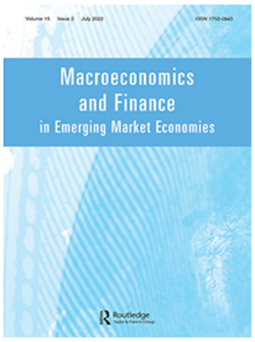

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Re-examining oil and BRICS' stock markets: new evidence from wavelet and MGARCH-DCC

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ABSTRACT

This study examines how the relationship between oil and stock market return of BRICS behaves at different investment horizons. Using data ranging from 2006 to 2020, the wavelet and MGARCH-DCC found that the stock markets' return of Russia, Brazil, and South Africa are comparatively more correlated with oil price return across the investment horizons and more volatile particularly during the Covid-19 period. However, the stock markets' return of China and India is less correlated with oil price return and less volatile. It is also revealed that oil price return leads the BRICS' stock markets' return and both are positively correlated.

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Oil; BRICS; stock price; wavelet; MGARCH-DCC; COVID-19

1. Introduction

The emerging markets, namely Brazil, Russia, India, China, and South Africa are jointly known as (BRICS), are growing faster and integrating more with the developed countries' economies particularly in terms of investment and trade. Collectively, they represent more than 25% of the world's land area, 3 billion people (42% of the world population), and almost 15% of the global GDP.[1] Though they are the most giant emerging markets but differ in characteristics. Russia ranked 3rd in the world after Saudi Arabia in terms of oil production, is one of the main net exporters of oil. On the other hand, China and India are the biggest oil importers, ranked 2nd and 3rd after the USA. Though Brazil is ranked 10th in oil production it is still a net importer of some light oil.

Approximately 60% of the Russian stock exchange is controlled by oil and gas companies. On the other hand, India and China being highly industrialized consumed a lot of energy and depend substantially on oil. Moreover, the growing population and lack of national oil reserves have a great influence on the petroleum industry in China and India. Almost 16% of the Shanghai composite index is dominated by oil and basic materials. Concerning South Africa, almost 4% of the total stock market capitalization comes from the oil and gas industry.[2]

BRICS being economically very important in the present world, international investors are becoming more interested in investing in the BRICS countries. Investors are particularly interested in investing in the stock markets of these countries because of the undervalued

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price of the stocks. Since oil is one of the most influential factors for the BRICS economies, the investors must study the behaviour of the return-volatility of oil and stock prices of the BRICS very closely. One of the effective ways is to study the time-varying co-movement and interdependency of BRICS' countries stock prices (return-volatility) with the oil prices (return-volatility) in detail at different investment horizons by deploying sophisticated econometric techniques.

The theory of equity valuation can explain the extent of the impact of oil price changes on the stock price. The stock price is theoretically equal to the sum of discounted future cash flows. Hence the potential primary impact of oil price changes on stock price can be attributed to the corporate cash-flows and earnings (Badeeb and Lean 2018). The conditions of economies (market confidence, production costs, inflation, interest rates, income, and economic growth, etc.), which can be influenced by the oil shocks reflect on discounted cash flows of the companies. Hence, Arouri et al. (2012) argued that through the projected cash flows on the one hand, and through the discount rate on the other hand, the oil price movement would directly affect stock prices. Similarly, Gomes and Chaibi (2014) state that the production cost of goods and services increases when the price of crude oil goes up, which constrain the consumption of consumers through inflationary pressure. Hence oil price impacts the capital markets, the macroeconomic as a whole, and also the confidence level of the consumers.

Based on that, the existing literature suggests that the oil price has an impact on the stock price. However, the findings from most of the existing literature have shown conflicting results. Some studies found a negative impact of oil price on stock prices (Raza, Shahzad, and Tiwari 2016; Creti, Ftiti, and Guesmi 2014; Fang and You 2014; Masih, Peters, and De Mello 2011; Kilian and Park 2009). In recent studies, some findings found a positive relationship (Mensi et al. 2018; Kang, de Gracia, and Ratti 2017; Caia et al. 2017; Xingguo and Shihua 2017; Ono 2011). On the other hand, a few studies supported that the relationship is mixed and ambiguous (Bouoiyour and Selmi 2016; Miller and Ratti 2009). In terms of causality, (Jammazi et al. 2017; Al.Maghyereh, Awartani, and Bouri 2016; Bouoiyour and Selmi 2016) found a bidirectional causal relationship.

The findings of the previous researchers are inconclusive. From the available literature, we find that 2007 to 2008 have been considered as global financial crisis period and 2009 to 2010 have been recognized as the recovery period. Many studies have already been done to analyse the crisis and recovery period. However, there are not many studies available in the existing literature that particularity focuses on the post-crisis period and Covid-19 periods. So we have investigated the co-movement and interdependency between oil and BRICS' stock markets for all the periods including the 2007–2008 financial crisis and on-going health pandemic Coivd-19. Moreover, only a few types of research have been conducted to investigate the time-varying co-movement and causal relationship between the oil and BRICS' stock markets at different investment horizons.

Many recent studies have applied Wavelet and MGARCH-DCC to analyze the oil and stock markets (Cai, et al. 2017; Pal and Mitra 2017; Ding, et al. 2017; Jammazi, et al. 2017; Dewandaru, Masih and Masih 2016; Raza, Shahzad and Tiwari 2016; Ftiti, Guesmi and Abid 2016). However, the findings from their studies are also inconclusive.

This is our humble effort to extend the existing literature and address the gaps mentioned above. First, we have investigated the time-varying conditional correlations and volatility between oil price return and the return of stock markets of BRICS. For that, we have deployed MGARCH-DCC to estimate the time-varying conditional correlations and volatility as well as unconditional correlations and volatility. This study also deployed comparatively new techniques, maximal overlap discrete wavelet transform (MODWT), for a deeper investigation of the relationship between BRICS' stock markets and oil at different investment horizons. In addition to exploring correlation and interdependence, this study also examine the positive-negative and lead-lag relationship between BRICS' stock return and oil price return at different investment horizons by using continuous wavelet transformations (CWT) analysis.

