the global markets. Investors are advised to diversify their portfolios, hedge their positions, or look for safe-haven possibilities from implied volatility in energy commodities while keeping an eye on local realised exchange rate volatility.

5. FUNDING STATEMENT

This work is based on the research supported wholly / in part by the National Research Foundation of South Africa (Grant Numbers: 129452)

REFERENCES

Amoako, G.K., Asafo-Adjei, E., Oware, K.O., 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.

Altunbaş, Y., Thornton, J. (2019), The impact of financial development on income inequality: A quantile regression approach. Economics Letters, 175, 51-56.

Archer, C., Junior, P.O., Adam, A.M., Asafo-Adjei, E., Baffoe, S. (2022), Asymmetric dependence between exchange rate and commodity prices in ghana. Annals of Financial Economics, 17(2), 2250012.

Asafo-Adjei, E., Frimpong, S., Owusu Junior, P., Adam, A.M., Boateng, E., Abosompim, R.O. (2022). Multi-Frequency information flows between global commodities and uncertainties: Evidence from COVID-19 pandemic. Complexity, 2022, 6499876.

Andersen, T.G., Bollerslev, T. (1998), Deutsche Mark-Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. The Journal of Finance, 539, 219-265.

Backus, D.K., Crucini, M.J. (2000), Oil prices and the terms of trade. Journal of International Economics, 50(1), 185-213.

Beckmann, J., Czudaj, R., Arora, V. (2017), The Relationship Between Oil Prices and Exchange Rates: Theory and Evidence, U.S. Energy Information Administration Working Paper Series. Washington, DC: United States Department of Energy.

Balcilar, M., Gupta, R., Kyei, C., Wohar, M.E. (2016), Does economic policy uncertainty predict exchange rate returns and volatility? Evidence from a nonparametric causality-in-quantiles test. Open Economies Review, 27(2), 229-250.

Barson, Z., Junior, P.O., Adam, A.M., Asafo-Adjei, E. (2022), Connectedness between gold and cryptocurrencies in COVID-19 pandemic: A frequency-dependent asymmetric and causality analysis. Complexity, 2022, 7648085.

Bassett, G. Jr., Koenker, R. (1978), Asymptotic theory of least absolute error regression. Journal of the American Statistical Association, 73(363), 618-622.

Boateng, E., Adam, A.M., Junior, P.O. (2021), Modelling the heterogeneous relationship between the crude oil implied volatility index and African stocks in the coronavirus pandemic. Resources Policy, 74, 102389.

Bodenstein, M., Erceg, C.J., Guerrieri, L. (2011), Oil Shocks and external adjustment. Journal of International Economics, 83(2), 168-184.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31, 307-327.

Bouazizi, T., Mrad, F., Hamida, A., Nafti, S. (2022), Effects of conditional oil volatility on exchange rate and stock markets returns. International Journal of Energy Economics and Policy, 12(2), 53-71.

Buetzer, S., Habib, M.M., Stracca, L. (2016), Global exchange rate configurations: Do oil shocks matter? IMF Economic Review, 64(3), 443-470.

Busch, T., Christensen, B.J., Nielsen, M.Ø. (2011), The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. Journal of Econometrics, 160 (1), 48-57.

Chen, S.S., Chen, H.C. (2007), Oil price and real exchange rates. Energy Economics, 29, 390-404.

Chen, Y., Rogoff, K., Rossi, B. (2010), Can exchange rates forecast commodity prices? Quarterly Journal of Economics, 125, 1145-1194.

Corsi, F. (2009), A simple approximate long-memory model of realized volatility. Journal of Financial Econometrics, 7, 174.

Coudert, V., Mignon, V., Penot, A. (2008), Oil price and the dollar. Energy Studies Review, 15(2), 45-58.

Covrig, V., Low, B.S. (2003), The quality of volatility traded on the over-the-counter currency market: A multiple horizons study. Journal of Futures Markets, 23, 261-284.

Das, S. (2019), China's Evolving Exchange Rate Regime, IMF Working Papers, 2019/050. United States: International Monetary Fund.

Demir, A., Pesqué-Cela, V., Altunbas, Y., Murinde, V. (2022), Fintech, financial inclusion, and income inequality: A quantile regression approach. The European Journal of Finance, 28(1), 86-107.

