SN Bus Econ (2023) 3:91
https://doi.org/10.1007/s43546-023-00463-y

ORIGINAL ARTICLE

High frequency volatility spillover between oil and non-energy commodities during crisis and tranquil periods

Mutaju Isaack Marobhe[1,2] · **Jonathan Mukiza Peter Kansheba**[3,4]

Received: 26 May 2022 / Accepted: 23 February 2023 / Published online: 29 March 2023

Abstract
In this article, we scrutinize volatility spillover between oil and individual non-energy commodities during crisis and non-crisis periods. We use high-frequency data to capture the effects of both the global financial crisis (2008) and the COVID-19 pandemic between 2008 and 2022. To this end, we utilize wavelet coherence analysis to diagnose the magnitudes of dynamic co-movements and lead-lag effects between commodities. Our results provide evidence of strong coherence between oil and the majority of individual non-energy commodities during both crises. Precious metals were generally found to exhibit heightened levels of co-movement with oil as opposed to other non-energy commodities. On the other hand, weak co-movements were found between oil and a few commodities, namely soy, wheat, zinc, and tin. The lead-lag effects of oil on agricultural commodities, base metals, and precious metals were evident, especially during crisis periods. However, aluminium and precious metals, especially gold, silver, and palladium, also had a lead-lag effect on oil at different points in time, including during the pandemic. We further utilize dynamic frequency-domain connectedness for capturing pairwise volatility spillover indices, with the results providing evidence of heightened volatility spillovers during turbulent times. Our findings have significant implications for retail investors, portfolio managers, and policymakers.

Keywords Oil · Precious metals · Base metals · Agricultural commodities · COVID-19 · The global financial crisis

JEL Classification G11 · G40 · Q02

✉ Mutaju Isaack Marobhe
mutaju.marobhe@tia.ac.tz

Extended author information available on the last page of the article

Introduction

The phenomenon of volatility connectedness between asset classes has piqued the interest of practitioners, scholars, and policymakers (Sun et al. 2021). This can be attributed to the growing financialization of major commodities, including oil, agricultural commodities, and metals (Zaremba et al. 2021). Capital has been pouring into commodity futures from investors with no apparent commercial intent in these commodities over the years (Dutta and Noor 2017). Investors have been increasingly seeking assets that are uncorrelated with other investments to hedge against financial risk (Maghyereh and Abdoh 2022). This is especially vital for portfolio managers who are continuously searching for safe-haven assets to mitigate the heightened risks caused by exogenous shocks such as COVID-19 (Umar et al. 2021a, 2022a, b). As such, commodities markets present investors with a variety of tradeoffs between asset classes, enabling them to design well diversified portfolios (Umar et al. 2021b). These commodities employ different pricing mechanisms as opposed to those of financial assets such as stocks, causing the two asset groups to be less correlated. Hence, mixing stocks and commodities in a portfolio may help to yield a better risk-return trade-off as opposed to focusing on stocks alone. The knowledge of volatility spillovers is important not only for investors, but also for regulators and policymakers, because fluctuating commodity prices can have a significant impact on macroeconomic health (Umar et al. 2021c).

Commodity markets have become more interconnected over time, though the nature of these interconnections may differ. The energy sector, led by oil, is among the main pivots of commodity markets and forms a crucial portfolio component for investors (Tiwari et al. 2021; Umar 2017). The past two decades have experienced rising levels of volatility in commodities markets, with oil being the dominant commodity (Naeem et al. 2020). Researchers are now looking into the nature and degree of volatility connectedness between oil and other commodity classes. Oil and agricultural commodities both form a significant portion of the commodity market, and they are interconnected in various ways (Dinku and Worku 2022; Umar et al. 2021a). For instance, capital-intensive agricultural systems, fertilization, and transportation of agricultural products all rely heavily on oil. Moreover, the rising use of corn and soybeans to manufacture biofuels due to the volatility of crude oil has made them increasingly connected (Wright 2014). On the other hand, oil price shocks affect production and transportation costs of industrial metals. Higher oil prices cause governments to increase interest rates, which adversely affect the base metals and steel reliant construction sector (Hammoudeh and Yuan 2008). Oil and precious metals are inextricably connected, rising oil prices increases general price levels in the economy. High inflation in turn increases the demand for precious metals since they are used by policy makers as inflationary hedge tools (Shah et al. 2021).

This paper adds to the empirical evidence on the volatility connectedness of the oil, agricultural commodity, and metal markets in various ways (Umar et al. 2021a, b; Zaremba et al. 2021). Findings on commodity connectedness have been mixed and ambiguous (Tiwari et al. 2019; Dutta and Noor 2017; Nazlioglu and Soytas 2011; Reboredo and Ugolini 2016; Umar et al. 2021a, b, c, d, e). Unlike previous studies, we employ wavelet coherence analysis (WCA), which is a powerful tool to assess dynamic lead-lag connectedness between two time series in different time periods, which suits best the changing nature of commodity prices (Aguiar-Conraria and Soares 2014). Previous studies have employed WCA to analyze the volatility connectedness of commodities by using low-frequency data, i.e., annual, monthly (Umar et al. 2020; Tiwari et al. 2019). To disentangle the multi-scale connectedness between commodity returns, we employ WCA using high-frequency data, i.e., daily, which enabled us to reveal crucial underlying patterns that may not be easily seen in weekly, monthly, or annual data (Umar et al. 2021a). We also use dynamic frequency-domain network connectedness (DF-DNC) to investigate the precise amounts of connectedness between oil and non-energy commodities (Barunk and Krehlik 2018). Our sample period allows us to examine commodity connectedness behaviour during tranquil periods and periods of global economic turmoil caused by the global financial crisis (2008) and the COVID-19 pandemic. We present a detailed examination of the volatility relationship between oil and individual commodities in each of the three groups, namely agricultural commodities, base metals, and precious metals. This enabled us to unpack unique patterns in volatility spillovers between oil and individual commodities, unlike previous studies that performed market-wise analyses (Sun et al. 2021; Umar et al. 2020; Tiwari et al. 2019; Dutta and Noor 2017).

The rest of this paper is organized as follows: "Literature review" covers a brief review of literature on the connectedness between oil, agricultural commodities, and industrial metals. "Methodology" provides a description of the data, an econometric model, and the methods employed in investigating the phenomenon. "Results" presents results from analyses; "Discussions, implications, and avenues for further research" covers discussions; and "Conclusions" provides conclusions.

Literature review

The literature on co-movement between commodities' markets has been burgeoning since the inception of the phenomenon in the 1990s. The GFC (2008) showed the extent to which stock markets have become so closely connected, causing volatility spillover among each other and thus arousing the need for commodities to diversify investment portfolios (Zhang and Broadstock 2018). Commodities are also important inputs into manufacturing processes; any price changes have significant macroeconomic consequences. Despite increased investor interest in connectedness of commodity markets, empirical evidence on the influence of oil on non-energy commodities is generally mixed and a bit ambiguous (Sun et al. 2021; Dutta and Noor 2017; Reboredo and Ugolini 2016; Umar et al. 2021a).

There has been a progressive growth in literature on the connectedness between oil and agricultural commodities (Umar et al. 2021a, b). However, the link between the two commodities still lacks clarity, which calls for more scholarly attention (Nazlioglu et al. 2013). For instance, Umar et al. (2021d) employed the Granger causality test and provided evidence to highlight how the prices of grains and wheat cause shocks in oil prices. Sun et al. (2021) investigated the long-term correlation between agricultural commodities and oil prices. The rolling window Granger causality test was used, and they discovered bi-directional causality between the two commodities. Wang et al. (2014) also employed a Structural Vector Autoregression (SVAR) model to examine the co-movement between US oil prices and agricultural commodity prices and found a uni-directional spillover from oil to agricultural commodities. These results are complimented by Mensi et al. (2014), who found a co-movement between the oil and cereal markets. Zhang and Qu (2015) used autoregressive moving average (ARMA) models to show asymmetrical effects of oil prices on agricultural product volatility, which is supported by Tiwari et al. 2019. Despite the evidence of co-movement between the two commodities, several studies have argued otherwise. Dutta and Noor (2017) employed the bivariate Vector Auto Regression-Generalized Autoregression Conditional Heteroskedasticity (VAR-GARCH) models and suggested an absence of volatility connectedness between oil and agricultural products. Nazlioglu and Soytas (2011) employed Toda-Yamamoto causality and reached a similar conclusion. These results are also substantiated by Kaltalioglu and Soytas (2009), who found no connectedness between oil and agricultural commodities, therefore confirming the oil and agricultural commodities connectedness neutrality hypothesis (Wiggins and Keats 2009).

Extant literature has also highlighted the connectedness between the oil and metal markets. For instance, Li et al. (2021) provide evidence of strong short-term returns and volatility spillovers between the oil and gold markets in China. This is supported by Mensi et al. (2021), whose findings suggested oil to be a diversifier and a weak safe haven for precious metals futures. In a study by Umar et al. (2020) that employed WCA, evidence was presented to reveal strong co-movement between oil and base metal markets, with oil being the main volatility transmitter. Dutta (2018) investigated the co-movement between oil and different types of metals, including industrial metals, using GARCH-Jump models. Their results revealed a significant volatility spillover from oil to industrial metals, with no evidence suggesting a similar effect on precious metals except for silver. However, Hammoudeh and Yuan (2008) utilized GARCH models and discovered volatility spillover runs from oil to precious metals alone, which debunks findings from other studies. In contrast, Reboredo and Ugolini (2016) observed that oil price volatility spillover significantly affects both industrial and precious metals. Zhang and Tu (2016) also explored how oil price shocks impact metal prices in China by employing autoregressive jump intensity (ARJI)-GARCH models and reported significant impacts of oil price volatility on aluminium and copper prices. Their results are corroborated by Umar et al. (2021b) and Kaulu (2021), who provide evidence to highlight why industrial metals are the net receivers of shocks from oil.

