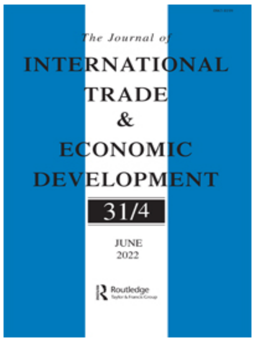

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Oil price volatility and US dollar exchange rate volatility of some oil-dependent economies

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ABSTRACT
This paper examines the relationship and related causality patterns of oil price volatility and exchange rate volatility of a group of oil-dependent economies before and after the 2008–2009 global financial crisis. We employed weekly time-series data of oil price and exchange rates for 2000–2007 (pre-crisis) and 2010–2016 (post-crisis). United States dollar exchange rates are for Ghanaian cedi, Nigerian naira, Russian ruble, Indian rupee, South African rand, and the Euro. To investigate the volatility impacts that exist between oil price and exchange rates during both sub-sample periods, we merged Vector Autoregressive (VAR) with GARCH and EGARCH models in the form of Bivariate VAR-GARCH and VAR-EGARCH. We further adopted the Toda-Yamamoto causality test to investigate related causality patterns. Empirical findings revealed both bidirectional and unidirectional relationship between oil price volatility and the exchange rates volatility of four out of the six oil-dependent economies considered for the study. These findings were more prevalent in the post-crisis period than the pre-crisis period. We also confirmed both bidirectional and unidirectional causality pattern between oil price volatility and exchange rate volatility of the same four currencies as observed with the VAR results in both sub-sample periods.

KEYWORDS Oil price; exchange rate; volatility; Toda-Yamamoto causality; oil-dependent; VAR

JEL CLASSIFICATIONS F31, L71, O13

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1. Introduction

Changes in crude oil prices influence economic activities at all levels of countries that depend heavily on oil for industrial production of goods and services and fiscal revenue (Basher, Hang, and Sadorsky 2012). For such economies, it is natural to hypothesize that crude oil price and its volatility correlate with changes in their macroeconomic variables such as exchange rates, Gross Domestic Product (GDP), interest rates, inflation rates, and others (Blanchard and Gali 2007). However, the volatility impact between oil price and exchange rates appears to be of great recognition in literature in the spirit of early evidence by Amano and Van Norden (1998) and Golub (1983). They documented that

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the oil price-exchange rate relationship tends to have a chain effect on related domestic macroeconomic variables of oil-dependent economies via the transfer of wealth by way of trade balances. Over the years, the United States dollar has been the most widely used currency for trading crude oil in the international market. Given this, one would expect that the volatility of crude oil prices would have an impact on the value of the US dollar relative to other currencies, which subsequently impacts economic activities of oil-dependent countries with currency value pegged to the United States dollar.

In 2007 through to early 2008, the United States financial market began to fall, leading to a crucial crisis moment since the Great Recession of the early 1930s (Tharkor 2015). The crisis moment resulted in the collapse of many global financial institutions, which included Lehman Brothers Holdings Inc., a leading global financial institution in the United States during the pre-crisis period. Before the crisis in 2008, a barrel of crude was sold for more than $140, and according to studies by Reboredo and Rivera-Castro (2013) and Ding and Vo (2012), the impact of the volatility interaction between oil price and exchange rate in this period was relatively insignificant. However, after the crisis in 2010, global oil price benchmarks started declining steadily, particularly that of West Texas Intermediate (WTI), dipping as low as $28 per barrel in 2016. Forthwith, the United States dollar surged significantly contrary to most floating currencies in the face of the fall in oil prices during the post-crisis period. Bechmann, Berger, and Czudaji (2016) acknowledged that the interaction over the post-crisis period between oil prices and the exchange rates unfolded rapidly, hence, relatively significant volatility in these variables after the 2008–2009 financial crisis.

The monotonic surge of the strength of the United States dollar relative to other floating currencies as crude oil price fell during the post-crisis period, raises a query about the interaction of their volatilities, particularly after the global financial crisis. In responding to this query, we adopted the approach of using oil price volatility and exchange rate volatility of six different highly endowed oil-dependent economies with variant economic growth. Unlike studies such as Ding and Vo (2012) and Salisu and Mobolaji (2013) that utilized currency index, this approach allows for the different behavioral qualities of each specific currency as influenced by their extent of respective economic growth or rate of economic dependence on crude oil before and after the global financial crisis.

Moreover, since an investigation into oil price-exchange rate dynamics is never complete without giving a thought to the causality pattern between them, we examined oil price-currency causality dynamics in terms of their second moments to ascertain the direction of the volatility impact between them. This study is quite different from other studies on the causality dynamics between oil price and exchange rates because it captures the common information factor (the volatility effect) which settles to some extent the ambiguity in the nature (linear and nonlinear) of causality between these variables in literature.

This study may be of great importance to domestic policymakers and implementers whose currencies are pegged to the United States dollar in a floating exchange rates system and are primary dependents of crude oil for revenue or consumption. We seek to prompt such stakeholders to put in place sustainable mechanisms that could mitigate their over-reliance on crude to stabilize their macro and micro-economic activities.

The remainder of the paper is structured as follows: Section 2 focuses on the literature review, Section 3 presents the data and methodology, Section 4 presents and discusses the findings, and Section 5 concludes the paper.

2. Literature review

Over the past decades, there have been vast theoretical literature about factors that dictate oil price volatility, which subsequently affects the volatilities of macroeconomic variables such as exchange rates. Kilian (2009) summarized these factors based on the findings of Barsky and Kilian (2001). Killian's framework identified three main ways through which oil prices are affected. First, volatility in international financial trading activities. Secondly, shocks to oil supply forces like the recent Russia–Saudi Arabia oil price war of 2020 and finally, a shift in precautionary demand for oil.

The findings by Kilian (2009) were complemented by Dvir and Rogoff (2010). They provided a similar theory of precautionary demand channels by showing that inventory hoarding during the period of persistent volatility in macroeconomic variables increases oil price volatility.

The response of macroeconomic variables on the impact of oil price volatility can be symmetrical or asymmetrical. Concerning the symmetrical relationship, studies have indicated that the size of a negative impact on exchange rates is associated with the degree of oil price volatility. Other studies documented the asymmetric effect theory of oil price volatility and economic activities as mainly influenced by monetary policy. For instance, the antagonistic monetary policies implemented by the central banks of oil-dependent economies contributed significantly to the fall of macroeconomic activities which led to an oil price rise (Bohi 1989). This assertion was recently supported by Bechmann, Berger, and Czudaji (2016), in which they attributed the recent intensified oil-currency relationship to changes in monetary supply.

