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Analysing Time-frequency Relationship between Oil price and Sectoral Indices in India using Wavelet Techniques

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ABSTRACT

Oil is considered an essential factor of any economy. This paper examines the time-varying correlation between oil price return, BSE SENSEX, and 14 sectoral indexes in India using multiscale wavelet decomposition and wavelet coherence analysis. The maximal wavelet discrete wavelet transform analysis shows a feedback relationship between 13 sectors at higher time horizons (dC_4, dC_5, and dC_6). Based on the wavelet coherence plot, the oil price and sectoral index return show a high co-movement at 32 to 128 s. The wavelet coherence plot shows that the oil price and sectoral index return show a high co-movement during the period of Mar-May 2020 (especially during the period of financial crisis widely spread due to the COVID19 pandemic and nationwide lockdown notification announced by the Government of India). We discuss the implications of these studies in detail.

Keywords: Wavelet Coherence, Multiscale Decomposition, Lead Lag Relationship, Sectoral Indices
JEL Classifications: L93, P18, O47, Q57, C22, C31, C32

1. INTRODUCTION

Any economy is highly dependent on oil prices because oil is one of the primary energy sources. The other energy sources are coal, natural gas, nuclear energy, and renewable energy. Among these energy sources that influence a country's economy, mineral oil perhaps plays the most crucial role due to its multi-dimensional influence on the socio-economy of a country. From transport to power generation, textile to the plastic industry, oil is one of the primary input raw materials. For the same reasons, crude oil is an essential strategic resource (Jiang and Yoon, 2020). It influences the economies and the stock market (Wu et al., 2020). For that reason, the oil market is considered to be a part of the financial asset market.

As per the EIA (Energy Information Administration) report ('https://www.iea.org/articles/e4-country-profile-energy-efficiency-in-india'), the energy consumption of India has increased by 50% in the last 10 years (from 2007 to 2017). India is also developing in the manufacturing sector and servicing sectors as a developing country. This development also increases the oil demand. As a result, India is becoming highly oil-dependent and importing oil to meet the demand. Hence, if there is a change in oil price, this will affect investment and economic activities (Roberts and Ryan, 2014). For example, if the oil price goes high, the cost of production and the cost of the product will be high. Thus increasing oil prices will harm the demand for that product and the stock price of the production company and the specified sector. As a result, the investors may reallocate their funds to other growing sectors. If oil prices change, the investor is likely to reassign their investments to maximise their returns and minimise risk.

The effect and influence of oil prices are heterogeneous across the different sectors, and we look at this through the sectoral indices. The in-depth study carried out in this paper guides in analysing investment diversification and risk minimisation. The stock market may be identified as an indicator of economic performance. So many studies have been performed earlier (Khan et al., 2020; Wu et al., 2020; Khraief et al., 2021; Xiang et al., 2021) to investigate how the oil price impacts an economy. Hence, distributing the investment among different sectors will allow diversification of the portfolio and management of risk (Arouri et al., 2011).

However, the oil price shock means a sudden change in the oil price (Baumeister and Kilian, 2016). The shock may be supply-driven (because of sudden considerable changes in oil supply) or demand-driven (due to sudden considerable changes in oil supply); either positive shock or negative shock may happen. For example, if the "Organization of the Petroleum Exporting Countries reduces production, the oil price will increase. It is a positive supply shock because the oil price has increased. In the same way, if the oil supply increases, it will be a negative oil price shock. Whatever the shock is, stock market returns will be affected by it.

Many studies have analysed how the oil price return impacts the economic performance of a country (Rasche and Tatom, 1977; Hamilton, 1983). Huang et al. (1996) have used the vector autoregression (VAR) model, and Sadorsky (1999) has used the generalised autoregressive conditional heteroscedastic (GARCH) model. Kumar et al. (2019) used a "multivariate generalised autoregressive conditional heteroskedasticity" (MGARCH) model to analyse the dynamic time-varying linkage. All these investigations were conducted in the time domain and not in the frequency domain, which is specifically followed in this study.

Some researchers have analysed the correlation in the frequency domain as well. To estimate the "power spectrum" of return, Mariani et al. (2018) have used "Dynamic Fourier Transform" and "Wavelet Transform." Wu et al. (2020) have used "partial and multiple wavelet coherence" to investigate the impact of oil price on the international stock market. Magazzino et al. (2021) used wavelet decomposition and "Granger Causality" to deal with Italy's economic growth concerning oil price. Xiang et al. (2021) have used wavelet analysis to study the time-varying linkage between the inflation and fluctuation of oil prices in China. Most frequency-based (wavelet) studies have investigated overall economic activities, not sector-specific ones. Concerning the investor, it is essential to get the details about the sector-specific return instead of the overall average (Tiwari et al., 2018). Also, it is necessary to investigate the impact in the short term and the long term to create a proper investment portfolio.

Therefore, (Tiwari et al., 2018) have studied the dynamic correlation between the oil price and sectoral indices in the Indian context with the help of quantile regression analysis. The direction of causality on sectoral indices also have been studied. Arouri and Khuong Nguyen (2010) have used the "two-factor market and oil" model to study the dynamic oil price dependence on European sectors. Again Arouri et al. (2011) used the "VAR-GARCH" model to inspect the sector level degree of volatility between "oil price" and the "stock market" in the United States and Europe and found significant spillover.

