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Oil Price Dynamics and Sectoral Indices in India – Pre, Post and during COVID Pandemic: A Comparative Evidence from Wavelet-based Causality and NARDL

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ABSTRACT

Due to the COVID pandemic, the stock market has been affected adversely around the globe and investment decisions are now more challenging and riskier. Hence, in this paper, we aim to investigate the impact of oil prices on the Indian stock market and eight sectoral indices for the period of pre, post, and during the COVID pandemic. The maximal overlap discrete wavelet transform (MODWT) is used to decompose and to denoise the original time series data as oil price and market return are found to be noisy. We employ the wavelet-based Granger causality (WGC) and non-linear, autoregressive distributed lag model (NARDL) to investigate the causality in the frequency domain as well as the short-run and long-run asymmetry of oil price impact. Our analysis shows a feedback relation between low frequency (higher investment horizon) and the long-run asymmetric impact of oil prices on all sectors during all three periods. We discuss the dynamic time-varying relationship between the oil price and sectoral return along with the investment implications in detail.

Keywords: MODWT, Multiscale Decomposition, Sectoral Indices, Causality, Asymmetry, NARDL
JEL Classifications: C22, C32, G11, G12, G41, O47, P52, Q43

1. INTRODUCTION

Energy plays a critical role in the growth of any economy as it serves as the fundamental driving factor for economic development (Magazzino et al., 2021). Developing countries, due to economic reforms, are experiencing a rising demand for energy. Among various energy sources, oil holds the most significant influence in the energy market (Khraief et al., 2021), being the primary source of energy for social and economic activities. While there are alternative energy resources such as coal, natural gas, renewables, and nuclear power, the impact of oil is multi-dimensional. Oil serves as a key raw material for every industry, making it a strategic resource with the highest influence on the economy (Jiang and Yoon, 2020). Any increase in oil prices raises production costs and reduces demand for products and services across industries. Consequently, this has a negative impact on both sectoral and overall stock indexes. Therefore, crude oil has now evolved into a traded financial asset (Arouri and Nguyen, 2010).

Rising oil prices reduce business activities, increasing production costs and resulting in losses or reduced profits (Brown and Yücel, 2002; Khraief et al., 2021). This leads to long-term economic underdevelopment. Consequently, investors strategically diversify their portfolios by investing or reallocating resources to high-profit, low-risk sectors.

India, like other developing countries, is expanding its industrial sectors, leading to increased demand for oil and reliance on oil imports. According to the EIA report (“https://www.iea.org/articles/e4-country-profile-energyefficiency-in-india”), energy consumption in India has grown by 50% between 2007 and 2017, with an expected annual demand growth of 4% over the next 25 years. To fulfill this demand, India needs to import 80% of its crude oil requirements (Tiwari et al., 2018). Therefore, any fluctuations in oil prices will impact investment and economic activities at the sectoral level (Bouzgarrou et al., 2023; Roberts and Ryan, 2014).

In the Indian stock market, numerous companies with similar business activities are traded at the sector level. Investors have two approaches when selecting their portfolios (Bisht and Kumar, 2023). The first approach involves analyzing individual stocks and selecting the ones with potential for better future performance (Bagheri, 2019; Vuković et al., 2020). The second approach involves analyzing sector-level performance and selecting the sectors that are performing well (Antonakakis et al., 2018). Since the performance of sectors within an economy varies, sector performance significantly influences portfolio selection (Gupta and Basu, 2009). Economists and investment managers generally prefer the second approach due to its direct impact on global economies and the convenience it offers when analyzing a large number of stocks listed on an exchange (Bisht and Kumar, 2023).

Given India's status as a major oil-importing country (Khraief et al., 2021), any fluctuations in oil prices will have implications for both the stock market and specific sectors (Abdlaziz et al., 2016). The cost of production or services for sectors such as energy, automobiles, and consumer goods will be raised if oil price is increased. Conversely, a diminution in oil prices will reduce the costs. However, this impact is not same for all sectors rather it varies significantly across different sectors and over time (Badeeb and Lean, 2018). This indicates that the responsiveness of sectoral returns to oil price changes is asymmetric and heterogeneous with respect to time (Salisu et al., 2019).

In December 2019, the COVID-19 virus outbreak emerged in China, rapidly escalating into a global pandemic and health crisis, as declared by the World Health Organization (WHO) on March 11, 2020. This led governments worldwide to implement "state of emergency" measures, including travel bans and social isolation (Phiri et al., 2023). The resulting worldwide shutdown, combined with natural disasters, had a severe impact on the global financial market, affecting every sector. The sharp decline in oil demand due to transportation and mobility restrictions led to an oversupply, causing oil prices to plummet. On April 20, 2020, for the first time in history, the price of a barrel of WTI crude oil turned negative (−36.98 USD per barrel) (Jareño et al., 2021). This global economic situation posed significant challenges for policymakers who were striving to mitigate the crisis (Gormsen and Koijen, 2020).

To overcome and to handle this pandemic, the Indian government implemented significant initiatives like lockdowns and social distancing to minimize virus transmission. The government of India announced four lockdowns and two unlock periods, as outlined in Table 1 (Soni, 2021). The pandemic and subsequent lockdown had a negative impact on the Indian economy (Ghosh et al., 2020). To address this economic slowdown, the government of India allocated 266 billion USD to bolster the GDP, with the aim of achieving up to 4% growth (India's Modi Promises $266 Billion to Protect Economy from Covid-19|CNN Business, 2020).

Numerous studies have inspected the economic effect of this pandemic at both the collective and sectoral levels (Sireesha and Haripriya, 2021). Zhu et al. (2022) investigated the hedge capabilities and asymmetric effects of gold and Bitcoin in the short and long term, focusing on COVID-19-related news sentiment risk by means of the NARDL model. Similarly, Jareño et al. (2021) utilized the NARDL model to study the oil price and cryptocurrency returns and explored the asymmetric interdependence. Ding et al. (2023) conducted a study on 19 international stock markets, specifically examining the predictability of crude oil future information before and during the COVID-19 pandemic. Varma et al. (2021) investigated the short-term effect of the pandemic on the Indian stock market and sectoral levels using market models. Liu et al. (2023) focused on the global tourism and hospitality industry, employing the Granger causality test and network analysis for their study.

Numerous studies have examined the impact and correlation of oil price shocks on the stock market and sectoral indices, independent of the COVID-19 pandemic. Tang and Kogid (2022) investigated the asymmetric influence of economic growth and energy consumption in Malaysia using the NARDL model. Khraief et al. (2021) employed the NARDL model and MODWT to analyze the short-run and long-run asymmetry relationship between oil prices and exchange rates in China and India. Mandal and Datta (2022) studied the impact of oil prices on sectoral indices using wavelet coherence. To examine the same impact Nitha et al. (2021) conducted a comparative study with respect to India utilizing correlation and multiple regression analysis. Bisht and Kumar (2023) utilized the Dempster-Shafer evidence theory and Granger causal network to examine the performance and interdependence among twelve sectors in India.

Previous studies have primarily focused on analyzing sectoral indices' sensitivity to oil price shocks in the time domain, specifically during the pre-COVID and COVID periods. However, a more comprehensive understanding can be gained by examining the asymmetric and heterogeneous sensitivity of sectoral indices in both the time and frequency domains (Salisu et al., 2019).

In this study, we investigate the period from September 11, 2012 to April 21, 2023, which is divided into three distinct time periods: (i) pre-COVID period (PRCP), (ii) during the COVID period (DUCP), and (iii) post-COVID period (POCP). To eliminate noise and achieve multiscale wavelet decomposition at different frequencies, we utilize the MODWT (Maximal Overlap Discrete Wavelet Transform). Furthermore, we employ the NARDL (Nonlinear Autoregressive Distributed Lag) model (Shin et al., 2014) to conduct a comparative analysis of short-run and long-run cointegration and asymmetry.

The remainder of this paper is structured as follows: Literature review and methodology are presented in Sections 2 and 3 respectively. Data analysis is done in section 4. Empirical results and discussions are described in the fifth section and finally, the sixth section reports the conclusion.

Table 1: Lockdown and unlock periods of India

S. No.	Phase	From date	To date	Number of days
i	Prelockdown	January 1st, 2020	March 24th, 2020	84
ii	Lockdown phase I	March 25th, 2020	April 14th, 2020	21
iii	Lockdown phase II	April 15th, 2020	May 3rd, 2020	19
iv	Lockdown phase III	May 4th, 2020	May 17th, 2020	14
v	Lockdown phase IV	May 18th, 2020	May 31st, 2020	14
vi	Unlock period phase I	June 1st, 2020	June 30th, 2020	30
vii	Unlock period phase II	July 1st, 2020	July 31st, 2020	31

2. LITERATURE REVIEW

The behaviour of financial and economic data is followed by complex dynamics and varies over time (Mariani et al., 2020) and that's why this is an exciting field of study for investors, academicians, and market researchers. Several investigations have been performed earlier to investigate the effect of oil price shock on the economic performance of a country ((Hamilton, 1983; Rasche and Tatom, 1977) and sectoral returns during an earlier COVID period. Zhu et al. (2011) applied a panel threshold cointegration approach to understand the interdependence between crude oil and the stock market. This relationship may be positive (Arouri and Rault, 2012; Zhu et al., 2011) or negative (Park and Ratti, 2008; Sadorsky, 1999).

