ON THE CO-movement of CRUDE, GOLD PRICES AND STOCK INDEX IN INDIAN MARKET

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ABSTRACT

This non-linear relationship in the joint time-frequency domain has been studied for the Indian National Stock Exchange (NSE) with the international Gold price and WTI Crude Price being converted from Dollar to Indian National Rupee based on that week’s closing exchange rate. Though a good correlation was obtained during some period, but as a whole no such cointegration relation can be found out. Using the Discrete Wavelet Analysis, the data was decomposed and the presence of Granger Causal relations was tested. Unfortunately no significant relationships are being found. We then studied the Wavelet Coherence of the two pairs viz. NSE-Nifty & Gold and NSE-Nifty & Crude. For different frequencies, the coherence between the pairs have been studied. At lower frequencies, some relatively good coherence have been found.

In this paper, we report for the first time the co-movements between Crude Oil, Gold and Indian Stock Market Index using Wavelet Analysis (both Discrete and Continuous), a technique which is most sophisticated and recent in market analysis. Thus for long term traders they can include gold and/or crude in their portfolio along with NSE-Nifty index in order to decrease the risk (volatility) of the portfolio for Indian Market. But for short term traders, it will not be effective, not to include all the three in their portfolio.

Keywords Wavelet Analysis · Time Series · Co-movement · National Stock Exchange of India · WTI Prices · Gold Prices

1 Introduction

In 2013 Wang [1] in his paper on gold as a hedging asset mentioned the statement by de Gaulle saying 'Gold has no nationality and is not controlled by governments'. In the introduction of the same paper, we find a review on how the research on Gold has been categorised into three groups. As pointed out by the author, the first group discusses the relationship between gold prices and macroeconomic variables such as exchange rate, interest rate, and income [2,5,42]. The second group discusses the factors affecting gold price fluctuations [3,43,44]. The third group discusses the long-term and short-term relationships between gold prices and the general price index as well as the effectiveness of gold in avoiding the risks of inflation [4,45,46,47]. Rest of the studies are mostly based on the linear relationship between gold price and macro-economic variables, and use time-series analysis [5,6,42]. Wang [1] also mentioned that the disadvantage of using linear models is that they cannot predict the relationships between variables under different situations. The author also claimed that, there is a non-linear relation between the exchange rates and gold prices based on sophisticated analysis models. Gold has been a hedge against Dollar and why this hedge has varied, has been discussed in the past [6]. Gold provided a safe haven for investors in the developed markets and has a weak safe haven in the emerging markets [7]. Gold is an excellent protective asset and its value rises due to the uncertainty involved in the introduction of new financial instruments [8]. There is a relationship between the open interests of equity futures, light sweet crude oil and Gold futures [9]. Gold works as a safe haven for stocks and not for bonds [10]. Moreover,
the hedging strategy works only for a period of not more than 15 trading days[10]. As a result of which traders and
investors from time to time kept Gold as a hedging tool.
Now, there have been several researches performed on the relation between stock markets, interest rates, inflation
and oil prices. Several such researches have been done on European markets[11]. Works on GCC (Gulf Cooperation
Council) countries have also been done on the oil exporting country’s perspective[12]. Increase in oil prices will create
a positive impact in the oil exporting countries, while it will create a negative impact on the oil importing countries[13].
Recently various works have been performed on the Chinese stock markets[14-17]. Based on Indian stock markets
too, several researches have been performed. Some claim there is a relationship between them[18,49]. But all these
researches were done assuming a linear relationship perspective. As a result of which, we are getting a contrasting
situation. This drawback is shunned and researches have also been done based on non-linear perspectives too[19-20].
However, the data used by both the groups of researchers had the same periodicity in time.
We can see that various researchers have worked on the interlinking between Gold Price, Crude and Indian Stock
Market index. There is a long term co-integration between them[21-22]. The above mentioned researches have been
done based on Augmented Dickey-Fuller test at levels and 1st differences; as well as Johansen’s system Co-integration
test. However, now sophisticated methods have been developed, which are being used to study the time-series with
different frequencies (or periodicities in time). This technique is known as Wavelet Analysis in literature. It basically
works on time-scale decomposition, time-frequency analysis etc. This helps in decomposing the frequency in order to
understand the market for the investors having different holding periods.
There have been many works carried out based on Wavelet Analysis. We find a relationship between Crude oil, Gold
and Shanghai Stock Exchange(Chinese Stock Market) by using Wavelet Analysis[23]. By Wavelet Analysis method, we find
that there is a co-movement between FTSE, DAX and CAC in which FTSE leads[24] (where these three market indices
correspond to UK, Germany and France). Based on Indian market too, there have been several studies conducted with
the help of wavelet analysis[58,59,60,61]. By Wavelet Analysis method, we find there is an important relation between
Indian stock market prediction and trading intervals [25]. Studies have been also reported on the relationship between
Indian stock market and world stock markets [26]. Wavelet Analysis is used to decompose the data for the prediction
of National Stock Exchange (NSE), the Indian Stock Market[27]. Wavelet Analysis was initially used to decompose
the data in the frequency domain, after which we get further enhancement in the prediction of NSE-Nifty (Nifty 50 is
the index for the first fifty companies of the NSE with respect to market capitalisation) by using artificial intelligence
algorithms like SVR and ANN [28]. Post 1997 we also find a high degree of coherence between all the Asian Gold
Markets across a group of frequencies [29]. We also find the relationship between the various Asian Stock Exchanges
and Bombay Stock Exchange (BSE) using Wavelet Analysis [30]. The scope of risk and portfolio diversification based
on Indian Stock Market perspective have also been studied [31].
So we can see that a large number of researches have been performed based on the Wavelet Analysis on the two Indian
Stock Markets(BSE and NSE). But as such no research has been performed on the study of co-movement between
Indian Stock Markets, Gold and Crude Oil Price based on the Wavelet Analysis. This paper tries to fill up that gap. As
of 2017, India is the 4th largest importer of crude oil, importing about 60.2 billion dollar oil that is 6.9 percent of the
global oil importing market[32]. As a matter of fact, India has the highest private gold holdings in the world, which is
about 24,000 metric tons thus surpassing the combined official gold reserves of the United States of America, Germany,
Italy, France, China and Russia[33].

