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Effect of Crude Oil Volatility Index (OVX) on the Energy Indices Return: Evidence from Wavelet Analysis

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ABSTRACT

This study investigates the co-movement and causal relationships between crude oil volatility (measured by the OVX) and the returns of three Indian energy indices: BSE Oil and Gas, BSE Power, and CNX Energy. Employing statistical techniques such as descriptive statistics, ADF and Phillips-Perron unit root tests, OLS regression, and wavelet analysis, we examine the dynamic linkages between these variables. Our findings reveal a predominantly negative relationship between OVX and the returns of the analyzed energy indices. These insights provide valuable information for investors to make informed investment decisions, particularly considering the impact of weather conditions on energy markets. Furthermore, the findings offer valuable guidance for policymakers, investment analysts, and other market participants.

Keywords: Implied Volatility Indices, Indian Stock Market, Wavelet Analysis
JEL Classifications: C21, G1, G15, Q43

1. INTRODUCTION

Crude oil, the lifeblood of modern economies, pulsates with inherent volatility, sending ripples through interconnected markets worldwide. According to a study by the international energy agency (IEA), oil accounted for 29% of the world's energy supply in 2020. Although the proportion of renewable energy in power production has been steadily increasing in recent years, oil continues to be the world's primary energy source, when transportation and heating has taken into account. From 2012 to 2022, the scenario drastically shifts when one looks at the change in oil usage. As the world's third-largest oil importer, India is particularly susceptible to these extreme shocks. Understanding the transmission of oil price uncertainty to Indian stock markets is crucial for investors navigating this fluid landscape. In addition, compared to the previous year, when the pandemic-imposed mobility constraints caused a fall in worldwide oil consumption, which in turn caused a decline in the demand for transportation fuel, this represented an increase of about 3%. In 2022, the global oil consumption was estimated to be 97.3 million barrels per day. Oil consumption has been rising steadily since 1998, except in the years of the financial crisis and the 2020 coronavirus pandemic (Global Oil Consumption 2022, n.d.). Several studies have shed light on this crucial nexus, employing diverse methodologies and data sets because every economy values its energy resources greatly (Zhu et al., 2014). It has also been demonstrated in different studies, that the price of energy commodities, and oil in particular, has a major global impact on the prices of other commodities, currencies, and equities markets (Gormus et al., 2014, Sari et al., 2010, Nazlioglu et al., 2013). Research has indicated that variations in the price of crude oil could result in notable disruptions to both the equities markets and the general economy (Hamilton, 2003; Charles and Darné, 2017). The available studies employed different methods to identify the price of crude oil. This is due to the introduction of different indicators of uncertainty over the state of the energy, financial, and petroleum markets CBOE volatility index (VIX), CBOE crude oil volatility index (OVX), and EPU markets. Mazzeu et al. (2019) mentioned that, since May 2007, the Chicago Board of options exchange (CBOE) has developed and publicized the crude oil ETF volatility index, highlighting its importance among commodities. The index, according to the Chicago Board of Trade, "measures the market's anticipation of 30-day fluctuation of crude oil prices. It is estimated by employing the market volatility index (VIX) methodology for the US Oil Fund." The OVX ticker symbol uses real-time bid/ask quotations of nearby stock options, with at least 8 days to expiration and weights them to generate a consistent 30-day volatility estimate. This is the first CBOE-designed volatility index for a commodity. Over the past few decades, the CBOE has released several implied volatility indices, which are important indicators of market expectations for the volatility expressed by option prices.

This paper is structured as follows: Section 2, presents the extended literature. Section 3 outlines the data analysis and methodological frameworks employed. The limitations and future directions are discussed in Section 4, and Section 5, presents a summary of conclusions and policy implications.

2. LITERATURE REVIEW

Oil prices have kindled the curiosity of researchers, investors, and authorities in the oil era. Numerous studies have examined the impact of oil prices on financial markets, including price changes, returns, and volatility (Vu, 2018) as well as the relationship between oil prices and stocks (Bondia et al., 2016). Kumar et al. (2012) explained in the study that oil price fluctuations impact the profitability of renewable energy companies while replacing finite resources with sustainable ones. Managi and Okimoto (2013) contended that the polymorphous rising oil prices could be a curse to specific industries but it brings favourable results for clean or renewable energy. Vu (2018), highlights in the study that EIA, 2007 declared that oil demand had risen sharply due to consumption demand increasing rapidly in developed and emerging nations. In other words, the price of crude oil price has been consistently influencing the entire world economy. The IEA created a specific paper for Southeast Asia, in the World Energy Outlook Specific Report because of the region's significant contribution to future global energy demand. Many studies have been conducted on the correlation between crude oil prices and stock market returns, especially in nations that import oil, like India but less research has been done on how the crude oil volatility index (OVX) affects Indian stock indices, by communicating oil price unpredictability. To comprehend the possible effect of OVX on the returns of Indian stock indices, this review looks at the body of available literature. There is scant literature on sector-level oil stock associations. Examining this connection is essential because different industries may react to shocks in oil prices differently, or the size of those reactions may vary as well (Degiannakis et al., 2013). In the earlier study on other developed countries, Amano and van Norden (1998) investigated the impact of oil prices on the US exchange rate. The study established a correlation between the exchange rate and oil prices during the post-Bretton Woods period. Exchange rate shocks suggest that energy costs play a crucial role in explaining the real exchange rate's movement. Basher and Sadorsky (2006) argue that less developed nations are normally more affected by changes in the oil market, and rising economies are typically more vulnerable to shocks to the price of oil. As a result, it is important to examine how the world's oil markets affect some emerging markets' returns. Arouri et al. (2011) mentioned that oil price volatility can have a greater impact on certain industries, based on whether oil and related products are inputs or outputs. Managi and Okimoto, (2013) examined the relationships between clean energy, oil and technology stock prices while naturally accounting for structural changes in the market. This study concluded that the price of clean energy and the price of oil did have a positive link after structural discontinuities were observed, through the application of Markov-switching vector autoregressive models to the economic system. Further, there appears to be a similarity in the way the market responds to technology and renewable energy stock prices. Sadorsky (2012a) found that clean energy businesses' stock prices reported a higher correlation with technology stocks than with oil prices. To examine the volatility spillovers between oil prices and the stock prices of renewable energy and technology companies was employed multivariate GARCH models. To get the expected result of this research, the author compares and contrasts four multivariate GARCH models: Diagonal, BEKK, Constant Conditional Correlation, and Dynamic Conditional Correlation. The findings revealed a positive connection between technology stock prices and renewable energy company stock prices rather than oil prices. Henriques and Sadorsky (2008) analyze the empirical relationship with four important factors. This study analyses the prices of alternative technology stocks, energy stocks, oil prices, and interest rates. The results show that changes in interest rates, oil prices, and technology stock prices may all be used to partially explain changes in the stock prices of alternative energy businesses. Additional simulation results indicate that the impact of a shock to technology stock prices on alternative energy stock prices is greater than that of an oil price shock. Reboredo et al. (2017) investigate the causal relationship and co-movement between oil and renewable energy stock prices. The causality tests suggest that unidirectional and bidirectional linear causation is more likely at lower frequencies, but linear causality is less likely at higher frequencies. This study demonstrates that while dependency on oil and renewable energy appears minimal in the short run, it gradually strengthens over time, particularly between 2008 and 2012. The analysis found nonlinear causation between renewable energy indices and oil prices over several periods, as well as mixed evidence of causality between oil and renewable energy prices. Wen et al. (2014) applied the asymmetric BEKK model. Daily samples collected between August 30, 2006, and September 11, 2012, revealed large and asymmetric dynamics in the new energy/fossil fuel stock overflow. This study also established how negative news, regarding the stock returns of fossil fuel and new energy companies could cause greater return changes in their counter assets as compared to positive news. The study of Reboredo (2015) found a considerable time-varying average and symmetric tail reliance between oil returns and various global and sectoral renewable energy stock indices. This study employed copulas, to analyse the relationship between oil and renewable energy markets, estimating the conditional value-at-risk as a measure of systemic risk.