Methodology

Data description

This study uses data for oil, base metals, precious metals and agricultural commodities prices retrieved from Bloomberg and DataStream. We utilize the equally weighted average of daily crude oil prices from Brent Crude, West Texas Intermediate (WTI) and Dubai Crude to create aggregate price of oil (Sun et al. 2021). For the case of non-energy commodities, we selected five agricultural commodities namely; corn, wheat, soy, oats and rice. In addition, a total of five base metals were selected namely; Aluminum, Zinc, Lead, Tin, Copper and Nickel. Lastly, we selected four precious metals namely; gold, silver, platinum and palladium. We utilized high frequency-daily commodity spot prices data ranging from 1st January 2008 to 31st October 2022. The price volatility represented by returns was calculated by using log ($\text{Price}_1/\text{Price}_{0)}$ for each commodity in each month. This time range was purposely chosen to study the volatility connectedness phenomenon during tranquil periods as well as periods of heightened global uncertainty as a result of two major global crises; GFC and COVID-19. Looking at Fig. 1, interesting trends for volatility of commodity prices can be observed during the entire period.

It can be clearly seen that commodities in similar commodities exhibit nearly identical volatility trends over the entire sample period. This is more evident in base metals as opposed to other commodity groups. High volatility can be visible during the beginning of the period which happens to be during the GFC. The other episode of higher volatility in commodity returns was evident from 2020 onwards signifying the beginning of the pandemic. Looking at individual commodities, oats appeared to exhibit higher volatility than other agricultural commodities during the entire period. For the case of base metals and precious metals, nickel and palladium were characterized by relatively higher volatilities than other commodities in their respective groups.

Analytical tools

In this current study, we are primarily interested in examining the magnitude of the volatility spillovers between oil and non-energy commodities. To this end, we first utilize WCA to analyze the co-movement and lead-lag effect between oil and individual non-energy commodities (Umar et al. 2020; Tiwari et al. 2019). We then use DF-DNC analysis to calculate the precise amounts of volatility spillovers between commodities of interest (Maghyereh and Abdoh 2022; Barunk and Krehlik 2018).

Wavelet coherence analysis

We employ WCA analysis to examine the lead-lag effect of co-movement between oil and individual non-energy commodities. WCA is a bivariate framework that examines the interaction between different time series over a continuous time and frequency space (Torrence and Compo 1998). The tool can decompose a time series into time–frequency space in order to determine the dominant modes of variability and their variation pattern (Uddin et al. 2016). This is done by effectively pinpointing time periods of high and low co-movement in the time–frequency space (Aguiar-Conraria and Soares 2014). We employ the same procedures used by Umar and Gubareva (2021) to carry out WCA. WCA is built up by two components, namely, the cross-wave transform (CWT) and coherence (Torrence and Compo 1998).

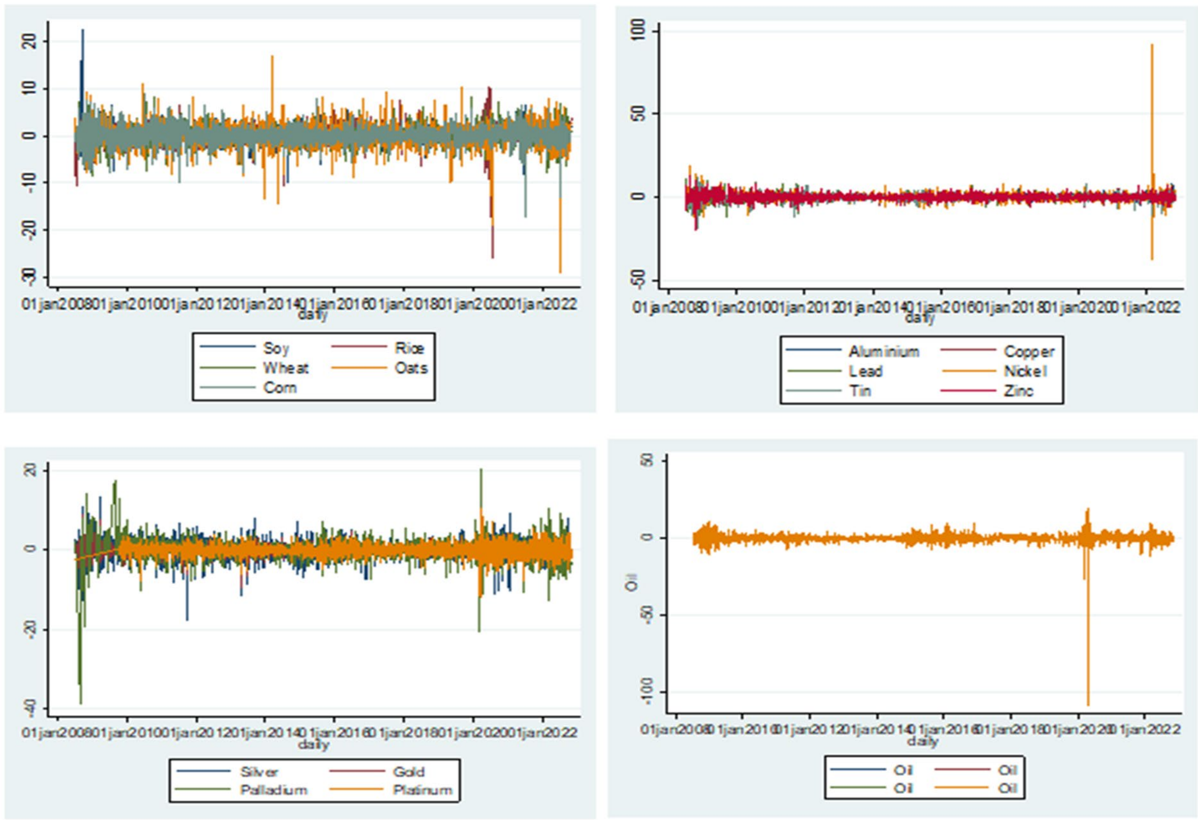

Fig. 1 Trends of returns for oil and non-energy commodities. The time series plots show the trend and volatility of commodity returns for oil and non-energy commodities from 1st January 2008 to 31st October 2022

Firstly, the CWT of the two time series dubbed x(t) and y(t) can be expressed in the form of their individual CWTs which are; $W_n^x(u,s)$ and $W_n^y(u,s)$ as follows:

$$W_n^{xy} = W_n^x(u,s) * W_n^y(u,s) \tag{1}$$

whereby; u = the location; s = the scale; * = complex conjugate

CWT captures the co-movement between the two time series, x(t) and y(t) at each time and frequency space. A CWT value close to one indicates a high magnitude of synchronization between the time series. On the contrary, a CWT value close to zero indicates the absence of any relationship between the time series. Then, the squared wavelet coherence (SWC) is computed to determine the co-movement between the two time series. The SWC represents the correlation coefficient in the time–frequency domain, and its value ranges between zero and one. It is different from the ordinary Pearson correlation, which assumes both positive and negative values. It is calculated as follows:

$$R^2(u,s) = \left|S\left(s^{-1}W^{xy}(u,s)\right)\right|^2 \tag{2}$$

$$S\left(s^{-1}|\,W^y(u,s)|^2\right)S\left(s^{-1}|W^y(u,s)|^2\right)$$

whereby; S = a smoothing operator over time and frequency scale. Finally, the Wavelet Coherence Phase Difference (WCPD) is used to differentiate between the positive and negative co-movements. WCPD is expressed as follows;

$$\Phi_{xy}(u,s) = tan^{-1}Im\left[\begin{array}{c}(S\left(s^{-1}W^{xy}(u,s)\right)\\ Re\,(S\left(s^{-1}W^{xy}(u,s)\right)\end{array}\right] \tag{3}$$

whereby; *Im* and *Re* are both the imaginary and real parts of the smoothed CWT.

Dynamic frequency-domain network connectedness

We utilize the Baruník and Křehlík (2018) (BK-18) spillover index, which uses generalized forecast error variance decompositions (GFEVDs), to estimate the exact amounts of volatility spillovers between oil and individual non-energy commodities. We decompose the data using the matrix of a vector autoregressive (VAR) model with local covariance stationarity (Diebold and Yilmaz 2012; Bossman et al. 2022). The $VAR(p)$ model is presented as follows:

$$Yt = \sum_{i=1}^{p} \varphi i\gamma t - i + \varepsilon t, \tag{4}$$

whereby; φi and εi = these are coefficients of covariance matrix Π. Returns for each commodity are regressed against other commodities, their ρ lags and the ρ lags of other commodities' returns. φ = *the information holder for the* relationships between commodities' returns. Our VAR model is built using moving average $MA(\infty)$ when the roots of the representative equation $|\theta(z)|$ lie outside of the unit circle. This is expressed as follows;

$$Yt = \Psi(L)\varepsilon t \tag{5}$$

whereby; $\Psi(L)$ = an infinitely lagged polynomial.