2 Methodology: Description of Analysing Tools

2.1 Data Description

The data have been collected from various resources. The NSE-Nifty data have been collected from investing.com[34].
The Gold and WTI crude oil data have been collected from quandl[35,36]. We have also collected the Rupees vs Dollar
exchange rate(average of the bid-ask rate of USD/INR) for the corresponding time and multiplied it with the
corresponding values of Gold and Crude Oil so as to get the valid comparison between them[37]. We have collected the
weekly data from 5 November, 1995 to 8 August, 2018.

2.2 Methodology

We perform the correlation test between Gold, Crude Oil (after conversion to Indian Rupees) and NSE-Nifty Index
(Nifty 50 is the index for the first fifty companies of the NSE with respect to market capitalisation) over three different
domains. We then perform the Regression analysis. These are for time domain. For frequency domain analysis we first
performed the Fourier Transform. For joint time-frequency domain we decomposed the original time series into small
wavelets based on Haar Wavelet transformation and performed various statistical tests to be discussed subsequently in
this literature.
Correlation and Regression:

We have the Co-Variance of two variable as the statistical measure, which finds the degree to which the two variables move together; thus capturing the linear relationship between the two variables. It is being defined as:

\[
\text{cov}_{XY} = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{n-1}
\]

(1)

where the symbols have their usual meaning.

Standard deviation is a measure which indicates the amount of variation or dispersion of a set of values.

We have the regression model which describes the relationship between two variables (say X and Y) via the equation:

\[
Y_i = b_0 + b_1 X_i + \varepsilon_1, i = 1, \cdots, n
\]

The correlation coefficient is a measure of the strength of the linear relationship between two variables. The formula is given by:

\[
r_{XY} = \frac{\text{cov}_{XY}}{(\sum_{i=1}^{n} \sqrt{X_i - \bar{X}})(\sum_{i=1}^{n} \sqrt{Y_i - \bar{Y}})}
\]

We used the correlation coefficient to detect the strength of linear relation between the variables.