The oil price fluctuations exerted a direct relationship with macroeconomic factors and the stock market return was influenced by macroeconomic factors. Moreover, oil price fluctuations are directly affected by OVX. At the same time, OVX transfers uncertainty to stock market return and macroeconomic factors.

According to Figure 1, oil price fluctuations can directly affect macroeconomic factors, such as inflation and economic growth. These factors, in turn, can affect stock market returns. For example, higher oil prices can lead to higher inflation, which can reduce corporate profits and investor confidence, leading to lower stock prices.

The model also shows that oil price fluctuations can directly impact the OVX. The OVX is a measure of expected volatility because it is likely to increase when oil prices are volatile. This increased volatility can then feed back into the stock market, leading to lower returns.

In short, oil price fluctuations can have a complex and indirect impact on the stock market through a variety of channels. However, the overall impact is usually negative, as higher oil prices tend to lead to lower stock returns.

3. METHODOLOGY AND DATA

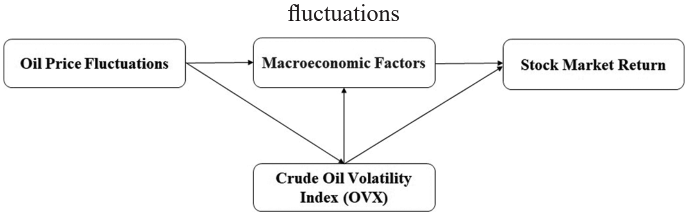
3.1. Objective of the Study
The main objective of this study was to examine the relationship between the crude oil volatility index (OVX) and Energy indices return in India, over the sample period.

3.2. Hypotheses of the Study
- NH_1—There is no normal distribution among the crude oil volatility index (OVX) on sample energy indices in India.
- NH_2—There is no stationarity among the crude oil volatility index (OVX) on sample energy indices in India.
- NH_3—There is no influence of the crude oil volatility index (OVX) on sample energy indices in India.

3.3. Data
For the purpose of this study, two types of data (Crude Oil Volatility Index (OVX) in line with the studies of Chen et al. (2018); Dutta (2017); Korley and Giouvris (2022); Choi and Hong (2020) and energy indices data) were collected, for the period from January 2010 to December 2023.

3.4. Crude Oil Volatility Index (OVX)
The present study covered the daily observations of the crude oil volatility index (OVX) published by Chicago Board Options Exchange (CBOE) (https://fred.stlouisfed. org/series/OVXCLS). The crude oil volatility index (OVX) measures the market expectation for the next 30-day crude oil price volatility, calculated by following the same methodology, used to construct the US volatility index (VIX). Specifically, the calculation relies on the real-time bid and ask prices of nearby options on the United States Oil Fund, having at least 8 days to expiration.

Figure 1: Conceptual framework for the oil volatility index price fluctuations



3.5. Stock Market Data
The stock market daily data were collected for India (BSE oil and gas, BSE power, CNX energy) from www.indiastat.com. The 13-year sample data covered the period from May 2010 to December 2023. Since the fluctuation in the sample data series was not constant, indicating a stochastic trend, the present study converted the raw data into a return series.

The returns were calculated as:

$$Rt = Ln\ (Pt) - Ln\ (Pt - 1) \quad \text{(i)}$$

Where, Rt is the daily index return, while Pt and Pt -1 are the closing index values at time t and t-1, respectively.

3.6. Tools Used for Analysis
To test the hypothesis, the following statistical techniques were applied.

- Descriptive statistics (to determine the normal distribution of returns of sample energy indices in India and OVX index)
- The unit root test (used to assess the stationarity in the returns of sample energy indices in India and OVX index)
- The OLS regression test (used to analyze the influence among the selected sample energy indices in India and OVX index).
- Wavelet analysis (used to analyze the frequency connectedness among the selected sample energy indices in India and OVX index).