Jiang and Yoon (2020) have investigated the lead-lag causality of oil prices in the six-stock market including India using wavelet multiscale decomposition and wavelet coherence. The impact of oil price shock on the Indian stock market and eight sectoral index returns has been investigated by Singhal and Ghosh (2016) using the VAR-DCC-GARCH framework. Their study could not reveal the volatility spillover from oil prices to the stock market at the aggregate level. In only three sectors out of eight, spillovers have been reported at the sectoral level, namely the financial, power, and automobile sectors. Multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model has been used by Kumar et al. (2019) to study the time-varying long-run and short-run dependency between crude oil, natural gas, and stock price in India. The impact of sectoral index return concerning oil price shock also has been studied by (Tiwari et al., 2018) using Quantile Regression Analysis. Also, the direction of causality has been investigated. Magazzino et al. (2021) and Xiang et al. (2021) have used wavelet analysis to investigate the same for China and Italy respectively.

Tang and Kogid (2022) have employed the NARDL model and have investigated short-run and long-run the asymmetric influence of economic growth on energy consumption in Malaysia. The NARDL model has been used by Allen and McAleer (2021) to study the behavioural linkage between FTSE 100 and S&P500 Indexes. Their study reveals that negative movements have a larger impact on the S&P500 index. They also studied the asymmetric behaviour of West Texas Intermediate (WTI) crude oil price over the Dow Jones index using the NARDL model (Allen and McAleer, 2020). The finding suggests that the impact negative movements is higher with respect to positive. Phong et al. (2019) have used the NARDL model to estimate the short-run asymmetric of Vietnam's Stock Market. The cointegration and asymmetric interdependence between oil price and food price in Indonesia has been studied by Abdlaziz et al. (2016) using the NARDL model. Similarly using the NARDL model Kamaruddin et al. (2021) have investigated the asymmetric impact of world oil prices on agricultural commodities in Indonesia. The result discloses that the agriculture commodity producers enjoy more benefit when oil prices decrease rather than increases.

But how does the oil price impact the economy at an aggregate level as well as at a sectoral level during the economic turbulence period of COVID? Much research has been done to get the answer. Jareño et al. (2021) have investigated the asymmetric interdependencies (short and long-term) between oil price shocks and leading cryptocurrency returns using the NARDL method during the first wave of the COVID-19 pandemic. From the study, it has been revealed that the demand shock shows the greatest connection with the return. The co-movement of stock return of G20 countries and COVID-19 have been studied by Phiri et al. (2023) using DCC-GARCH and Wavelet coherence. The analysis shows that the negative co-movement exists at low frequency and positive in case of high frequency. Similarly, Insaidoo et al. (2023) have studied the co-movement of the COVID-19 pandemic and the performance of stock markets of four emerging economies including India using the Quantile-on-Quantile regression model. Dharani et al. (2022) have investigated the influence of COVID-19 on the behaviour of the S&P 1200 Shariah and non-Shariah sectoral indices. Considering the fact of COVID-19 economic slowdown, Alam et al. (2023) have investigated the pre and post-COVID scenarios concerning the price of oil, coal, and natural gas in India. Also under this crisis scenario, Ding et al. (2023) have tried to explore the changes in the predictability of crude oil future information before and during the pandemic.

In all these studies the dynamic time-varying asymmetric relationship between oil price and sectoral index return in the time and frequency domain for pre, post, and during the COVID period is not conclusive with respect to India. In this paper, we have used wavelet transform (MODWT and multiresolution analysis) and NARDL model to study the cointegration and asymmetric sensitivity of the stock price return and sectoral index return concerning oil price shock for pre, post, and during COVID period in time-frequency domain in the Indian context.

3. METHODOLOGY

In the field of economics, finance, and different field of applied science the analysis of time series has gained a special interest. NARDL and wavelet analysis are becoming widely used tools for asymmetry analysis and insight view in time-frequency dimension of a time series.

In our study, we have used (i) DWT (Discrete Wavelet Transform) for multiscale decomposition, (ii) MODWT for noise removal of time series data and (iii) NARDL to analyse the asymmetry.

From signal theory point of view wavelet transform is the projection of a signal into a set of basic functions (Kehtarnavaz, 2008). Ramsey (2002) defined the "father" and "mother" wavelets. The father wavelet describes the long-term scale and smooth component of the time series. The mother wavelet describes the deviation from the smooth component. The father wavelet is integrated to one and the mother wavelet is integrated to zero. Hence the mother wavelet specifies the differencing coefficient while the father wavelet specifies the scaling coefficient.

The father wavelet can be defined as

$$\phi(\mathrm{t}) = \sqrt{2}\sum_k \mathrm{l_k}\phi(2\mathrm{t} - \mathrm{k}), \int\phi(t)\,dt = 1 \quad (1)$$

Mother wavelet can be defined as

$$\psi(\mathrm{t}) = \sqrt{2}\sum_k \mathrm{h_k}\phi(2\mathrm{t} - \mathrm{k}), \int\psi(t)\,dt = 0 \quad (2)$$

The coefficients l_k and h_k are low-pass and high-pass filter respectively.

$$\mathrm{l_k} = \frac{1}{\sqrt{2}}\int\phi(t)\phi(2t-k)\,dt \quad (3)$$

$$\mathrm{h_k} = \frac{1}{\sqrt{2}}\int\psi(t)\phi(2t-k)\,dt \quad (4)$$

The wavelet representation of time series Y (t) can be expressed as:

$$\begin{aligned} Y(t) &= \sum_k S_{j,k}\phi_{j,k}(t) + \sum_k d_{j,k}\psi_{j,k}(t) \\ &+ \sum_k d_{j-1,k}\psi_{j-1,k}(t) + \sum_k d_{j-2,k}\psi_{j-2,k}(t) \\ &+ \ldots + \sum_k d_{2,k}\psi_{2,k}(t) + \sum_k d_{1,k}\psi_{1,k}(t) \end{aligned} \quad (5)$$

Here $S_{j,k}$ and $d_{j,k}$ are wavelet transform coefficients specified by the projection onto father and mother wavelets over scaling and translation.

$$S_{j,k} = \int d\phi_{j,k}(t)\ Y(t)\ dt \quad (6)$$

$$d_{j,k} = \int \psi_{j,k}(t)\ Y(t)\ dt,\ for\ j = 1,\ 2,\ 3,\ \ldots,\ J \quad (7)$$

The approximating wavelet functions $\phi_{j,k}$ and $\psi_{j,k}(t)$ are defined as scaled and translated decompositions of ϕ and ψ, with scale factor 2^j and translation parameter 2^{jk}:

$$\phi_{\mathrm{j,k}} = 2^{-\mathrm{j}/2}\phi\left(\frac{t-2^j k}{2^j}\right)\mathrm{where}\int\phi(\mathrm{t})\,\mathrm{dt} = 1 \quad (8)$$

$$\psi_{j,k} = 2^{-j/2}\psi\left(\frac{t-2^j k}{2^j}\right) where \int\psi(t)\,dt = 0\ and\ j = 1,2,\ldots,\ J \quad (9)$$

Considering equation 5, if we define the detail coefficients and smooth coefficients as:

$$DC_j = \sum_k d_{j,k}\psi_{j,k}(t), SC_j = \sum_k S_{j,k}\phi_{j,k}(t) \quad (10)$$

Y(t) can be written as

$$Y(t) = \sum_{j=1}^{J} DC_j + SC_J \quad (11)$$

This is the multi-resolution decomposition of Y(t) where DC_j defines the wavelet detailed association and SC_j is the cumulative sum of variation which becomes smothered when j increases (Gençay et al., 2002). There are many wavelet families, and this DWT is one of the most useful tools that is being used to get in-depth analytical view over time and frequency domain by transforming a time series into wavelets.

The requirements of dyadic length and the non-shift invariant characteristics are the deficiencies of DWT. Using MODWT, we can overcome this gap that allows to any sample size and the MODWT can produce an efficient variance estimator than DWT (Gençay et al., 2002; Percival and Walden, 2000).

Following Percival and Walden (2000) MODWT wavelet and scaling coefficients $\tilde{\omega}$ and $\tilde{\upsilon}$ are given by

$$\tilde{\omega}_{\mathrm{j,t}} = 2^{\frac{-j}{2}}\sum_{i=0}^{L_{j-1}}\tilde{h}_{j,1}X_{t-1} \quad (12)$$

$$\tilde{\upsilon}_{\mathrm{j,t}} = 2^{\frac{-j}{2}}\sum_{i=0}^{L_{j-1}}\tilde{g}_{\mathrm{j,1}}\mathrm{X_{t-1}} \quad (13)$$

Here $\tilde{h}_{j,1}$ and $\tilde{g}_{j,1}$ are the wavelet and scaling filters obtained by rescaling the DWT filters as

$$\tilde{h}_{\mathrm{j,1}} = 2^{\frac{-j}{2}}h_{j,1}\ \text{and}\ \tilde{g}_{j,1} = 2^{\frac{-j}{2}}\mathrm{g_{j,1}} \quad (14)$$

In this study, we have used a wavelet filter of length 8 from an asymmetric family developed by Daubechius (1992) and this moderate filter length is adequate to investigate the hidden properties of data (Hassan and Rashid, 2018). We have decomposed the time series into detailed coefficients from DC1 to DC6 which signifies the short-term (high frequency) to long-term (low frequency) variation. SC6 specifies the smooth coefficient and that signifies the long-term trend.

The asymmetric extension of the linear autoregressive distributed lag (ARDL) model (Pesaran et al., 2001) is the NARDL model which has been proposed by Shin et al. (2014). This model is also being used to analyse economic and financial data because it can detect hidden co-integration relationships between variables. This model also has the competence to analyse the sensitivity of positive or negative changes of the explanatory variables on the explained variables with the help of decomposing the partial sums of explanatory variables even with small samples (Phong et al., 2019; Shin et al., 2014; Zhang et al., 2022).

The impact of oil price on stock market return or sectoral index return can be modelled as:

$$SR_t = \alpha_0 + \rho OP_t + \varepsilon_t \quad (15)$$

SR_t denotes the logarithm of stock market return or sectoral index return and OP_t denotes the logarithm of oil price return. ρ specifies the long-run impact of oil price return on SR_t.