Again considering the degree of oil price dependence in different sectors, most of the studies have been done in the time domain, not in the frequency domain. If we analyse the impact in the frequency domain, we can have a better inside view. As mentioned earlier, most studies have looked at emerging and developing countries. However, the frequency domain has not inspected the sectoral impact and causality in the Indian context. In this study, with the help of multiscale wavelet decomposition and wavelet coherence, we re-examine the linkage of oil price return in different sectors in India. The contribution of this paper is as follows: First, we have applied "multiscale wavelet decomposition." We have identified the dynamic correlation between the oil price and sectoral returns in the frequency domain (high and low frequency), including the time domain (short, medium, and long term). Second, concerning the earlier studies, this wavelet-based investigation attempts to provide more specific and in-depth correlation insight using "Continuous Wavelet Transform" (CWT) and "Discrete Wavelet Transform" (DWT).

2. A BRIEF LITERATURE REVIEW

Jiang and Yoon (2020) has shown that the stock market index may be considered an overall performance parameter for any economy. Zhu et al. (2011) and Arouri and Rault (2012) found a positive relationship between an oil price change and the stock market. On the other hand, the study of Sadorsky (1999); Park and Ratti, (2008) indicated that the oil price negatively impacted the stock market.

The oil price dynamically impacts the stock market, and it varies over time, as reported by Mariani et al. (2020). Similarly, for investment and diversification, industrial sectors are also significant (Tiwari et al., 2018). Khan et al. (2020) found a time-dependent asymmetric relation between crude oil price and US industrial production and a short-term supply-driven relation was identified. In the medium term, the linkage was demand-driven, and in the long run, it was an asymmetric relation. Degiannakis et al. (2013) found a "contemporaneous correlation" of oil price changes in ten European sectors. The relationship was specific to the industry and dynamic over time. Also, the extent of impact varies over sectors (Arouri et al. 2011). As per Arouri et al. (2010), oil price shock depends differently on the different activity sectors. That means a correlation exists between sectoral index and oil price return, and it varies for the type of industry (Tiwari et al., 2018).

Concerning the studies in the Indian context, Ghosh and Kanjilal (2016) conducted their study to explore how the Indian stock market correlates with the price of crude oil in the international market. They could find cointegration only for the post-economic crisis period (after Dec 2008) and explored that the oil price Granger caused the stock market. The study of Singhal and Ghosh (2016) on the Indian stock market and crude oil price return using the VAR-DCC-GARCH framework explored the co-movement at aggregate and sectoral levels. They could not find any such volatility spillover from oil prices to the stock market. In only three sectors out of ten, spillovers have been reported at the sectoral level, namely the financial, power, and automobile sectors. The study also revealed time-varying differential dependence of sectoral index return and oil price. Masih et al. (2014) used DCC-MGARCH and continuous wavelet transformation to explore the oil price volatility in 16 sectors.

In all these studies, the dynamic time-varying relationship in the time and frequency domain between oil price and sectoral index return in the Indian context is not conclusive. We have used wavelet transform (coherence plot and multiresolution analysis) to study the time-varying co-movement of the oil price and the stock market at the aggregate level and at the sectoral level in the Indian context.

3. METHODOLOGY

In recent decades, the analysis of time series that is non-stationary has gained a particular interest in the different fields of applied science. Wavelet analysis is a valuable tool and widely used in finance and economics. In this study, we have used wavelet transform as: (i) DWT for multiresolution or multiscale decomposition and (ii) CWT for measuring the wavelet coherence.

The Wavelet Transform decomposes a signal into a different time and frequency components. It is defined as a set of basic functions. Ramsey (2002) has defined the "father" and "mother" wavelets. The father wavelet (FW) describes the smooth component (very long scale) of the time series, and it is integrated into one; the mother wavelet (MW) describes the deviation from the smooth component, and it is integrated to zero. Hence "the mother wavelet" specifies a "differencing coefficient" and the "father wavelet" generates a "scaling coefficient."

FW can be expressed as:

$$\Phi_{a,b} = 2^{-a/2}\, \Phi\left(\frac{t-2^a b}{a}\right) \quad \text{where } \int \Phi(t)\,dt = 1 \tag{1}$$

Mother wavelet is defined as

$$\Psi_{a,b} = 2^{-a/2}\, \psi\left(\frac{t-2^a b}{2^a}\right) \quad \text{where } \int \psi(t)\,dt = 0 \text{ and } a = 1,2,\ldots, J \tag{2}$$

Here the function f(.) can be denoted by

$$f(t) = \sum_b S_{A,b}\, \Phi_{A,b}(t) + \sum_b d_{A,b}\, \psi_{A,b}(t) + \sum_b d_{a,b}\, \psi_{a,b}(t) + \ldots \sum_b d_{1,b}\, \psi_{1,b}(t) \tag{3}$$

or f(t) can be denoted as

$$f(t) = sC_A + sC_A + dC_{A-1} + dC_{A-2} + \ldots + dC_a + \ldots + dC_1 \tag{4}$$

Here

sC_A (Smooth Coefficient) = $\sum_b sC_{A,b}\, \Phi_{A,b}(t)$

dCa (Detail Coefficient) = $\sum_b d_{a,b}\, \psi_{a,b}(t)$; $a = 1,\ldots, J$

Means f(t) is simplified as

$$f(t) = \sum_{a=1}^{A} sC_A + dCa \tag{5}$$

This is the multiresolution decomposition of f(t). Hence the multiresolution decomposition of f(t) is $\{dC_A, DC_{A-1},\ldots, dC_1,$ and $sC_A\}$. $_{DCA}$ is the wavelet detail coefficient at the a[th] level. At every scale, the summed variations are defined by side-channel analysis (SCA). This study used a wavelet filter of length 8 (DB4) from an asymmetric family developed by I. Daubechius (1992). In this analysis, we have used MODWT for its advantages in analysing the financial or economic data. Moving differential and averaging operators are used in MODWT, and precise observations are maintained for each decomposition time (Percival and Walden, 2000).