However, a study by Lee and Ralti (1995) contended that the asymmetric results of oil price volatility and macroeconomic growth is influenced by sectorial reallocation and uncertainty that arise from new investment theory. Thus, the sectorial shift is seen from the point where a decline in oil price leads to resource reallocation with vantage sectors that have a negative impact on macroeconomic growth.

In recent years, several studies have contributed empirically to literature concerning the volatility interaction of oil price-currency nexus. However, the findings of these studies concerning oil price-currency volatility impact are inconclusive. Cifarelli and Pladino (2010) investigated speculation that affects oil price volatility. They adopted a tri-variate Constant Correlation Coefficient GARCH-in-mean model with a composite nonlinear conditional expected equation to link oil price volatility with exchange rate dynamics and stock market behavior. They concluded that shifts in the oil prices are contrarily related to exchange rate volatility. Besides, Ding and Vo (2012) investigated the reciprocal action of oil price and foreign exchange rate nexus to extricate information twirl in the two markets for forecasting. Using multivariate GARCH and Multivariate Stochastic Volatility (MSV) models, they concluded that in times of crisis, there appears to be bidirectional volatility between both markets. Thus, volatility shock in one market tends to impact the other market's volatility.

Further, in a study to examine the transmission of return and volatility linking oil price and Nigerian naira exchange rate, Salisu and Mobolaji (2013) adopted daily data to confirm the existence of spillover effect emanating from the oil-currency relationship in terms of volatility and returns. Earlier, Zhang et al. (2008) were of the contrary view that, although volatility clustering persists in these two markets' prices, it does not spillover between them, suggesting, volatility in the exchange rate has no significant effect on oil price volatility whilst the opposite is true.

Seminal papers by Golub (1983) and Amano and Van Norden (1998) pioneered the causal tie-in between these two markets. For instance, Amano and Van Norden (1998) concluded that oil price causes exchange rates movement but not in the opposite direction. Consistent with their findings, Chen and Chen (2007) also examined the causal relationship between these two markets using different measures of oil including the West Texas Intermediate (WTI), Brent, and the United Arab Emirates prices of crude oil against G7 economies exchange rates. They concluded that oil prices cause changes in the exchange rate of the G7 countries. More recently, Lizardo and Mollick (2010) used extensive data spanning from 1970 to 2008 to investigate the relationship between these two markets. They documented that oil price Granger causes the US dollar exchange rate volatility relative to major trading currencies.

On the contrary, other empirical studies concluded in the opposite direction, indicating that changes in exchange rate Granger cause oil price volatility. For instance, a study by Zhang and Wei (2010) documented a significant co-integration relationship between oil price and exchange rate and found return causality from dollar exchange rate to oil price but not in the opposite direction. An earlier study by Sadorsky (2000) examined empirically the relation connecting future prices of crude oil and exchange rate dynamics. He concluded that the exchange rate causes exogenous shock to oil prices. Another earlier study by Indjehagopian, Lantz, and Simon (2000) used a limited version of the Vector Autoregression (VAR) model, described in error correction structure to show a short– and long-run correlation linking exchange rates and oil prices. They identified causality from exchange rate variations to oil price variations.

Although bidirectional causality may exist as shown by other studies (Gomez-Gonzalez, Hirs-Garzon, and Uribe 2020; Zhang 2017), this was not strong before the 2008 global financial crisis. However, after the crisis, there was strong relationship between oil price and exchange rates (Mensah, Obi, and Bokpin 2017). Crude oil price was identified as the major spillover transmitter to exchange rates (Gomez-Gonzalez, Hirs-Garzon, and Uribe 2020). After the crisis, the dollar, which is the major trading currency of crude oil in the international market, surged relative to most floating currencies. Hence, the need to focus on how oil price contributed to the rise of the US dollar relative to the currencies of oil dependent economies, particularly in the aftermath of the 2008 global financial crisis.

Given the above literature, it is obvious that the widely documented direction of oil-currency causality in literature is uncertain. These studies, as much as possible, adopted the Granger causality test that has been criticized in the literature to be inefficient in revealing the exact nonlinear causal relationship between these two variables (see Baek and Brock 1992; Benhmad 2012). The nonlinear arguments of Baek and Brock (1992) and Benhmad (2012) suggest that, when investigating the existence of causality between these two markets, it is prudent to add a nonlinear modeling technique to any adopted linear modeling technique in investigating oil-currency causal relationship. For instance, Bal and Rath (2015) investigated nonlinear causality between crude oil price and exchange rate, adopting Hiemstra and Jones (1994) approach of nonlinear Granger Causality to test the residuals of Vector Autoregression (VAR). They identified a highly significant bidirectional Granger causality in nonlinear form between exchange rates and oil prices.

In this paper, we test causality between oil price volatility and exchange rates volatility by adopting a modified Wald test (MWald) known as Toda-Yamamoto causality test introduced by Toda and Yamamoto (1995). This approach is an alternative procedure to causality test based on modified Granger noncausality test to overcome the shortfalls of the conventional Granger noncausality test based on Wald's F-statistics. The Wald test statistic that is usually used when testing for Granger non-causality follows a Chi-squared distribution asymptotically, if the null hypothesis is true. However, this distribution becomes non-standard if any of the data are non-stationary (and/or cointegrated). To overcome this problem, Toda and Yamamoto (1995) proposed a technique that involves the estimation of an augmented VAR and the construction of a slightly modified application of the Wald test, to ensure that the latter's statistic has the usual asymptotic Chi-square distribution.

Despite the extensive works on the impact that exist between oil-currency relationship, this study extends existing literature in unique a way. Originally dissimilar from other studies, and following Kuttu (2014), Abdalla (2013), and Ling and McAleer (2003), we merged vector autoregressive (VAR) with GARCH and EGARCH models in the form VAR-GARCH and VAR-EGARCH to investigate the impacts between oil-currency relationship. This approach allows for the joint modeling of volatilities in oil price returns and exchange rates return to determine whether returns volatility in oil price impact the conditional variance (volatility) in exchange rates return.

3. Data and methodology

For this study, we obtained weekly time-series data for one month's crude oil futures contracts from West Texas Intermediate (WTI) trading on the New York Mercantile Exchange (NYME). The retrieved settlement data from the United States Energy Information Administration are for different maturities.

Nominal exchange rates are obtained from Oanda and are for Ghanaian cedi, Indian rupee, South African rand, Russian ruble, Nigerian naira, and the Euro. Calculated dollar exchange rates are for units of each currency per dollar. Time series data obtained are for the subsample periods from 2000 to 2007 (pre-crisis) and 2010–2016 (post-crisis) (Mensah, Obi, and Bokpin 2017). The choice of subsample periods reflects the downturn in market value due to the 2008–2009 global financial crisis (Reboredo and Rivera-Castro 2013). The analytical package for statistical estimation and analysis for each variable was E-views (10).