A linear error correction model (ECM) has been adopted for the equation (15) and then we can write:

$$\Delta SR_t = \alpha_0 + \rho_1 SR_{t-1} + \rho_2 OP_{t-1} + \sum_{i=1}^{r} \alpha_i \Delta SR_{t-i} + \sum_{i=0}^{s} \beta_i \Delta OP_{t-i} + \varepsilon_t \quad (16)$$

The sensitivity of stock market or sectoral index with respect to the oil price may be nonlinear and asymmetrical, which means the degree and direction of changes in oil price may have different impacts on a stock market or sectoral index. That's why OP_t has been decomposed into a partial sum of positive (OP^+_t) and (OP^-_t) changes (Zhang et al., 2022).

$$OP_t = OP_0 + OP^+_t + OP^-_t \quad (17)$$

$$OP^+_t = \sum_{j=1}^{t} \Delta OP_j^+ = \sum_{j=1}^{t} \max\left(\Delta OP_j,\ 0\right) \quad (18)$$

$$OP^-_t = \sum_{j=1}^{t} \Delta OP_j^- = \sum_{j=1}^{t} \max\left(\Delta OP_j,\ 0\right) \quad (19)$$

By adding OP^+_t and OP^-_t to the equation (16) of the ARDL model we get the error correction model of the NARDL model as:

$$\Delta SR_t = \alpha_0 + \rho_1 SR_{t-1} + \rho_2^+ OP^+_{t-1} + \rho_2^- OP^-_{t-1} + \sum_{i=1}^{r} \alpha_i \Delta SR_{t-i} + \sum_{i=0}^{s} \left(\beta^+_i \Delta OP^+_{t-i} + \beta^-_i \Delta OP^-_{t-i}\right) + \varepsilon_t \quad (20)$$

Here the long-run impact of an increase or decrease in oil price on a stock market or sectoral index can be explained from $-\rho_2^+/\rho_1$ and $-\rho_2^-/\rho_1$.

Additionally, we have employed the Wald test to inspect whether there is a long-run asymmetric effect of oil price on SR with H0: $-\rho_2^+/\rho_1 = -\rho_2^-/\rho_1$. Similarly, the short-run asymmetry can be examined with H0: $\sum_{i=0}^{s} \beta_i^+ = \sum_{i=0}^{s} \beta_i^-$.

4. DATA AND ANALYSIS

In our study, we have used the daily data starting from September 10th, 2012 to April 21st, 2023 and this period has been divided into three categorical periods i.e., (i) pre-COVID period (PRCP), (ii) during the COVID period (DUCP) and (iii) post-COVID period (POCP). We have collected eight sectoral indices data and SENSEX data set from the Bombay Stock Exchange (BSE) official website (https://www.bseindia.com/). The sector details are mentioned in Table 2. In the world oil market "WTI Oil Price" is widely used as a benchmark (Basher et al., 2012). Hence, we have considered the WTI oil price and collected daily data sets from EIA official website (https://www.eia.gov/).

The oil price return, stock market return (BSE SENSEX), and sectoral returns have been calculated on the first difference of logarithmic values as $r_t = \ln(Y_t) - \ln(Y_{t-1})$ where Y_t and Y_{t-1} are the current value at lag 1 of the time series respectively. We have used wavelet multiresolution decomposition using the wavelet filter of length L= 8 (LA8, least asymmetric, with level = 6) (Daubechius, 1992). As per Hassan and Rashid (2018) using moderate filter length (e.g. L = 8) the hidden properties of data can be explained. The detail of the data variables and the sample period have been presented in Tables 2 and 3 respectively. The time horizon (frequency) and the decomposed coefficients are presented in Table 4.

Table 2: Details of ten variables and sample periods

S. No.	Sector index name	Symbol	Sample period duration
1	BSE Carbon	carbon	September 10th, 2012–April 21st, 2023
2	BSE Energy	energy	September 10th, 2012–April 21st, 2023
3	BSE Fast Moving Consumer Goods	fmcg	September 10th, 2012–April 21st, 2023
4	BSE Greenex	greenex	September 10th, 2012–April 21st, 2023
5	BSE Health	health	September 10th, 2012–April 21st, 2023
6	BSE Industry	industry	September 10th, 2012–April 21st, 2023
7	BSE Information Technology	info_tech	September 10th, 2012–April 21st, 2023
8	BSE Metal	metal	September 10th, 2012–April 21st, 2023
9	BSE SENSEX	sensex	September 10th, 2012–April 21st, 2023
10	WTI oil price	oil	September 10th, 2012–April 21st, 2023

Table 3: Details of categorical sample periods

S. No.	Period category	Time period category description	Sample period duration		Number of days/ samples
			From	To	
1	PRCP	Pre-COVID period	September 10th, 2012	December 31st, 2019	2668
2	DUCP	During COVID period	January 1st, 2020	July 31st, 2020	213
3	POCP	Post-COVID period	August 1st, 2020	April 21st, 2023	994

In our study, we have decomposed the time series data into wavelet detail coefficients and have been defined as DC1, DC2., and DC6 (Table 4, Figure 1). DC1 (with a 2-4 days' time scale) and DC2 (with a 4-8 days time scale) signify the short-term decomposed series with high frequency. DC3 (with 8-16 days time scale) and DC4 (with 16-32 days time scale) signify medium-term decomposed series with medium frequency. DC5 with a 32-64 days time scale and DC6 with a 64-128 days time scale represents long-term low frequency decomposed series. SC6 is the smoothing coefficient with a time horizon of more than 128 days.

Tables 5-7 explain the details of investigated return series with their descriptive statistics and the ADF (Augmented Dickey-Fuller) stationarity test result for three periods i.e., PRCP: Pre COVID-Period, DUCP: During COVID-Period and POCP: Post-COVID-Period respectively. For all periods oil shows the highest volatility (standard deviation) with a negative mean for pre and during the COVID period. But after the COVID period, the mean is positive. Stationarity is maintained by all-time series data for all periods as per the ADF test. The last column of every table summarises the correlation coefficient of that variable with oil price return. We have observed a positive correlation between all sectoral indices and SENSEX during PRCP. BSE Greenex has the highest correlation coefficient value of 0.0997 and it is followed by BSE carbon and metal. BSE energy shows the lowest correlation coefficient during PRCP. In the case of the COVID period, we can find that the correlation coefficient of BSE FMCG and BSE health goes negative which indicates these two sectors are adversely influenced with respect to the oil price shock. BSE metal shows the highest correlation coefficient during this period and BSE energy is the second highest in the correlation coefficient. In post COVID period all variables show a positive correlation with oil price shock including the BSE FMCG and BSE health. BSE Metal shows the highest and BSE FMCG shows the lowest correlation coefficient. We also observe that during the three periods, the correlation with oil price has varied dynamically in different directions.

Table 4: Associations between decomposed series by time scale and time horizon

Serial number	Decomposed series by time scale	Time horizon (frequency) (days)
1	D1	2-4
2	D2	4-8
3	D3	8-16
4	D4	16-32
5	D5	32-64
6	D6	64-128
7	S6	>128

The correlation and the Wavelet-based Granger causality of the SENSEX and 8 sectoral indices with oil have been examined at different frequency levels. We also have employed the NARDL model innovated by Shin et al. (2014) for all periods to inspect the asymmetry in short-run and long-run at different periods. The dynamic relationship between the three periods has been compared.

5. EMPIRICAL RESULTS

The relation and sensitivity of oil price shock over sectoral indices have caught the special attention of many researchers and they have applied approaches to investigate the same. In this study, the relationship has been analysed in time domain as well as in frequency domain to have a better insight. The oil price return, SENSEX return including the eight sectoral index returns have been decomposed with MODWT into seven components as

Table 5: Descriptive statistics of return – pre-COVID-period

Variables under study	Mean	Median	SD	Skewness	Kurtosis	ADF	Correlation with oil
carbon	0.00031	0.0	0.0074	−0.255	9.114	−14.037	0.085
energy	0.00032	0.0	0.0104	−0.396	10.116	−14.427	0.043
fmcg	0.00028	0.0	0.0082	−0.250	9.409	−14.162	0.069
greenex	0.00025	0.0	0.0075	−0.1892	7.834	−13.951	0.0997
health	0.00021	0.0	0.0086	−0.516	8.139	−13.924	0.081
industry	0.0002	0.0	0.01017	−0.1148	8.099	−13.1	0.0627
info_tech	0.00036	0.0	0.0096	−0.60008	18.489	−13.684	0.0626
metal	0.00001	0.0	0.0131	0.0558	6.43	−13.017	0.083
sensex	0.000316	0.0	0.007200	−0.14183	9.00266	−14.384	0.084
oil	−0.000171	0.0	0.018	0.19969	9.838904	−12.982	1

ADF: Augmented Dickey-Fuller, SD: Standard deviation

Table 6: Descriptive statistics of return – during COVID-period

Variables under study	Mean	Median	SD	Skewness	Kurtosis	ADF	Correlation with oil
carbon	−0.00041	0.0	0.020	−1.835	16.768	−5.6755	0.072
energy	0.00078	0.0	0.025	−0.528	11.357	−5.773	0.122
Fmcg	0.00001	0.0	0.0168	−0.624	17.46	−5.4572	−0.011
greenex	−0.00015	0.0	0.018	−1.84	17.66	−5.339	0.053
health	0.0014	0.0	0.016	−0.721	14.94	−4.5564	−0.019
industry	−0.00105	0.0	0.0194	−2.759	19.94	−4.9899	0.063
info_tech	0.00077	0.0	0.02	−0.627	9.696	9.696	0.076
metal	−0.0013	0.0	0.025	−1.073	8.676	−6.1248	0.133
sensex	−0.0004	0.0	0.021	−1.66	15.74	−5.8513	0.074
oil	−0.00198	0.0	0.088	−1.88	27.59	−5.853	1