Our study decomposes the time series into detailed coefficients from dC_1 to dC_6. DCA represents a time scale resolution from 2^a to 2^{a+1} (Jiang and Yoon, 2020). In this study dC_1, dC_2., to dC_6 signifies the short-run variation to long-run movement. sC6 specifies "Smooth Coefficient," and it signifies the trend in the long term. Here dC1 is the high frequency means the duration is short, and dC_6 is for long-duration means low frequency. We also employ the CWT to inspect the dynamic relationship. The Maximal Overlap DWT (MODWT) can only provide a two-dimensional view, but wavelet coherence can provide a three-dimensional view with a better insight. The wavelet coherence of 2 time series can provide a detailed view of interdependence in the time and frequency domains (Aguiar-Conraria and Soares, 2014).

The correlation between two variables is defined by coherence. If x (t) and y (t) are 2 time series, the correlation between these two series can be explained by the wavelet spectrum, and the correlation might have a lead and lag relation. Torrence and Compo (1998) have defined this "cross wavelet spectrum" of 2 time-series with "Continuous Wavelet Transform" (CWT) as

$$C_{x,y}(l,m) = C_x(l, m)\, C^*_y(l, m) \tag{6}$$

Here l and m are the position or translation and scaling parameters, respectively. $C_x(l, m)$ is the CWT of x(t), and $C_y(l, m)$ is the CWT of y(t). * indicates the complex conjugate of $C_y(l, m)$. $C_{x,y}(l, m)$ is a complex number. Hence $|C_{x,y}(l, m)|$ specifies its power, which defines the local covariance between two series at each scale or frequency. So, the "wavelet squared coherence" of x(t) and y(t), as defined by Torrence and Webster (1999), can be mentioned as

$$R^2(l, m) = \frac{S\left(S^{-1}C_{x,y}(l,m)\right)^2}{S} \tag{7}$$

Here S is the smoothing and $0 <= R^2(l, m) <= 1$.

With the help of this squared coherence and its graphical representations, we can identify the co-movement in the time and frequency domains. If the value of $R^2(l, m)$ is low and close to zero, it means there is low dependency, and if the value is high, there is a high dependency between the 2 time series. Since it is a squared coherence, it is always a positive value, and we cannot identify whether the correlation is positive or negative separately. The same wavelet coherence with phase difference can be defined as (Torrence and Webster, 1999)

$$\theta_{xy} = \tan^{-1}\left(\frac{I\left\{S\left(S^{-1}C_{xy}(l,m)\right)\right\}}{R\left\{S\left(S^{-1}C_{xy}(l,m)\right)\right\}}\right) \tag{8}$$

Here I is the imaginary portion and R is the real portion. The black arrows in the wavelet coherence plot indicate phase differences. The zero-phase difference indicates a perfect linkage in the specified frequency. If x(t) and y(t) are positively correlated, they are in-phase and are negatively correlated, which means they are in anti-phase. In-phase is indicated by → and ← indicates anti-phase. If x(t) leads y(t), it is indicated by ↗ and ↙ (Jiang et al., 2017). Similarly, ↘ and ↖ indicate y(t) leads x(t).

4. DATA AND ANALYSIS

In our study, the weekly data from 10th September 2012 to 5th September 2021 have been used. We have gathered the dataset from the Bombay Stock Exchange (BSE) website (https://www.bseindia.com/). Fourteen sectoral indices in India and BSE SENSEX have been considered for the study. The sectors are (i). BSE automobiles (auto) (ii) BSE bank (bank) (iii) BSE capital goods (cap_goods) (iv) BSE carbon (carbon) (v) BSE consumer durables (con_durables) (vi) BSE discretionary goods and services (con_goods) (vii) BSE energy (energy) (viii) BSE fast moving consumer goods (FMCG) (ix) BSE Greenex (greenex) (x) BSE health (health) (xi) BSE industry (industry) (xii) BSE information technology (it) (xiii) BSE metal (metal) (xiv) BSE realty (realty). Crude oil prices are the spot price-cushing, Oklahoma 'west texas intermediate (WTI) spot price FOB (Dollars per Barrel). As a benchmark "WTI Oil Price" is being used widely in the world oil market (Basher et al., 2012), we have used WTI oil price for our study. The oil price data has been collected from EIA (https://eia.gov).

The return has been calculated based on the first difference of the logarithmic values as $ret_t = \ln(TS_t) - \ln(TS_{t-1})$ where TS_t and TS_{t-1} are the current and the value at lag 1, respectively. The data variables and the sample periods have been presented in Tables 1-3.

Regarding MODWT, we have used the wavelet filter of length L= 8 (db4, least asymmetric) (Daubechius, 1992). In earlier studies on time series data where the data frequency is high, it has been observed that, when the filter length is moderate (e.g. L = 8), it is adequate to understand the hidden aspect of the data (Hassan and Rashid, 2018).