In the fast-paced and ever-evolving world of economic research, the wavelet theory is the most attractive mathematical tool for economists, to analyze nonstationary time series. This mathematical tool is commonly used in finance and economics fields, due to its incomparable visual analyzing power. In addition, it provides a time-frequency representation of series, allowing for more accurate analysis. Moreover, the Morelet wavelet, also known as the continuous wavelet, is an outstanding tool, that exhibits remarkable versatility by functioning smoothly without any data constraints. The wavelet technique is highly proficient in managing non-stationary signals, effectively eliminating polynomial components, and efficiently circumventing the ineffective utilization of typical correlation measurements, to distinguish between risk components and variable co-movements. When wavelet transform deals with fractal signals, the first question is, how to quantify their fractal properties. The wavelet transform quantifies a signal's frequency components across time while the Fourier transform assumes the signal to be stationary at relevant time scales. This methodology has gained significant popularity in the financial literature. Numerous studies by esteemed authors, including Das (2021) Jammazi (2012), Rua and Nunes (2009), Gençay et al. (2005), Kim and In (2007), He et al. (2009), Genest et al. (2009), He et al. (2012) and Masih et al. (2010) have made significant contributions in this area. A wavelet study of the link between the crude oil volatility index (OVX) and Bombay stock indices (BSE) indexes, used two components (time and frequency) to divide the series into distinct time scales and examine the short and long periods of the relationship.

The wavelet transform (WT) is a process, used on time series data, that operates sequentially. It starts with varying frequencies and communicates its findings in messages. Then, it divides the original time series data into several series and each decomposed time series represents a specific characteristic of the time horizon. Wavelet analysis can help determine the relationship between frequency and scale. The frequency-scale connection is simply defined as:

Fa = Fc/a. (ii)

This equation captures the fundamental relationship between scale (a) and frequency (Fa) in wavelet analysis. In the equation, Fc represents the wavelet's Centre frequency, while Fa represents the frequency corresponding to scale. As the time frame grows (high-scale), the wavelet spreads out, resulting in decreased frequency.

The three major types of wavelet analysis are continuous wavelet, cross wavelet, and wavelet coherence. Continuous Wavelet Transformation is a technique for analysing a given time series over all frequencies. Cross-wavelet analysis is a useful tool for analysing two signals in both the frequency and temporal domains, as demonstrated by Shahzad et al., 2020; Rua and Nunes, 2009. This approach is useful for detecting changes in spectral patterns over time. Wavelet coherence is another sort of wavelet analysis, that assesses the relationship between two signals. It examines the frequency domain relationship between time-series variables and can be used to identify whether one variable leads or lags another over a certain period. Wavelet analysis has numerous practical uses and it is an effective technique for helping academics to analyse complex data and signals.

A cross-wavelet transformation is a mathematical tool, that is widely employed to analyze 2-time series, a(t) and b(t), as per the research conducted by Torrence and Webster (1999). The technique is expressed in terms of x(t) and y(t). It is a powerful method, that allows one to visualize and examine the relationship between two signals in both the time and frequency domains. The cross-wavelet transformation permits the identification of patterns, trends, and anomalies in the data, that might not be evident through a simple inspection of the time series. Consequently, it is an indispensable tool for conducting accurate and detailed analyses of complex time series data.

The expression for it is x(t) and y(t).

(x,y) = La(x,y)*Lb*(x,y) (iii)

In the given equation, the complex conjugate is indicated by the mathematical symbol "×." This equation also involves two continuous wavelet transformations, namely, La(x,y) and Lb(x,y). The vertical bars, enclosing La,b(x,y) in the equation, represent the cross wavelet transformation power. Cross-wavelet transformations are instrumental in highlighting regions of high common power between 2-time series over time, covering all frequencies. In contrast, the continuous wavelet transformations maintain the energy levels. Therefore, the given equation plays an essential role in analyzing the relationship between 2-time series over time, by identifying areas of high common power and conserving energy (Torrence and Compo, 1998). The wavelet coherence of 2-time series of x and y, is calculated as follows:

$$R^2 = \frac{\left|S(s^{-1}W_{xy}(u,s))\right|^2}{S(s^{-1}\left|Z_x(u,s)\right|^2 S(s^{-1}\left|W_y(u,s)\right|^2))}$$

In this case, the smoothing operator S has a value of 1, indicating a substantial co-movement between the time series, and 0≤R2(u,s)≤1. The wavelet-squared coherence analysis only considers positive values. It, therefore, does not distinguish between the positive and negative directions of the time series connection. The squared wavelet coherence coefficient has a value between 0 and 1. A value around zero, signifies an absence of correlation while a value near unity, suggests a strong association. The fictitious wavelet allocation is analysed, by using the Monte Carlo simulation technique.

4. ANALYSIS AND EMPIRICAL RESULTS

This section analyses the effect of crude oil volatility index (OVX) on sample stock indices in India, by using descriptive statistics, unit root test, OLS Regression and Wavelet analysis. The analysis is presented as follows.

- Normality test for the energy indices in India and crude oil volatility index (OVX)
- Stationarity test for the energy indices in India and crude oil volatility index (OVX)
- OLS Regression test for the energy indices in India and crude oil volatility index (OVX)
- Wavelet analysis for the energy indices in India and crude oil volatility index (OVX).