ADF: Augmented Dickey-Fuller, SD: Standard deviation

Figure 1: Wavelet (MODWT) decomposed series oil price return, BSE SENSEX, and 14 sector index return

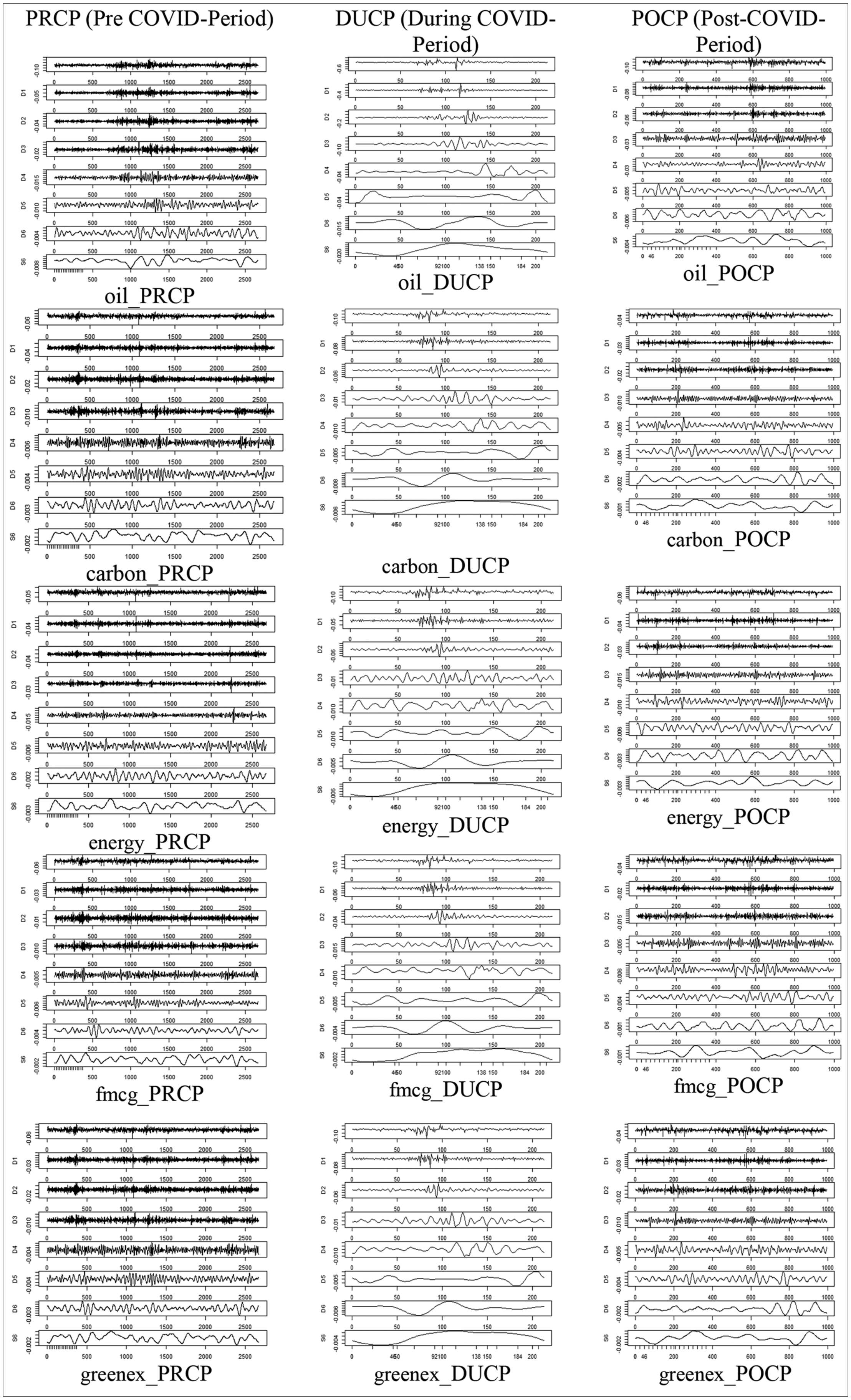
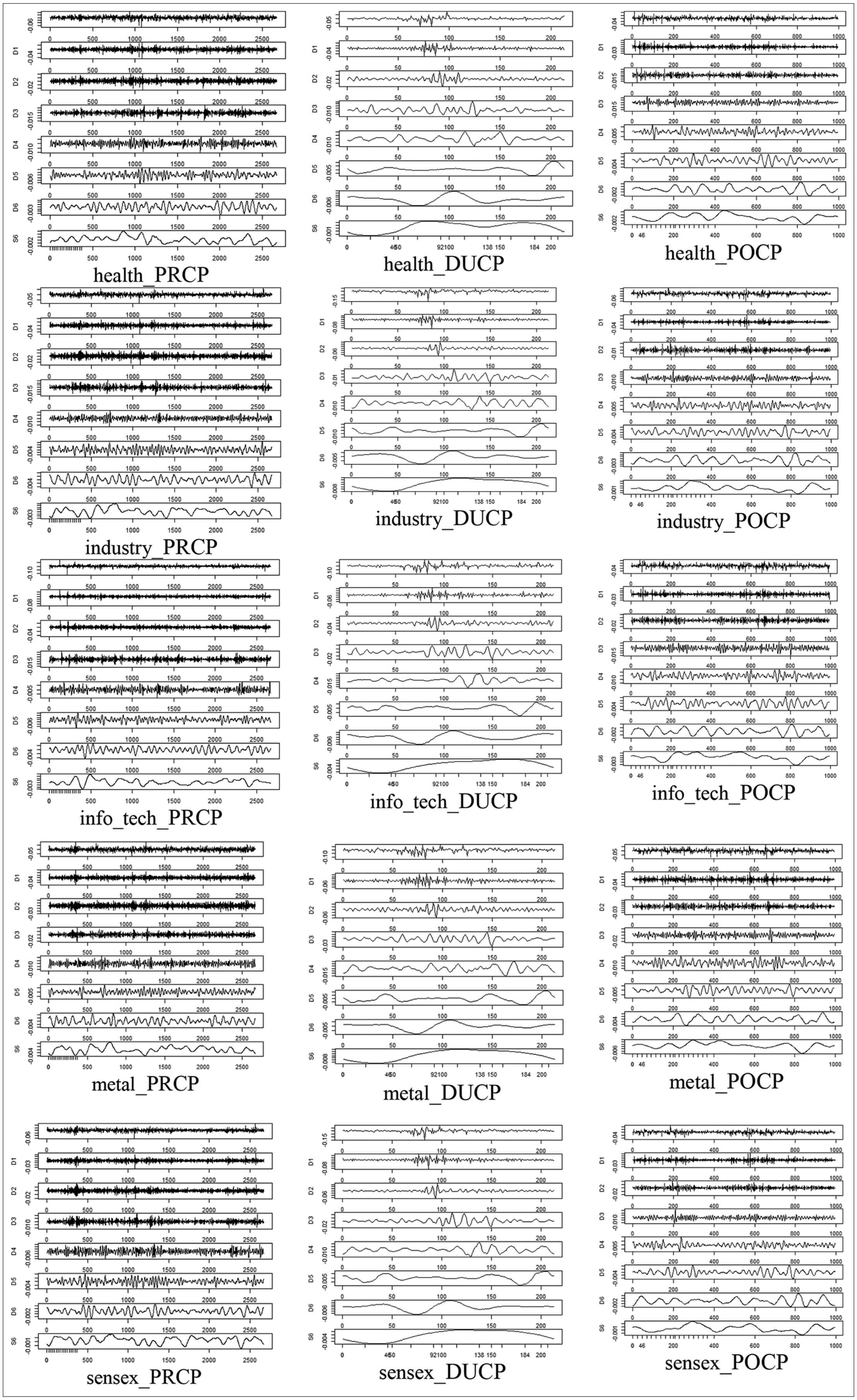


Figure 1: *(Continued)*



DC1, DC2, DC3, DC4, DC5, DC6, and SC6 for all three periods (i.e., PRCP: Pre, DUCP: During and POCP Post COVID period). All the decomposed series have been plotted along with the actual series. DC1 indicates the high frequency with a 2–4 days time scale. DC2 specifies 4-8 days time scales followed by DC3, DC4, DC5, and DC6 as SC6 as per Table 4.

All the return series data for three periods have been decomposed and have different frequencies. How the oil price return is corelated with the sectoral index return at different time horizon has been mentioned in Table 8. We find that the correlation is significant at low frequencies. All sectoral index returns including the SENSEX hold a high correlation during the COVID period on the long-time scale. During the COVID period, we also find a negative correlation with oil at the DC2-DC4 time horizon except for metal. During post COVID period fmcg, health, and info_tech maintain a negative correlation at low frequency. At high frequency (D1) only health shows a negative correlation and also it shows mostly the same (negative) correlation with oil price return for PRCP and POCP. Based on the findings we can conclude that the correlations are dynamic over time as well as frequency. Also considering the pre and post-COVID periods, we can find that there is an impact of the COVID pandemic's overall frequency, and this supports the result of (Mandal and Datta, 2022).