We then re-write element "*j*" of GFEVD denoted by the *kth* variable as follows;

$$\left(\Theta_H\right)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \psi_h \Pi\big)\left(\psi_h \Pi\right)\left(\psi_h \Pi\right)_{j,k}\big)^2}{\sum_{h=0}^{H} \left(\psi_h \Pi_{h'}\right)_{j,k}} \tag{6}$$

whereby; $h = 1,\ldots,H$ *and* $\sigma_{kk} = \Pi_{kk}$. We then standardize the matrix Θ_H to generate the following model for generating pairwise volatility spillovers;

$$\left(\widetilde{\Theta}_H\right)_{j,k} = \frac{\left(\widetilde{\Theta}_H\right)_{j,k}}{\sum_{k=1}^{N} \left(\widetilde{\Theta}_H\right)_{j,k}} \tag{7}$$

We aggregated the pairwise volatility spillovers presented in Eq. (7) for estimating general volatility connectedness between commodities. This is shown as follows;

$$C_H = 100 * \frac{\sum_{j \neq k} \left(\widetilde{\Theta}_H\right)_{j,k}}{\sum \widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\left\{\widetilde{\Theta}_H\right\}}{\sum \widetilde{\Theta}_H}\right) \tag{8}$$

whereby; $Tr\{\}$ = arithmetic summation of all elements in the matrix. Therefore volatility connectedness represents FEVD's contribution to the variables in the model. This enabled us to examine bi-directional connectedness between commodity market "*i*" from other commodity markets "*k*". The positive value from the model indicates that a respective commodity is the "*net transmitter*," while negative spillover values indicate that a commodity is a "*net receiver*" of volatility spillovers. A frequency response function of $\psi\left(e^{-i\omega}\right) = \sum_h e^{-i\omega h} \psi_h$ is then created which is subsequently transformed by Fourier transforms ψ_h with $i = \sqrt{-1}$, a spectral density of Y_t at frequency, ω can be defined as $MA(\infty)$ filtered series as follows;

$$S_{y(\omega)} = \sum_{h=-\infty}^{\infty} E\left(Y' Y_{t-h}\right) e^{-i\omega h} = \psi\left(e^{-i\omega}\right) \Pi \psi'\left(e^{+i\omega}\right) \tag{9}$$

Whereby; $S_{y(\omega)}$ = the power spectrum that defined variance distribution of Y_t over the frequency components ω. Equation (10) defines the causation spectrum over $\omega\ \epsilon(-\pi;\pi)$ as follows;

$$(\mathcal{F}(\omega))_{j,k} = \frac{\sigma_{kk}^{-1}\left|\psi\left(e^{-i\omega}\right)\Pi_{j,k}\right|^2}{\left(\psi\left(e^{-i\omega}\right)\Pi\psi'\left(e^{+i\omega}\right)\right)_{j,j}} \tag{10}$$

The following weighting function is defined to obtain a natural decomposition of GFEVD to frequencies, we weigh $\mathcal{F}(\omega))_{j,k}$ by the frequency share of the variance of the *jth* commodity;

$$\Gamma_j = \frac{\left(\psi\left(e^{-i\omega}\right)\Pi\psi'\left(e^{+i\omega}\right)\right)_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\psi\left(e^{-i\lambda}\right)\Pi\psi'\left(e^{+i\lambda}\right)\right)_{j,j}d\lambda} \tag{11}$$

We then use Eq. (12) to measure volatility spillover between commodity returns across different frequency bands represented as d, as $d=(a;b)$: $a;b \; \epsilon \; (-\pi;\pi)$, $a<b$;

$$\left(\Theta_d\right)_{jk} = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)(\mathfrak{I}(\omega))_{jk}d\omega \tag{12}$$

Then a scaled GFEVD mode may be constructed in the same frequency band d as follows;

$$\left(\dot{\theta}_d\right)_{jk} = \left(\Theta_d\right)_{jk} / \sum_k \left(\Theta_\infty\right)_{jk} \tag{13}$$

Ultimately, the within-frequency and frequency connectivity across d are expressed in Eqs. (14) and (15) respectively as follows;

$$c_d^w = 100 \cdot \left(1 - \frac{\mathrm{Tr}\left\{\dot{\Theta}_d\right\}}{\sum \dot{\Theta}_d}\right) \tag{14}$$

$$c_d^j = 100 \cdot \left(\frac{\sum \dot{\theta}_d}{\sum \dot{\theta}_\infty} - \frac{\mathrm{Tr}\left\{\dot{\theta}_d\right\}}{\sum \dot{\theta}_\infty}\right) = c_d^w \cdot \left(\frac{\sum \dot{\theta}_d}{\sum \dot{\theta}_s}\right) \tag{15}$$

Results

Descriptive statistics and correlation results

Table 1 presents the descriptive statistics for daily returns of oil and non-energy commodities in the entire time frame of the study. The mean returns for all commodities are positive with the exception of oil, platinum, and oats. The positive returns for the majority of commodities are, however, less extreme, i.e., less than 1%, and this is the case for all commodities that exhibit positive returns. On the other hand, oil and palladium both exhibit the highest standard deviations, indicating higher magnitudes of volatility in these two commodities, with the former

Table 1 Descriptive statistics

Variables	Obs	Mean	SD	Min	Max	Skew	Kurtosis	JB Stat	ADF	PP
Oil	5229	−0.051	3.233	−108.44	19.790	−14.14	421.565	3807**	−40.08**	−1233**
Agricultural commodities										
Soy	5229	0.046	1.386	−9.96	22.533	0.661	23.289	9004**	−42.82**	−2049**
Rice	5229	0.018	1.407	−25.89	10.299	−1.478	30.778	1705**	−42.37**	−1768**
Wheat	5229	0.010	1.693	−8.60	8.435	0.172	4.908	818**	−44.71**	−2012**
Oats	5229	−0.020	2.065	−28.96	16.684	−0.94	17.539	4704**	−42.73**	−1988**
Corn	5229	0.034	1.613	−17.38	9.000	−0.462	9.293	8814**	−44.38**	−2014**
Base metals										
Aluminum	5229	0.035	1.770	−13.51	13.732	−0.214	11.804	1703**	−47.41**	−2057**
Copper	5229	0.028	1.474	−10.58	12.659	−0.258	10.031	1104**	−45.63**	−2174**
Lead	5229	0.050	1.819	−13.51	13.732	−0.203	10.399	1204**	−45.75**	−2049**
Nickel	5229	0.035	2.911	−37.98	92.101	11.92	348.554	2607**	−64.32**	−2537**
Tin	5229	0.003	1.673	−18.71	12.911	−0.946	13.568	2514**	−43.43**	−2032**
Zinc	5229	0.014	1.729	−20.18	13.120	−0.338	11.491	1604**	−47.55**	−2208**
Precious metals										
Silver	5229	0.046	1.930	−17.76	13.280	−0.514	9.59	9693**	−53.67**	−3832**
Gold	5229	0.033	1.040	−9.34	8.990	−0.184	10.069	1104**	−52.56**	−3606**
Palladium	5229	0.078	3.362	−38.53	20.470	−3.208	38.874	2905**	−26.44**	−1351**
Platinum	5229	−0.085	1.269	−12.11	10.440	−0.15	9.979	1114**	−58.62**	−4970**

Table 1 presents the descriptive statistics of daily returns for oil and non-energy commodities. The sample spans from 1st January 2009 to 31st October 2022.The statistics include mean, standard deviation (SD.), minimum (Min.) and maximum (Max.) values, Skewness and Kurtosis measures. The Jarque–Bera (JB) statistic tests for normality. The table also reports the augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) unit root tests with *, **, *** denoting statistical significance at the 0.1, 0.05 and 0.01 levels, respectively being the most traded one. Looking at the difference between the maximum and minimum returns for each commodity, oil exhibits the biggest difference, i.e., − 108.441 and 19.790. This provides preliminary evidence to show higher magnitudes of returns' volatility experienced by oil, which suffered immensely during the GFC and the first wave of COVID-19 pandemic (Maghyereh and Abdoh 2022).

The normality diagnostics reveal some interesting facts about our data. First, the Jarque–Bera (JB) test for normality revealed high values that were all significant at the 0.05 level, thus rejecting the null hypothesis of normality (Wu 2021). Skewness and kurtosis values for all the commodities also present evidence to support the non-normality of the data since they are all non-zero (Marobhe and Kansheba 2022). The kurtosis values for all commodities appeared to be greater than 3, indicating that the distributions of their returns are leptokurtic. These denote that their distributions are fat-tailed with many outliers, and their returns have a higher probability for extreme events (Kansheba and Marobhe 2022). The augmented-Dickey Fuller (ADF) and Phillips–Perron (PP) t-statistic values for all commodities' returns were greater than their respective 0.05 values, thus showing the absence of unit root (Adi et al. 2022; Dickey and Fuller 1979).

In Fig. 2, we present correlation results in the form of heat maps based on the full sample and sub-samples covering specific events, namely the GFC, post-GFC, and COVID-19. The full sample results show little correlation between oil and non-energy commodities. This is with the exception of precious metals and copper, which have a higher correlation with oil than other non-energy commodities. Silver and platinum showed higher degrees of correlation with oil as opposed to gold and palladium. For the case of correlations during the GFC, the results show a growing degree of correlation between oil and precious metals, with the exception of palladium. During the pandemic, there was also some degree of correlation between oil and corn, with other agricultural commodities and base metals exhibiting negligible correlations with oil.

In the post-GFC period, correlations between oil and base metals were higher than those in precious metals. This was especially true in the case of copper, nickel, and zinc, whose correlations were higher than those of other base metals. Palladium and platinum also showed relatively higher correlations with oil compared with other precious metals. No visible correlations were present between oil and agricultural commodities during this period. During the pandemic, some degrees of correlation were observed between oil and all precious metals, as well as tin and copper.

Johansen co-integration test results

We further carried out the Johansen co-integration test to examine the presence of a long-term association between returns on oil and individual non-energy commodities (Johansen 1991). In Table 2, the results are presented, and they show the absence of any co-integration between oil and any non-energy commodity.