ANOVA Table

Analysis of Variance or ANOVA table has been found out for different pairs and the explanatory power of the regressions has been studied.

Augmented Dickey Fuller Test:

We performed the Augmented Dickey Fuller Test[39] for all three time series viz. NSE-Nifty index, Gold Prices and Crude Oil Prices. It helped us to check whether they have unit root or not[39]. Test for the presence of unit root is necessary so as to check whether the given data is stationary or not[40]. It is necessary as it eases the data analysis of the data under consideration. We then performed the same test on their first order difference.

The Augmented Dickey Fuller Test is given below:

\[
\Delta y_t = \alpha + \beta \ast t + \gamma y_{t-1} + \delta_1 \Delta \ast y_{t-1} + \cdots \delta_p \Delta \ast y_{t-p+1} + \epsilon_t
\]

The unit root test is then carried out for the null hypothesis that \( \gamma = 0 \) against the alternative hypothesis that \( \gamma < 0 \). Then the value of the test statistic is calculated and if the test statistic is less than the larger critical value, then the null hypothesis is rejected and no unit root is present.

2.3 Phillips-Perron Tests

We then use the Phillips-Perron Test to detect the presence of any Unit Root present in the data. The only difference between Augmented Dickey Fuller Test and Phillips-Pearson(PP) test is that the PP test makes a non-parametric correction to the t-statistic[56].

2.4 KPSS

We then performed the KPSS test[57] in order to detect the presence of any Unit root in the three time series data.

Johansen Co-integration Tests

We then performed the Johansen Co-integration Integration [48]on the time-series of NSE-Nifty index, Gold and Crude prices. It is basically a linear combination of the I(1) time series \( (X_1, X_2, X_3, \ldots, X_k) \) to get a new time series

\[
Y = b_1 X_1 + b_2 X_2 + \ldots + b_n X_k
\]

, which is I(0), i.e. integrated of order zero (0).
Fourier Transform

Fourier Transform of a function $f(x)$, denoted by $I[f(x)]$, is defined as

$$I[f(x)] = F(s) = \int_{-\infty}^{\infty} f(x)e^{isx}dx$$

We performed the Fourier Transform in order to detect if any frequency $s$ is present in the data? Where $s$ is the independent variable in this case.

2.4.1 Wavelet Analysis

We perform the Granger Causality test[38] on the data obtained by operating on them the Discrete Wavelet Transform. That is, basically we perform Granger Causality Test on different frequencies.

Discrete Wavelet Transform  We used the Haar Wavelet Transform[41] to decompose the signal into different frequencies. Haar Scaling Function is the simple unit-width, simple unit-height pulse function $\phi(t)$ and $\phi(2t)$ can be constructed from $\phi(t)$ by

$$\phi(t) = \phi(2t) + \phi(2t - 1)$$

Haar Wavelet Transform does not do the sampling and interpolation, thereby keeping the information intact. Here we represent the data as a linear combination of wavelet coefficients and scale coefficients.

As a matter of fact, if we want a construction from fine scale to coarser scale, the expansion coefficients at a lower level can be derived from a higher scale by the following relation:

$$c_j = \sum_m h(m - 2k)c_{j+1}(m)$$

where $j,k \in \mathbb{Z}$, $\mathbb{Z}$ is the set of integers.

And if we want a reconstruction from coarse scale to fine scale, the expansion coefficients of higher scale can be derived from lower scale by the following relation:

$$c_{j+1}(k) = \sum_m c_j(m)h(k - 2m) + \sum_m d_j(m)h_1(k - 2m)$$

where, $c_j$ represents the $i^{th}$ scaling coefficients; $d_j$ is the $j^{th}$ Wavelet coefficients, $h(x)$ being the filter. Discrete wavelet transform decomposes the data by separating the high frequency and low frequency. It has got the inverse relationship with scale. By increasing the frequencies we get lower scales. It is somewhat similar to Heisenberg’s uncertainty principle, we cannot measure position and the velocity of an object exactly, simultaneously.