4.1. Normality Test for the Energy Indices in India and Crude Oil Volatility Index (OVX)

The results of descriptive statistics of daily returns of sample energy indices (BSE oil and gas, BSE power, CNX energy) and crude oil volatility index (OVX), during the study period from 2010 to 2023, are presented in Table 1. It is to be noted that the summary statistics, namely, mean, minimum, maximum, median, standard deviation (SD), skewness, kurtosis and the Jarque- Bera, were used to analyse the sample indices and OVX factor during the study period. It is clear from Table 1, that the mean value of OVX 0.0218 was the highest among other variables and it indicated a general upward trend, followed by BSE oil and gas, with a value of 0.0173, indicating a modest overall upward trend, BSE power, with a value of 0.0128, implying significant overall trend. CNX energy earned the lowest value 0.0093, suggesting a mild downward trend, on average during the study period. Mean

Table 1: The results of descriptive statistics for the returns of Energy Indices in India and Crude Oil Volatility Index (OVX) during the study period from January 01, 2010 to December 30, 2023

Descriptive Statistics	BSE OIL& GAS	BSE POWER	CNX ENERGY	OVX
Mean	0.0173	0.0128	0.0093	0.0218
Maximum	0.1448	0.4682	0.1076	0.8631
Minimum	−0.1268	−0.3301	−0.0795	−0.5759
Std. Dev.	0.0139	0.0164	0.0129	0.0567
Skewness	−0.3102	4.7187	0.6423	0.4703
Kurtosis	14.0327	245.5683	8.6840	29.6972
Jarque-Bera	17522	8456230	4872	102405
Sum Sq. Dev.	0.6692	0.9221	0.5754	11.0835
Observations	3444	3444	3444	3444

Source: Compiled from https://www.indiastat.com/and https://policyuncertainty.com/india_monthly.htmland computed using E-views of 11 version

values, for all of the sample indices and the OVX, were positive, indicating high returns over the study period. In terms of market unpredictability, as measured by the standard deviation of daily returns, the standard deviation of OVX 0.0567 was significantly higher than other indices, indicating the most significant price fluctuations. The standard deviation of BSE power, with a value of 0.0164, reported more significant price fluctuations compared to BSE oil and gas, which earned 0.0139. CNX energy, with a value of 0.0129, was between BSE oil and gas and BSE power in terms of price movement variability. It is to be noted that all four variables recorded positive skewness. In other words, the distribution of returns was skewed to the right. The kurtosis of all sample variables is >3. In other words, the distribution of returns was more peaked than a normal distribution. The Jarque-Bera test statistic was significant for all four indices. Overall, these descriptive statistics revealed that the returns of all four indices were not normally distributed. Hence the Null Hypothesis NH_1: There is no normal distribution among the crude oil volatility index (OVX) on sample Energy indices in India, was rejected during the study period.

4.2. Stationarity Test for the Energy Indices in India and Crude Oil Volatility Index (OVX)

Table 2 shows the results of stationarity, for daily returns of sample energy indices (BSE oil and gas, BSE power, and CNX energy) and crude oil volatility index (OVX), during the study period from 2010 to 2023. The present study employed the Augmented Dickey-Fuller (ADF) Said and Dickey (1984), and Phillips-Perron (PP) Tests (Perron (1988), to assess the stationarity of the sample factors. It is to be noted that all the sample variables attained significant levels of 1%, 5% and 10%. The result revealed that the P-values of sample energy indices and crude oil volatility index (OVX) were nearly zero (0.0000-0.0001), under ADF and Phillips Perron Tests during the study period. The statistical values of sample energy indices and crude oil volatility index (OVX) were less than that of test critical values. In other words, there was stationarity of the returns data of all sample variables during the study period. Hence the null hypothesis (NH_2) - There is no stationarity among the crude oil volatility index (OVX) on sample Energy indices in India, was rejected. The results of raw and return data series of the crude oil volatility index (OVX) on

Table 2: The results of unite root test for the returns of energy Indices in India and crude oil volatility index (OVX) during the study period from January 01, 2010 to December 30, 2023

Variables	ADF		PP	
	t-statistic	Prob.*	t-statistic	Prob.*
OVX				
Test statistic				
Test critical values	−61.6668	0	−62.8300	0.0001
1% level	−3.43206		−3.43206	
5% level	−2.86218		−2.86218	
10% level	−2.56716		−2.56716	
CNX ENERGY				
Test statistic	−57.9288	0.0001	−57.9399	0
Test critical values				
1% level	−3.43206		−3.43206	
5% level	−2.86218		−2.86218	
10% level	−2.56716		−2.56716	
BSE power				
Test statistic	−65.9823	0.0001	−65.5479	0.0001
Test critical values				
1% level	−3.43206		−3.43206	
5% level	−2.86218		−2.86218	
10% level	−2.56716		−2.56716	
BSE oil and gas				
Test statistic	−59.8008	0.0001	−59.7974	0
Test critical values				
1% level	−3.43206		−3.43206	
5% level	−2.86218		−2.86218	
10% level	−2.56716		−2.56716	

*Critical value at 1, 5, and 10% level of significant
Source: Compiled from https://www.indiastat.com/and https://policyuncertainty.com/india_monthly.htmland computed using E-views of 11 version

sample energy indices (namely BSE oil and gas, BSE power, and CNX energy) in India are presented in Figures 2 and 3.

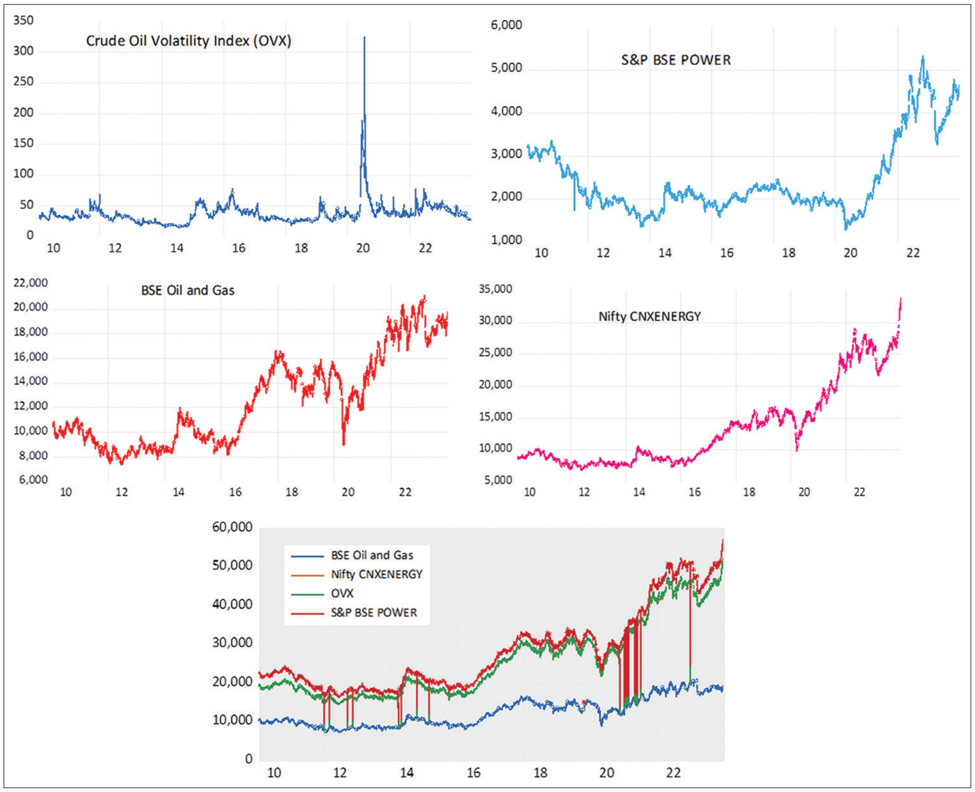
4.2.1. Graphical exposition of energy indices in India and crude oil volatility index (OVX)