The findings of the study reveal that the stock markets' return of Russia, Brazil, and South Africa, oil producing countries, are comparatively more correlated with oil price return across the investment horizons and also appear to be more volatile particularly during the Covid-19 period. However, the stock markets' return of China and India, major oil importing countries, appears to be comparatively less correlated with oil price return across the investment horizons and also less volatile. Hence these results tend to indicate that the opportunities to hedge the portfolio risk are present in these two markets by taking efficient strategies. It is also revealed that oil price return leads the BRICS' stock markets' return at most of the investment horizons and both are positively correlated.

In the following ways, this study contributes to the literature: First, we extend the existing literature by investigating the volatility, co-movement, and interdependency between oil and BRICS' stock markets returns for the period of pre-financial crisis, financial crisis 2007–2008, post-financial crisis and Covid-19. Second, instead of generalizing the same findings for everyone, we have deployed the time-frequency analysis to specify our findings for investors investing at different investment horizons (i.e. 2–4, 4–8, 8–16, etc. days holding periods). The findings of our study would provide important insights for the market players, investors, and policymakers to set their future strategies on stock markets in BRICS.

The rest of the paper is structured as follows. Section II reviews the empirical studies related to the BRICS stock markets and oil prices. Section III discusses the data and methodologies. The empirical results are discussed in Section IV. Finally, Section V deals with conclusions and the policy implications of the study.

2. Literature review

Many studies have been undertaken to examine the relation between oil price and stock markets. A very recent study by Mensi et al. (2018) has examined the co-movement of BRICS stock markets with the oil price and gold price using the wavelet approach. They found that the BRICS stock market co-move with the oil price at a lower frequency. Simlerly, Reboredo, Rivera-Castro, and Ugolini (2017) investigated causality and co-movement between oil and stock price of renewable energy and found that interdependences between them are strong in the long run. In line with reasoning, Jing et al. (2017) investigated the East Asian stock market and findings from their studies show that oil price and stock return move together. However, they also found that oil pice leads the stock return of the East Asian stock market. On the other hand, Abdullah, Saiti, and Masih (2016) studied the relationship between Philippine Shariah stock and crude oil price and found that both are less correlated in the short run.

Recently another multiscale framework has been used by Jammazi et al. (2017) to investigate the presence of time-varying causal linkage between stock return and oil price changes for six major oil-importing countries. Findings from their study show that there are bidirectional causal relations between oil and stock markets. Shupei et al. (2016) also studied the effects of oil price and stock return and their results show that oil price decrease and increase have significant impacts on the stock returns; moreover, oil price also gets reverse influence from the stock market. Mensi et al. (2014) found that BRICS stock markets have a dependence on the global stock and commodity markets. Ono (2011) examines the impact of oil prices on real stock returns of BRIC using VAR models and found that real stock returns of China, India, and Russia positively respond to some of the oil price indicators. In contrast, the research work conducted by Bouoiyour and Selmi (2016) focused on seeing the casual relationship between BRICS stock markets and oil prices find that the impact of oil price on stock returns is not uniform across the investigated countries. Fang and You (2014) in their work suggests that stock markets of NIEs' (China, India, and Russia) are 'partially integrated' with the other stock markets and shocks in oil. Bernanke (2016) confirms the positive correlation between stocks and oil prices.

Another group of researchers investigated oil price volatility and its impact on the stock market. Boubaker and Raza (2017) investigated the spillover effects of volatility and shocks between BRICS stock markets and oil price. Their findings showed strong evidence of time-varying volatility among all markets under study. In another study, based on the six major oil-importing and exporting economies, Boldanov, Degiannakis, and Filis (2016) found that over time, the association between oil price volatility and stock market volatility shifts with both positive and negative values. On the other hand, the Nonlinearity of the relationship has been investigated by Raza, Shahzad, and Tiwari (2016) by deploying nonlinear ARDL to examine the asymmetric impact of oil prices, gold prices, and associated volatility of them on emerging economy stock markets. It is shown that oil prices have a negative impact on stock markets of all emerging economies. Zhihua et al. (2017) investigated Chinese stock market investor sentiment by analysing the contagion effect of international crude oil price fluctuation. They found that oil price volatility causes Chinese stock market investor sentiment. The work of Fatima and Bashir (2014) shows that a very low level of reaction is being observed in the stock market from the fluctuations in international oil prices. Using the GARCH model, Bhuyan et al. (2016) found the US stock market has a significant mean return and volatility spillover effects on the BRICS stock markets.

From the macroeconomic demand and supply aspect, few studies have been conducted. For example, Antonakakis, Chatziantoniou, and Filis (2017) examined the dynamic structural relationship of oil price shocks and stock returns and concluded that the aggregate demand shocks seem to act as the key transmitters of shocks to stock markets, but supply-side and oil–specific demand shocks during periods of geopolitical unrest. Kang, de Gracia, and Ratti (2017) examined the shock of oil price and economic policy uncertainty on the oil & gas companies' stock return and found that demand-side shock of the oil has a positive effect on the stock returns of oil and gas companies. In the study of oil and US stock market, Kilian and Park (2009) showed that the reaction of the stock market to oil price changes greatly depends on whether the oil price changes are driven by demand or supply shocks. Interesting findings of Sadorsky (1999), suggest that the impact of the changes in the oil price effect more on the economic activity but, fluctuations in the economic activity have tiny impact on oil prices.

3. Data and methodology

3.1 Sources of data and variables

The data consists of time series of daily, Crude Oil-WTI Spot Cushing U$/BBL, Standard and Poor's China Broad Market Index (BMI), Standard and Poor's India Broad Market Index (BMI),

Table 1. List of the variables.

Variable	Explanation
OIL	Crude Oil-WTI Spot Cushing U$/BBL
BRAZIL	S&P Brazil Broad Market Index (BMI)
CHINA	S&P China Broad Market Index (BMI)
INDIA	S&P India Broad Market Index (BMI)
RUSSIA	S&P Russia Broad Market Index (BMI)
SAF	S&P South Africa Broad Market Index (BMI)

Standard and Poor's Russia Broad Market Index (BMI) and Standard and Poor's South Africa Broad Market Index (BMI) from the index starting date, 17 July 2006, to 6 November 2020. Data have been collected from the Refinitiv datastream starting from the date of the index inception to the November 2020 to cover the global financial crisis 2007–2008 and Covid-19 pandemic. We have used the following six variables for our study (Table 1):

Figure 1 plots oil and BRICS' stock prices return. Red colour fluctuating lines between 2007–2009, in Figure 1, indicate the global financial crisis period and red colour fluctuating lines, from 2020, indicate the Covid-19 period.