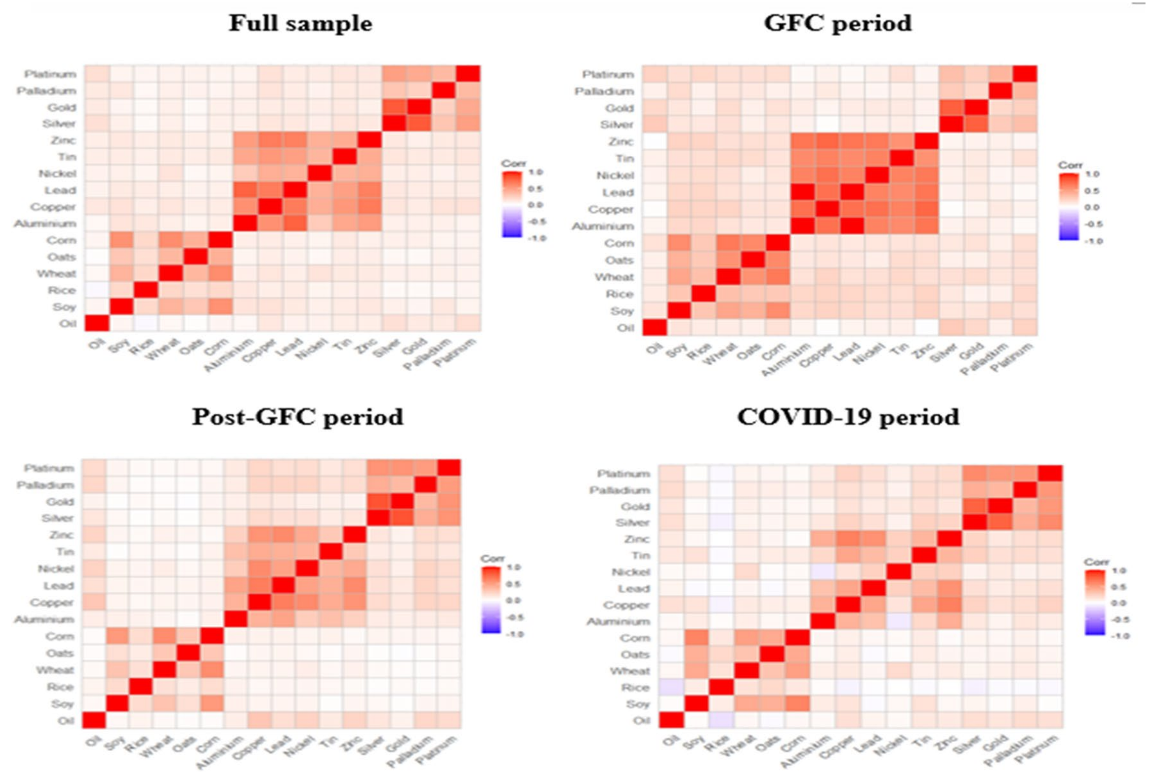

Fig. 2 Oil and non-energy commodities correlation matrix heat maps. Figure 1 represents the correlation matrix heat maps between returns of oil and non-energy commodities over the full sample from 1st January 2008 to 30th October 2022, sub-sample during GFC from 1st January 2008 to 5th August 2011, sub-sample during post-GFC period from 6th August 2011 to 31st December 2019 and the sub-sample during COVID-19 from 1st January 2020 to 31st October 2022. The color scale at the right indicates the values of the correlations

Table 2 Johansen co-integration test results

Commodities	Eigen value	Trace statistic	5% critical value
Oil and agricultural commodities			
Oil and soy	0.08877	474.7875	6.4000
Oil and rice	0.08686	456.4528	6.4000
Oil and wheat	0.08785	420.2128	6.4000
Oil and oats	0.08691	400.0589	6.4000
Oil and corn	0.08857	439.1377	6.4000
Oil and base metals			
Oil and aluminum	0.08734	424.0004	6.4000
Oil and copper	0.08775	383.226	6.4000
Oil and lead	0.08776	404.9093	6.4000
Oil and nickel	0.0908	473.3173	6.4000
Oil and tin	0.08819	447.0158	6.4000
Oil and zinc	0.08688	415.731	6.4000
Oil and precious metals			
Oil and silver	0.24246	1005.1394	3.7600
Oil and gold	0.24747	1007.9521	3.7600
Oil and palladium	0.17501	345.0380	3.7600
Oil and platinum	0.26610	1005.2522	3.7600

When the trace statistic value is less than the 5% critical value, the null-hypothesis on the non-presence of co-integration is rejected

Structural breaks diagnosis results

The absence of any co-integration between oil and non-energy commodities may be a result of structural breaks that may be present in their returns (Chang et al. 2017). We therefore conducted a structural breaks test for individual time series for commodity returns based on Bai and Perron's (2006) methodology, which can detect multiple breaks. Table 3 presents the results for this test by revealing the presence of at least one structural break in the returns time series for all commodities. During the GFC, the majority of commodities experienced structural breaks in their returns. Oil and gold had their structural breaks during the first quarter of 2020, which lies within the timeline for the first outbreak of COVID-19 that immensely affected oil prices (Umar et al. 2021d).

Wavelet coherence analysis results

Because of the presence of structural breaks in commodity returns, analytical tools that can assess dynamic/time-varying volatility connectedness between commodities were required. To this end, we first employed WCA to examine and visualize the co-movement between oil and individual non-energy commodities by showing the lead-lad effect between them (Umar et al. 2021a). We commenced by carrying out WCA

Table 3 Bai and Perron (2006) structural breaks test results

Commodities	Sup. F	p value	Break date (1)	Break date (2)
Oil	16.671	0.0021	5/3/2018	27/04/2020
Agricultural commodities				
Soy	50.329	0.0000	6/9/2010	NIL
Rice	37.474	0.0000	25/06/2016	NIL
Wheat	20.841	0.0002	6/9/2010	NIL
Oats	40.262	0.0003	7/9/2012	NIL
Corn	50.833	0.0009	5/9/2010	NIL
Industrial metals				
Aluminum	21.878	0.0002	15/10/2011	NIL
Copper	84.446	0.0000	26/11/2014	NIL
Lead	7.6197	0.0647	3/10/2011	NIL
Nickel	8.1974	0.1281	9/5/2019	NIL
Tin	30.904	0.0000	3/9/2010	NIL
Zinc	5.7478	0.0353	14/05/2019	NIL
Precious metals				
Silver	31.742	0.000	05/09/2010	NIL
Gold	18.533	0.000	28/03/2020	NIL
Palladium	2156.700	0.000	08/09/2010	NIL
Platinum	417.44	0.000	08/09/2010	NIL

The presence of structural breaks is shown when p values of Sup. F statistic for individual commodities are below 0.05 level

for pairs of commodities involving oil and individual agricultural commodities, as visualized in Fig. 3.

The results indicate lower degrees of co-movement between oil and soy returns during the pre-pandemic periods, with lead-lag effects being absent. An out-of-phase, negative co-movement was observed between the two commodities during the GFC alone. An out-of-phase, negative co-movement was also vivid between oil and rice returns during the GFC at low frequency between 256 and 1024 days. However, strong co-movements with the lead-lag effects of oil on rice were visible in 2016 and during the second wave of the pandemic at a high frequency of between 16 and 64 days. The other out-of-phase, negative co-movement between the two commodities was also evident during the second wave of COVID-19, but with the absence of the lead-lag effect at a similar time frequency. The results for the oil-wheat pair show a strong out-of-phase co-movement between the pair at a low frequency of between 256 and 1024 days during the GFC alone. The results further present evidence of the lead-lag effect of oil on wheat during the pandemic at a high frequency of about 64 days. A significant out-of-phase and negative co-movement between oil and oats was evident during the GFC at low frequency between 256 and 1024 days. Another low-frequency out-of-phase co-movement was observed from 2019 to mid-2020, which was during the first wave of COVID-19. However, during the pandemic, a lead-lag effect of oil on oats was observed at a relatively higher frequency of about 64 days. Lastly, corn and oil exhibited an out-of-phase negative

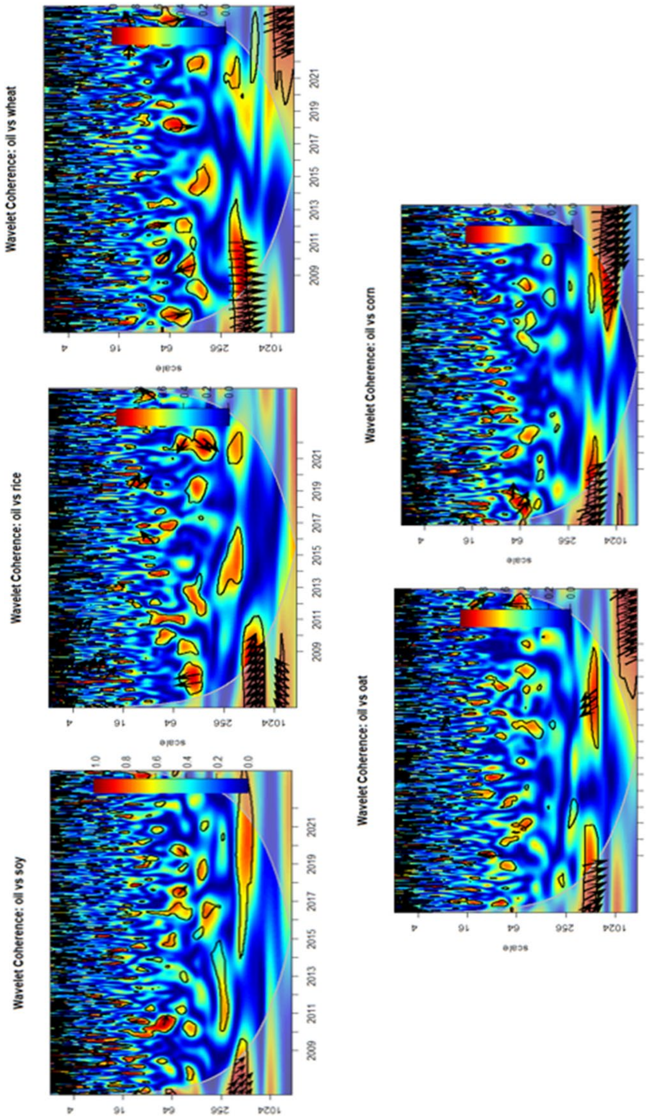

Fig. 3 WCA results for co-movement between oil and agricultural commodities. Figure 3 presents WCA results for returns co-movement between oil and individual agricultural commodities namely; soy, rice, wheat, oats and corn. The horizontal and left vertical axes denote the time and frequency dimensions (days). The multi-colored bar to the right of the plot denotes the wavelet coherence power. Highest wavelet coherence power is shown by red colour at the top of the bar and it diminishes downwards to blue colours at the bottom of the bar denoting lower power. Significant areas are located within the white bordered curve at 0.05 level generated using Monte Carlo simulations. The (→, ←) black arrows signify an in-phase/out-of phase or positive/negative correlation. The (↗, ↙) directed arrows signify the lead-lag effect of the first/second time series respectively. The black arrow with the directions (↖, ↘) in WCA graph signifies an out-of-phase relationship/negative covariance between the two time series with the leading effect of the first/second time series respectively