The results of raw and return data series of the Crude Oil Volatility Index (OVX) on sample energy indices (namely BSE oil and gas, BSE power, and CNX energy) in India are presented in Figures 1 and 2.

4.3. OLS Regression Test for the Energy Indices in India and Crude Oil Volatility Index (OVX)

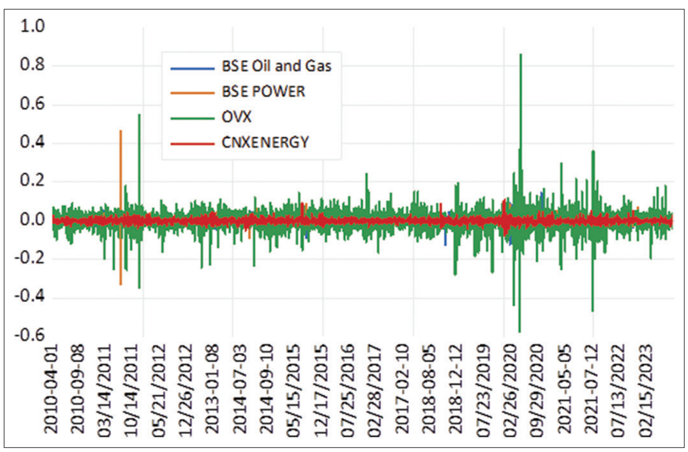
The results of OLS Regression, for the daily returns of sample energy indices (BSE oil and gas, BSE power, and CNX energy) and crude oil volatility index (OVX), during the study period from 2010 to 2023, are given in Table 3. It is worth noting that the coefficient values, for all the sample variables, were mixed (positive and negative), during the study period. For the analysis of the study, energy indices in India were considered as dependent variables. While the OVX was taken as the independent variable, during the study period. According to the Table, there was a positive value (0.0443) for BSE oil and gas but the values for CNX energy (−0.0015) and BSE power (−0.0871) were negative, during the study period. Further, the R2 was at 0.6709 during the study period. From the analysis of the F-statistic value, it was found that there was a positive value (4.0579). According to the Durbin-Watson analysis (2.4395), there were residuals but the value of R2 was at 0.6709 and coefficient values were positive (0.00683) while the values of F-statistic (4.0579) and

Figure 2: Graphical exposition of raw data series



Source: Compiled from https://www.indiastat.com/ and https://policyuncertainty.com/india_monthly.htmland computed using E-views of 11 version

Figure 3: Graphical exposition of return data series



Source: Compiled from https://www.indiastat.com/ and https://policyuncertainty.com/india_monthly.htmland computed using E-views of 11 version

Table 3: The results of OLS regression analysis for for the returns of Energy Indices in India and crude oil volatility index (OVX) during the study period from January 01, 2010 to December 30, 2023

Variable	Coefficient	Std. error	t-statistic	Prob.
Constant	0.00683	0.247	−3.727	0.000
CNXENERGY	−0.0015	0.0748	−0.0203	0.0438*
BSE_POWER	−0.0871	0.0636	−1.3713	0.0004**
BSE_OIL_AND_GAS	0.0443	0.0746	0.5938	0.0007**
R-squared	0.6709	Durbin-Watson stat		2.4395
F-statistic	4.0579	Prob (F-statistic)		0.5374
Independent variable: OVX				

*Significant at 1% level, **Significant at 10% level.

Source: Compiled from https://www.indiastat.com/and https://policyuncertainty.com/india_monthly.htmland computed using SPSS.

Prob (F-statistic) (0.5374) were low. Durbin-Watson statistic value (2.4395) indicated residuals. According to the analysis of Table 3, the coefficient of the CNX energy variable was negative and statistically insignificant at the 10% level. In other words, there was no statistically significant evidence to suggest that a change in CNX energy would lead to a change in OVX. The coefficient of the BSE power variable was negative and statistically significant at the 1% level, which indicated a statistically significant negative relationship between BSE power and OVX. A decrease in BSE PO was associated with an increase in OVX. The coefficient of the BSE oil and gas variable was positive and statistically significant at the 1% level, which reported a statistically significant positive relationship between BSE oil and gas and OVX. In other words, an increase in BSE oil and gas was associated with an increase in OVX. Hence the Null hypothesis (NH_3): There is no influence of the crude oil volatility index (OVX) on sample energy indices in India, was partially accepted.