It is observed that returns of the sample assets were highly volatile during the global financial crisis which originated from the US financial markets in mid-2007 and spread globally. After the global financial crisis period, post-crisis, and normal periods, stock and oil price returns became comparatively more stable. However, following the world health pandemic Covid-19 in 2020, returns of the sample assets exhibit high volatility.

The descriptive statistics of prices are summarized in Table 2. The mean return of the stock index of China is comparatively high followed by the stock index return of India and South Africa. Contrary, the mean return of Brazilian and Russian stock indices shows a negative value. The volatility of stock markets and oil prices index return, denoted by the standard deviation

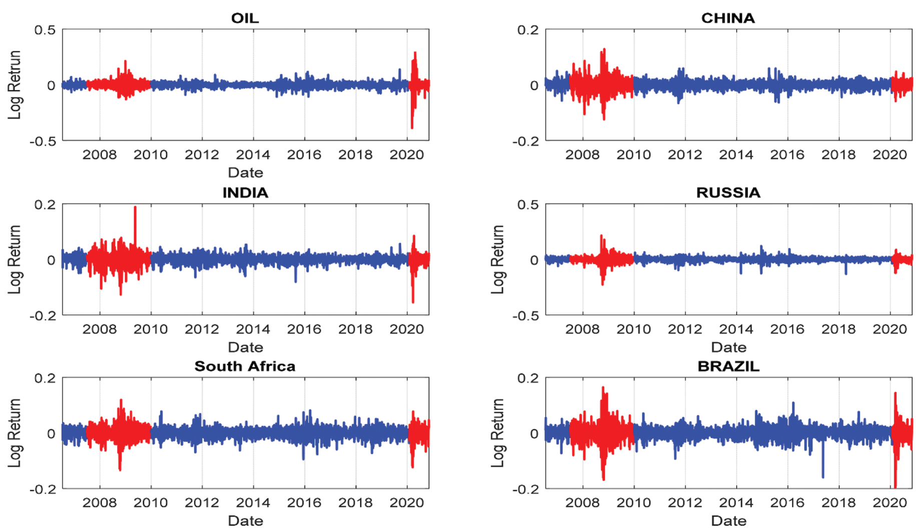

Figure 1. This figure plots the log-return of oil price and BRICS' stock prices from 17 July 2006, to 6 November 2020 using daily frequency. The X-axis denotes the time and the Y-axis denotes the log returns. Red colour fluctuating lines, between 2007–2009, indicate the global financial crisis period and red colour fluctuating lines, from 2020, indicate the Covid-19 period.

Table 2. Summarizes the descriptive statistics of the log return of oil and BRICS stock indices. Summary stats i.e. mean, standard deviation (sd), Minimum (min), Maximum (max), Skewness, and Kurtosis are presented in the above table.

Stats	Brazil	China	India	Russia	South Africa	Oil
mean	−0.0000014	0.0003250	0.0002587	−0.0001272	0.0000568	0.0000221
sd	0.0226364	0.0158586	0.0160368	0.0207442	0.0188271	0.0280077
min	−0.1962440	−0.1243588	−0.1544521	−0.2266118	−0.1335396	−0.3882931
max	0.1640154	0.1280064	0.1884824	0.2145948	0.1191951	0.3002293
skewness	−0.6204874	−0.1227383	−0.3454654	−0.5765865	−0.4410084	−0.0046879
kurtosis	12.9943300	10.3447000	15.2255300	18.1765200	7.7482370	29.9808700

(SD), exhibits that oil is the most volatile asset followed by the volatility of stock index return of Brazil, Russia, South Africa, India, and China. The minimum return for all indices shows negative values. Oil price provides the maximum return followed by the maximum stock index return of Russian, India, Brazil, China, and South Africa. All the return series exhibit the leptokurtic, positive kurtosis (picked-curve), which indicates that more values of the series are higher than the mean values of the returns. Table 2 also shows that all return series are negatively skewed.

3.2 Methodologies

3.2.1 Multivariate GARCH-DCC

This study applied the Multivariate Generalized Autoregressive Conditional Heteroscedastic-Dynamic Conditional Correlation (MGARCH-DCC) model suggested by Engle (2002) and (Pesaran and Hashem Pesaran (2010) to see how volatility and correlations between oil price and stock performance change over time, including their size (stringer or weaker) and directions (positive or negative). We adopted this methodology because DCC enables both mean and variance equations to evaluate the time variation, discover how asset correlations change over time. Moreover, the DCC method is relatively versatile in modelling individual volatility and can be applied to portfolios with broad asset numbers. The MGARCH-DCC model can be stated as the following equation:

$$r_t = \beta_0 + \sum\nolimits_{i=1}^{k} \beta_i r_{t-1} + u_t = \mu_t + u_t \qquad \text{iv}$$

Where, $\mu_t = \mathrm{E}\left[r_{t|\Omega_{t-1}|}\right]$

$$u_t \mathrm{l} \Omega_{t-1} \sim N(0, H_t)$$

$$H_t = G_t R_t G_t$$

$$G_t = diag\left\{\sqrt{h_{ii,t}}\right\}$$

$$Z_t = G_t^{-1} u_t$$

Where, $h_{ii,t}$ refers the individual univariate GARCH model's estimated conditional variance, G_t indicates the diagonal matrix of conditional standard deviations, R_t is the correlation coefficient matrix of returns of the time-varying conditional correlation, and z_t is the standardized residuals vector with mean zero and variance one. Based on Hsu Ku and Wang (2008), the DCC model can be further defined after the above basic construction:

$$R_t = (diag(Q_T))^{-\frac{1}{2}} Q_t (diag(Q_t))^{-\frac{1}{2}} \tag{v}$$

Where,

$$Q_t = (q_{ij,t})$$

$$(diag(Q_t))^{-1/2} = diag\left(\frac{1}{\sqrt{q_{11,t}}}, , , , , \frac{1}{\sqrt{q_{nn,t}}}\right)$$

$$q_{ij,t} = \bar{p}_{ij} = \alpha\left(Z_{i,t-1}Z_{j,t-1} - \bar{p}_{ij}\right) + \beta\left(q_{ij,t-1} - \bar{p}_{ij}\right) \tag{vi}$$