To ensure a greater likelihood of stationarity of each series over time and considering time-additivity, immaterial of repetition of compounding, we converted the time series data of each variable from their raw form into returns. We achieved this by using logarithm, estimating the first difference, and multiplying by one hundred. Thus, continuously compounded return formulae adopted to derive the weekly returns is as follows:

$$\mathrm{RET}_{\mathrm{i,t}} = ln\left(\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}}\right)*100 \quad (1)$$

Where i = Oil price, or dollar exchange rate for Ghanaian cedi, Nigerian naira, Russian ruble, Indian rupee, South African rand, and the euro, $\mathrm{P_t}$ represents the closing oil price or exchange rate at week t, $\mathrm{P_{t-1}}$ indicates the closing oil price or exchange rate at lag one and *ln* represents natural logarithm.

The nature of oil price volatility, as shown in Figures 1 and 2, was determined using Bollerslev's (1986) Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Specifically, GARCH (1 1) was adopted to generate the conditional volatility

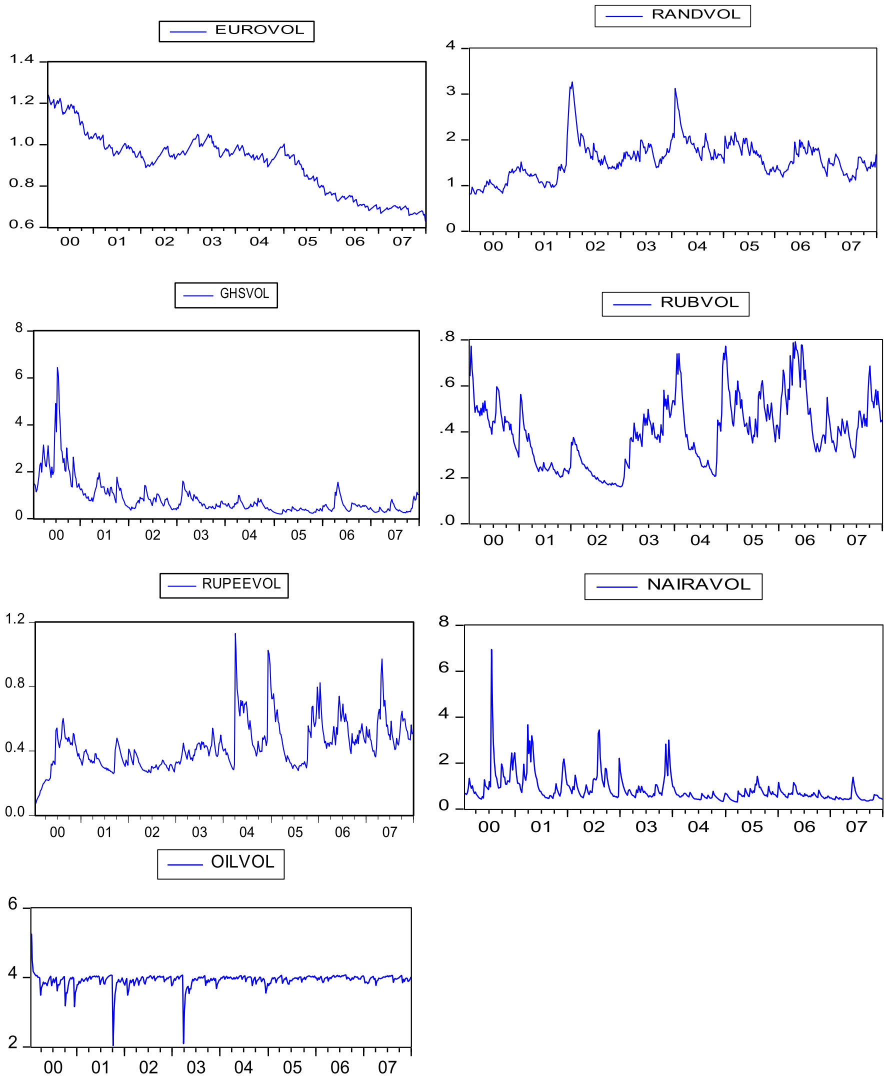

Figure 1. Variables volatility dynamics for the pre-crisis period (2000–2007).

series of oil price returns. As an upgrade of Engle's (1982) Autoregressive Conditional Heteroskedasticity (ARCH), GARCH models have been proven in the literature to be more parsimonious, avoids overfitting, and sufficient to capture the clustering and persistence in oil price returns series (Brooks 2008). The GARCH (1 1) model adopted for oil returns volatility is as follows:

$$\mathrm{OILRET_t} = \alpha + \beta \mathrm{OILRET_{t-1}} + \varepsilon_\mathrm{t}\,, \tag{2}$$

$$\varepsilon_\mathrm{t} \sim \mathrm{N}(0,\ \delta^2{}_\mathrm{t})\,,$$

$$\delta^2{}_\mathrm{t} = \theta_0 + \theta_1 \varepsilon^2_{\mathrm{t}-1} + \theta_2 \delta^2{}_{\mathrm{t}-1}, \tag{3}$$