In our study, the data series have been decomposed into wavelet detail coefficients and that has been defined as dC_1, dC_2., dC_6. Table 3 shows the relationship between the time horizon and

Table 1: Details of variables and sample periods

Serial number	Sector index name	Symbol	Sample period duration
1	BSE automobiles	auto	10th September, 2012 to 5th September, 2021
2	BSE bank	bank	10th September, 2012 to 5th September, 2021
3	BSE capital goods	cap_goods	10th September, 2012 to 5th September, 2021
4	BSE carbon	carbon	10th September, 2012 to 5th September, 2021
5	BSE consumer durables	con_durables	10th September, 2012 to 5th September, 2021
6	BSE discretionary goods and services	goods_svc	10th September, 2012 to 5th September, 2021
7	BSE energy	energy	10th September, 2012 to 5th September, 2021
8	BSE fast moving consumer goods	FMCG	10th September, 2012 to 5th September, 2021
9	BSE greenex	greenex	10th September, 2012 to 5th September, 2021
10	BSE health	health	10th September, 2012 to 5th September, 2021
11	BSE industry	industry	10th September, 2012 to 5th September, 2021
12	BSE information technology	it	10th September, 2012 to 5th September, 2021
13	BSE metal	metal	10th September, 2012 to 5th September, 2021
14	BSE realty	realty	10th September, 2012 to 5th September, 2021
15	BSE SENSEX	Sensex	10th September, 2012 to 5th September, 2021
16	WTI oil price	oil	10th September, 2012 to 5th September, 2021

Table 2: Descriptive statistics of return

Sector index symbol	Mean	SD	Median	Minimum	Maximum	Skew	Kurtosis	ADF	Corr with oil
auto	0.0018	0.026	0.0033	−0.14	0.13	−0.44	3.74	−16.36	0.206
bank	0.002676	0.029	0.004	−0.2	0.13	−0.59	6.17	−16.18	0.194
cap_goods	0.002380	0.0309	0.002355	−0.15	0.22	0.44	6.24	−14.57	0.173
carbon	0.002463	0.01965	0.0032	−0.15	0.08	−1.15	8.22	−15.75	0.2423
con_durables	0.003742	0.0265	0.00388	−0.16	0.1	−0.85	4.75	−16.01	0.1769
goods_svc	0.002718	0.02236	0.005265	−0.15	0.08	−1.06	5.3	−15.42	0.170
energy	0.002495	0.0261	0.002605	−0.14	0.09	−0.42	3.09	−16.54	0.151
fmcg	0.002125	0.0196	0.00215	−0.08	0.08	−0.3	2.27	−16.39	0.1206
greenex	0.002294	0.01988	0.002890	−0.14	0.09	−0.87	6.82	−15.60	0.2583
health	0.002665	0.0224	0.003850	−0.08	0.14	0.09	3.85	−16.01	0.1196
industry	0.002229	0.02775	0.002815	−0.16	0.09	−0.55	3.14	−15.33	0.2061
it	0.003651	0.0231	0.004570	−0.14	0.07	−0.84	4.34	−15.77	0.2064
metal	0.001489	0.0335	0.000720	−0.15	0.12	−0.23	1.65	−15.78	0.325
realty	0.001499	0.03902	0.004050	−0.19	0.21	−0.15	2.81	−16.50	0.1632
sensex	0.002457	0.019	0.0037	−0.15	0.07	−1.16	8.93	−16.13	0.235
oil	−0.00043	0.07	0.002	−0.83	0.58	−2.89	68.42	−18.46	1

ADF: Augmented dickey-fuller, SD: Standard deviation the detailed coefficients. dC_1 with 2–4 weeks time scale and dC_2 with 4–8 weeks time scale signify short-term decomposed series with high frequency. dC_3 (with 8–16 time scale) and dC_4 (with 16–32 weeks time scale)denote medium-term decomposed series with medium frequency. dC_5 (with 32–64 weeks time scale) and dC_6 (with 64–128 weeks time-scale) represents the decomposed series of long-term (low frequency). sC_6 is an approximation or smooth coefficient with a time horizon of more than 128 weeks.

Table 2 illustrates the studied return series with their descriptive statistics and the ADF (Augmented Dickey-Fuller) stationarity test result. Oil shows a negative mean and highest volatility (Standard Deviation). According to the ADF test, all the sectoral indices and SENSEX data hold stationarity. By calculating the correlation coefficients, we can observe a linear co-movement between oil price (OP) and other sectoral indexes (SI) returns. The last column of Table 2 outlines the correlation coefficients. All correlation coefficients are positive and significant. This indicates a dynamic and positive correlation between the OP and SI return. BSE Metal has the highest correlation coefficient value of 0.325, and BSE Greenex and BSE Carbon follow this. In general oil-dependent sectors are closely linked with the oil price return. BSE Health has the lowest correlation coefficient means the health sector is least affected by the oil price shocks.

In Figure 1, the dynamics of sectoral index returns, including BSE SENSEX and oil price return, have been plotted. It shows the volatility feature. Also, we can see high volatility around March-May 2020 for each sector. The financial crisis had widely spread due to the COVID19 pandemic and the nationwide lockdown notification announced by Govt. of India at the end of March 2020. However, all the sectoral index returns positively correlate with the oil price shock (Table 4).

Table 3: Associations between decomposed series by time scale and time horizon

Decomposed series by time scale	Time horizon (frequency) in weeks
dC1	2–4
dC2	4–8
dC3	8–16
dC4	16–32
dC5	32–64
dC6	64–128
sC6	>128

5. EMPIRICAL RESULTS

The dynamic influence of change in oil price on SI return has been analysed both in frequenc time domain. Figure 2 represents the multiresolution analysis of oil price, BSE SENSEX, and 14 sector index return based on MODWT. All the returns have been decomposed into seven components, and those components are dC_1, dC_2, dC_3, dC_4, dC_5, $dC_{6,}$ and sC_6. dC_1 specifies the high frequency with a 2–4 week time scale. dC_2 represents a 4–8 week time scale followed by dC_3, dC_4, dC_5, $dC_{6,}$ and sC_6 as per Table 3.