Where $\bar{p}_{ij}$is the unconditional correlation coefficient & the time-varying conditional correlation coefficient is $p_{i,j,t} = q_{i,j,t} l \sqrt{q_{ii,t} q_{jj,t}}$. Since the financial assets have skewness in return distribution, the student-t distribution setting could be applied instead of the normal distribution. That is the conditional distribution $u_t|\Omega_{t-1} \sim \mathrm{N}(0, \mathrm{H_t})$ is replaced by $u_t|\Omega_{t-1} \sim$ $\text{student} - \mathrm{t}(\mathrm{u_t}; \mathrm{v}), (0, \mathrm{H_t})$where v refers the degree of freedom parameter.

3.2.2 Maximal overlap discrete wavelet transformation (MODWT)

For wavelet-based correlations, we apply the Maximal Overlap Discrete Wavelet Transform (MODWT). This will tell us if the association between oil and stock markets return changes for different holding periods and we can rank them highest to lowest. Unlike the classical discrete wavelet transform (DWT), the MODWT can accommodate any sample size, and it does not require to be the multiple of 2. The wavelet covariance and wavelet-based correlation coefficient at scale j between X and Y can be obtained as two formulas using MODWT (see Fernandez 2008):

$$\hat{v}^2{}_{XY}(T_j) = \frac{1}{M_j} \sum_{t-L'_j}^{n-1} \tilde{d}_{j,t}^{(X)} \tilde{d}_{j,t}^{(Y)} \tag{vii}$$

$$\hat{\rho}X, Y\left(\tau_j\right) = \frac{\hat{V}\mathrm{X}, \mathrm{Y}(^{\tau_j})}{\hat{V}\mathrm{X}, (^{\tau_j})\hat{V}, \mathrm{Y}(^{\tau_j})} \tag{viii}$$

Here $\left|\hat{\rho}X.Y\left(\tau_j\right)\right| \leq 1$ indicates the Wavelet correlation is analogous to its Fourier equivalent, the complex coherency (see Gençay, Selçuk, and Whitcher 2002)

3.2.3 Continuous wavelet transform (CWT)

Continuous Wavelet Transformation (CWT) approach has been applied to find how the oil price return and stock markets' return behave at various holding periods or investment horizons. Unlike MODWT, CWT helps us extend the decomposition in more frequency bands with longer time horizons. Based on the time and frequency domain, CWT captures the heterogeneity at different investment horizon (see details Haque et al. 2018). The continuous wavelet transform $w_{x(u,s)}$ is obtained by projecting a mother wavelet Ψ onto the examined time series $x(t) \in l^2$(R) with the following formula:

$$W_x(u, s) = {}_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi\left(\frac{t-u}{s}\right) dt \tag{ix}$$

Here *u* indicates to the time domain and *s is* for the frequency domain. Adopted from Torrence and Webster (1999), the following equation for wavelet coherence for the two-time series is applied:

$$\mathrm{R}_{\mathrm{n}}^{2}(s)=\frac{\mathrm{I}S\left(s^{-1}W_{n}^{xy}(s)\right)\mathrm{I}^{2}}{S\left(s^{-1}\mathrm{I}W_{n}^{x}(s)\right)\mathrm{I}^{2}.S\left(s^{-1}\mathrm{I}W_{n}^{y}(s)\right)\mathrm{I}^{2}} \quad \text{(x)}$$

While S refers a smoothing operator, s is for the wavelet scale, WWn^x(S) is the continuous transformation of the time series X,Wn^y(S) is the continuous wavelet transform of the time series Y, Yn^{xy} (s) is a cross wavelet transform of the two-time series X and Y (see In and Kim 2013).

The phase pattern. To examine the degree of interdependency and the lead-lag relationship between oil price and stock prices of BRICS countries, this study has applied wavelet phase difference following Bloomfield et al. (2004). The phase difference between m(t) and n(t) is represented as follows:

$$\emptyset_{mn}=tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{mn}(u,s))\}}{\Re\{S(s^{-1}W_{mn}(u,s))\}}\right)$$
$$(xi)with\ \varphi_{mn}\in[-\pi,\pi]$$

Arrows can be seen from wavelet coherency maps. It can be described, if the arrows point to the right, then M(t) and N(t) are positively related. On the other hand, if the arrows point to the left, then M(t) and N(t) are negatively related. The lead-lag (causality) relationship can also be observed from the arrows. Arrows point right and down or left and up means M(t) follows N(t). On the other hand, if the arrows point right and up and left and down, it infers that M(t) leads N(t) (Karim and Masih 2019).

4. Empirical results

4.1 MGARCH-DCC

Maximum likelihood estimates of λ_1 and λ_2 for oil price return and BRICS' stock index return, δ_1 and δ_2 are summarized in Table 3 to compare the multivariate normal distribution with multivariate t-distribution. The maximized log-likelihood value obtained from multivariate t-distribution is 63801.1 and it is greater than the maximized log-likelihood value estimated from the multivariate normal distribution. Moreover, the degree of freedom for multivariate t-distribution is 8.20 which is well below the 30. These suggest that for this study, to capture the fat-tailed nature of the distribution of the index returns, multivariate t-distribution is more appropriate (Pesaran and Hashem Pesaran 2010). Therefore, our study follows the multivariate t-distribution approach.

Table 3 also exhibits that asset-specific estimate of volatility decay parameters, denoted by λ_1 and λ_2, are highly significant as t-ratios are highly significant. The results indicate that the volatility of the assets is mean-reverting. For example, if we sum the estimated volatility decay parameters of oil, Lambda1 (λ_1) and Lambda2 (λ_2), we can find that the value is, (0.9195 + 0.0701), 0.9843 which is lower than 1 indicating that the shock to the volatility is not permanent but mean-reverting. The same finding also holds for the other stock index returns. The results imply that the volatility of asset returns in our sample may increase or

Table 3. Summarizes the Maximum likelihood estimates of λ_1 and λ_2 for oil price return and BRICS' stock index return, δ_1 and δ_2.