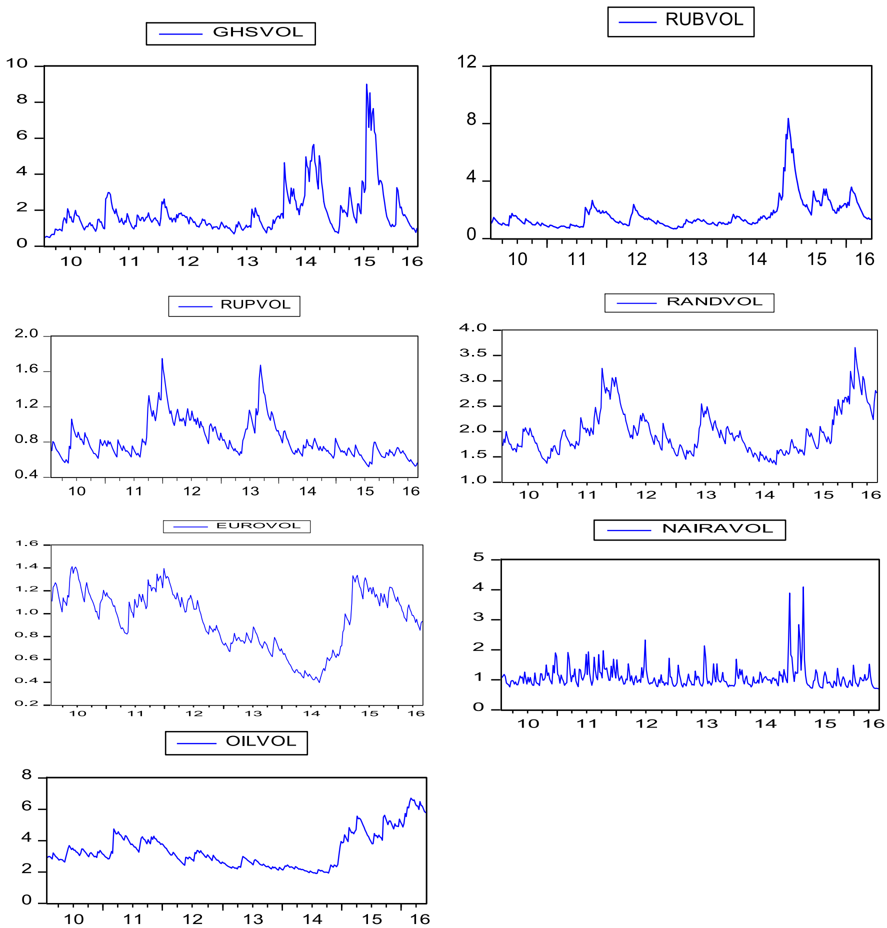

Figure 2. Variables volatility dynamics for the post-crisis period (2010–2016).

Where $OILRET_t$, and $OILRET_{t-1}$ represent respective end of the current week and the previous week's oil price returns. β,θ_0, and θ_1 are coefficients to be determined and ε_t is identically independent distributed error term. ε_t is also distributed normally with expectation zero and time-dependent variance. $\delta^2{}_t$ represents the conditional variance of oil price return which depends on the lags of the error term and its own previous values. α is constant and represents the intercepts to basically avoid forcing the regression line to pass through the origin.

To capture the same magnitude of a negative relationship between the dollar and each currency's exchange rate's returns and volatility that is driven by the opposite forces, we specifically adopted the Exponential Generalized Autoregressive Conditional Heteroskedasticity EGARCH (1 1) model in the spirit of Nelson (1991). Unlike Bollerslev's (1986) GARCH, the Exponential GARCH accounts for the same magnitude of asymmetric volatility shocks existing between the dollar and each currency's exchange rate due to its embedded leverage effect parameter. The average returns of exchange rates are modeled as follows:

$$\text{EXCRET}_{\text{i,t}} = \beta_0 + \beta_1 \text{EXCRET}_{\text{i,t}-1} + \varepsilon_{\text{i, t}}, \tag{4}$$

$$\log(\sigma^2_{\text{i,t}}) = \omega + \theta \log\ (\sigma^2_{\text{i,t}-1}) + \alpha \left| \frac{\varepsilon_{\text{i,t}-1}}{\sigma_{\text{i,t}-1}} \right| + \gamma \frac{\varepsilon_{\text{i,t}-1}}{\sigma_{\text{i,t}-1}}, \tag{5}$$

where equation 4 and 5 are the mean equation and conditional variance respectively; i = Dollar exchange rate for the Ghanaian cedi, Nigerian naira, South Africa rand, Euro, Russian ruble and Indian rupee; EXCRET_{t} and $\text{EXCRET}_{\text{t}-1}$ represent the end of the current week and the previous week's exchange rate returns respectively; α, β_0,β_1,ω, θ and γ are coefficients to be determined and ε_{t} is the error term. log $(\sigma^2_{\text{i,t}})$ represents logarithm of the conditional variance; it explains the exponential nature of the leverage effect, relative to quadratic, so that the predictions of the conditional variance are assured to be positive to avoid negativity constraint. The existence of leverage effects can be examined by the hypothesis that $\gamma < 0$; the impact is asymmetric if $\gamma \neq 0$.

We further introduced the conditional volatility series of the returns of the variables into the Vector Autoregressive (VAR) model to connect the lead-lag system of the variables to examine the existence of the random disturbances between the exchange rates volatility and oil price volatility. Sims (1980) popularized the VAR model as the univariate autoregressive model generalization in the literature (Brooks 2008). Typically, the VAR model, which consist of two endogenous variables, oil price volatility and exchange rate volatility, is constructed as:

$$\begin{bmatrix} \delta^2{}_{\text{i,t}} \\ \sigma^2{}_{\text{i,t}} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \sum_{\text{k}=1}^{\text{K}} \text{A}_{\text{k}} \begin{bmatrix} \delta^2{}_{\text{i,t}-\text{k}} \\ \sigma^2{}_{\text{i, t}-\text{k}} \end{bmatrix} + \begin{bmatrix} \varepsilon_{(\delta^2)\text{i,t}} \\ \varepsilon_{(\sigma^2)\text{i,t}} \end{bmatrix} \tag{6}$$

Where $\delta^2{}_{\text{t}}$ and $\sigma^2{}_{\text{t}}$ are the oil price volatility and exchange rates volatility at week t; i = Ghana, Nigeria, South Africa, Europe, Russia, and India. The regression coefficients A_{k} estimate the time series that links exchange rate - oil price volatilities.

Table 1 reports the variables' data summary statistics for the pre-crisis and post-crisis periods. We observed that the average weekly oil price return during the pre-crisis period was high and very volatile, measured by the standard deviation. The oil price returns have significant leptokurtosis in the two subsample periods. Also, the distribution has a long-left tail in the pre-crisis period but a long-right tail in the post-crisis period. The Jarque-Bera test result rejects the weekly oil return normality hypothesis in both subsample periods. The Ljung Box Statistic also rejected the null hypothesis of no serial correlation in oil price returns in both subsample periods, which indicates autocorrelation in the oil price returns series that needs to be corrected. From the standard deviations, we observed volatile exchange rates return for all currencies relative to their average returns in both subsample periods. Specifically, the rand and cedi exchange rates return recorded the highest volatility value respectively in both subsample periods. The exchange rates return for all currencies are positively skewed except for the naira and the rupee exchange rates returns in the pre-crisis period as well as cedi and ruble exchange rates return in the post-crisis period. Relative to the normal distribution, these variables distributions have long-right and long-left tails in both subsample periods. The returns of these currencies are leptokurtic in both subsample periods. Jarque-Bera test result rejects the normality hypothesis of all the currencies' exchange rate returns except

Table 1. Descriptive statistics of oil price and bilateral exchange rate of the dollar.