co-movement during the GFC as well as the COVID-19 pandemic. A lead-lag effect of oil on corn was observed during the early days of the GFC in 2008 at a high frequency of between 4 and 16 days. Similar effects were observed towards the end of the GFC in 2011, at a frequency of between 16 and 64 days. The last co-movement with the lead-lag effect of oil on wheat was observed during the first outbreak of the pandemic in 2020 at a high frequency of between 4 and 16 days.

In Fig. 4, we examine the co-movement between oil and individual base metals. For the case of oil and aluminum, an out-of-phase co-movement was observed at a frequency between 16 and 64 days at the beginning of the GFC as well as towards the end. In mid-2014, a lead-lag effect of aluminium on oil was observed at a frequency between 16 and 64. During the pandemic, a lead-lag effect of oil on aluminium was evident, especially during the first wave in the first quarter of 2020 and towards the end of 2022. The WCA analysis for the oil-copper pair reveals an out-of-phase negative co-movement between the two commodities at low frequency between 256 and 1024 days. A lead-lag effect of oil on copper was evident in 2009, which was the height of the GFC, at a relatively higher frequency of between 16 and 64 days, followed by similar effects towards the end of the crisis in 2011. An out-of-phase co-movement was also observed in 2015 at a frequency of 256 days. A lead-lag effect of oil on copper was visible during the second wave of the pandemic in 2021.

An out-of-phase co-movement in the frequency between 16 and 64 days was also observed between oil and lead in 2009 and 2011, which is the timeframe in which the GFC happened. In 2014, there was a lead-lag effect of oil on lead with a similar frequency as during the GFC period. An out-of-phase negative correlation was observed between the two commodities in mid-2021, which was during the second wave of COVID-19. A lead-lag effect of oil on lead was observed in 2022, which can be attributed to oil price shocks caused by the Russia–Ukraine war. In the case of oil and tin, a lead-lag effect of oil on tin at the 64-day frequency was evident during the early days of the GFC in 2008. This was followed by an out-of-phase negative co-movement at a similar frequency during 2009. An out-of-phase positive co-movement between the two commodities was evident in 2010, followed by both positive and then negative co-movements from 2015 to 2016 at a 64-day frequency. No significant co-movements were observed between oil and tin during the pandemic. Lead-lag effects of oil on zinc were observed in 2008. This was followed by an out-of-phase, strong negative co-movement between the two commodities from 2010 to 2011, with a time frequency between 16 and 64 days. Another lead-lag effect of oil on zinc was evident in 2014 between the frequency of 16 and 64 days. Similar to tin, no significant co-movements were experienced between oil and zinc during the pandemic.

Lastly, in Fig. 5, we display WCA results for return co-movement between oil and individual precious metals. By analyzing the oil-silver pair, we can see a strong lead-lag effect of oil on silver between the frequencies of 16 and 64 days during 2008. This was later reversed, with silver showing a lead-lag effect on oil at a frequency ranging from 64 to 256 days. During the height of the GFC in 2009, a significant co-movement and lead-lag effect of oil on silver was observed. Surprisingly, silver exhibited a lead-lag effect on oil at a frequency between 16 and 64 days

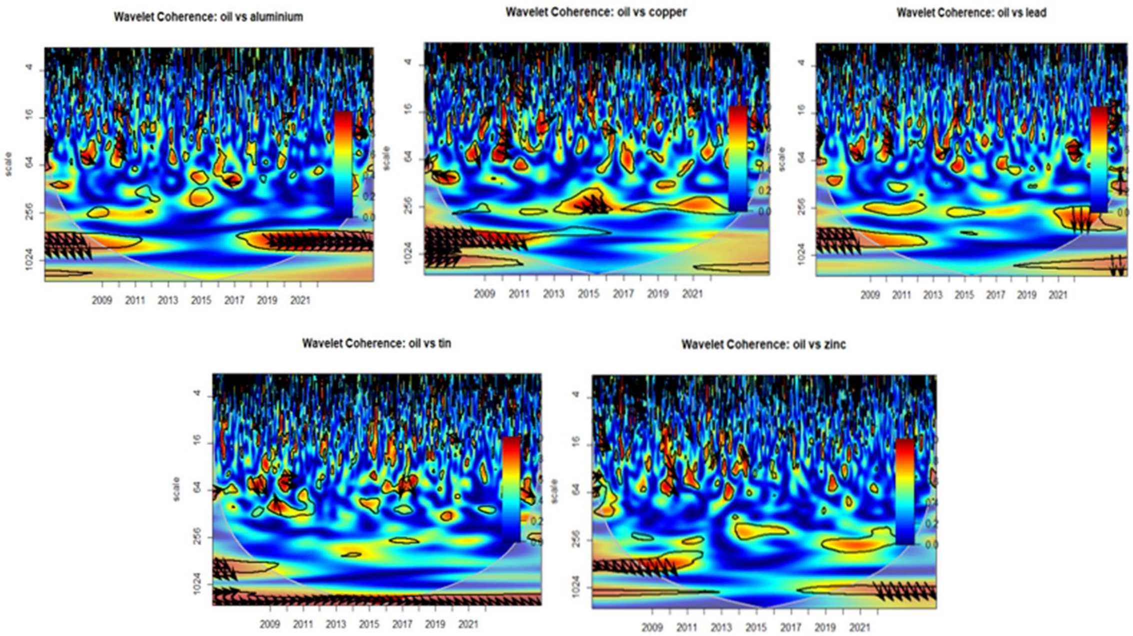

Fig. 4 WCA results for co-movement between oil and base metals. Figure 4 presents WCA results for returns co-movement between oil and individual base metals namely; aluminum, copper, lead, tin and zinc. The horizontal and left vertical axes denote the time and frequency dimensions (days). The multi-colored bar to the right of the plot denotes the wavelet coherence power. Highest wavelet coherence power is shown by red colour at the top of the bar and it diminishes downwards to blue colours at the bottom of the bar denoting lower power. Significant areas are located within the white bordered curve at 0.05 level generated using Monte Carlo simulations. The ($\rightarrow$, $\leftarrow$) black arrows signify an in-phase/out-of phase or positive/negative correlation. The ($\nearrow$, $\swarrow$) directed arrows signify the leading effect of the first/second time series respectively. The black arrow with the directions ($\nwarrow$, $\searrow$) in WCA graph signifies an out-of-phase relationship/ negative covariance between the two time series with the leading effect of the first/second time series respectively