		Multivariate Normal distribution		Multivariate t-distribution	
		Estimate	T-Ratio[Prob]	Estimate	T-Ratio[Prob]
Lambda1 (λ_1)	OIL	0.9140	116.0231[.000]	0.9195	121.7143[.000]
	CHINA	0.9321	130.9035[.000]	0.9447	141.0959[.000]
	INDIA	0.8983	107.3465[.000]	0.9139	103.5472[.000]
	BRAZIL	0.9119	112.6830[.000]	0.9354	139.0593[.000]
	RUSSIA	0.9223	129.7997[.000]	0.9365	138.5162[.000]
	SOUTH AFRICA	0.9302	118.5091[.000]	0.9424	125.6156[.000]
Lambda2 (λ_2)	OIL	0.0703	11.9827[.000]	0.0701	11.3396[.000]
	CHINA	0.0617	10.0450[.000]	0.0494	8.6676[.000]
	INDIA	0.0907	12.7579[.000]	0.0764	10.2710[.000]
	BRAZIL	0.0736	11.5851[.000]	0.0551	10.1811[.000]
	RUSSIA	0.0668	11.6442[.000]	0.0576	9.8826[.000]
	SOUTH AFRICA	0.0557	9.8969[.000]	0.0445	8.4053[.000]
Delta1 (δ_1)		0.9884	797.0268[.000]	0.9871	572.6883[.000]
Delta2 (δ_2)		0.0074	11.2749[.000]	0.0077	9.7569[.000]
Maximized Log-Likelihood		62917.7		63801.1	
Degrees of Freedom (DF)				8.1931	23.1253[.000]

decrease depending on the market condition but it tends to converge to the mean in the long run.

Table 4 shows the estimated unconditional volatility and correlation of the sample assets' return. On diagonal elements, shaded values, in Table 4 shows the estimated unconditional volatility of the return of the sample indices. Oil price return exhibits the highest volatility followed by stock index return of Brazil, Russia, South Africa, India, and China.

Off-diagonal elements, given in the first column of Table 4, show the correlation between oil price return and stock index return of China, India, Brazil, Russian, and South Africa respectively. Table 4 shows that Russian, a major oil-producing country, stock index return exhibits the highest correlation with oil price return followed by Brazil and South Africa. The high association of oil price return with stock index return of these countries indicates that there is less diversification benefit in these markets. Contrary, in China and India, the major oil-importing countries, stock index return shows the lowest correlation with oil price return.

Unconditional volatility and correlation, given in Table 4, do not tell us the full story. Since they are based on constant volatility and correlation assumption, they give us only one value for the entire sample period. However, in reality, volatility and correlation are stochastic, not constant. Hence, for better understanding, time-varying conditional volatility and correlation, given in Figure 2, are estimated using MGARCH-DCC.

The left panel of Figure 2 shows the time-varying conditional volatility of the sample assets' return. It exhibits that volatility of assets' return increases sharply following the global financial crisis (2007–2008) and, among the BRICS' stock indices, Russian stock index return tends to be the most volatile during the financial crisis period followed by the volatility of stock index return of Brazil, China, India, and South Africa respectively. Among all assets in our sample, oil price return seems to be the most volatile across the sample periods. Russian stock market's return, one of the major oil-producing countries, seems to be the 2nd highest volatile across the time followed by another oil-producing country, Brazil, stock market return volatility. Contrary, stock markets' return of India and China, major oil-importing countries, exhibit less volatility across the time compared to other sample assets' return volatility.

Table 4. Shows the unconditional volatilities (Standard Errors) on the diagonal elements. And unconditional correlations on the Off-Diagonal Elements.

	Estimated Unconditional Volatility Matrix					
	OIL	CHINA	INDIA	BRAZIL	RUSSIA	SOUTH AFRICA
OIL	0.028059	0.18255	0.19041	0.34731	0.36083	0.30596
CHINA	0.18255	0.015889	0.53827	0.4202	0.47234	0.51373
INDIA	0.19041	0.53827	0.016039	0.37915	0.4209	0.46733
BRAZIL	0.34731	0.4202	0.37915	0.022657	0.55145	0.60306
RUSSIA	0.36083	0.47234	0.4209	0.55145	0.020766	0.63445
SOUTH AFRICA	0.30596	0.51373	0.46733	0.60306	0.63445	0.018835

The left panel of Figure 2 also shows that, in 2020, due to the shock of the Covid-19 health pandemic, the volatility of oil price return sharply increases to an all-time high. And the world has witnessed the negative price of oil in the future market. This is mostly due to the demand side shock of oil during the Covid-19 period. Following the locked down and travelling ban in China, India, Europe, and other world's major economies, the global oil demand reduces sharply which leads to the lowest oil price. Among the BRICS countries, the most affected country is India, in terms of the number of Covid-19 cases, followed by next Brazil, Russia, South Africa, and China. The left panel of Figure 2 shows that the Brazilian stock market return exhibits the highest volatility during the ongoing Covid-19 health pandemic followed by stock markets' return volatility of India, Russia, South Africa, and China. The stock market return of China seems to be the least volatile among the BRICS countries. Though China is the first country that has gone through the severe Covid-19 cases it has managed to control the spread of the virus.