	$OILRET_t$	$GHSRET_t$	$NAIRARET_t$	$RANDRET_t$	$EURRET_t$	$RUBRET_t$	$RUPRET_t$
Panel A: Pre-Crisis (3/3/00 – 28/12/07) - 416 Observations							
Mean	0.3239	0.2403	0.0363	0.0305	−0.0830	−0.0261	−0.0236
Std. Dev.	4.0025	1.1177	1.1041	1.7362	1.0078	0.4599	0.4588
Skewness	−0.8590	2.9368	−2.0756	0.7954	0.1622	1.8752	−0.5432
Kurtosis	5.0995	22.6135	29.5581	5.0947	2.8880	20.1741	9.0975
Jarque Bera	127.5690	7265.957	12524.44	119.9232	2.0403	5356.289	664.9110
Probability	0.0000	0.0000	0.0000	0.0000	0.3605	0.0000	0.0000
Q (36)	59.109***	227.05***	68.361***	107.69***	96.880***	40.517	84.159***
Panel B: Post-Crisis (10/1/10 – 29/05/16) – 333 Observations							
Mean	−0.1559	0.3002	0.0833	0.2281	0.0759	0.2370	0.1148
Std.Dev.	3.6522	2.2755	1.1936	2.0478	1.0410	2.2100	0.964
Skewness	0.0698	−2.0675	0.4799	0.3790	0.0274	−0.1138	0.4513
Kurtosis	4.4944	24.9134	5.5976	3.9329	3.2300	19.7566	5.5797
Jarque Bera	31.2566	6899.964	106.4019	20.0475	0.7756	3896.581	103.6409
Probability	0.0000	0.0000	0.0000	0.0000	0.6785	0.0000	0.0000
Q(36)	52.879**	57.094**	64.910***	40.122	87.456***	83.411***	130.62***

Note: OILRET = Oil price returns; GHSRET = Ghana cedis/dollar exchange rate returns; NAIRARET = Nigeria naira/dollar exchange rate returns; RANDRET = South Africa rand/dollar exchange rate returns; EURRET = Euro/dollar exchange rate returns; RUBRET = Russia ruble/dollar exchange rate returns; RUPRET = Indiana rupee/dollar exchange rate returns; Q (k) is the Ljung Box Statistic.

for the euro exchange rate returns in both subsample periods. The Ljung Box Statistic rejected the null hypothesis of no serial correlation for all currencies' exchange rates returns except the ruble and rand exchange rates returns respectively in both subsample periods.

We finally ascertain whether the current values of exchange rates volatility are explained by past values as might be presented by the VAR estimation. Thus, oil price volatility is claimed to cause exchange rates volatility if the previous week's oil price volatility explains the current week's exchange rates volatility and, thus, oil price volatility predicts exchange rate volatility. Similarly, exchange rates volatility is claimed to cause oil price volatility if the previous week's exchange rate volatility explains the current week's oil price volatility and, hence, exchange rate volatility predicts oil price volatility.

Often, the stationarity of financial time series data is unknown, thus, requiring some pre-test strategy in a form of a unit root test (such as those of Dickey and Fuller 1979; or Phillips and Perron 1988) to determine the distribution's stationarity. Our attention is not on the stationarity of the data per se but, as has been noted already, if any of the data are non-stationary, then the usual Wald test for Granger non-causality is inappropriate, and so we have adopted the modified non-causality testing procedure introduced by Toda and Yamamoto (1995) to test the causality hypothesis between oil price volatility and exchange rates volatility. This procedure requires that we pre-test the time-series data to determine their levels of integration. Toda-Yamamoto causality is an alternative procedure to causality test based on modified Wald's test (MWald). This approach overrides the shortcomings of the Granger (1969) noncausality test of validating the asymptotic theory by the estimation of an augmented VAR of order ($k+d_{max}$), where k is the chosen lag length and d_{max} is the anticipated maximum order of integration with its coefficient matrices of the last lagged vectors ignored. Specifically, a bivariate Toda-Yamamoto causality test of the form shown below (in equations 7 and 8) is adopted to empirically test the causal relationship between oil price volatility and exchange rate volatility:

$$\delta^2{}_t = \alpha_{11} + \sum_{j=1}^{p} \beta_{11j}\delta^2{}_{t-j} + \sum_{j=p+1}^{P+d_{max}} \beta_{11j}\delta^2{}_{t-j} + \sum_{j=1}^{p} \beta_{12j}\sigma^2{}_{t-j} + \sum_{j=p+1}^{P+d_{max}} \beta_{12j}\sigma^2{}_{t-j} + \varepsilon_{1t} \tag{7}$$

$$\sigma^2{}_t = \alpha_{21} + \sum_{j=1}^{p} \beta_{21j}\delta^2{}_{t-j} + \sum_{j=p+1}^{P+d_{max}} \beta_{21j}\delta^2{}_{t-j} + \sum_{j=1}^{p} \beta_{22j}\sigma^2{}_{t-j} + \sum_{j=p+1}^{P+d_{max}} \beta_{22j}\sigma^2{}_{t-j} + \varepsilon_{2t} \tag{8}$$

Where $\delta^2{}_t$ represents oil price volatility at week t, and $\sigma^2{}_t$ represents exchange rate volatility at week t. The coefficients, β_{12j} and β_{21j} estimate the time series impacts linking exchange rate volatility and oil price volatility. d_{max} is the maximum order of integration, j denotes the number of lagged observations and p is the last or the nth lag observation considered. α_{11} and α_{21} are constants while ε_{1t} and ε_{2t} are the error terms. Based on equations (7) and (8), a collective hypothesis of the form shown in equation (9) is tested, and the modified Wald Statistics (MWALD) is reported in the next section:

$$\beta_{12j} = \beta_{21j} = 0, \tag{9}$$

The null hypothesis for this test states that $\sigma^2{}_t$ does not cause $\delta^2{}_t$ regarding equation (7) and $\delta^2{}_t$ does not cause $\sigma^2{}_t$ with respect to equation (8). The decision criterion in this test is that, if the corresponding probability value of the MWald test is less than 1%, 5%, or 10% significance level, the null is rejected.

In literature, financial and overconfidence bias theories do not specify the appropriate lag order for a VAR model and its associated dynamic analysis. Thus, we employed Akaike Information Criterion (AIC) to the VAR model with different lag orders on the series, and the lag length that provides the minimum information criterion value is selected. From Tables 2 and 3, the AIC test unanimously revealed lag1 as the optimal lag length for constructing the VAR model for each pair of oil price volatility and all currencies' exchange rates volatility except the Ghanaian cedi and the euro during the pre-crisis period. In the post-crisis period, the AIC test revealed the same VAR lag length of 8, 8, 1, 1 for the construction of the VAR model for oil price volatility and respective exchange rate volatilities for the Ghanaian cedi, South African rand, euro, and the Indian rupee.