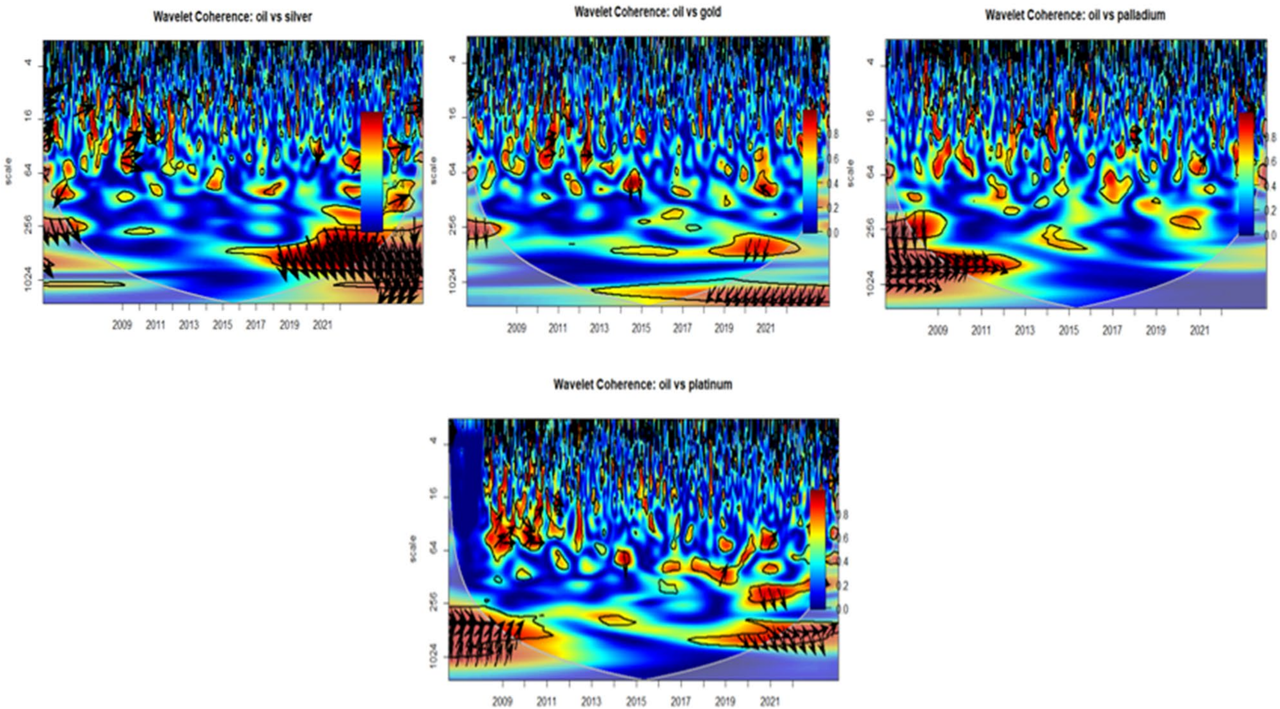

Fig. 5 WCA results for co-movement between oil and precious metals. Figure 5 presents WCA results for returns co-movement between oil and individual precious metals namely; silver, gold, palladium and platinum. The horizontal and left vertical axes denote the time and frequency dimensions (days). The multi-colored bar to the right of the plot denotes the wavelet coherence power. Highest wavelet coherence power is shown by red colour at the top of the bar and it diminishes downwards to blue colours at the bottom of the bar denoting lower power. Significant areas are located within the white bordered curve at 0.05 level generated using Monte Carlo simulations. The (→,←) black arrows signify an in-phase/out-of phase or positive/negative correlation. The (↗, ↙) directed arrows signify the leading effect of the first/second time series respectively. The black arrow with the directions (↖, ↘) in WCA graph signifies an out-of-phase relationship/ negative covariance between the two time series with the leading effect of the first/second time series respectively

during the first wave of COVID-19 in the first quarter of 2020. However, in 2021, a lead-lag effect of oil on silver was evident at the 64-day frequency, which was followed by a similar effect in 2022 at both low and high frequencies of between 4 and 16 days, which may also be associated with the oil price shocks triggered by the Russia–Ukraine war. In another commodity pair, oil and gold exhibited significant co-movement in 2010, with oil leading gold at a frequency between 16 and 64 days. Similar effects were observed towards the end of the GFC in late 2011. Between 2014 and 2015, a significant out-of-phase negative co-movement was observed between the pair at a frequency of about 64 days. During the entire period of the pandemic, strong co-movement between oil and gold was evident, with gold leading oil at a frequency between 256 and 1024 days.

Co-movements in the oil-palladium pair were observed in 2009, with oil leading at a low frequency between 256 and 1024 days. From mid-2010 to 2011, co-movements between the two commodities were evident with the lead-lag effect of oil on palladium at a high frequency of between 4 and 16 days. Out-of-phase negative co-movements can also be seen towards the end of 2011 and in the year 2013 at a time frequency of about 16 days. From the beginning of 2015 towards mid-2015, a lead-lag effect of oil on palladium was observed. In 2018, there was an out-of-phase negative co-movement between the pair at a frequency between 16 and 64 days. The last strong co-movement between oil and palladium was observed in the first half of 2020, with the leading effect of palladium being visible at a frequency between 16 and 64 days. Lastly, the WCA results for the oil-platinum pair reveal strong co-movement between the two commodities from 2009 to 2010 in the frequency range between 16 and 64 days. Lead-lag effects of oil on platinum were observed in this particular co-movement. However, towards the end of 2011, there was an out-of-phase negative co-movement between the two commodities in the frequency range between 16 and 64 days. Lead-lag effects of oil on platinum were observed from 2018 to 2019 as well as during the first half of 2020, both at a frequency of about 64 days.

Dynamic frequency-domain connectedness results

Using WCA, we have shown evidence of dynamic co-movement and lead-lag effects existing between oil and different non-energy commodities. This, however, has not shown the approximate degree of connectedness between the commodities in question. We thus supplement WCA results by carrying out DF-DNC analysis to determine the spillover indices for commodity pairs. We calculate volatility spillovers using a short-term time horizon because we are looking at high-frequency volatility connectedness between commodities. Figure 8 displays the magnitudes of volatility spillover between oil and individual agricultural commodities. The volatility indices for all agricultural commodities during the GFC were higher than in the post-GFC period, ranging from 0 to 10%. However, volatility spillover between oil and oats appeared to be less as compared to other agricultural commodities. During the pandemic, volatility indices for all agricultural commodities reached a staggering 30%, with corn subsequently exhibiting lower degrees of spillover volatility after the initial pandemic oil shock (Fig. 6).

In Fig. 7, we present trends in volatility spillover indices for the relationship between oil and individual base metals. During the GFC period, aluminium lead and tin exhibited higher magnitudes of volatility spillovers with oil, registering indices up to more than 10%. However, during the pandemic, volatility spillovers were slightly higher, especially between oil and base metals, namely aluminum, copper, lead, and nickel.

In Fig. 8, we present volatility spillover index trends between oil and individual precious metals. During the GFC, the volatility spillover between oil and silver was the greatest compared to other precious metals. During the period, volatility spillover indices for silver and oil peaked at about 20%. This was followed by palladium, which also exhibited slightly higher volatility spillover with oil compared to gold and platinum during the GFC. During the pandemic, volatility spillovers between oil–gold and oil–platinum commodity pairs were the highest when compared to the remaining precious metals following the initial shock from oil that affected all precious metals.

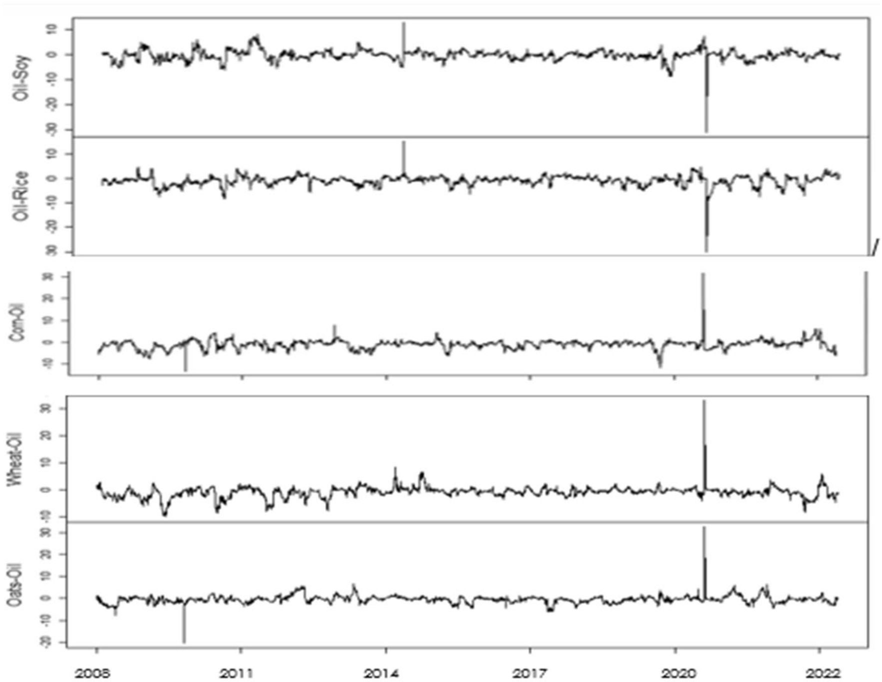

Fig. 6 Oil and agricultural commodities BK-18 volatility spillover index trends. Figure 6 displays the trends of BK-18 spillover indices generated by the dynamic frequency-domain connectedness analysis within the spillover band between 3.14 and 0.79. The index denotes the total information returns volatility between oil and individual agricultural commodities. It is measured at a short-term horizon of 1–4 days

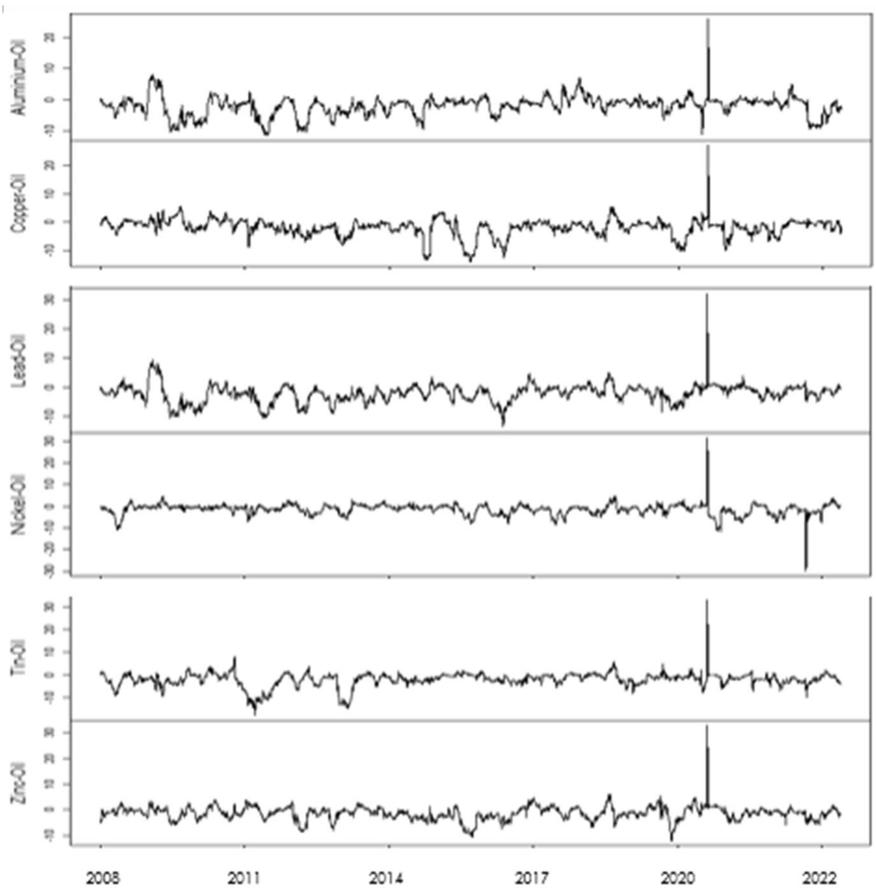

Fig. 7 Oil and base metals BK-18 volatility spillover index trends. Figure 7 displays the trends of BK-18 spillover indices generated by the dynamic frequency-domain connectedness analysis within the spillover band between 3.14 and 0.79. The index denotes the total information returns volatility between oil and individual base metals. It is measured at a short-term horizon of 1–4 days

Discussions, implications, and avenues for further research

Discussions

In this current paper, we comprehensively evaluate time-varying volatility spillovers between oil and non-energy commodities from both the time and frequency domains. Our general results suggest dynamic volatility spillovers between oil and the majority of non-energy commodities. Moreover, the time–frequency volatility spillover between oil and individual non-energy commodities varies across different frequency bands and the sampled timeframe. These results provide evidence to suggest that the co-movement between oil and non-energy commodities markets is dynamic and non-synchronous.