The right panel of Figure 2 shows the correlation between oil price return and the BRICS' stock market return. Following the global financial crisis 2007–2008, the correlation between oil and stock markets returns increases sharply. During the financial crisis time, the commodity market and financial markets both integrated highly. The same finding has already been documented in previous literature (Goetzmann, Li, and Rouwenhorst 2005; Driessen, Maenhout, and Vilkov 2009). The figure also shows that the correlation between oil price

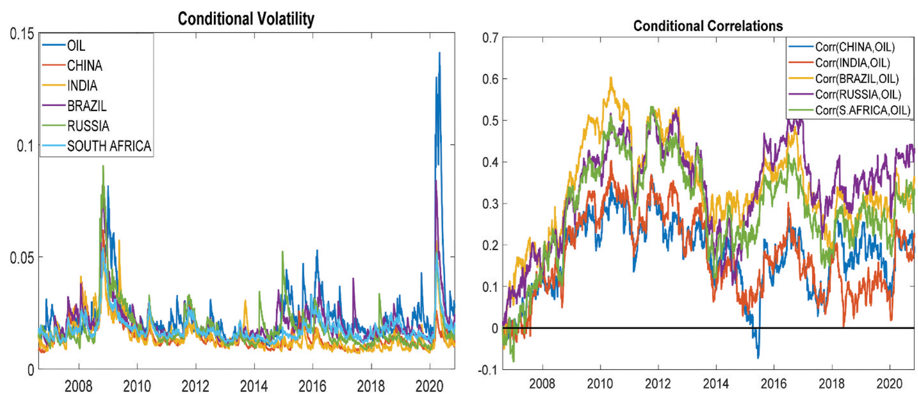

Figure 2. Shows the time-varying conditional volatilities (left panel) and correlations (right panel) estimated using MGARC-DCC. The conditional correlations are estimated between oil price return and BRICS' stock market return. And the conditional volatilities are estimated for oil price return and BRCIS's stock market returns.

return and stock market return of oil-producing countries, i.e. Russia, Brazil, and South Africa, is high compared to the correlation of oil price return with the stock market return of major oil-importing countries i.e. India and China. Being oil-producing countries, the stock market of Russia, Brazil, and South Africa are more exposed to oil price fluctuations.

The right panel of Figure 2 also shows that due to Covid-19, beginning of 2020, there is a sudden decline in the correlation between oil price return and stock price return of BRICS countries. However, this correlation breakdown lasted for only a short period and regain back to the normal level in the subsequent month. This was the time when the oil price has exhibits the highest volatility.

4.2 MODWT

For further in-depth analysis, we have deployed the Maximal Overlap Discrete Wavelet transform (MODWT) to decompose the time series data into different frequencies or holding periods. The stock market has heterogeneous investors with short, medium, and longtime investment horizons i.e. 1–2, 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, 128–256, etc. days. The combined activities of each of the investors having heterogeneous investment horizons generate the outcome in the market.

Figure 3 shows the estimated wavelet-based correlation between oil price return and BRICS' stock markets return. The X-axis shows the investment horizons or scales i.e. 2 days, 4 days, 8 days, etc. holding periods and Y-axis shows the correlation for each of the investment horizons. One can observe some important findings from these figures. First, long-term investors, 128 and 256 days holding periods, have fewer diversification benefits, since the correlation between oil price return and stock market return of BRICS countries are high at scale 128 and 256 compared to other short and medium-term scales. Second, across

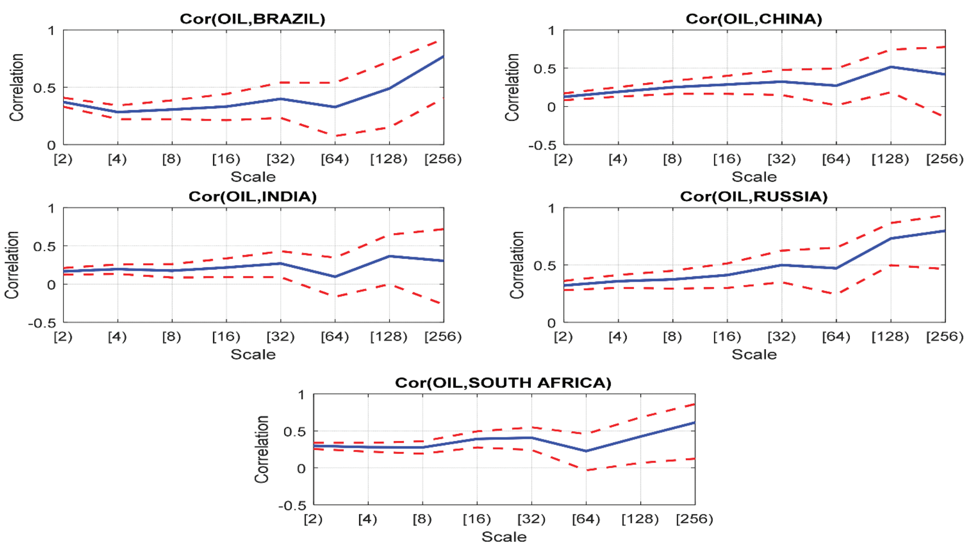

Figure 3. Exhibits the MODWT based correlations between oil price return and BRICS' stock market return for different investment horizons (1–2, 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, 128–256 days holding periods).

the scales, the stock markets' return of oil-producing countries, i.e. Russia, Brazil, and South Africa, tends to be more correlated with oil price return compared to the correction of oil price return with stock market returns of major oil-importing countries i.e. China and India. It implies that diversification benefit is less in oil-producing countries compared to oil-importing countries. It is because stock markets of oil-producing countries are highly exposed to oil price fluctuation compared to major oil-importing countries i.e. China and India. For a better view, in Table 5, the wavelet-based correlations, shown in Figure 3, have been ranked from the highest to lowest for all the investment horizons.

4.3 Wavelet Coherence

Figure 4(a) represent the estimated wavelet coherence and phase differences of oil price returns with the stock market returns. In these figures, the vertical axis represents the investment horizons in respect of investors' holding periods (e.g. 2–4 days, 4–8 days, 8–16 days, 16–32 days, 32–64 days, 64–128 days, etc.). On the other hand, the horizontal axis represents time in respect of the number of trading days from 17 July 2006, to 6 November 2020. The arc line below, approximated using Monte Carlo simulation, represents the level of significance (at 5%). Area afar from the arc is statistically insignificant (at a 95% level of confidence).

The yellow area at the left-hand (right-hand) side of the wavelet coherence shows the existence of significant correlation at the beginning (end) of the sample period, on the other hand, the yellow part at the bottom (top) of the wavelet coherence indicates the strong correlation at low (high) frequencies (different holding periods). (see Karim and Masih 2019).