Granger Causality  In 1969, Granger Causality was proposed by C.W.J. Granger [38] which basically says, a time-series $X$ is said to Granger cause $Y$, if the present $X$ values can predict future $Y$ values. We used the Vector Auto Regression (VAR) model to find the causality relation among the wavelet coefficients of Oil, Gold and Stock Index. Vector Autoregressive Model is performed in a multi-variate framework, with k-dimensional multi-variate time-series. A VAR model is represented as follows:

$$X(t) = a_1X(t - 1) + a_2X(t - 2) + a_3X(t - 3) + \ldots + a_kX(t - k) + \epsilon(t)$$

where $\epsilon(t)$ is the white noise. Our job is to find at least one $a_i$, so that we can declare that the time series $X_i$ can Granger cause $X_j$. This marks the end of Data Analysis as far as time domain and frequency domain are concerned. Now we shall move towards Data Analysis in joint Time-Frequency domain.

Continuous Wavelet Transform:  In the joint Time-Frequency domain, we study the relationship between Gold Price & NSE-Nifty and Crude Oil Price & NSE-Nifty Index for times and different time-period(or frequencies). We find out the Wavelet Coherence between Oil & NSE-Nifty and Gold & NSE-Nifty. Then the multiple wavelet coherence(being defined later) has been calculated and subsequently it has been compared with wavelet coherence(being defined later) of the pairs. But to do so, by virtue of Heisenberg’s uncertainty principle, we lose the information of either the frequency part or the time part.
A wavelet can be defined [50,51,52,53] as a real valued function \( \psi(\cdot) : \mathbb{R} \rightarrow \mathbb{R} \) such that
1. \( \int_{-\infty}^{\infty} \psi(t)dt = 0 \)
2. \( \int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1 \)

We then choose a reference wavelet known as mother wavelet. We have

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right)
\]

provided \( a \neq 0 \) and \( b \) are real constants. Here, we are having \( a \) as the scaling parameter and \( b \) as the translation parameter. Unlike Fourier analysis, we have a variety of mother Wavelets, which we can use based on our requirements.

Thus, we define the Continuous Wavelet Transform as

\[
W_{\psi}[f](a, b) = \int_{-\infty}^{\infty} f(t) \overline{\psi\left(\frac{t-b}{a}\right)} dt
\]

where \( \overline{\psi} \) is the complex conjugate of \( \psi \).

From the square of the amplitude \( |W_{\psi}|^2 \), known as the Wavelet Power Spectrum, we can determine the variance of the time-series under consideration for various frequencies, by virtue of Wavelet Power Spectrum; where large power indicates higher variances between the two time series and vice versa. The Continuous Wavelet Transform should satisfy the following condition:

\[
C_{\psi} = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty
\]

Wavelet Coherence This is basically the correlation counterpart in time-frequency domain of the correlation in time domain. We have the Wavelet Transform of two Time-series \( x(t) \) and \( y(t) \) as \( W_{x,y}^n = W_x^n W_y^n \). \( W_y^n \) represents the complex conjugate of the wavelet transform of the time series \( y(t) \). Then we get the cross-wavelet power spectrum as \( |W_{x,y}^n| \). This will give us the variance between the two time series at different frequencies. The mathematical formula for the wavelet coherence is given below:

\[
R(x, y) = \frac{|S(s^{-1}W_{x,y}^n)|}{S(s^{-1}|W_x^n|) \overline{S(s^{-1}|W_y^n|) \overline{}}}^{\frac{1}{2}}
\]

S being the smoothing process.[54,55]

Multiple Wavelet Coherence Multiple Wavelet Coherence is just the counterpart of multiple correlation. It is basically done for time-frequency domain and is useful to detect wavelet coherence of a group of independent time series on a dependent one. For three time series \( x(t) \), \( y(t) \) and \( z(t) \) we get:

\[
R(x, y) = \frac{|S(s^{-1}W_{x,y}^n)|}{S(s^{-1}|W_x^n|) \overline{S(s^{-1}|W_y^n|) \overline{}}}^{\frac{1}{2}}
\]

\[
R^2(y, x) = R(y, x). R(y, x)^\ast
\]

\[
R(x, z) = \frac{|S(s^{-1}W_{x,z}^n)|}{S(s^{-1}|W_x^n|) \overline{S(s^{-1}|W_z^n|) \overline{}}}^{\frac{1}{2}}
\]

\[
R^2(z, x) = R(z, x). R(z, x)^\ast
\]

\[
R(z, y) = \frac{|S(s^{-1}W_{z,y}^n)|}{S(s^{-1}|W_z^n|) \overline{S(s^{-1}|W_y^n|) \overline{}}}^{\frac{1}{2}}
\]

\[
R^2(y, z) = R(y, z). R(y, z)^\ast
\]