Ding, L., Vo, M. (2012), Exchange rates and oil prices: A multivariate stochastic volatility analysis. The Quarterly Review of Economics and Finance, 52(1), 15-37.
Engle, R.F. (1982), Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987-1008.
Ferraro, D., Rogoff, K., Rossi, B. (2015), Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. Journal of International Money and Finance, 54, 116-141.
Fratzscher, M., Schneider, D., Van Robays, I. (2014), Oil Prices, Exchange Rates and Asset Prices, ECB Working Paper, No. 1689. Frankfurt: European Central Bank.
Hu, C., Xiong, W. (2013), Are Commodity Futures Prices Barometers of the Global Economy? NBER Working Paper, No. 19706. Cambridge: National Bureau of Economic Research, Inc.
International Energy Agency (IEA). (2019), World Energy Outlook. Paris: International Energy Agency.
IMF. (2009), Global Financial Stability Report. United States: International Monetary Fund.
Jan van de Ven, D., Fouquet, R. (2017), Historical energy price shocks and their changing effects on the economy. Energy Economics, 62, 204-216.
Jena, S.K., Tiwari, A.K., Hammoudeh, S., Roubaud, D. (2019), Distributional predictability between commodity spot and futures: Evidence from nonparametric causality-in-quantiles tests. Energy Economics, 78, 615-628.
Jiang, M.N. (2019), A comparative analysis of the exchange rate system of the BRICS. Modern Economy, 10, 1168-1177.
Jorion, P. (1995), Predicting volatility in the foreign exchange market. Journal of Finance, 50, 507-528.
Kilian, L., Park, C. (2009), The impact of oil price shocks on the U.S. Stock market. International Economic Review, 50(4), 1267-1287.
Liu, Y., Failler, P., Peng, J., Zheng, Y. (2020), Time-varying relationship between crude oil price and exchange rate in the context of structural breaks. Energies, 13, 2395.
Mahdavi, S., Zhou, S. (1997), Gold and commodity prices as leading indicators of inflation: Tests of long-run relationship and predictive performance. Journal of Economics and Business, 49(5), 475-489.
Mensi, W., Hammoudeh, S., Reboredo, J.C., Nguyen, D.K. (2014), Do global factors impact BRICS stock markets ? A quantile regression approach. Emerging Markets Review, 19(159), 1-17.
Naifar, N. (2016), Do global risk factors and macroeconomic conditions affect global Islamic index dynamics? A quantile regression approach. Quarterly Review of Economics and Finance, 61, 29-39.
Nusair, S.A., Al-Khasawneh, J.A. (2018), Oil price shocks and stock market returns of the GCC countries: Empirical evidence from quantile regression analysis. Economic Change and Restructuring, 51, 339-372.
Pong, S., Shackleton, M.B., Taylor, S.J., Xu, X. (2004), Forecasting currency volatility: A comparison of implied volatilities and AR[FI]MA models. Journal of Banking & Finance, 28, 2541-2563.
Qabhobho, T., Wait, C.V.R., Le Roux, P. (2020), Exchange rate volatility, the contagion and spillover effect from South African to other SADC currency markets: 2007-2015. African Journal of Business and Economic Research, 15(2), 7-24.
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.
Rickne, J.K. (2014), Oil prices and real exchange rate movements in oil-exporting countries: The role of institution, IFN Working Paper, No. 810. Stockholm: Research Institute of Industrial Economics.
Salisu, A.A., Adekunle, W., Alimi, W.A., Emmanuel, Z. (2019), Predicting exchange rate with commodity prices: New evidence from Westerlund and Narayan (2015) estimator with structural breaks and asymmetries. Resources Policy, 62, 33-56.
Salisu, A.A., Cuñado, J., Isah, K., Gupta, R. (2021), Oil price and exchange rate behaviour of the BRICS. Emerging Markets Finance and Trade, 57(7), 2042-2051.
Turhan, M.I., Sensoy, A., Hacihasanoglu, E. (2014), A comparative analysis of the dynamic relationship between oil prices and exchange rates. Journal of International Financial Markets Institutions and Money, 32, 397-414.
Tokarick, C. (2008), Commodity currencies and the real exchange rate. Economics Letters, 101, 60-62.
Xinzhong, X., Taylor, S.J. (1995), Conditional volatility and the informational efficiency of the phlx currency options market. Journal of Banking & Finance, 19, 803-821.
Zhu, H.M., Guo, Y., You, W., Xu, Y. (2016), The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. Energy Economics, 55, 30-41.