In Figure 4(e), the WTC figures exhibit that the correlations between oil and BRICS' stock markets return are stronger, indicated by yellow colour pockets, during the 2007–2008 financial crisis period and during Covid-19 periods. It supports the findings that we have discussed earlier. In Figure 4, it also reveals that the interdependency, during the financial crisis 2007–2008, is higher at longer-time investment horizons (256 to 1024 days). This is because the global financial crisis initially originated from the financial markets and gradually spread to the commodity markets in the long-run. On the other hand, the interdependency, during Covid-19, is stronger at mid-term investment horizons (32 to 256 days holding periods). Unlike the global financial crisis, Covid-19 is a health pandemic that spreads very fast all over the world and affected every aspect of human life.

In Figure 4(a,b), the WTC figures exhibit that the interdependence is stronger in the longer time scales (256 to- 1024 days' time horizons) compared to the short time scales (4 to 32 holding days) and medium scales (128 to 256 days' time horizons). It also appears that the Russian stock market return is more correlated with oil price return followed by the Brazilian stock market among the BRICS countries. The result is obvious. Russia is the third-highest net oil producer and also approximately 60% of the Russian stock exchange is controlled by oil and gas companies. The finding implies that the portfolio diversification benefit for the long term investors (256 to 1024 days' time horizons) is very low. However, short-term and midterm investors have more diversification opportunities.

In the case of Brazil in Figure 4(a), the correlation with oil price became strong at 256–1024 holding period. It implies that the investors investing in this particular holding period will have less diversification benefit. However, investors investing in the other holding periods can diversify their portfolio risk. We observe a few small areas with only

Table 5. Shows the Wavelet-based correlation and their ranking (highest to lowest) across the scales (1–2, 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, 128–256 days holding periods) between oil price return and the return of BRICS stock markets.

Rank		2 days		4 days		8 days		16 days
1	OILvBRAZIL	0.3702	OILvRUSSIA	0.3580	OILvRUSSIA	0.3741	OILvRUSSIA	0.4124
2	OILvRUSSIA	0.3212	OILvBRAZIL	0.2832	OILvBRAZIL	0.3061	OILvSAFRICA	0.3903
3	OILvSAFRICA	0.2971	OILvSAFRICA	0.2792	OILvSAFRICA	0.2773	OILvBRAZIL	0.3320
4	OILvINDIA	0.1666	OILvINDIA	0.1954	OILvCHINA	0.2516	OILvCHINA	0.2868
5	OILvCHINA	0.1249	OILvCHINA	0.1904	OILvINDIA	0.1750	OILvINDIA	0.2167
Rank		32 days		64 days		128 days		256 days
1	OILvRUSSIA	0.4998	OILvRUSSIA	0.4718	OILvRUSSIA	0.7309	OILvRUSSIA	0.7982
2	OILvSAFRICA	0.4061	OILvBRAZIL	0.3266	OILvCHINA	0.5166	OILvBRAZIL	0.7700
3	OILvBRAZIL	0.3983	OILvCHINA	0.2710	OILvBRAZIL	0.4898	OILvSAFRICA	0.6138
4	OILvCHINA	0.3224	OILvSAFRICA	0.2263	OILvSAFRICA	0.4236	OILvCHINA	0.4184
5	OILvINDIA	0.2683	OILvINDIA	0.0960	OILvINDIA	0.3655	OILvINDIA	0.3050

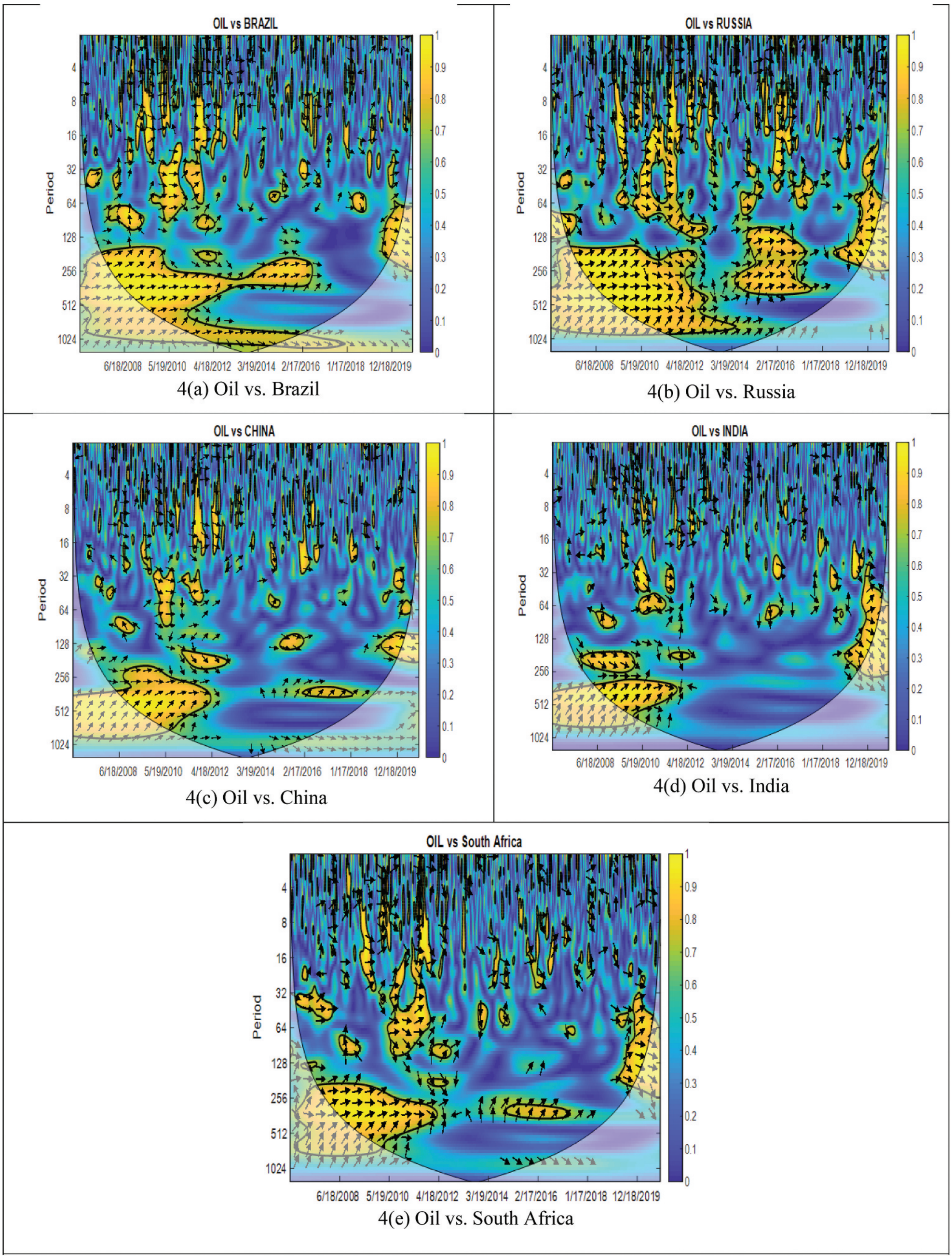

Figure 4. Wavelet transform coherence (WTC) of oil and BRICS stock markets' return.