We then calculate the Multiple Wavelet Coherence as follows:

\[
RM^2(z, x, y) = \frac{R^2(z, y) + R^2(z, x) - 2Re[R(z, y). R(z, x)^\ast . R(x, y)^\ast]}{1 - R^2(x, y)}
\]

This will give the amount of the contribution of the independent time series \( x(t), y(t) \) on the dependent time series \( z(t) \) at a specific time and frequency.
3 Programming, Results and Discussions

The codes for this research have been written partly in R Programming Language and partly in Python. To specifically study the relation between the three time series we first studied the correlation between Crude & NSE-Nifty and then Gold & NSE-Nifty for three different periods. The specific time has been chosen based on our visual inspection. Then we studied the ANOVA table followed by ADF tests. These were part of our time domain tests. As far as frequency domain is concerned, we studied the Fourier Transform result to detect any hidden frequency. Subsequently, we decomposed the original time series and studied by virtue of the Granger Causality for various frequencies.

3.1 Correlation

By visual inspection, we find three periods where the participating time series will be either positively or negatively correlated. The first period is chosen from 0 week to 200 week, the next period is chosen from 201 week to 700 week and the last period is chosen from 700 week to 1200 week. The results are shown below:

| Period       | \( r_{NG} \) | \( r_{GO} \) | \( r_{NO} \) |
|--------------|--------------|--------------|--------------|
| 0-200 weeks  | -0.22601402  | 0.2157788    | 0.33104342   |
| 200-700 weeks| 0.8840319    | 0.83914254   | 0.8587848    |
| 700-1200 weeks| -0.55126758  | 0.52345134   | -0.25074974  |

The weekly data time series from 5 November 1995 to 8 August 2018 has been shown in the Fig. 1:

As we can see from the graph that till 200 week Crude and NSE-Nifty were a bit correlated but Gold was not correlated with them. From 200 - 700 weeks the three time series were correlated and after 700 week, it has got messed up. All these are evident by simple inspection. But it should be quantified. Also we can see that there is a frequency mismatch. In the next ANOVA table, we can see the regression part:

3.2 ANOVA Table

From the ANOVA table (Fig. 2) we can see that the coefficients are statistically significant. The F-statistic is also showing that the coefficients are statistically significant at 5% and 2.5% . Here we can see the Adj. R-squared is 0.848 which means that 84.8 percent of the variations of the dependent variable is explained by the independent variable. But the Durbin-Watson test shows that the error terms are positively correlated. So there may be any non-linear relationships.

3.3 Augmented Dickey Fuller Test

We, then carried out the ADF test to find out the order of integration for the three time series, i.e. Crude, Gold and NSE-Nifty.

| TimeSeries  | ADF Statistics | p.value | lags |
|-------------|----------------|---------|------|
| Oil         | -1.908         | 0.329   | 10   |
| \( \Delta \)Oil | -9.327        | 0.000000| 9    |
| Gold        | -0.985         | 0.759   | 21   |
| \( \Delta \)Gold | -6.277        | 0.000000| 23   |
| NSE-Nifty   | 1.071          | 0.995   | 3    |
| \( \Delta \)NSE – Nifty | -19.773       | 0.000000| 2    |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10 %                  | -2.57           |
| 5 %                   | -2.86           |
| 1 %                   | -3.44           |
Figure 1: The graph depicting the asset value movements during the period Nov 1995 to Aug 2018. The asset values of Crude, Gold and NSE-Nifty are expressed in India National Rupees. The color codes are: Green (Crude), Orange (Gold) and Blue (NSE-Nifty).