We also have performed the Wavelet Based Granger Causality (WGC) test at all frequencies for all variables during the three periods. Here the time horizon or the frequency scale specifies the holding period of the investors in the market (Karim et al., 2022). The stock market is heterogeneous. Investors invest as per their choice with different time horizons – short-term, long term or medium-term. That's why in our study we have the investing period as per Table 4 and using the WGC, we have specified our result in Table 9. At different time horizons (investment horizon)

Table 7: Descriptive statistics of return – post-COVID-period

Variables under study	Mean	Median	SD	Skewness	Kurtosis	ADF	Correlation with oil
carbon	0.00048	0.0	0.0082	−0.5831	7.61	−10.179	0.12
energy	0.00023	0.0	0.0116	−0.323	8.18	−9.7865	0.079
fmcg	0.00038	0.0	0.007	−0.241	6.207	−9.8253	0.049
greenex	0.00049	0.0	0.0089	−0.666	6.992	−9.9947	0.129
health	0.00022	0.0	0.0084	−0.230	7.5297	−10.229	0.127
industry	0.0011	0.0	0.0102	−0.739	8.10	−10.083	0.098
info_tech	0.00038	0.0	0.0109	−0.321	6.482	−9.7992	0.0504
metal	0.0009	0.0	0.0163	−0.340	6.598	−10.234	0.156
sensex	0.00046	0.0	0.0083	−0.370	7.289	−10.231	0.0998
oil	0.00066	0.0	0.021	−0.638	7.239	−10.936	1

ADF: Augmented Dickey-Fuller, SD: Standard deviation

Table 8: Dynamic correlation with the oil price at different time horizons at PRCP, DUCP and POCP

Correlation with oil for	Time-period	High frequency (short time scale) → low frequency (long time scale)						
		DC1	DC2	DC3	DC4	DC5	DC6	SC6
carbon	PRCP	0.0708	0.0779	0.1295	0.1372	0.1305	0.1113	0.0622
	DUCP	0.1429	−0.0422	−0.3040	0.0600	0.2798	0.4253	0.9428
	POCP	0.0846	0.1452	0.1350	0.1740	0.2187	0.1383	0.1470
energy	PRCP	0.0223	0.0327	0.0889	0.1030	0.0534	0.1247	0.2716
	DUCP	0.1578	−0.0120	−0.0084	0.1344	0.3801	0.1745	0.9135
	POCP	0.0360	0.0938	0.0689	0.2497	0.1781	0.2404	0.1859
fmcg	PRCP	0.0551	0.0820	0.1225	0.0446	0.1594	−0.0037	−0.1094
	DUCP	0.0726	−0.1845	−0.3757	0.0945	0.3818	−0.0761	0.8860
	POCP	0.1429	0.0244	−0.0844	−0.1447	0.0094	−0.1668	−0.0698
greenex	PRCP	0.0832	0.1069	0.1430	0.1317	0.1146	0.0858	0.1007
	DUCP	0.0915	−0.0339	−0.2826	0.1439	0.3121	0.4636	0.9521
	POCP	0.0938	0.1483	0.1632	0.1977	0.2523	0.0948	0.1768
health	PRCP	0.0546	0.1167	0.0980	0.1292	0.1122	0.1003	−0.0034
	DUCP	−0.0291	−0.1094	−0.1481	0.2591	0.3715	0.1292	0.7350
	POCP	0.1390	0.0893	0.1421	0.1750	0.2426	−0.0029	−0.0364
industry	PRCP	0.0580	0.0423	0.1149	0.0979	0.0918	0.0476	−0.0113
	DUCP	0.1096	−0.0562	−0.2413	0.1338	0.2002	0.4965	0.9545
	POCP	0.0699	0.0981	0.1497	0.1245	0.2658	0.1154	0.1365
info_tech	PRCP	0.0422	0.0586	0.0938	0.0562	0.2195	0.2366	0.1445
	DUCP	0.0909	0.1032	−0.2546	−0.1226	0.4112	0.4967	0.8304
	POCP	0.0210	0.0174	0.1064	0.2212	0.2909	−0.0722	−0.0033
metal	PRCP	0.0577	0.0407	0.1369	0.1971	0.2882	0.1886	0.3010
	DUCP	0.0870	0.1335	0.0572	0.2790	0.3534	0.5198	0.9614
	POCP	0.0482	0.2355	0.2401	0.4180	0.3223	0.1401	0.2345
sensex	PRCP	0.0632	0.0821	0.1313	0.1414	0.1485	0.1364	0.0868
	DUCP	0.1545	−0.0362	−0.3142	0.0048	0.2538	0.4163	0.9337
	POCP	0.0687	0.1318	0.1127	0.1320	0.1827	0.1788	0.0976

PRCP: Pre-COVID-period, DUCP: During COVID-period, POCP: Post-COVID-period

Table 9: Results of Wavelet-based Granger causality at different frequency horizons

Periods	Variables	High frequency (short time scale) → low frequency (long time scale)						
		DC1	DC2	DC3	DC4	DC5	DC6	SC6
PRCP	carbon	0.8338 (0.3613)	0.2324 (0.6298)	2.7666 (0.09637)	5.0856 (0.0242)	66.088 (0.00)	0.2698 (0.6035)	16.044 (0.00)
	energy	0.244 (0.621)	2.14 (0.14)	23.36 (0.00)	1.6271 (0.20)	24.645 (0.00)	0.0045 (0.9468)	20.469 (0.00)
	fmcg	0.87 (0.31)	0.57 (0.447)	2.22 (0.136)	25.691 (0.00)	53.538 (0.00)	13.53 (0.0002)	0.0594 (0.807)
	greenex	1.8025 (0.179)	0.9057 (0.3413)	2.8238 (0.092)	13.405 (0.000)	37.275 (0.000)	16.696 (0.000)	21.59 (0.000)
	health	0.0325 (0.857)	8.4421 (0.0036)	5.8925 (0.015)	3.1234 (0.077)	1.1871 (0.27)	149.11 (0.00)	41.563 (0.00)
	industry	0.7858 (0.3754)	1.1188 (0.2903)	1.8995 (0.1682)	4.9908 (0.025)	123.8 (0.00)	6.0535 (0.01)	33.265 (0.00)
	info_tech	0.954 (0.328)	4.344 (0.037)	18.259 (0.00)	1.7802 (0.182)	4.7428 (0.0295)	19.956 (0.00)	3.405 (0.065)
	metal	5.1641 (0.023)	8.497 (0.0035)	14.227 (0.00)	17.729 (0.00)	68.806 (0.00)	44.731 (0.00)	54.713 (0.00)
	sensex	1.5842 (0.208)	0.373 (0.540)	4.314 (0.037)	2.898 (0.088)	48.102 (0.00)	2.6043 (0.10)	25.168 (0.00)
DUCP	carbon	2.615 (0.107)	0.2206 (0.6391)	6.051 (0.01)	1.9394 (0.165)	16.386 (0.00)	30.66 (0.00)	26.72 (0.00)
	energy	0.105 (0.745)	0.071 (0.789)	4.089 (0.044)	0.319 (0.57)	16.87 (0.00)	73.958 (0.00)	99.448 (0.00)
	fmcg	0.0103 (0.919)	3.64 (0.057)	19.71 (0.00)	7.354 (0.007)	15.595 (0.00)	25.52 (0.00)	0.848 (0.357)
	greenex	2.50 (0.11)	0.005 (0.94)	3.01 (0.084)	0.0024 (0.96)	77.271 (0.00)	39.19 (0.00)	0.325 (0.568)
	health	2.0746 (0.151)	0.025 (0.873)	4.914 (0.027)	11.95 (0.000)	122.64 (0.00)	57.021 (0.00)	42.394 (0.00)
	industry	2.8386 (0.093)	0.046 (0.830)	0.7613 (0.383)	6.0766 (0.01)	80.033 (0.00)	21.561 (0.00)	66.763 (0.00)
	info_tech	11.805 (0.000)	0.0484 (0.826)	4.652 (0.032)	1.4829 (0.22)	12.09 (0.000)	105.41 (0.000)	42.81 (0.00)
	metal	4.1853 (0.042)	0.123 (0.726)	14.852 (0.000)	0.0049 (0.94)	43.973 (0.00)	25.093 (0.000)	4.961 (0.026)
	sensex	3.0739 (0.081)	0.1435 (0.705)	5.0388 (0.025)	2.435 (0.12)	7.97 (0.005)	28.81 (0.00)	43.321 (0.00)
POCP	carbon	2.2744 (0.131)	3.568 (0.059)	0.008 (0.92)	22.88 (0.00)	2.08 (0.14)	28.735 (0.00)	31.621 (0.00)
	energy	11.45 (0.000)	3.9827 (0.046)	1.237 (0.26)	0.2249 (0.635)	1.9745 (0.160)	3.9447 (0.0472)	0.3096 (0.069)
	fmcg	4.0852 (0.0435)	0.683 (0.408)	9.474 (0.002)	42.09 (0.00)	24.033 (0.00)	0.7679 (0.3811)	32.965 (0.00)
	greenex	1.88 (0.17)	4.2407 (0.039)	0.312 (0.576)	15.704 (0.00)	3.017 (0.082)	9.21 (0.002)	27.88 (0.00)
	health	0.0697 (0.7918)	1.654 (0.198)	7.542 (0.006)	0.963 (0.326)	8.5684 (0.003)	0.012 (0.911)	9.359 (0.002)
	industry	3.4944 (0.061)	10.641 (0.0011)	0.206 (0.649)	10.446 (0.001)	6.6695 (0.009)	33.466 (0.00)	14.899 (0.000)
	info_tech	0.1172 (0.73)	0.926 (0.33)	0.032 (0.85)	1.862 (0.172)	0.824 (0.364)	19.251 (0.000)	9.733 (0.001)
	metal	7.8085 (0.005)	16.192 (0.000)	7.2388 (0.007)	12.65 (0.000)	3.449 (0.063)	37.21 (0.00)	12.391 (0.000)
	sensex	2.2483 (0.1341)	2.777 (0.095)	0.3671 (0.54)	27.889 (0.000)	2.117 (0.14)	27.73 (0.00)	51.462 (0.00)

The values indicate the F statistics and the values with () specified the *P* value. POCP: Post-COVID-period, DUCP: During COVID-period, PRCP: Pre-COVID-period