4. Findings and discussion

From Table 4, oil price volatility is very significantly autocorrelated at lag 1 for the panel A to F with a low adjusted R-square of about 0.30, which indicates a weak influence of the previous week's oil price volatility on the current week's oil price volatility during the pre-crisis period. Unlike the pre-crisis period, oil price volatility was significantly autocorrelated for only panel A at lag 2 with a high adjusted R-square of 0.96 in the post-crisis period. More importantly, out of the six currencies, only the Ghanaian cedi exchange rate volatility was found to have a significant impact on the volatility of oil price return at lag 1. Consistent with the findings of Reboredo and Rivera-Castro (2013) and Ding and Vo (2012), oil-currency volatility impact in the pre-crisis period, in general,

Table 2. VAR lag selection of oil volatility and exchange rates volatility for the pre-crisis period.

Lag	GHSVOL	NAIRAVOL	RUBVOL	RANDVOL	EUROVOL	RUPVOL
0	8.727529	8.361707	2.038569	0.958282	−1.319996	0.486518
1	7.149312	7.822754*	−0.155474*	4.487586*	−1.631137	1.070716*
2	7.149107	7.825890	−0.140860	4.497408	−1.629538*	1.082454
3	7.162548	7.843599	−0.129171	4.489004	−1.629838	1.084363
4	7.140741*	7.858211	−0.109984	4.500990	−1.613172	1.101757
5	7.151995	7.873544	−0.091666	4.516907	−1.599139	1.119079
6	7.156897	7.890494	−0.079461	4.535252	−1.587951	1.134936
7	7.145774	7.906160	−0.062001	4.533462	−1.569126	1.143909
8	7.163133	7.918419	−0.049464	4.537573	−1.555380	1.160155

∗ indicates lag order selected by criterion

Table 3. VAR lag selection of oil volatility and exchange rate volatility for the post-crisis period.

Lag	GHSVOL	NAIRAVOL	RUBVOL	RANDVOL	EUROVOL	RUPVOL
0	11.51256	7.638864	11.02471	8.279146	5.392862	5.245577
1	10.28426	7.481599*	8.915630	6.124938	2.481857*	3.183813*
2	10.25336	7.493334	8.924223	6.133190	2.503000	3.192601
3	10.24101	7.485030	8.576506	6.148510	2.504014	3.196159
4	10.20810	7.505954	8.575450	6.139805	2.527150	3.213714
5	10.21903	7.503780	8.586762	6.142863	2.542498	3.235842
6	10.20845	7.490289	8.552544*	6.120460	2.553203	3.249855
7	10.21554	7.508292	8.571335	6.136912	2.571992	3.262291
8	10.18681*	7.500618	8.587247	6.117029*	2.585798	3.263193

∗ indicates lag order selected by criterion

appeared to be very weak as per our findings. We further observed a very significant weekly autocorrelation, mostly at lag 1, for the entire currencies' exchange rates volatility during the pre-crisis period. This implies that the immediate past week's exchange rate volatility for a given country had a significant influence on the current week's exchange rate volatility attained.

From panels A, C and E of Table 5, we observed a significant bidirectional effect between oil price volatility and exchange rates volatility of Ghanaian cedi, South African rand and the Russian ruble. First, we observed impacts of the cedi exchange rate volatility on oil price volatility at lags 6 and 8 and oil price volatility on cedi-dollar exchange rates volatility at lag 2. Secondly, we observed a significant impact of oil price volatility on rand-dollar exchange rates volatility at lag 1 in panel C, and an impact of the rand-dollar exchange rate volatility on oil price volatility at lags 5, 6, 7, and 8. Finally, with the bidirectional effect, the ruble-dollar exchange rate volatility significantly impacted oil price volatility at lags 2, 4, 5 and 6 whiles oil price volatility significantly impacted the ruble-dollar exchange rate volatility at lag 5. This evidence supports the findings of various papers that have shown that bidirectional effects exist between oil price and currency exchange rates (Gomez-Gonzalez, Hirs-Garzon, and Uribe 2020; Du and He 2015; Zhang 2017).

However, earlier in panel B, we also observed a significant unidirectional impact of oil price return volatility on the Nigerian naira-dollar volatility at lag 1. This evidence is consistent with the findings of Bilan, Gedek, and Mentel (2018). For each oil-currency VAR model, we identified that the immediate past week's exchange rates volatility had a very significant influence on the current week's exchange rates volatility for the entire six oil-dependent economies currencies. It is worthy of note that the adjusted R-square

Table 4. VAR estimation results for pre-crisis period.

	Coeff.	St. error	*p*-value	Coeff.	St. error	*p*-value
Panel A: VAR results of Cedi volatility and Oil volatility						
		$OILVOL_t$			$GHSVOL_t$	
$OILVOL_{t-1}$	0.5290**	0.0410	0.0000	0.0138	0.0867	0.8738
α	7.2118**	0.8718	0.0000	0.0868	1.5123	0.9542
$GHSVOL_{t-1}$	0.0467*	0.0285	0.0992	0.7925***	0.0490	0.0000
$GHSVOL_{t-3}$	0.0244	0.0284	0.3905	0.1753***	0.0627	0.0053
$GHSVOL_{t-4}$	0.0244	0.0284	0.3905	−0.1969***	0.0493	0.0001
R^2		(0.2968)			(0.7355)	
Adj.R^2		(0.2828)			(0.7303)	
Panel B: VAR results of Naira returns Volatility and oil price volatility						
		$OILVOL_t$			$NAIRAVOL_t$	
$OILVOL_{t-1}$	0.5037***	0.0373	0.0000	−0.0579	0.0911	0.5250
α	7.6652**	0.5812	0.0000	1.5291	1.4176	0.2810
$NAIRAVOL_{t-1}$	−0.0106	0.0180	0.5564	0.4548***	0.0439	0.0000
R^2		(0.3081)			(0.2083)	
Adj.R^2		(0.3048)			(0.2045)	
Panel C: VAR results of Rand returns volatility and oil price volatility						
		$OILVOL_t$			$RANDVOL_t$	
$OILVOL_{t-1}$	0.5047**	0.0374	0.0000	−0.0185	0.0172	0.2815
α	7.6127**	0.5914	0.0000	0.4500*	0.2723	0.0988
$RANDVOL_{t-1}$	0.0095	0.0358	0.7905	0.9396***	0.0165	0.0000
R^2		(0.3077)			(0.8881)	
Adj.R^2		(0.3043)			(0.8876)	
Panel D: VAR results of Euro returns volatility and oil price return volatility						
		$OILVOL_t$			$EUROVOL_t$	
$OILVOL_{t-1}$	0.5359**	0.0499	0.0000	0.0009	0.0011	0.4049
α	7.1682**	0.7348	0.0000	−0.0024	0.0163	0.8841
$EUROVOL_{t-1}$	−0.5841	2.2136	0.7919	−0.1282***	0.0491	0.0093
R^2		(0.3025)			(0.9917)	
Adj.R^2		(0.2991)			(0.9916)	
Panel E: VAR results of Ruble return volatility and oil price return volatility						
		$OILVOL_t$			$RUBVOL_t$	
$OILVOL_{t-1}$	0.5025**	0.0376	0.0000	0.0017	0.0018	0.3195
α	7.6415**	0.5801	0.0000	−0.0117**	0.0270	0.6650
$RUBVOL_{t-1}$ 0.16370.4161	0.6941		0.9142***	0.0194	0.0000	
R^2		(0.3078)			(0.8471)	
Adj.R^2		(0.3044)			(0.8463)	
Panel F: VAR results of Rupee returns volatility and oil price return volatility						
		$OILVOL_t$			$RUPVOL_t$	
$OILVOL_{t-1}$	0.5049**	0.0373	0.0000	0.0015	0.0031	0.6253
α	7.5730**	0.5853	0.0000	0.0147	0.0490	0.7646
$RUPVOL_{t-1}$	−0.2915	0.3343	0.3836	0.8215***	0.0280	0.0000
R^2		(0.3088)			(0.6772)	
Adj.R^2		0.3057)			(0.6757)	