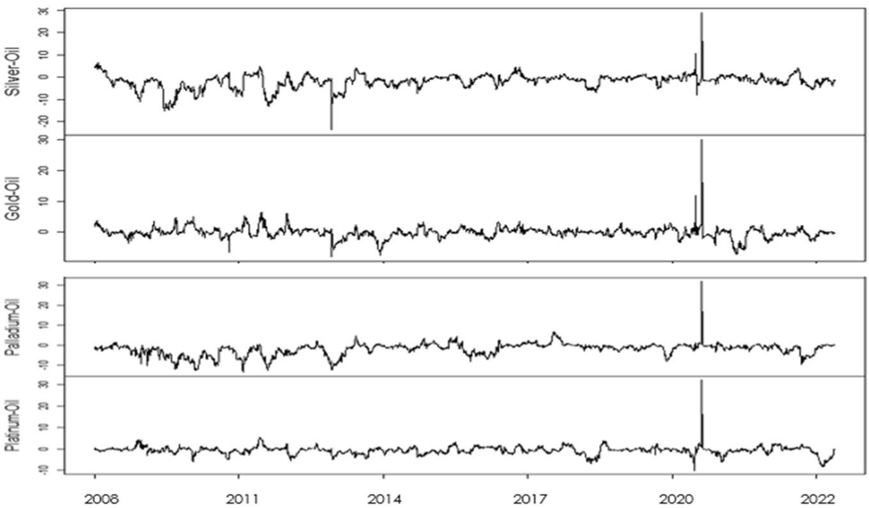

Fig. 8 Oil and precious metals BK-18 volatility spillover index trends. Figure 8 displays the trends of BK-18 spillover indices generated by the dynamic frequency-domain connectedness analysis within the spillover band between 3.14 and 0.79. The index denotes the total information returns volatility between oil and individual precious metals. It is measured at a short-term horizon of 1–4 days

Looking at the oil-agricultural commodities pair, soy and wheat exhibited the lowest degrees of time-varying co-movement with oil, even during both crises. Significant time-varying co-movements were observed between oil and other agricultural commodities at high frequency in the time domain during both crises. Abrupt shocks in oil prices have been observed to trigger price shocks in agricultural commodities, as postulated by Taghizadeh-Hesary et al. (2019). Moreover, the lead-lag effect was present, with oil leading the three agricultural commodities. Our findings back up previous research by Wang et al. (2014) and Mensi et al. (2014), which show unidirectional co-movement of oil and agricultural commodities, with the former being the leader. The growing reliance of the agricultural sector on fossil fuels, especially oil, can well explicate the unidirectional volatility spillover from oil to the sector (Zhang et al. 2010). The findings, however, contradict the work by Sun et al. (2021), Umar et al. (2021d), and Barbaglia et al. (2020) that showed a bi-directional co-movement between the oil and agricultural commodities markets.

Our findings also present evidence of asymmetrical co-movement between oil and different base metals, as depicted by Dutta (2018). A less powerful co-movement between oil-zinc and oil-tin pairs was observed only during the GFC, with no apparent effects seen during the pandemic. However, copper, aluminum, and lead each exhibited heightened co-movements at high frequencies with oil during both crises. The lead-lag effect of oil on these three metals during both crises was evident, but during specific tranquil periods, aluminium appeared to have a lead-lag effect on oil, thus supporting a bi-directional linkage between the two. Our findings therefore corroborate those of works by Umar et al. (2020, 2021b), Kaulu (2021), Zhang and Tu (2016), Reboredo and Ugolini (2016), and

Dutta (2018) that all depict powerful co-movement between oil and base metal markets, with oil being the main volatility transmitter. We specifically corroborate findings by Zhang and Tu (2016) that provide evidence for strong volatility spillovers from oil to copper and aluminium markets in China.

Finally, we examined the co-movement between oil and individual precious metals. Magnified volatility spillovers between oil and all four precious metals were evident during the GFC and COVID-19 at high frequency. This shows the fact that the precious metal market is highly susceptible to volatility spillovers as opposed to base metals and agricultural commodities. Our results corroborate works by Li et al. (2021) and Mensi et al. (2021) that both present a case against oil as a diversifier in portfolios incorporating precious metals. We further refute the findings by Dutta (2018) that showed silver to be the sole precious metal susceptible to oil shocks. The results further reveal bi-directional volatility spillovers between oil–gold, oil–silver, and oil–palladium pairs. This piece of finding does not corroborate works by Reboredo and Ugolini (2016) and Hammoudeh and Yuan (2008) that reported uni-directional volatility spillover from oil to precious metals.

Implications and avenues for further research

Our findings provide vital implications for theory and practice. They provide evidence to debunk the oil-agricultural commodity connectedness neutrality hypothesis (Wiggins and Keats 2009). The findings corroborate the assertion that commodity price co-movement tends to intensify during volatile periods such as COVID-19 and the GFC (Sun et al. 2021; Umar et al. 2021c). The biggest takeaway from our findings is the fact that volatility spillovers differ among commodities belonging to the same market, as such, it is important to study the phenomenon at the individual commodity level as opposed to market. Our findings are instrumental for investors in designing effective portfolios that ensure risk diversification and the generation of desirable risk-adjusted returns. For instance, tin and zinc would be good diversifiers for portfolios composed of oil as opposed to other base or precious metals. Policy makers in countries that rely on agriculture may as well benefit from the knowledge generated from our findings. With oil being the main transmitter of volatility, policymakers can take action to control oil prices during turbulent times to avoid disturbances in food prices through mechanisms such as subsidization. Businesses that rely on the importation of base metals such as aluminium and copper may find our results beneficial to them in managing the risk of abrupt changes in input prices caused by oil price shocks. The use of futures contracts for commodities that are "net receivers" of volatility from oil could be vital in these situations. Future researchers can also use high-frequency data and other methodologies to examine volatility spillovers between individual commodities and emerging financial assets such as Bitcoin to help provide knowledge to investment managers to improve their portfolios' performance.

Conclusions

In this article, we examine the dynamic volatility spillover between oil and non-energy commodities, namely agricultural commodities, base metals, and precious metals. We study the phenomenon in the timeframe from 2008 to 2022 to capture time-varying volatility spillovers during the GFC and COVID-19 pandemic. Unlike the majority of works that examine a similar phenomenon, we employ high-frequency daily data for commodities' spot prices to capture underlying patterns that may not be detected in low-frequency data. We further scrutinize the dynamic volatility spillover between oil and individual commodities to detect how the phenomenon differs across non-energy commodities in similar markets. We employ WCA and DF-DNC to examine the nature and magnitudes of time-varying volatility spillovers between commodities. Our findings provide evidence to prove the existence of time-varying volatility spillover between oil and the majority of non-energy commodities in different markets. However, the significance of coherence and volatility spillover between oil and commodities in the same market appears to vary, especially in agricultural commodities and base metal markets. Precious metals have been shown to have the strongest co-movement with oil during both crises, with bi-directional volatility spillovers being evident. A detailed comprehension of volatility spillovers between commodities for both financial and overall economic well-being.

Data availability The datasets generated during and/or analyzed during the current study are available in the websites [https://datastreamgroup.com/our-data/ and https://www.bloomberg.com/markets/commodities].

Declarations

Conflict of interest The authors declare no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Compliance with ethical standards Not applicable.