Table 10: Result for NARDL model estimation

NARDL model with variable and period	Period	Short run		Long run	
		Oil (positive)	Oil (negative)	Oil (positive)	Oil (negative)
carbon	PRCP	0.0355	0.0347	0.0357	0.0349
	DUCP	0.013	0.012	0.013	0.012
	POCP	0.041	0.048	0.040	0.047
energy	PRCP	0.0308	0.0201	0.031	0.020
	DUCP	0.029	0.027	0.026	0.024
	POCP	0.065	0.019	0.065	0.018
fmcg	PRCP	0.0315	0.0315	0.0319	0.0319
	DUCP	0.001	−0.008	0.001	−0.007
	POCP	0.022	0.016	0.022	0.016
greenex	PRCP	0.0442	0.0402	0.0443	0.0403
	DUCP	0.0088	0.0079	0.008	0.007
	POCP	0.053	0.054	0.052	0.052
health	PRCP	0.0378	0.012	0.039	0.045
	DUCP	−0.004	−0.005	−0.005	−0.005
	POCP	0.049	0.050	0.048	0.048
industry	PRCP	0.029	0.042	0.031	0.043
	DUCP	−0.001	0.020	−0.001	0.021
	POCP	0.041	0.047	0.041	0.048
info_tech	PRCP	0.0312	0.0275	0.031	0.040
	DUCP	0.013	0.012	0.012	0.0116
	POCP	0.024	0.024	0.0243	0.0246
metal	PRCP	0.0475	0.0798	0.046	0.077
	DUCP	0.033	0.033	0.032	0.031
	POCP	0.1156	0.1141	0.107	0.106
sensex	PRCP	0.0351	0.0327	0.0351	0.0327
	DUCP	0.014	0.013	0.014	0.013
	POCP	0.037	0.040	0.03	0.03

PRCP: Pre-COVID-period, DUCP: During COVID-period, POCP: Post-COVID-period, NARDL: Non-linear, autoregressive distributed lag

Table 11: Cointegration test result (Pesaran et al., 2001) for the three periods

Periods	Variables	*F*-statistics	Critical values			Conclusion
			α (%)	Upper bound	Lower bound	
PRCP	carbon	669.009	10	3.17	4.14	Cointegration
	energy	637.089	5	3.79	4.85	Cointegration
	fmcg	874.056	1	5.15	6.36	Cointegration
	greenex	675.215				Cointegration
	health	488.44				Cointegration
	industry	624.13				Cointegration
	info_tech	525.99				Cointegration
	metal	575.50				Cointegration
	sensex	673.29				Cointegration
DUCP	carbon	73.76	10	3.17	4.14	Cointegration
	energy	91.51	5	3.79	4.85	Cointegration
	fmcg	61.19	1	5.15	6.36	Cointegration
	greenex	69.41				Cointegration
	health	62.86				Cointegration
	industry	47.36				Cointegration
	info_tech	81.386				Cointegration
	metal	58.78				Cointegration
	sensex	74.18				Cointegration
POCP	carbon	262.90	10	3.17	4.14	Cointegration
	energy	205.09	5	3.79	4.85	Cointegration
	fmcg	204.86	1	5.15	6.36	Cointegration
	greenex	353.257				Cointegration
	health	367.61				Cointegration
	industry	197.684				Cointegration
	info_tech	324.07				Cointegration
	metal	235.565				Cointegration
	sensex	253.596				Cointegration

POCP: Post-COVID-period, DUCP: During COVID-period, PRCP: Pre-COVID-period

using the MODWT decomposed data we can easily conclude about the existence of causal relationship between the oil price shock and the return. It replicates the dynamic behaviour of the market in India as the investors participate in the stock market for specific

Figure 2: Cumulative sum of squares square (CUSUMSQ) test for stability of the model (Brown et al., 1975)

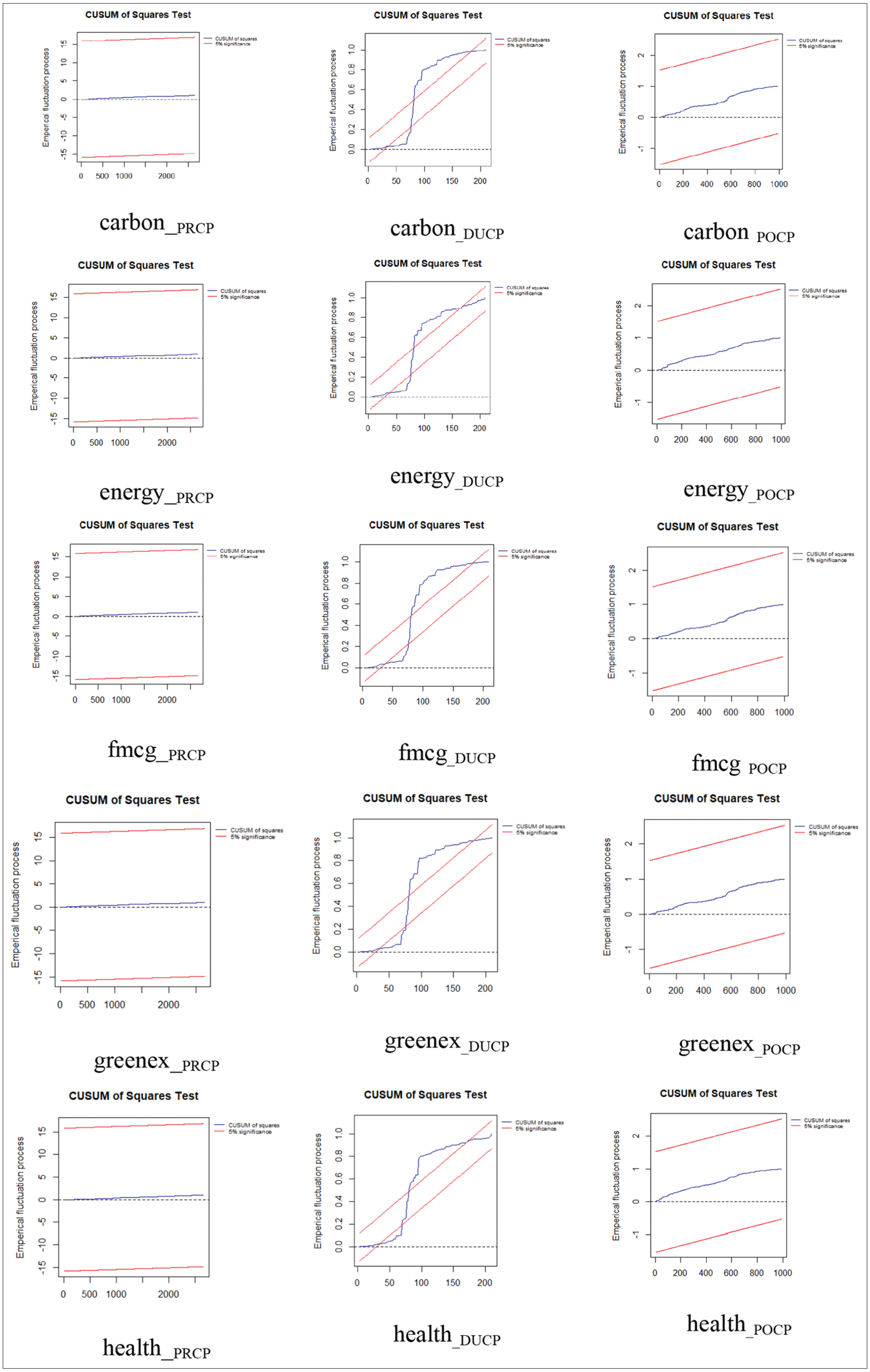
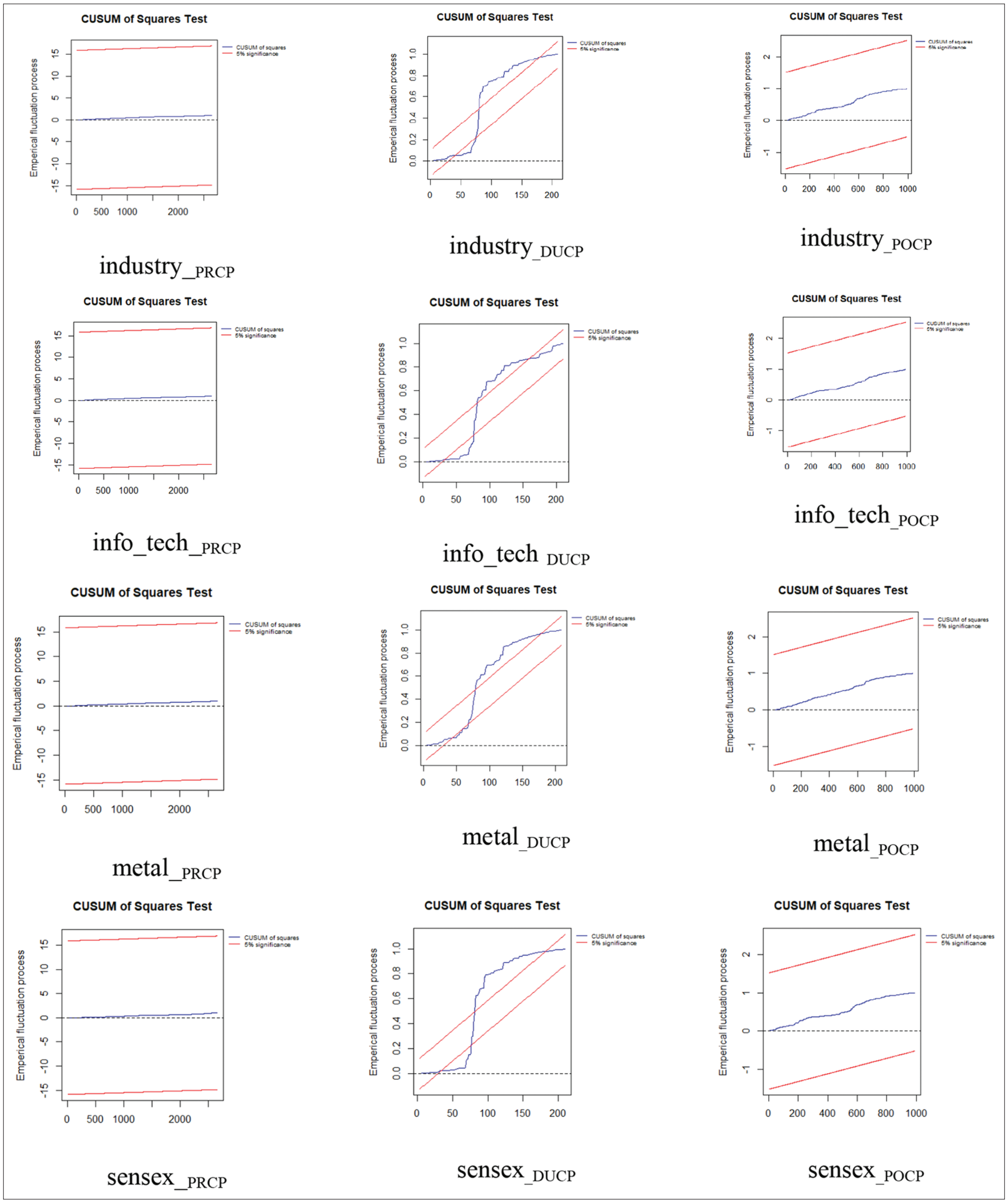