4.4. Wavelet Analysis for the Energy Indices in India and Crude Oil Volatility Index (OVX)

4.4.1. Coherence function estimate

Figure 4, shows that crude oil volatility index (OVX) and CNXENERGY reported deep association between two series frequencies. It also represented the strongest coherence between periods of 500 and 1000, which corresponds to frequencies of 0.002-0.004 cycles per time unit. The values of the wavelet coherence range from 0 to 1, with higher values indicating stronger coherence. According to Figure 4, the wavelet coherence values were close to 1, in a large area extending diagonally from the bottom left to the top right of the plot. It also revealed strong coherence between the two series, across a wide range of scales or frequencies. Moreover, the COI is a triangular region that indicates the part of the wavelet coherence plot where the values are statistically significant.

Figure 4: Wavelet coherence analysis for the returns of crude oil volatility index (OVX) and CNXENERGY from 1st January 2010 to 30st December 2023

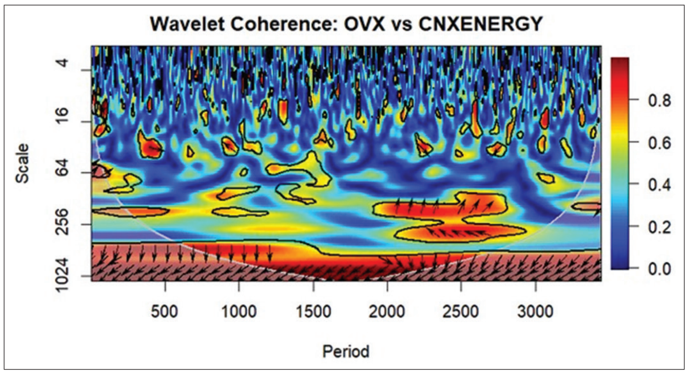


Figure 5: Wavelet coherence analysis for the returns of crude oil volatility index (OVX) and BSE POWER from 1st January 2010 to 30st December 2023

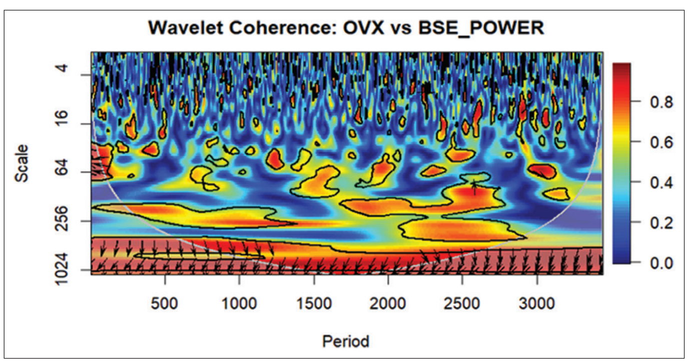


Figure 6: Wavelet coherence analysis for the returns of crude oil volatility index (OVX) and BSE OIL AND GAS from 1st January 2010 to 30st December 2023

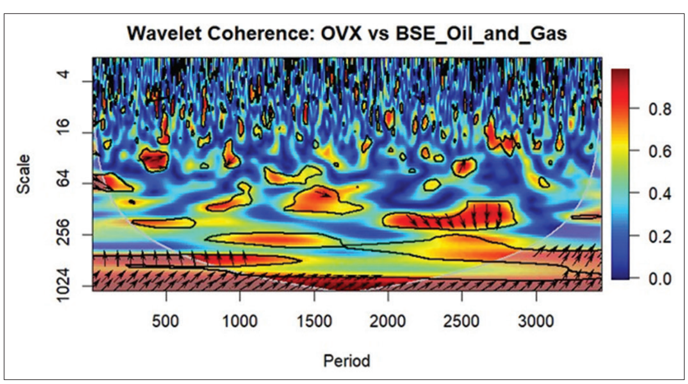


Figure 5, represents the Wavelet coherence analysis between OVX and BSE POWER, revealing a strong correlation in specific frequency ranges. High coherence was observed at low frequencies (around 3000 period) and high frequencies (around 4 period), indicating strong relationship between the two indexes at these timescales. However, the coherence was weak at other frequencies.

In Figure 6, wavelet coherence analysis between OVX and BSE OIL AND GAS, there is a consistent wavelet coherence pattern throughout most of the plot which reveals that the time series are highly correlated across a wide range of frequencies. Specifically, the strongest coherence is observed at lower frequencies (around period 3000), its evidence that there is a strong relationship between the low-frequency movements of the two series. The stronger coherence visualizes from the range 0-1. The wavelet coherence values are close to 1 in a large area extending diagonally from the bottom left to the top right of the plot.

4.4.2. Cross wavelet transform (XWT)

The Y- and X-axis of the cross wavelet transform show the scale frequency and time, respectively. To make the time-frequency easier to understand, it is divided into four cycles: Medium-scale (64-128 days), long-scale (128-256 days), and short-scale (16-32 and 32-64 days). Time-frequency analysis is a useful tool for identifying both low-frequency or gradual changes resulting from significant advances and high-frequency or fast changes with short-term effects while examining time series. The convenience of three stock indices with the crude oil volatility index (OVX) is displayed in the three Cross Wavelet Transform images. Cross wavelet transform analysis shows the significant covariance between the OVX and CNXENERGY, BSE POWER, BSE OIL and GAS from January 1st, 2010 to December 31st, 2023, to find out the distinctive period of specific three financial markets.

Figure 7 shows a considerable area of yellow and red power in the mid-frequency band (32-128 days) over the majority of the time series. In other words, there was considerable co-movement between the two series at these frequencies. In the early section of the time series, there was also some indication of co-movement at longer periodicities (256 days or more). The cone of influence is larger at lower frequencies and hence the results in this region are less dependable. The cross-wavelet power spectrum indicates a time-varying connection between the OVX and CNXENERGY series. The series co-moves most strongly at periodicities ranging from 32 to 128 days.