Note: ∗∗∗, ∗∗ and ∗ indicates significant at 1%, 5% and 10% level respectively.

in oil price volatility VAR model for panels A, B, C, and E is approximately 0.96, and the respective exchange rate volatility VAR model is 0.75, 0.89, and 0.91.

Tables 6 and 7 depict Toda-Yamamoto causality outcomes over the pre-crisis and post-crisis periods, respectively. From panel A of Table 6, weekly oil price volatility does not cause weekly exchange rate volatility of the Ghanaian cedi at any conventional level (10%, 5%, and 1%). However, at a 10% significance level, we observed that there was enough evidence to suggest that weekly exchange rate volatility for the Ghanaian cedi

Table 5. VAR estimation results for post-financial crisis period.

	Coeff.	St. error	*p*-value	Coeff.	St. error	*p*-value
Panel A: VAR results of Cedi volatility and Oil volatility						
		$OILVOL_t$			$GHSVOL_t$	
$OILVOL_{t-2}$	0.0328**	0.0570	0.0564	−0.3544**	0.1572	0.0245
α	−0.0564	0.1209	0.6413	0.0868***	0.3334	0.0072
$GHSVOL_{t-1}$	0.0079	0.0206	0.7028	−0.6962***	0.0569	0.0000
$GHSVOL_{t-3}$	0.0237	0.0252	0.3467	0.3748***	0.0694	0.0000
$GHSVOL_{t-4}$	−0.0234	0.0258	0.3650	−0.2995***	0.0712	0.0000
$GHSVOL_{t-5}$	0.0199	0.0258	0.4418	0.2664***	0.0712	0.0002
$GHSVOL_{t-6}$	−0.0533**	0.0253	0.0358	−0.0938	0.0698	0.1798
$GHSVOL_{t-8}$	0.0515**	0.0205	0.0123	−0.1458**	0.0565	0.0102
R^2		(0.9627)			(0.7651)	
Adj.R^2		(0.9607)			(0.7529)	
Panel B: VAR results of Naira returns Volatility and oil price volatility						
		$OILVOL_t$			$NAIRAVOL_t$	
$OILVOL_{t-1}$	−0.0621	0.0551	0.2607	0.1574**	0.0398	0.0001
α	0.1794	0.1372	0.1914	0.8480***	0.0991	0.0000
$NAIRAVOL_{t-1}$	−0.0753	0.0702	0.2836	0.3511***	0.0507	0.0000
R^2		(0.9600)			(0.1209)	
Adj.R^2		(0.9598)			(0.1156)	
Panel C: VAR results of Rand returns volatility and oil price volatility						
		$OILVOL_t$			$RANDVOL_t$	
$OILVOL_{t-1}$	−0.0505	0.0568	0.3744	0.0413*	0.0212	0.0516
α	0.1661	0.2460	0.4999	0.2165**	0.0917	0.0185
$RANDVOL_{t-1}$	0.0428	0.1543	0.7818	0.8826***	0.0575	0.0000
$RANDVOL_{t-4}$	−0.3009	0.2045	0.1418	0.2451***	0.0762	0.0014
$RANDVOL_{t-5}$	0.5723***	0.2057	0.0056−	−0.1613**	0.0766	0.0357
$RANDVOL_{t-6}$	−0.4006*	0.2092	0.0560	0.1056	0.0780	0.1759
$RANDVOL_{t-7}$	0.3656*	0.2109	0.0835	0.0299	0.0786	0.7036
$RANDVOL_{t-8}$	−0.5363***	0.1588	0.0008	−0.1090*	0.0592	0.0660
R^2		(0.9637)			(0.8955)	
Adj.R^2		(0.9619)			(0.8901)	
Panel D: VAR results of Euro returns volatility and oil price return volatility						
		$OILVOL_t$			$EUROVOL_t$	
α	0.1553	0.2312	0.5020	0.0260**	0.0138	0.0595
$EUROVOL_{t-1}$	−0.0781	0.2135	0.7148	0.9712***	0.0127	0.0000
R^2		(0.9599)			(0.9460)	
Adj.R^2		(0.9556)			(0.9456)	
Panel E: VAR results of Ruble return volatility and oil price return volatility						
		$OILVOL_t$			$RUBVOL_t$	
$OILVOL_{t-5}$	0.0100	0.0553	0.8566	− 0.1209*	0.0722	0.0943
α	−0.0445	0.1134	0.6949	0.3052**	0.1479	0.0394
$RUBVOL_{t-1}$	0.1383***	0.0436	0.0016	0.9532***	0.0569	0.0000
$RUBVOL_{t-2}$	−0.0734	0.0601	0.2222	0.5275***	0.0784	0.0000
$RUBVOL_{t-3}$	−0.2210***	0.0646	0.0007	− 0.6549***	0.0842	0.0000
$RUBVOL_{t-4}$	−0.1555**	0.0645	0.0163	−0.0075	0.0720	0.9171
$RUBVOL_{t-5}$	0.2076***	0.0601	0.0006	−0.1209	0.0722	0.0943
$RUBVOL_{t-6}$	−0.1734***	0.0437	0.0001	− 0.0125***	0.0735	0.8654
R^2		(0.9642)			(0.9191)	
Adj.R^2		(0.9628)			(0.9161)	
Panel F: VAR results of Rupee returns volatility and oil price return volatility						
		$OILVOL_t$			$RUPVOL_t$	
α	0.2664	0.1995	0.1822	0.0460***	0.0168	0.0063
$RUPVOL_{t-1}$	−0.2519	0.2319	0.2777	0.9368***	0.0195	0.0000
R^2		(0.9601)			(0.8758)	
Adj.R^2		(0.9599)			(0.8750)	

Note: ∗∗∗, ∗∗ and ∗ indicates significant at 1%, 5% and 10% level respectively.