References

Adi A, Adda S, Wobilor A (2022) Shocks and volatility transmission between oil price and Nigeria's exchange rate. SN Bus Econ 2:47. https://doi.org/10.1007/s43546-022-00228-z

Aguiar-Conraria L, Soares M (2014) The continuous wavelet transform: moving beyond uni- and bivariate analysis. J Econ Surv 28:344–375

Bai J, Perron P (2006) Multiple structural change models: a simulation analysis. In: Corbae D, Durlauf S, Hansen BE (eds) Econometric theory and practice: frontier of analysis and applied research (essays in honor of Peter Phillips). Cambridge University Press, Cambridge

Barbaglia L, Croux C, Wilms I (2020) Volatility spillovers in commodity markets: a large t-vector autoregressive approach. Energy Econ 85:104555. https://doi.org/10.1016/j.eneco.2019.104555

Baruník J, Krehlik T (2018) Measuring the frequency dynamics of financial connectedness and systemic risk. J Financ Econom 16(2):271–296

Bossman A, Owusu P, Tiwari A (2022) Dynamic connectedness and spillovers between Islamic and conventional stock markets: time- and frequency-domain approach in COVID-19 era. Heliyon. https://doi.org/10.1016/j.heliyon.2022.e09215
Chang T, Tsai S, Haga K (2017) Uncovering the interrelationship between the US stock and housing markets: a bootstrap rolling window Granger causality approach. Appl Econ. https://doi.org/10.1016/10.1080/00036846.2017.1346365
Dickey D, Fuller W (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74(366):427–431
Diebold F, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 28:57–66
Dinku T, Worku G (2022) Asymmetric GARCH models on price volatility of agricultural commodities. SN Bus Econ 2:181. https://doi.org/10.1007/s43546-022-00355-7
Dutta A (2018) Impacts of oil volatility shocks on metal markets: a research note. Resour Policy 55:9–19. https://doi.org/10.1016/j.resourpol.2017.09.003
Dutta A, Noor M (2017) Oil and non-energy commodity markets: an empirical analysis of volatility spillovers and hedging effectiveness. Cogent Econ Financ 5(1):1324555. https://doi.org/10.1080/23322039.2017.1324555
Hammoudeh S, Yuan Y (2008) Metal volatility in presence of oil and interest rate shocks. Energy Econ 30:606–620. https://doi.org/10.1016/j.eneco.2007.09.004
Johansen S (1991) Estimation and hypothesis testing of co-integration vectors in Gaussian vector autoregressive models. Econom Econom Soc 59(6):1551–1580
Kaltalioglu M, Soytas U (2009) Price transmission between world food, agricultural raw material, and oil prices. In: GBATA international conference proceedings. Prague, pp 596–603
Kansheba J, Marobhe M (2022) Institutional quality and resource-based economic sustainability: the mediation effects of resource governance. SN Bus Econ. https://doi.org/10.1007/s43546-021-00195-x
Kaulu B (2021) Effects of crude oil prices on copper and maize prices. Future Bus J 7:54. https://doi.org/10.1186/s43093-021-00100-w
Li Y, Huang J, Gao W, Zhang H (2021) Analyzing the time-frequency connectedness among oil, gold prices and BRICS geopolitical risks. Resour Policy. https://doi.org/10.1016/j.resourpol.2021.102134
Maghyereh A, Abdoh H (2022) COVID-19 and the volatility inter-linkage between Bitcoin and financial assets. Empir Econ 63:2875–2901. https://doi.org/10.1007/s00181-022-02223-7
Marobhe M, Kansheba J (2022) Stock market reactions to COVID-19 shocks: do financial market interventions walk the talk? China Financ Rev Int. https://doi.org/10.1108/CFRI-01-2022-0011
Mensi W, Hammoudeh S, Nguyen D, Yoon S (2014) Dynamic spillovers among major energy and cereal commodity prices. Energy Econ 43:225–243. https://doi.org/10.1016/j.eneco.2014.03.004
Mensi W, Nekhili R, Vinh X, Kang S (2021) Oil and precious metals: volatility transmission, hedging, and safe haven analysis from the Asian crisis to the COVID-19 crisis. Econ Anal Policy 71:73–96. https://doi.org/10.1016/j.eap.2021.04.009
Naeem M, Umar Z, Ahmed S, Ferrouhi M (2020) Dynamic dependence between ETFs and crude oil prices by using EGARCH-Copula approach. Phys A 557:1–26. https://doi.org/10.1016/j.physa.2020.124885
Nazlioglu S, Soytas U (2011) World oil prices and agricultural commodity prices: evidence from an emerging market. Energy Econ 33(3):488–496. https://doi.org/10.1016/j.eneco.2010.11.012
Nazlioglu S, Erdem C, Soytas U (2013) Volatility spillover between oil and agricultural commodity markets. Energy Econ 36:658–665. https://doi.org/10.1016/j.eneco.2012.11.009
Reboredo J, Ugolini A (2016) The impact of downward/upward oil price movements. Resour Policy 72:1–8. https://doi.org/10.1016/j.resourpol.2021.102131
Shah A, Paul M, Bhanja N, Dar A (2021) Dynamics of connectedness across crude oil, precious metals and exchange rate: evidence from time and frequency domains. Resour Policy 73:1–19. https://doi.org/10.1016/j.resourpol.2021.102154
Sun Y, Mirza N, Qadeer A, Hsueh H (2021) Connectedness between oil and agricultural commodity prices during tranquil and volatile period. is crude oil a victim indeed? Resour Policy 72:102–131. https://doi.org/10.1016/j.resourpol.2021.102131
Taghizadeh-Hesary F, Rasoulinezhad E, Yoshino N (2019) Energy and food security: linkages through price volatility. Energy Policy 128:796–806. https://doi.org/10.1016/j.enpol.2018.12.043

Tiwari AK, Nasreen S, Shahbaz M, Hammoudeh S (2019) Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals. Energy Econ. https://doi.org/10.1016/j.eneco.2019.104529

Tiwari A, Umar Z, Alqahtani F (2021) Existence of long memory in crude oil and petroleum products: generalised Hurst exponent approach. Res Int Bus Financ 57:1–18. https://doi.org/10.1016/j.ribaf.2021.101403

Torrence C, Compo G (1998) A practical guide to wavelet analysis. Bull Am Meteorol Soc 79:605–618. https://doi.org/10.1175/1520-0477(1998)0792.0

Uddin G, Muzaffar T, Mohamed A, Sjö B (2016) Understanding the relationship between inflation and growth: a wavelet transformation approach in the case of Bangladesh. World Econ. https://doi.org/10.1111/twec.12429

Umar Z (2017) The demand of energy from an optimal portfolio choice perspective. Econ Model 61:478–494. https://doi.org/10.1016/j.econmod.2016.12.027

Umar Z, Gubareva M (2021) The relationship between the Covid-19 media coverage and the environmental, social and governance leaders equity volatility: a time-frequency wavelet analysis. Appl Econ. https://doi.org/10.1080/00036846.2021.1877252

Umar Z, Zaremba A, Olson D (2020) Seven centuries of commodity co-movement: a wavelet analysis approach. Appl Econ Lett 29:1–6. https://doi.org/10.1080/13504851.2020.1869151

Umar Z, Aziz S, Tawil D (2021a) The impact of COVID-19 induced panic on the return and volatility of precious metals. J Behav Exp Financ 31:1–5. https://doi.org/10.1016/j.jbef.2021.100525

Umar Z, Gubareva M, Naeem M, Akhter A (2021b) Return and volatility transmission between oil price shocks and agricultural commodities. PLoS ONE 16(2):1–18. https://doi.org/10.1371/journal.pone.0246886

Umar Z, Jareño F, Escribano A (2021c) Oil price shocks and the return and volatility spillover between industrial and precious metals. Energy Econ 99:1–13. https://doi.org/10.1016/j.eneco.2021.105291

Umar Z, Riaz Y, Zaremba A (2021d) Patterns of spillover in energy, agricultural, and metal markets: a connectedness analysis for years 1780–2020. Financ Res Lett 43:1–7. https://doi.org/10.1016/j.frl.2021.101999

Umar Z, Jareño F, Escribano A (2021e) Agricultural commodity markets and oil prices: an analysis of the dynamic return and volatility connectedness. Resour Policy 73:1–14. https://doi.org/10.1016/j.resourpol.2021.102147

Umar Z, Jareño F, Escribano A (2022a) Analysis of the dynamic return and volatility connectedness for non-ferrous industrial metals during the COVID-19 pandemic crisis. Stud Econ Financ. https://doi.org/10.1108/SEF-01-2022-0045

Umar Z, Zaremba A, Olson D (2022b) Seven centuries of commodity co-movement: a wavelet analysis approach. Appl Econ Lett 29(4):355–359. https://doi.org/10.1080/13504851.2020.1869151

Wang Y, Wu C, Yang L (2014) Oil price shocks and agricultural commodity prices. Energy Econ 44:22–35

Wiggins S, Keats S (2009) Grain stocks and price spikes. Overseas Development Institute Research Report

Wright B (2014) Global biofuels: key to the puzzle of grain market behavior. J Econ Perspect 28(1):73–98. https://doi.org/10.1257/jep.28.1.73

Wu S (2021) Co-movement and return spillover: evidence from Bitcoin and traditional assets. SN Bus Econ 1:122. https://doi.org/10.1007/s43546-021-00126-w

Zaremba A, Umar Z, Mikutowski M (2021) Commodity financialisation and price co-movement: lessons from two centuries of evidence. Financ Res Lett 38:1544–6123. https://doi.org/10.1016/j.frl.2020.101492

Zhang D, Broadstock D (2018) Global financial crisis and rising connectedness in the international commodity markets. Int Rev Financ Anal. https://doi.org/10.1016/j.irfa.2018.08.003

Zhang C, Qu X (2015) The effect of global oil price shocks on China's agricultural commodities. Energy Econ 51:354–364. https://doi.org/10.1016/j.eneco.2015.07.012

Zhang C, Tu X (2016) The effect of global oil price shocks on China's metal markets. Energ Policy 90:131–139. https://doi.org/10.1016/j.enpol.2015.12.012

Zhang Z, Lohr L, Escalante C, Wetzstein M (2010) Food versus fuel: what do prices tell us? Energy Policy 38(1):445–451. https://doi.org/10.1016/j.enpol.2009.09.034

Authors and Affiliations

Mutaju Isaack Marobhe[1,2] · **Jonathan Mukiza Peter Kansheba**[3,4]

Jonathan Mukiza Peter Kansheba
jonathan.kansheba@uia.no

1 Department of Finance and Accounting, Tanzania Institute of Accountancy, Dar es Salaam, Tanzania

2 SSM-ESAMI Research Centre, Swiss School of Management, Bellinzona, Switzerland

3 Department of Management, School of Business and Law, Universitetet i Agder, Kristiansand, Vest-Agder, Norway

4 Thomas School of Business, University of North Carolina, Pembroke, NC, USA