weak interdependence between the oil price and the stock prices of India, China, and South Africa, which are oil importing countries, in short, and medium time scales in the Figure 4(c–Figure 4(e)) respectively. This suggests that the investors in India, China, and South Africa have more opportunity to diversify the risks by investing in the oil market and stocks market compared to major oil-producing countries i.e. Russia and Brazil.

Moreover, we also observe the phase pattern between the oil and BRICS' stock markets return. We find that arrows point right, meaning that the correlations between the crude oil prices return and BRICS' stock prices return are positive. The phase pattern indicates that the relationship between the two of them is homogenous across the time and scales since the orders of the arrows always point right.

The causality directions between the oil and BRICS' stock market return can be observed from arrows pointing upwards and downwards. Arrows pointing down and right imply that the oil price return leads to BRICS' stock prices return. Information indicates that the causal relationship is less heterogeneous across time and scales for all the countries. It implies that most of the time, oil price returns are leading the BRICS' stock markets return. Our result is consistent with Cai et al. (2017) who found that the oil price and the stock markets move in-phase and the oil price can minimize the risk in the short run and increases the risk over the long run in the East Asian stock markets.

5. Conclusions

This study attempts to explore the relationship between oil price return and stock market return of BRICS countries. The data consist of time series of daily stock and oil prices return from 17 July 2006 to 6 November 2020. By deploying MGARCH-DCC, we have studied the time-varying conditional correlations and volatility between oil and BRICS' stock markets return. To study the correlations between the oil and stock markets returns at different investment horizons, we have decomposed data into different time-frequency domains using maximal overlap discrete wavelet transform (MODWT). Estimated wavelet-based correlation-pairs are then ranked from the highest to lowest for each of the investment horizons. Finally, to understand markets' dynamics of asymmetric behaviour at different holding periods, we have further decomposed data using continuous wavelet transforms (CWT).

The results from MGARCH-DCC tend to indicate several findings. First, the volatilities of the return of the assets, oil, and BRICS stock markets, tend to increase or decrease depending on the condition of the markets but it tends to converge to the mean in the long run. Second, Oil price return exhibits the highest volatility followed by stock index return of Brazil, Russia, South Africa, India, and China. Third, the volatility of assets' return increases sharply following the global financial crisis (2007–2008) and, in 2020, following the shock of the Covid-19 health pandemic, the volatility of oil price return increases sharply to an all-time high due to oil demand-side shock. Moreover, the number of Covid-19 cases has a greater impact on BRICS' stock markets, especially on Brazil and India. Stock markets of Brazil and India exhibit the highest volatility during the Coivd-19 periods since both of them have the highest number of Covid-19 cases among the BRICS countries. Fourth, Russian, a major oil-producing country, stock index return exhibits the highest correlation with oil price return followed by Brazil and South Africa indicating the less portfolio diversification benefits. In contrast, in China and India, the major oil-importing countries, stock index return shows the lowest correlation with oil price return indicating the existence of portfolio diversification benefits.

The results from MODWT tend to suggest the following findings. First, 128 and 256 days holding periods have fewer diversification benefits since the correlation between oil price return and stock market return of BRICS countries are high at scale 128 and 256 compared to other short and medium-term scales. Second, across the scales, the stock markets' return of oil-producing countries, i.e. Russia, Brazil, and South Africa, tends to be more correlated with oil price return compared to the correction of oil price return with stock market returns of major oil-importing countries i.e. China and India. Hence, investors of the stock markets of China and India have more diversification benefits by holding oil with the stock of any of these countries in their portfolio.

The CWT analysis shows that the Russian stock market return is more correlated with oil price return among the BRICS countries. Overall interdependence between oil and BRICS' stock markets return is stronger in the longer time scales (256 to- 512 days' time horizons) compared to the short time scales (4 to 32 holding days) and medium scales (128 to 256 days' time horizons) for Brazil and Russia. For all markets, investors of short and medium-term investors have some portfolio diversification benefits but have to be cautious with oil-producing countries i.e. Russia, Brazil, and South Africa. The positive phase patterns indicate that BRICS' stock market returns are positively correlated with oil price return across the investment horizons. Findings also indicate that the causal relationship is less heterogeneous across the time and scales for all the countries and most of the time oil price return is leading the BRICS' stock markets' return.

The findings of the study suggest that overall association between oil price return and stock price return of oil-producing countries, such as Russia, Brazil, and South Africa, is high compared to the association of oil price return with the stock price return of major oil-importing countries, i.e. China and India. That is because Russia is the third-highest net oil producer and approximately 60% of the Russian stock exchange is controlled by oil and gas companies. Though Brazil is ranked 12th in oil production it is still a net importer of some light oil. About South Africa, almost 4% of the total stock market capitalization comes from the oil and gas industry. In contrast, China and India are the biggest oil importers, ranked 2nd and 3rd after the USA.

Policymakers and investors would find the results of this study valuable for policy formulations and decision making. Policymakers should be cautious about the price of oil because oil is the most exogenous (leading) variable among them. Findings from the study would be helpful for the investors particularly for those who are persistently looking for portfolio diversification benefit at different investment horizons or stock-holding periods.

Notes

1. http://time.com/4923837/brics-summit-xiamen-mixed-fortunes.
2. How Differently Does Oil Price Influence BRICS Stock Markets? (Bouoiyour and Selmi 2016).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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