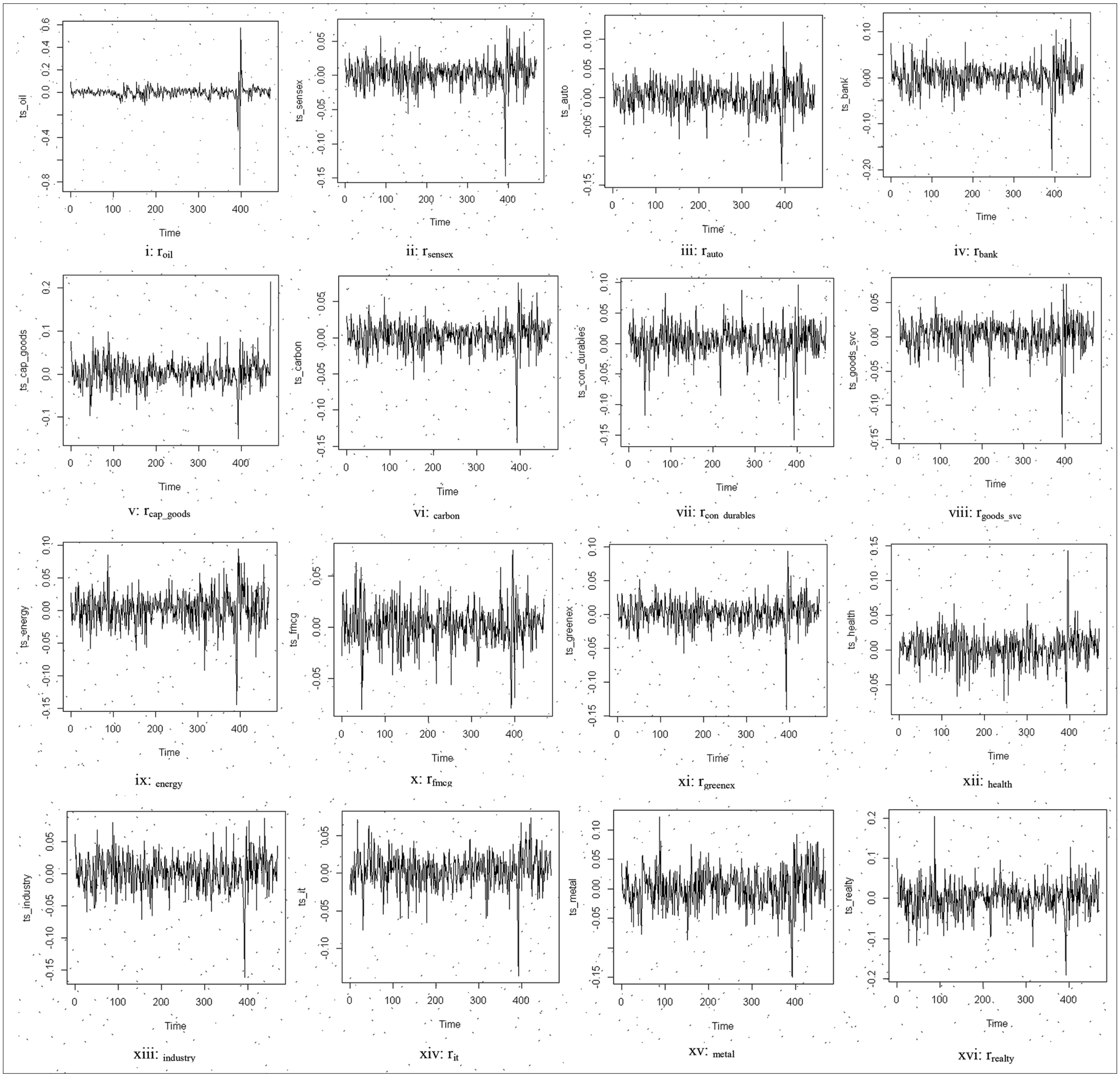
The oil series price returns and other indices have been decomposed at different time horizons (frequency at dC_1, dC_2, dC_3, dC_4, dC_5, $dC_{6,}$ and sC_6) the respective correlations are mentioned in Table 4. We find that the correlation is significant at low frequency (long time scale). Only in the case of FMCG, health, and IT, do we find a negative correlation at dC_6. At the dC_3 level, we see all returns have negative correlations. Based on this finding, we can conclude that there are time-varying correlations and that depends on the frequency or time-horizon, whether the time horizon is long term (dC_5, dC_6), medium-term (dC_3, dC_4), or short term (dC_1, dC_2).

Figure 3 represents the plot of CWT. It describes the coherence and phase differences between the OP (Oil Price) return and SI (Sectoral Indices) return in the Indian context from the time horizon of scale from dC_1 to dC_6 (1 to 128 weeks). The black arrows specify the phase difference. The x-axis represents the time horizon in the number of trading weeks (the sample data range). The coherence plot maintains a color standard, as explained on the right side. The power is ranging from blue to red. Blue indicates low correlation and red means high correlation.