Table 6. Toda-Yamamoto causality test results for the pre–crisis period.

Null Hypothesis	Df	Chi-Sq.	*P*-value	Decision
Panel A				
OILVOL does not cause GHSVOL	4	1.2046	0.8773	Fail to reject
GHSVOL does not cause OILVOL	4	8.5730	0.0727	Reject
Panel B				
OILVOL does not cause NAIRAVOL	1	0.8159	0.6650	Fail to reject
NAIRAVOL does not OILVOL	1	3.6130	0.1642	Fail to reject
Panel C				
OILVOL does not cause RANDVOL	1	0.9210	0.3372	Fail to reject
RANDVOL does not cause OILVOL	1	0.0315	0.8590	Fail to reject
Panel D				
OILVOL does not cause EUROVOL	4	4.0977	0.3929	Fail to reject
EUROVOL does not cause OILVOL	4	9.9326	0.0416	Reject
Panel E				
OILVOL does not cause RUBVOL	1	1.9438	0.1633	Fail to reject
RUBVOL does not cause OILVOL	1	1.2711	0.6026	Fail to reject
Panel F				
OILVOL does not cause RUPVOL	1	0.0224	0.8810	Fail to reject
RUPVOL does not cause OILVOL	1	0.6066	0.4361	Fail to reject

Table 7. Toda-Yamamoto causality test results for the post–crisis period.

Null Hypothesis	Df	Chi-Sq.	*P*-value	Decision
Panel A				
OILVOL does not cause GHSVOL	16	33.9372	0.0055	Reject
GHSVOL does not cause OILVOL	16	61.6233	0.0000	Reject
Panel B				
OILVOL does not cause NAIRAVOL	3	14.6417	0.0021	Reject
NAIRAVOL does not OILVOL	3	8.1927	0.0422	Reject
Panel C				
OILVOL does not cause RANDVOL	1	1.7561	0.1851	Fail to reject
RANDVOL does not cause OILVOL	1	0.7820	0.3765	Fail to reject
Panel D				
OILVOL does not cause EUROVOL	1	0.1188	0.7303	Fail to reject
EUROVOL does not cause OILVOL	1	0.0744	0.7850	Fail to reject
Panel E				
OILVOL does not cause RUBVOL	6	4.5997	0.5961	Fail to reject
RUBVOL does not cause OILVOL	6	28.8126	0.0001	Reject
Panel F				
OILVOL does not cause RUPVOL	1	0.2713	0.6025	Fail to reject
RUPVOL does not cause OILVOL	1	0.0122	0.9118	Fail to reject

causes oil price volatility. Hence, we have a unidirectional causality running from Ghana cedi exchange rate volatility to oil price volatility. Similarly, in panel D, we observed a unidirectional causality from euro exchange rate volatility to oil price volatility at 5% significance level. Notably, in the pre-crisis period, we did not observe any bidirectional causality between the volatilities of the distribution.

However, unlike the pre-crisis period, we observed a highly significant bidirectional causality between oil price volatility and Ghanaian cedi exchange rate volatility in panel A at 1% significance level. A similar situation between oil price volatility and the Nigerian naira volatility was also observed in panel B of Table 7, at significance levels of 1% and 5%. Thus, there was enough statistical evidence to conclude that bidirectional causality existed between oil price volatility and exchange rate volatilities of the Ghanaian cedi and the Nigerian naira in the post 2008 global financial crisis period. The findings of bidirectional prediction between oil price volatility and exchange rates volatility are consistent with recent papers in the literature (Gomez-Gonzalez, Hirs-Garzon, and Uribe 2020; Du and He 2015; Zhang 2017).

On the contrary, we observed a unidirectional causality running from Russian ruble volatility to oil price volatility at a highly significant level of 1%. This was not the case for causality from oil price volatility to Russian ruble volatility at any conventional level (10%, 5% and 1%).

5. Conclusion

In this paper, we examined the relationship and related causality dynamics of crude oil price volatility and exchange rates volatility of six variant oil-dependent economies. The weekly settlement crude oil price is for the West Texas Intermediate Crude oil futures contract, and the bilateral exchange rate series obtained are from Oanda for two sub-sample periods, 2000–2007 and 2010–2016. The break-in data depicts the downturn of fair market value resulting from the Global financial crisis in 2008–2009. Dollar exchange rates are for the currencies of major oil-dependent economies. To achieve the aim of the study, we generated volatility series of oil price return and exchange rates return using GARCH proxies and later investigated their volatility interactions using the Vector autoregressive (VAR) model. We further used the Toda-Yamamoto causality test to complement the volatility impact results obtained using the VAR model.

In the pre-crisis period, when the global economy was not recovering from any crisis, we observed the volatility impact of oil price on dollar exchange rate volatility for only Ghanaian cedi out of the six currencies used. This finding reflects the weak volatility impact between these two variables when the global economy was not recovering from any crisis.

In the period after the crisis, we found evidence of a significant impact of oil price volatility on the dollar exchange rate for both major oil exporters and importers currencies. Specifically, we found evidence of volatility impact, mostly negative, of oil price on the exchange rate for the Russian ruble, Nigerian naira, South African rand, and the Ghanaian cedi. However, this outcome was not the same for the euro and the rupee exchange rate volatility. These findings empirically confirm how high oil price volatility explained the variations of most of the oil-dependent economies exchange rates and vice versa, especially in the post-crisis period, as stated anecdotally in literature. In the case of the exchange rates, the findings explain how high exchange rates volatility for the oil-dependent economies also influenced the rate of oil price volatility after the crisis in 2010.

Policymakers and implementers in these economies should diversify their portfolio and shift their attention to other internationally tradable natural resources such as gold, bauxite, and manganese. In addition, they should implement sustainable measures to secure vulnerable industries that could be affected by oil price volatility. This way, their currencies' exchange rates volatility would be strengthened to withstand shocks from oil price volatility.

Causality test revealed some variable results. During the pre-crisis period, we identified evidence of some causality patterns between the volatilities of oil price and exchange rates of two out of the six currencies observed in this paper. More specifically, causality patterns were found to exist from the volatilities of the dollar exchange rates for both the euro and the Ghanaian cedi to the volatility of oil price. These outcomes are altogether not too surprising since the European union is noted as a major consumer of crude oil internationally with daily consumption of over 20 million barrels before the global crisis. For the Ghanaian economy, much as it depends heavily on oil imports for consumption, it started trading crude oil in commercial quantities on the international market within that same period. This made the Ghanaian economy's fiscal revenue highly dependent on crude oil export receipts. Also, post-crisis causality test confirmed the VAR results of how the exchange rate volatilities of major oil exporters such as Nigeria and Russia caused crude oil price volatility.

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