Figure 7: Cross wavelet transform for the returns of crude oil volatility index (OVX) and CNXENERGY from 1st January 2010 to 30st December 2023

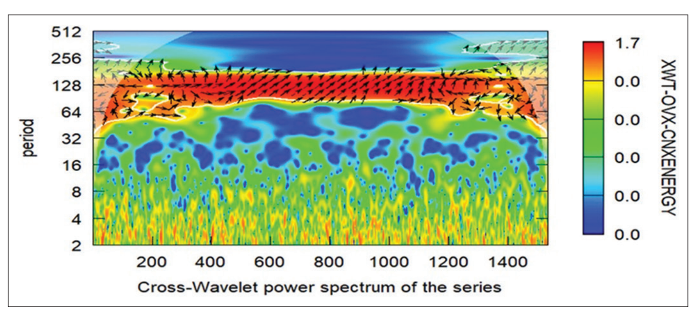


Figure 8: Cross Wavelet Transform for the returns of crude oil volatility index (OVX) and BSE POWER from 1st January 2010 to 30st December 2023

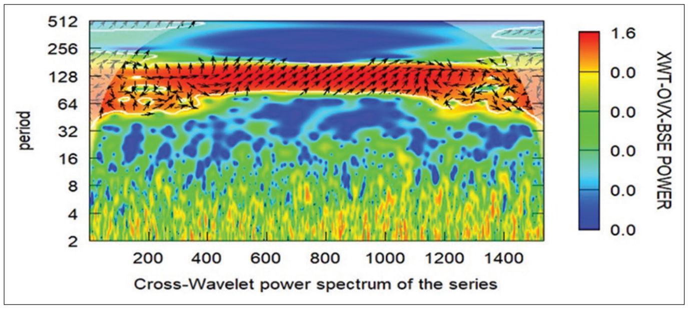
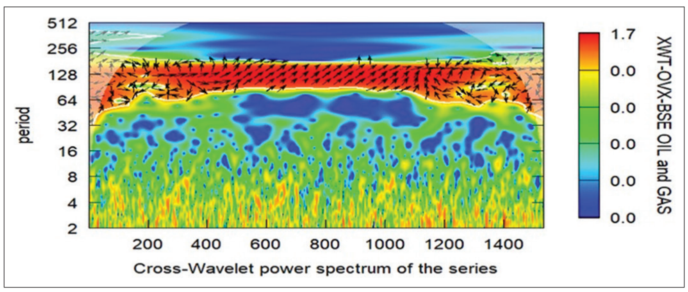


Figure 9: Cross wavelet transform for the returns of crude oil volatility index (OVX) and BSE OIL and GAS from 1st January 2010 to 30st December 2023



There was strong co-movement between OVX and BSE POWER. Figure 8 reveals that the OVX and BSE POWER reported a time-varying relationship, with the strongest co-movement at periodicities between 32 and 128 days. There were yellow and red colour regions in the middle of the spectrum, ranging from a period of roughly 32-128 days across most of the time series, indicating a strong correlation between the two series at these periodicities. There were also hints of co-movement at longer periods (above 256 days) in the earlier parts of the time series, although the colours were cooler (weaker) compared to the mid-frequency range. The cone-shaped white area, towards the bottom left corner, indicates the region where results might be less reliable due to edge effects from the wavelet transform.

Figure 9 shows the strong co-movement between OVX and OIL and GAS. It reveals that OVX and BSE OIL and GAS experienced a time-varying relationship, with the strongest co-movement at periodicities between 32 and 128 days. The yellow and red coloured regions in the middle of the spectrum, ranging from a period of roughly 32-128 days across most of the time series, established a strong correlation between the two series at these periodicities. The hints of co-movement were reported for longer periods (above 256 days) in the earlier parts of the time series, although the colours were cooler (weaker) compared to the mid-frequency range. The cone-shaped white area towards the bottom left corner indicates the region where results might be less reliable due to edge effects from the wavelet transform.

5. CONCLUSION

The initial intention of this research was to identify how OVX clouted the BSE OIL AND GAS, CNXENERGY and BSE POWER, based on the Indian vibrant economy. Finally, this study explored the intricate relationship, through the ordinary least squares (OLS) regression analysis and the Wavelet analysis, to explain the nonstationary time series with a powerful mathematical visual tool. The empirical results are evidence of an existing dynamic relationship and long-term significant influence on oil price volatility, as assessed by OVX on the selected BSE indices. The negative coefficient of the BSE POWER index suggests a negative relationship between rising volatility in oil prices and falling returns, which could be detrimental to the power sector. On the other hand, the basic features of the oil and gas sectors may account for the positive coefficient for BSE OIL AND GAS, which indicates that more volatility in oil prices translates into higher returns for this sector. The CNXENERGY coefficient is negative, indicating that oil volatility harms energy sector returns. This is consistent with the widely held belief that oil price shocks have unpleasant consequences. Moreover, the wavelet coherence analysis yielded diverse coherence patterns, indicating varying degrees of association between the OVX index and the three other financial indices (CNXENERGY, BSE_POWER, BSE_OIL_AND_GAS). CNXENERGY exhibited coherence at low frequencies while BSE_POWER and BSE_OIL_AND_GAS reported broader coherence, with the latter having the strongest overall link. These results highlight the need to consider volatility, in addition to oil price levels while examining the impact of oil on stock market performance. The study would contribute to the body of literature, by highlighting the OVX component and providing empirical data from an Indian perspective. However, it is crucial to recognize the limitations of the study. The study included only short study time and focused only on particular BSE indices. Subsequent investigations may examine effects on certain industries, utilize advanced methodologies, and examine how investors react to changes in OVX. Notwithstanding these limitations, the study would provide insightful information to scholars, investors, and policymakers that might help them create informed risk-management plans and strategies, to lessen the negative impacts of oil price volatility on the Indian stock market and economy.

REFERENCES

Amano, R.A., van Norden, S. (1998), Oil prices and the rise and fall of the US real exchange rate. Journal of International Money and Finance, 17(2), 299-316.

Arouri, M.E.H., Lahiani, A., Nguyen, D.K. (2011), Return and volatility transmission between world oil prices and stock markets of the GCC countries. Economic Modelling, 28(4), 1815-1825.

Basher, S.A., Sadorsky, P. (2006), Oil price risk and emerging stock markets. Global Finance Journal, 17(2), 224-251.