Table 4: Dynamic correlation at different time horizon

Correlation	High frequency (short time scale)				Low frequency (long time scale)		
	dC_1	dC_2	dC_3	dC_4	dC_5	dC_6	sC_6
oil	1	1	1	1	1	1	1
sensex	0.1655	0.1909	−0.1309	0.6747	0.5556	0.2789	0.7843
auto	0.1592	0.1472	−0.2547	0.6965	0.6115	0.4811	0.5255
bank	0.2141	0.1411	−0.1203	0.5163	0.4839	0.4573	0.6794
cap_goods	0.1431	0.1537	−0.0675	0.3925	0.2594	0.3060	0.7021
carbon	0.1744	0.2160	−0.1485	0.6817	0.5704	0.3783	0.8116
con_durables	0.1426	0.2440	−0.2634	0.3668	0.3554	0.3910	0.6491
goods_svc	0.1080	0.1475	−0.2613	0.6037	0.4454	0.4605	0.6777
energy	−0.0721	0.2041	−0.0662	0.5836	0.5914	0.01086	0.7053
fmcg	0.0610	0.2359	−0.3146	0.2208	0.3317	−0.3020	0.7829
greenex	0.2445	0.2373	−0.2141	0.7015	0.5528	0.4292	0.7859
health	0.0692	0.2543	−0.2058	0.3229	0.2911	−0.3508	0.4665
industry	0.1824	0.1634	−0.2028	0.6228	0.4940	0.6834	0.7592
it	0.1400	0.0967	0.0058	0.5498	0.5644	−0.1099	0.7586
metal	0.3309	0.2978	−0.0813	0.5971	0.4778	0.7657	0.8837
realty	0.0614	0.1883	−0.1584	0.6325	0.2669	0.4094	0.7985

Figure 1: Dynamics of returns in oil, BSE SENSEX and sectors



At first glance, we can find higher correlations of oil price with other sector index returns on a larger scale as there are more red spots on the coherence diagram. Especially at high frequency (short time horizon consisting of 2–4, 4–8 weeks), weak correlations were identified for all sectors for the last 8 years. Thus this provides the opportunity for effective portfolio diversification in the shorter run. For the time-horizon of 8–16 weeks again, we find almost all sectors have a lower correlation for the longer period. However, moving towards the medium time horizon (16–32 weeks), interestingly, we find higher correlations for the majority of the sectors except for a few, namely energy, FMCG, and health. Hence investors with this holding period will be unable to exploit the diversification opportunity against oil price except in those three sectors. Strong positive correlations for energy, greenex, FMCG, industry, IT, and metal have been identified in the long run. Most of the strong correlations are identified from March-May 2020 for each sector. Again due to COVID-19 pandemic, the nationwide lockdown was announced by the Government of India in March 2020, and it was extended till May 2020 (Saha and Chouhan, 2021; Soni, 2021). It impacted the Indian economy negatively (Ghosh et al., 2020). As a result, all the sectors were impacted (Varma et al., 2021). Hence the strong correlations during the period from March-May 2020 signify the impact of COVID-19 pandemic.

Oil is leading Sensex in the long run concerning the phase plot, similarly for auto, carbon, con_durables, goods_svc, industry, and metal. This means, in the long run, sensex, auto, con_durables, goods_svc, industry, and metal are following the oil price. Health,

Figure 2: Wavelet decomposed series oil price return, BSE SENSEX, and 14 sector index return