Figure 2: *(Continued)*



sectors for different holding periods. We can easily observe that the causality relation exists for pre, during, and post-COVID duration at long-term investment horizon (D6 & S6) for all returns. During the COVID period, only Information Technology and Metal industry has a causal relationship with oil at short-term investment. Metal is one of the sectors which holds the causality at short-term investment for all three periods. The result also reveals that the causality was distributed over all investment horizons after the COVID lockdown.

To investigate sensitivity (in short-run as well as in long-run) of sector return with oil, we have used NARDL. To estimate the NARDL model we need to select an information criterion. Akaike information criterion (AIC) is one of the widely used information criterion used in NARDL (Badeeb and Lean, 2018; Shahbaz et al., 2017). Hence, we have used AIC in our NARDL model. The estimation coefficients are presented in Table 10. The coefficients represent the impact oil shock (positive and negative) in short and long run to the studied sectors. For example, in short run the value of oil-positive is 0.0355 and oil-negative is 0.0347. This indicates that if oil price is increased by 1% the carbon sector will increase by 0.0355% but if oil price decrease by 1% the carbon sector will decrease by 0.0347% in short run. This indicates the asymmetry. To examine the stability, we have applied the CUSUM of square test in Figure 2. We can observe that for the period pre- and post-COVID, the model is perfectly stable. But for the period of during COVID period, the blue line crossed the critical lines

Table 12: Wald test for asymmetry

Periods	Variables	W_{long}	P	W_{short}	P
PRCP	carbon	32855.48	0.000	1.15817	0.560
	energy	189080.8	0.000	14.282	0.0007
	fmcg	24860.71	0.000	1.8117	0.4041
	greenex	31342.11	0.000	0.635	0.727
	health	73445.36	0.000	0.156	0.924
	industry	270911.3	0.000	0.875	0.645
	info_tech	51607.44	0.000	0.579	0.748
	metal	369661.4	0.000	3.157	0.206
	sensex	29890.29	0.000	0.956	0.619
DUCP	carbon	1167.44	0.000	5.502	0.06
	energy	151.348	0.000	0.2495	0.882
	fmcg	648.06	0.000	2.808	0.245
	greenex	828.2763	0.000	4.758	0.092
	health	3455.35	0.000	6.949	0.0309
	industry	3434.83	0.000	12.06	0.002
	info_tech	4167.631	0.000	9.513	0.008
	metal	6.783	0.033	0.0366	0.981
	sensex	1020.72	0.000	5.321	0.069
POCP	carbon	50753.7	0.000	1.9791	0.371
	energy	4597.865	0.000	1.2022	0.548
	fmcg	26294.63	0.000	5.223	0.07
	greenex	2533.264	0.000	0.0866	0.957
	health	53989.86	0.000	2.2569	0.323
	industry	79046.9	0.000	3.084	0.213
	info_tech	127013	0.000	1.245	0.5364
	metal	18940.69	0.000	0.650	0.722
	sensex	15014.23	0.000	0.695	0.706

W_{long}: Long run asymmetric effect test statistics and W_{short}: Short run asymmetric effect test statistics. POCP: Post-COVID-period, DUCP: During COVID-period, PRCP: Pre-COVID-period

only during the lockdown period. In the result, we can notice that the value of the coefficient is negative during the COVID period only. The test result of cointegration is presented in Table 11. The F statistics value is greater than the critical value as mentioned, hence cointegration has been identified for all the sectors and all over the periods. Regarding the asymmetry test, we have used the Wald test statistics as presented in Table 12. The null hypothesis of symmetry is rejected for all long-run asymmetry tests. But in the case of the short run, the null hypothesis is rejected only during the Covid period for the energy sector in pre COVID period, the health sector, the information technology sector, and the industry sector. This means that oil price shock has a significant impact on sectoral indices return and this supports the result of Khraief et al. (2021) and (Tiwari et al., 2018). Hence, considering the oil price sensitivity and investing horizon the investors should diversify their investment opportunity to mitigate the oil price shock.

6. CONCLUSION

This study analyses, how the oil price impacts the Indian economy in aggregate and sectoral levels during three periods: pre, during, and post-COVID.

Our study focuses on eight sectors with investment potential in India. We employed MODWT, WGC, and NARDL techniques to examine the relationship and impact of oil prices on sectoral index returns. The first part of our study involved a comparative analysis using wavelet decomposition, while the second part explored causal relationships using wavelet-based Granger Causality. Finally, we utilized NARDL to examine the asymmetric influence of oil price shocks.

The findings of the study can be summarized as follows:

i. The results confirm a dynamic and time-varying relationship between oil prices and sectoral indices across all three periods: pre-COVID, post-COVID, and during COVID.
ii. The returns of each sector have been decomposed into different frequencies, representing various investment horizons. Different investment timeframes exhibit distinct correlations with oil prices. During the COVID period, all sectoral indices demonstrate a high correlation in the long-term investment period, while exhibiting a negative correlation in the medium-term investment horizons.
iii. Causality is observed for the majority of investment horizons in the post-COVID period, while a higher investment period shows causality during the COVID period.
iv. Cointegration between oil prices and returns has been identified, indicating a long-term relationship between the two variables.
v. The impact of oil prices exhibits an asymmetric effect on returns, particularly in the short term, across all sectors and periods. However, during the COVID period, short-run asymmetry is observed only in the health, industry, and information technology sectors.

The investigation results have important implications for stock market investors and policymakers in India:

i. In the long-term investment horizon, all sectors exhibit a high correlation and causality with oil prices. This implies that investors may have limited opportunities for portfolio diversification and timing.
ii. The interdependence between oil prices and sectoral indices varies across different investment horizons and time periods. Portfolio managers should adjust their investment compositions opportunistically based on these dynamics.
iii. Oil price returns and sectoral index returns are cointegrated, indicating a long-term relationship. The impact of oil prices on sectoral indices is asymmetric in the long run, providing valuable insights for portfolio diversification and asset selection.

The COVID-19 pandemic has distinct effects on sectoral returns at different time horizons. Long-term and speculative investors should apply different strategies to mitigate risks associated with sectoral responses during this pandemic. Therefore, investors should carefully consider the impact of oil price shocks when diversifying their portfolios to minimize losses and oil price risk.

The results and conclusions presented in this paper are based on empirical calculations. There are no a priori economic models that are developed or suggested to explain the interdependence of oil price and the sectoral indices. This is a limitation of this study. Also, the oil price considered here is the international crude oil price. The oil price in India is regulated by the Government and the domestic oil prices do not reflect the international prices at all times. Therefore, the various sectoral indices may be affected differently depending on their level of dependence on international oil prices and domestic oil prices. Future studies in this area may look into such dependencies.

REFERENCES

Abdlaziz, R.A., Rahim, K.A., Adamu, P. (2016), Oil and food prices co-integration nexus for Indonesia: A non-linear autoregressive distributed lag analysis. International Journal of Energy Economics and Policy, 6(1), 82-87.

Alam, M.S., Murshed, M., Manigandan, P., Pachiyappan, D., Abduvaxitovna, S.Z. (2023), Forecasting oil, coal, and natural gas prices in the pre-and post-COVID scenarios: Contextual evidence from India using time series forecasting tools. Resources Policy, 81, 103342.

Allen, D.E., McAleer, M. (2020), A nonlinear autoregressive distributed lag (NARDL) analysis of West Texas intermediate oil prices and the DOW JONES index. Energies, 13(15), 4011.

Allen, D.E., McAleer, M. (2021), A nonlinear autoregressive distributed lag (Nardl) analysis of the ftse and s&p500 indexes. Risks, 9(11), 195.

Antonakakis, N., Cunado, J., Filis, G., Gabauer, D., Perez de Gracia, F. (2018), Oil volatility, oil and gas firms and portfolio diversification. Energy Economics, 70, 499-515.

Arouri, M.E.H., Rault, C. (2012), Oil prices and stock markets in gcc countries: Empirical evidence from panel analysis. International Journal of Finance and Economics,17, 242-253.

Badeeb, R.A., Lean, H.H. (2018), Asymmetric impact of oil price on Islamic sectoral stocks. Energy Economics, 71, 128-139.

Bagheri, N. (2019), Deterministic goal programming approach for Islamic portfolio selection. Operational Research, 21(3), 1447-1459.