Bondia, R., Ghosh, S., Kanjilal, K. (2016), International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. Energy, 101, 558-565.

Charles, A., Darné, O. (2017), Forecasting crude-oil market volatility: Further evidence with jumps. Energy Economics, 67, 508-519.

Chen, H., Liu, L., Li, X. (2018), The predictive content of CBOE crude oil volatility index. Physica A: Statistical Mechanics and its Applications, 492, 837-850.

Choi, S.Y., Hong, C. (2020), Relationship between uncertainty in the oil and stock markets before and after the shale gas revolution: Evidence

from the OVX, VIX, and VKOSPI volatility indices. PLoS One, 15(5), e0232508.
Das, S. (2021), The time-frequency relationship between oil price, stock returns and exchange rate. Journal of Business Cycle Research, 17(2), 129-149.
Degiannakis, S., Filis, G., Floros, C. (2013), Oil and stock returns: Evidence from European industrial sector indices in a time-varying environment. Journal of International Financial Markets Institutions and Money, 26, 175-191.
Dutta, A. (2017), Modeling and forecasting oil price risk: The role of implied volatility index. Journal of Economic Studies, 44(6), 1003-1016.
Gençay, R., Selçuk, F., Whitcher, B. (2005), Multiscale systematic risk. Journal of International Money and Finance, 24(1), 55-70.
Genest, C., Rémillard, B., Beaudoin, D. (2009), Goodness-of-fit tests for copulas: A review and a power study. Insurance: Mathematics and Economics, 44(2), 199-213.
Global Oil Consumption 2022. (n.d.), Statista. Available from: https://www.statista.com/statistics/265239/global-oil-consumption-in-barrels-per-day [Last accessed on 2024 Jan 28].
Gormus, S., Tosato, F., Fan, Z., Bocus, Z., Kulkarni, P. (2014), Opportunistic RPL for reliable AMI mesh networks. Wireless Networks, 20(8), 2147-2164.
Hamilton, J.D. (2003), What is an oil shock? Journal of Econometrics, 113(2), 363-398.
He, K., Xie, C., Chen, S., Lai, K.K. (2009), Estimating var in crude oil market: A novel multi scale non-linear ensemble approach incorporating wavelet analysis and neural network. Neurocomputing, 72, 3428-3438.
He, Z., Zhong, C., Su, S., Xu, M., Wu, H., Cao, Y. (2012), Enhanced power-conversion efficiency in polymer solar cells using an inverted device structure. Nature Photonics, 6(9), 591-595.
Henriques, I., Sadorsky, P. (2008), Oil prices and the stock prices of alternative energy companies. Energy Economics, 30(3), 998-1010.
Jammazi, R. (2012), Oil shock transmission to stock market returns: Wavelet-multivariate Markov switching GARCH approach. Energy, 37(1), 430-454.
Kim, S., In, F. (2007), On the relationship between changes in stock prices and bond yields in the G7 countries: Wavelet analysis. Journal of International Financial Markets Institutions and Money, 17(2), 167-179.
Korley, M., Giouvris, E. (2022), The impact of oil price and oil volatility index (OVX) on the exchange rate in sub-Saharan Africa: Evidence from oil importing/exporting countries. Economies, 10(11), 272.
Kumar, S., Singh, J., Nanoti, S.M., Garg, M.O. (2012), A comprehensive life cycle assessment (LCA) of Jatropha biodiesel production in India. Bioresource Technology, 110, 723-729.
Managi, S., Okimoto, T. (2013), Does the price of oil interact with clean energy prices in the stock market? Japan and the World Economy, 27, 1-9.
Masih, M., Alzahrani, M., Al-Titi, O. (2010), Systematic risk and time scales: New evidence from an application of wavelet approach to the emerging Gulf stock markets. International Review of Financial Analysis, 19(1), 10-18.
Mazzeu, J.H.G., Veiga, H., Mariti, M.B. (2019), Modeling and forecasting the oil volatility index. Journal of Forecasting, 38(8), 773-787.
Nazlioglu, S., Erdem, C., Soytas, U. (2013), Volatility spillover between oil and agricultural commodity markets. Energy Economics, 36, 658-665.
Perron, P. (1988), Trends and random walks in macroeconomic time series: Further evidence from a new approach. Journal of Economic Dynamics and Control, 12(2-3), 297-332.
Reboredo, J.C. (2015), Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics, 48, 32-45.
Rua, A., Nunes, L.C. (2009), International comovement of stock market returns: A wavelet analysis. Journal of Empirical Finance, 16(4), 632-639.
Sadorsky, P. (2012a), Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. Energy Economics, 34(1), 248-255.
Said, S.E., Dickey, D.A. (1984), Testing for unit roots in autoregressive-moving average models of unknown order. Biometrika, 71(3), 599-607.
Sari, R., Hammoudeh, S., Soytas, U. (2010), Dynamics of oil price, precious metal prices, and exchange rate. Energy Economics, 32(2), 351-362.
Shahzad, U., Ferraz, D., Doğan, B., Aparecida do Nascimento Rebelatto, D. (2020), Export product diversification and CO_2 emissions: Contextual evidences from developing and developed economies. Journal of Cleaner Production, 276, 124146.
Torrence, C., Compo, G.P. (1998), A practical guide to wavelet analysis. Bulletin of the American Meteorological Society, 79(1), 61-78.
Torrence, C., Webster, P.J. (1999), Interdecadal changes in the ENSO-monsoon system. Journal of Climate, 12(8), 2679-2690.
Vu, T.N. (2018), Impact of Crude Oil Volatility on Stock Returns: Evidence from Southeast Asian Markets. Master's Thesis.
Wen, X., Guo, Y., Wei, Y., Huang, D. (2014), How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. Energy Economics, 41, 63-75.
Zhu, H.M., Li, R., Li, S. (2014), Modelling dynamic dependence between crude oil prices and Asia-Pacific stock market returns. International Review of Economics and Finance, 29, 208-223.