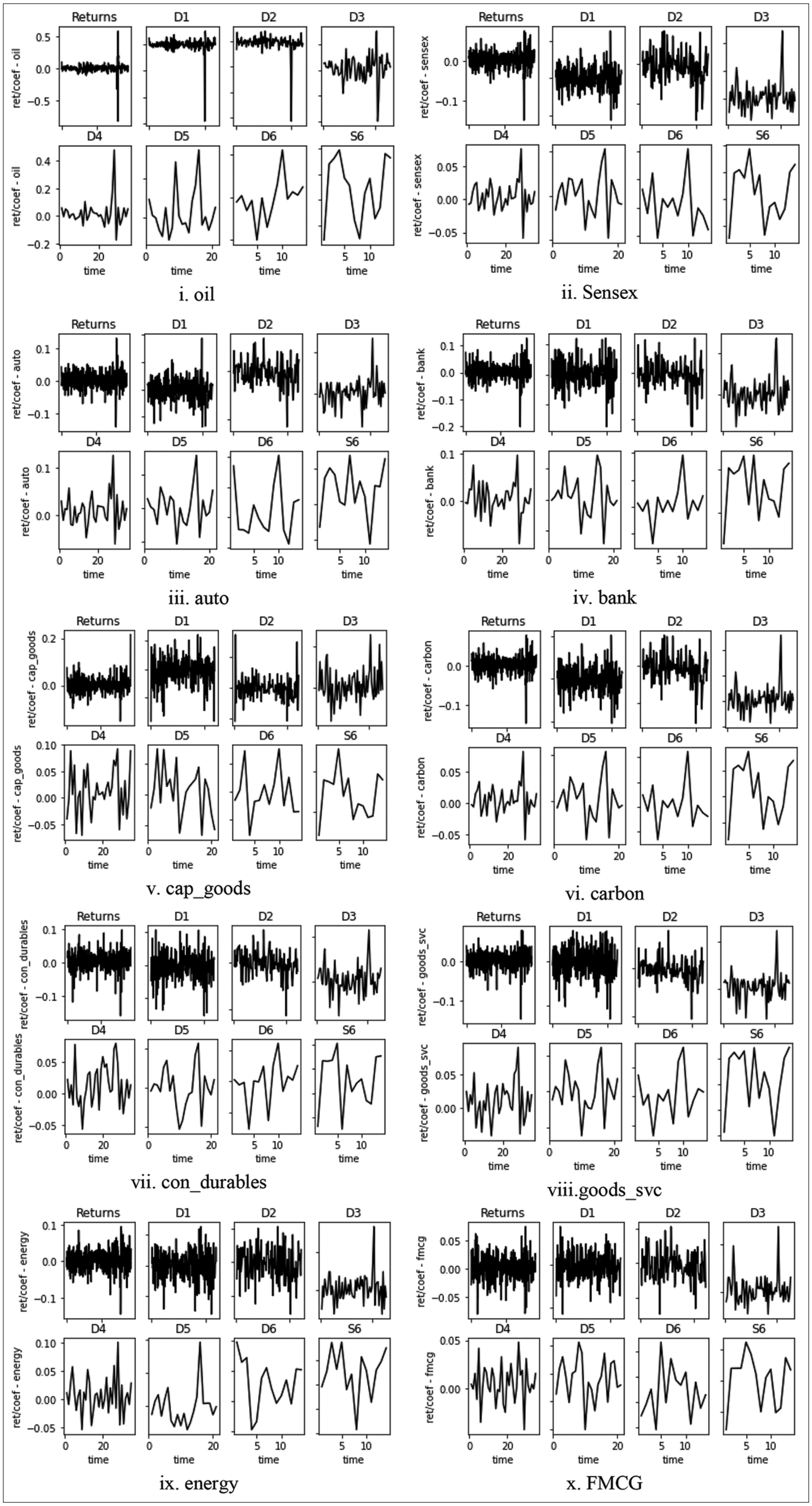
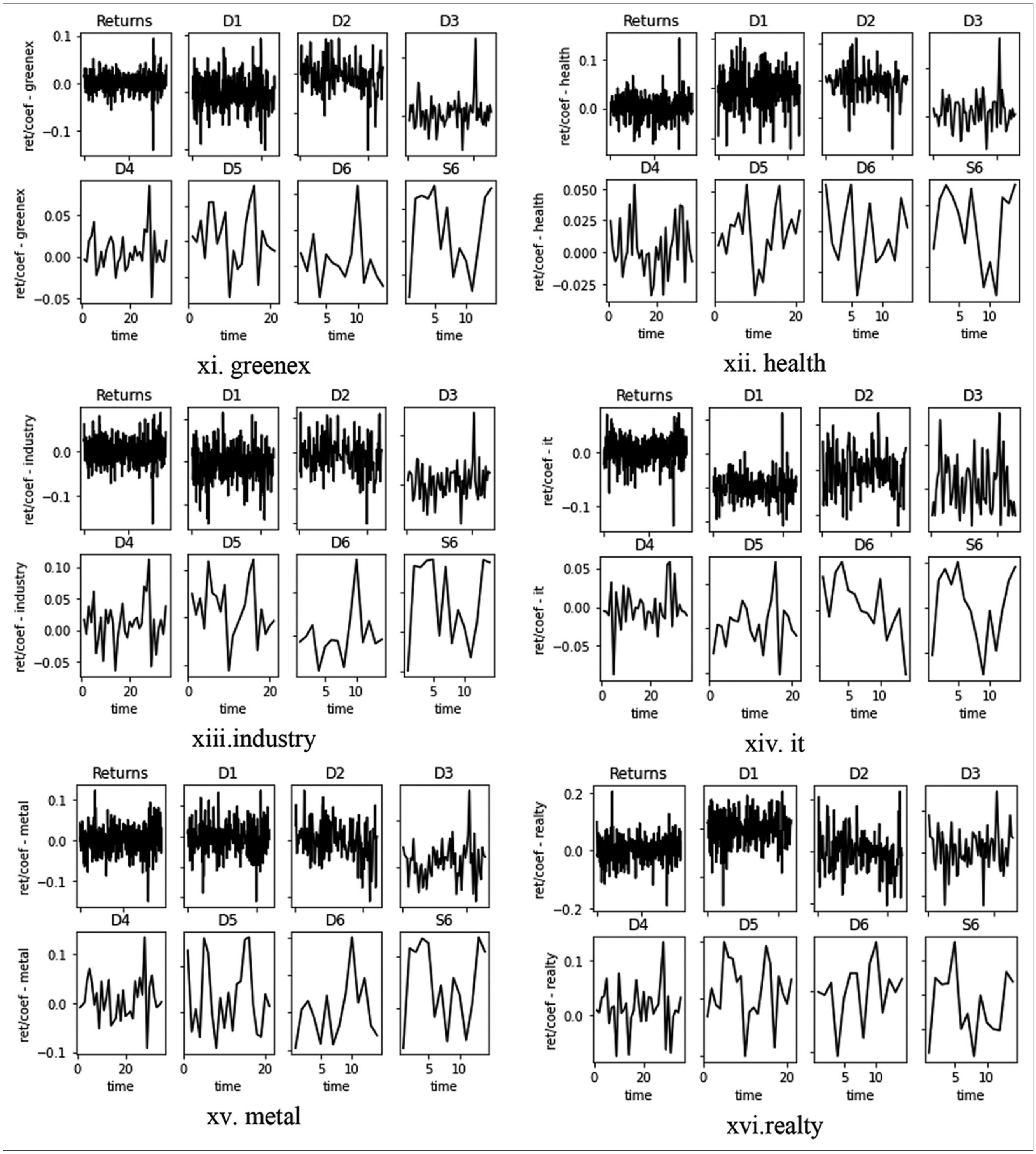


Figure 2: (Continued)