Basher, S.A., Haug, A.A., Sadorsky, P. (2012), Oil prices, exchange rates and emerging stock markets. Energy Economics, 34(1), 227-240.

Bisht, K., & Kumar, A. (2023), A portfolio construction model based on sector analysis using Dempster-Shafer evidence theory and Granger causal network: An application to National stock exchange of India. Expert Systems with Applications, 215, 119434.

Bouzgarrou, H., Ftiti, Z., Louhichi, W., and Yousfi, M. (2023), What can we learn about the market reaction to macroeconomic surprise? Evidence from the COVID-19 crisis. Research in International Business and Finance, 64(January), 101876.

Brown, R.L., Durbin, J., Evans, J.M. (1975), Techniques for testing the constancy of regression relationships over time. Journal of the Royal Statistical Society: Series B (Methodological), 37(2), 149-163.

Brown, S. P. A., and Yücel, M. K. (2002), Energy prices and aggregate economic activity: An interpretative survey. Quarterly Review of Economics and Finance, 42(2), 193-208.

Daubechius, I. (1992), Ten Lectures of Wavelets. Philadelphia, PA: Sosiety for Industrial and Applied Mathematics Analysis. p1544-1576.

Dharani, M., Hassan, M.K., Rabbani, M.R., Huq, T. (2022), Does the Covid-19 pandemic affect faith-based investments? Evidence from global sectoral indices. Research in International Business and Finance, 59, 101537.

Ding, H., Huang, Y., Wang, J. (2023), Have the predictability of oil changed during the COVID-19 pandemic: Evidence from international stock markets. International Review of Financial Analysis, 87, 102620.

Gençay, R., Selçuk, F., Whitcher, B. (2002), An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. Amsterdam: Elsevier.

Ghosh, A., Nundy, S., and Mallick, T. K. (2020). How India is dealing with COVID-19 pandemic. Sensors International, 1, 100021.

Ghosh, S., Kanjilal, K. (2016), Co-movement of international crude oil price and Indian stock market: Evidences from nonlinear cointegration tests. Energy Economics, 53, 111-117.

Gormsen, N. J., & Koijen, R. S. J. (2020), Coronavirus: Impact on stock prices and growth expectations. Review of Asset Pricing Studies, 10(4), 574-597.

Gupta, R., & Basu, P. K. (2009), Sector Analysis And Portfolio Optimisation: The Indian Experience. International Business and Economics Research Journal (IBER), 8(1), 119.

Hamilton, J.D. (1983), Oil and the macroeconomy since World War II. Journal of Political Economy, 91(2), 228-248.

Hassan, M.K., Rashid, M., editors. (2018), Management of Islamic Finance: Principle, Practice, and Performance. Vol. 19. Bingley: Emerald Group Publishing.

Hedi Arouri, M. El, Khuong Nguyen, D. (2010), Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. Energy Policy, 38(8), 4528-4539.

Insaidoo, M., Ullah, A., Dziwornu, R.K., Amoako, S. (2023), Heliyon COVID-19 pandemic and stock market performance: A comparative study of emerging economies. Heliyon, 9(5), e16054.

Jareño, F., de la O González, M., López, R., Ramos, A.R. (2021), Cryptocurrencies and oil price shocks: A NARDL analysis in the COVID-19 pandemic. Resources Policy, 74, 102281.

Jiang, Z., Yoon, S.M. (2020), Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. Energy Economics, 90, 104835.

Kamaruddin, K., Hazmi, Y., Masbar, R., Syahnur, S., Majid, M.S.A. (2021), Asymmetric impact of world oil prices on marketing margins: Application of nardl model for the indonesian coffee. International Journal of Energy Economics and Policy, 11(6), 212-220.

Karim, M.M., Kawsar, N.H., Ariff, M., Masih, M. (2022), Does implied volatility (or fear index) affect Islamic stock returns and conventional stock returns differently? Wavelet-based granger-causality, asymmetric quantile regression and NARDL approaches. Journal of International Financial Markets, Institutions and Money, 77, 101532.

Kehtarnavaz, N. (2008), Digital signal processing system design: LabVIEW-based hybrid programming. Amsterdam: Elsevier Science. p1-325.

Khraief, N., Shahbaz, M., Mahalik, M.K., Bhattacharya, M. (2021), Movements of oil prices and exchange rates in China and India: New evidence from wavelet-based, non-linear, autoregressive distributed lag estimations. Physica A: Statistical Mechanics and Its Applications, 563, 125423.

Kumar, S., Pradhan, A.K., Tiwari, A.K., Kang, S.H. (2019), Correlations and volatility spillovers between oil, natural gas, and stock prices in India. Resources Policy, 62, 282-291.

Liu, Y., Cheng, X., Liao, S. S., Yang, F. (2023), The impact of COVID-19 on the tourism and hospitality Industry: Evidence from international stock markets. North American Journal of Economics and Finance, 64, 101875.

Magazzino, C., Mutascu, M., Mele, M., Sarkodie, S.A. (2021), Energy consumption and economic growth in Italy: A wavelet analysis. Energy Reports, 7, 1520-1528.

Mandal, K., Datta, R.P. (2022), Analysing time-frequency relationship between oil price and sectoral indices in India using Wavelet Techniques. International Journal of Energy Economics and Policy, 12(5), 192-201.

Mariani, M.C., Bhuiyan, M.A.M., Tweneboah, O.K., Beccar-Varela, M.P., Florescu, I. (2020), Analysis of stock market data by using dynamic fourier and wavelets techniques. Physica A: Statistical Mechanics and Its Applications, 537, 122785.

Nitha, K. P., Sivakumari, S., and Suraj, E. S. (2021), The upshot of COVID-19 on sensex and sectoral Indices in Indian stock market – A comparative analysis during pre COVID and COVID period. Turkish Journal of Computer and Mathematics Education, 12(8), 2081-2089.

Park, J., Ratti, R.A. (2008), Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Economics, 30(5), 2587-2608.

Percival, D.B., Walden, A.T. (2000), Wavelet Methods for Time Series Analysis. Cambridge: Cambridge Press.

Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289-326.

Phiri, A., Anyikwa, I., Moyo, C. (2023), Co-movement between Covid-19 and G20 stock market returns: A time and frequency analysis.

Heliyon, 9(3), e14195.
Phong, L.H., Van, D.T.B., Bao, H.H.G. (2019), A nonlinear autoregressive distributed lag (Nardl) analysis on the determinants of Vietnam's stock market. Studies in Computational Intelligence, 809, 363-376.
Ramsey, J.B. (2002), Wavelets in economics and finance: Past and future. Studies in Nonlinear Dynamics and Econometrics, 6, 514-539.
Rasche, R.H., Tatom, J.A. (1977), Energy resources and potential GNP. Review, 59, 98-104.
Roberts, D., and Ryan, L. (2014), Evidence of speculation in world oil prices. Australian School of Business, 40(4), 630-651.
Sadorsky, P. (1999), Oil price shocks and stock market activity. Energy Economics, 21(5), 449-469.
Salisu, A. A., Raheem, I. D., and Ndako, U. B. (2019), A sectoral analysis of asymmetric nexus between oil price and stock returns. International Review of Economics and Finance, 61, 241-259.
Shahbaz, M., van Hoang, T.H., Mahalik, M.K., Roubaud, D. (2017), Energy consumption, financial development and economic growth in India: New evidence from a nonlinear and asymmetric analysis. Energy Economics, 63, 199-212.
Shin, Y., Yu, B., Greenwood-Nimmo, M. (2014), Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Festschrift in Honor of Peter Schmidt. New York: Springer. p281-314.
Singhal, S., Ghosh, S. (2016), Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. Resources Policy, 50, 276-288.
Sireesha, P. B., and Haripriya, T. (2021), Impact of Covid-19 Pandemic on the Indian Stock Market: Sectoral Indices Wise Analysis. Journal of Tianjin University Science and Technology, 54(10), 611–623.
Soni, P. (2021), Effects of COVID-19 lockdown phases in India: an atmospheric perspective. Environment, Development and Sustainability, 23(8), 12044-12055.
Tang, C.S., Kogid, M. (2022), Asymmetric responses of energy consumption in Malaysia: Evidence from nonlinear ARDL. International Journal of Energy Economics and Policy, 12(4), 160-165.
Tiwari, A.K., Jena, S.K., Mitra, A., Yoon, S.M. (2018), Impact of oil price risk on sectoral equity markets: Implications on portfolio management. Energy Economics, 72, 120-134.
Varma, Y., Venkataramani, R., Kayal, P., and Maiti, M. (2021), Short-Term Impact of COVID-19 on Indian Stock Market. Journal of Risk and Financial Management, 14(11), 558.
Vuković, M., Pivac, S., and Babić, Z. (2020), Comparative analysis of stock selection using a hybrid MCDM approach and modern portfolio theory. Croatian Review of Economic, Business and Social Statistics, 6(2), 58-68.
Xiang, L., Zhang, H., Gao, K., Xiao, Z. (2021), Oil volatility-inflation pass through in China: Evidence from wavelet analysis. Energy Reports, 7, 2165-2177.
Zhang, Z., Sun, Q., Ma, Y. (2022), The hedge and safe haven properties of non-fungible tokens (NFTs): Evidence from the nonlinear autoregressive distributed lag (NARDL) model. Finance Research Letters, 50(40), 103315.
Zhu, H.M., Li, S.F., Yu, K. (2011), Crude oil shocks and stock markets: A panel threshold cointegration approach. Energy Economics, 33(5), 987-994.
Zhu, X., Niu, Z., Zhang, H., Huang, J., and Zuo, X. (2022), Can gold and bitcoin hedge against the COVID-19 related news sentiment risk? New evidence from a NARDL approach. Resources Policy, 79, 103098.