Trend: No Trend

| TimeSeries | ADF Statistics | p.value | lags |
|------------|----------------|---------|------|
| Oil        | -0.409         | 0.533   | 10   |
| ∆Oil       | -9.307         | 0.000000| 9    |
| Gold       | -0.109         | 0.647   | 21   |
| ∆Gold      | -6.265         | 0.000000| 23   |
| NSE-Nifty  | 2.620          | 0.999   | 3    |
| ∆NSE−Nifty | -22.494        | 0.000000| 1    |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10%                   | -1.62           |
| 5%                    | -1.94           |
| 1%                    | -2.57           |
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Figure 2: The ANOVA table showing the power of regression for the three time series

| Trend: Constant and Linear Trend |
|-----------------------------------|
| TimeSeries | ADF Statistics | p.value | lags |
|------------|----------------|---------|------|
| Oil        | -3.180         | 0.088   | 10   |
| ΔOil       | -9.324         | 0.000000| 9    |
| Gold       | -1.163         | 0.918   | 21   |
| ΔGold      | -6.277         | 0.000000| 23   |
| NSE-Nifty  | -1.714         | 0.745   | 3    |
| ΔNSE – Nifty| -19.865     | 0.000000| 2    |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10%                   | -3.13           |
| 5%                    | -3.41           |
| 1%                    | -3.97           |

So clearly we can see that it is a I(1) series i.e. it is integrated of order one (1).

3.4 Phillips-Perron Test

We, then carried out the Phillips-Pearson test to find out the order of integration for the three time series, i.e. Crude, Gold and NSE-Nifty.
Trend: Constant

| TimeSeries     | ADF Statistics | p.value | lags |
|----------------|----------------|---------|------|
| Oil            | -1.745         | 0.408   | 23   |
| ΔOil           | -33.751        | 0.000000| 23   |
| Gold           | -0.907         | 0.786   | 23   |
| ΔGold          | -34.238        | 0.000000| 23   |
| NSE-Nifty      | 1.121          | 0.995   | 23   |
| ΔNSE – Nifty   | -33.306        | 0.000000| 23   |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10 %                  | -2.57           |
| 5 %                   | -2.86           |
| 1 %                   | -3.44           |
Trend: No Trend

| TimeSeries  | ADF Statistics | p.value   | lags |
|------------|----------------|-----------|------|
| Oil        | -0.257         | 0.593     | 23   |
| ΔOil       | -33.770        | 0.000000  | 23   |
| Gold       | -0.032         | 0.674     | 23   |
| ΔGold      | -34.243        | 0.000000  | 23   |
| NSE-Nifty  | 2.667          | 0.999     | 23   |
| ΔNSE – Nifty | -33.276   | 0.000000  | 23   |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10 %                  | -1.62           |
| 5 %                   | -1.94           |
| 1 %                   | -2.57           |
Trend: Constant and Linear Trend

| TimeSeries   | ADFStatistics | p.value | lags |
|--------------|---------------|---------|------|
| Oil          | -2.900        | 0.162   | 23   |
| ∆Oil         | -33.738       | 0.000000 | 23   |
| Gold         | -1.106        | 0.928   | 23   |
| ∆Gold        | -34.224       | 0.000000 | 23   |
| NSE-Nifty    | -1.827        | 0.692   | 23   |
| ∆NSE – Nifty | -33.348       | 0.000000 | 23   |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10 %                  | -3.13           |
| 5 %                   | -3.41           |
| 1 %                   | -3.97           |

So clearly we can see that it is a I(1) series i.e. it is integrated of order one (1).

3.5 KPSS

We then carried out the Phillips-Pearson test to find out the order of integration for the three time series, i.e. Crude, Gold and NSE-Nifty.
Trend: Constant

| TimeSeries | ADF Statistics | p.value | lags |
|------------|----------------|---------|------|
| Oil        | 3.783          | 0.000000| 23   |
| ΔOil       | 0.033          | 0.965   | 23   |
| Gold       | 3.456          | 0.000   | 23   |
| ΔGold      | 0.255          | 0.182   | 23   |
| NSE-Nifty  | 4.647          | 0.000   | 23   |
| ΔNSE – Nifty | 0.308      | 0.129   | 23   |