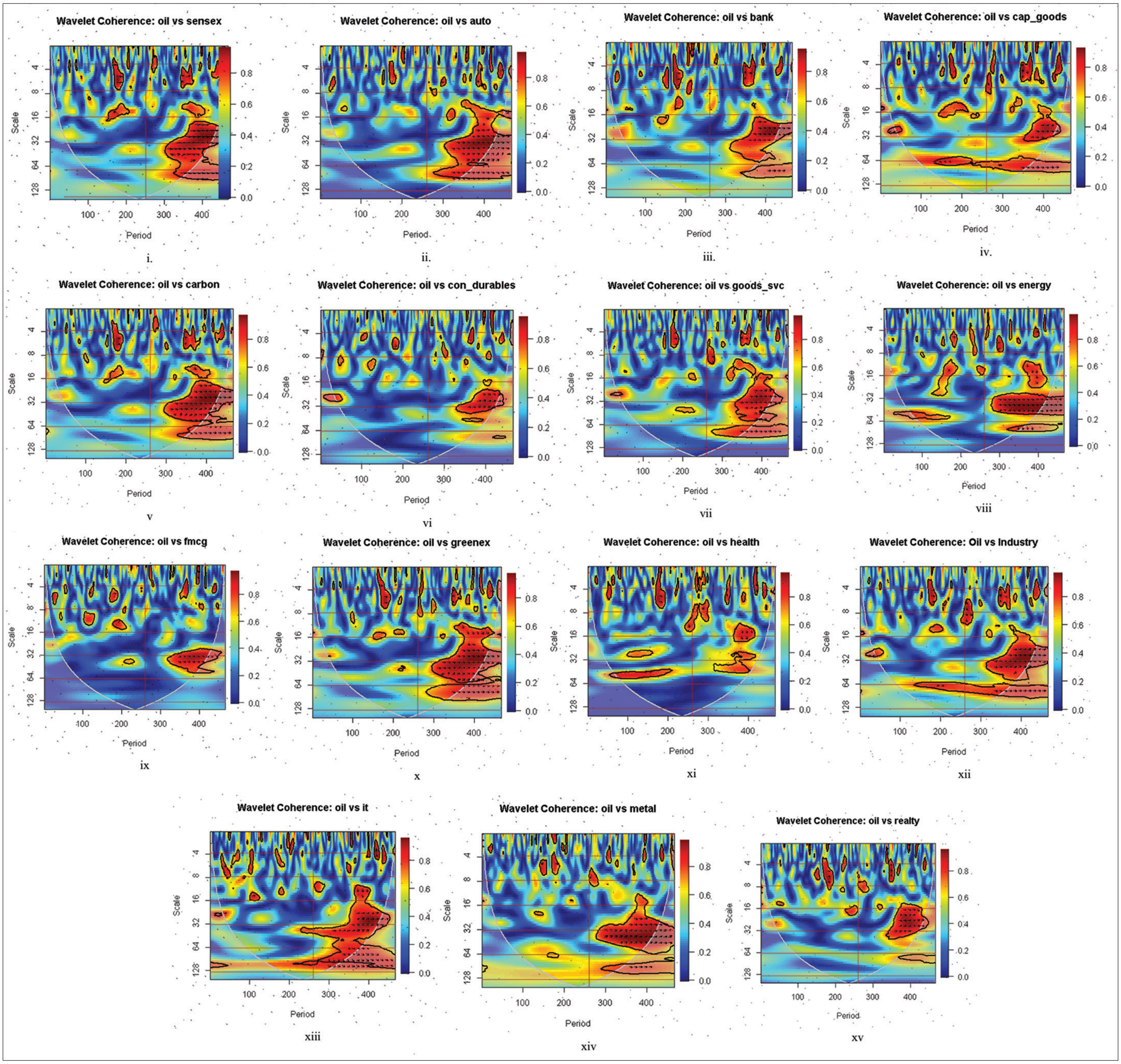
con_goods, FMCG, and realty have very little impact on oil price shock. Greenex shows leading and lagging relations, and the result supports Tiwari et al. (2018). Hence investors will select the sectors and time horizon for which there is a diversification opportunity where the impact of oil price is less.

6. CONCLUSION

We have considered 14 sectors with investment diversification opportunities. This paper explores the influence of OP (Oil Price) on SI (Sectoral Indices) return. We have analysed MODWT and CWT (wavelet coherence) to study the relation. In the first part of our study, we have studied the returns with wavelet decomposition, and in the send part of our study, we have studied the lead-lag relation with wavelet-coherence.

Our finding can be summarised as (i) the result confirms a dynamic relation between OP return and sectoral index return and varies over time. (ii) All the returns have been decomposed with different frequencies in our study. Different time horizons have shown different

Figure 3: Continuous Wavelet Transform (Coherence with Phase plot) between OP and SI return. The X-axis represents the number of trading weeks and Y-axis represents the frequency in weeks as per Table 3. The colour standard is explained at the right side. It ranges from blue to red. Blue and red indicate low and high correlations respectively



correlations. However, a positive and strong correlation has been observed for the long-duration scale. (iii) As per the wavelet coherence plot, no such strong positive correlation was observed during the period from 2012 to 2018, hence providing a diversification opportunity to the investor against oil price rise. (iv) At 16–128 week scale of the wavelet coherence plot, high co-movement is observed between the OP return and the SI return. In time-scale, a high co-movement has been observed during the period between 1999 and 2021.

The above findings provide important suggestions to the policymakers and stock market investors in India as follows: (i) In cases where the co-movement is higher at a long term time horizon, the investors have limited scope to earn the advantages of “portfolio diversification as well as “time diversification” simultaneously. (ii) In the wavelet coherence plot, we have lead-lag interdependence. This interdependence varies over frequency and time horizon. This signifies that the investors should be opportunists and continuously adjust investment composition as well as investment decisions. (iii) With regards to the time scale, at the long-term horizon, a linkage between OP return and SI return is observed only during March-May 2020 for each sector. During the other time, there is no such linkage. This is a vital factor for asset allocation and portfolio diversification. Furthermore, this study suggests that the policies and investment strategies should consider the oil price volatility to reduce the oil price risk.

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