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10%                   | 0.35            |
| 5%                    | 0.46            |
| 1%                    | 0.74            |
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Trend: Constant and Linear Trend

| TimeSeries | ADF Statistics | p.value | lags |
|------------|---------------|---------|------|
| Oil        | 0.394         | 0.000   | 23   |
| ∆Oil       | 0.031         | 0.856   | 23   |
| Gold       | 0.508         | 0.000   | 23   |
| ∆Gold      | 0.251         | 0.005   | 23   |
| NSE-Nifty  | 0.715         | 0.000   | 23   |
| ∆NSE – Nifty | 0.029     | 0.883   | 23   |

∆ being the first order differences

The critical value for different levels of significance for this test is:

| Level of Significance | Critical Values |
|-----------------------|-----------------|
| 10 %                  | 0.12            |
| 5 %                   | 0.15            |
| 1 %                   | 0.22            |

So clearly we can see that it is a I(1) series i.e. it is integrated of order one (1).

3.6 Johansen Cointegration Test

We now go for the Johansen cointegration test which is done by the help of R urca library. The results are shown below:

Test type: trace statistic , with linear trend

Eigenvalues (lambda):

0.0088648918 0.0013532634 0.0006105299

Values of test statistic and critical values of test:

| Hypothesis | teststatistics | 10pct | 5pct | 1pct |
|------------|----------------|-------|------|------|
| r <= 2     | 0.72           | 6.50  | 8.18 | 11.65|
| r <= 1     | 2.33           | 15.66 | 17.95| 23.52|
| r = 0      | 12.89          | 28.71 | 31.52| 37.22|

Eigenvectors, normalised to first column: (These are the cointegration relations)

| Hypothesis | a.12        | b.12        | c.12        |
|------------|-------------|-------------|-------------|
| a.12       | 1.00000000  | 1.00000000  | 1.00000000  |
| b.12       | -0.06039987 | -0.2392422  | 0.2546972   |
| c.12       | -0.06972624 | -2.2453992  | -2.0694282  |

Taking the Eigenvectors, we can formulate an equation, \( s = 1 \times Oil - 0.06039987 \times Gold - 0.06972624 \times NSE - Nifty \) and plot it graphically in Fig. 3 to see whether it is Stationary or not. Moreover from the table above we can very well understand that the time-series are not co-integrated.
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Figure 3: The plotting of the cointegrated portfolio. The portfolio has been calculated using the relation $s = 1 \ast Oil - 0.06039987 \ast Gold - 0.06972624 \ast NSE - Nifty$, the details of which are discussed in Section 3.4

3.7 Discrete Wavelet Transform

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Scale 1 (2-4 weeks)

| DependentVariable | IndependentVariable | F – stat | Prob.   |
|------------------|---------------------|----------|---------|
| Crude            | NSE – Nifty         | 4.1512   | 0.006325* * |
| NSE – Nifty      | Crude               | 0.9627   | 0.41    |
| Gold             | NSE – Nifty         | 0.4798   | 0.6964  |
| NSE – Nifty      | Gold                | 1.7937   | 0.1472  |

Scale 2 (4-8 weeks)

| DependentVariable | IndependentVariable | F – stat | Prob.   |
|------------------|---------------------|----------|---------|
| Crude            | NSE – Nifty         | 2.2017   | 0.08804 |
| NSE – Nifty      | Crude               | 1.3195   | 0.2682  |
| Gold             | NSE – Nifty         | 1.9166   | 0.127   |
| NSE – Nifty      | Gold                | 2.0308   | 0.1097  |

Scale 3 (8-16 weeks)
| Dependent Variable | Independent Variable | F – stat | Prob. |
|--------------------|----------------------|----------|-------|
| Crude              | NSE – Nifty          | 1.2056   | 0.3101|
| NSE – Nifty        | Crude                | 0.8665   | 0.4602|
| Gold               | NSE – Nifty          | 0.9789   | 0.4047|
| NSE – Nifty        | Gold                 | 0.5528   | 0.6471|
Scale 4 (16-32 weeks)

| Dependent Variable | Independent Variable | F - stat | Prob.  |
|--------------------|----------------------|----------|--------|
| Crude              | NSE – Nifty          | 2.0094   | 0.1215 |
| NSE – Nifty        | Crude                | 3.1395   | 0.03129* |
| Gold               | NSE – Nifty          | 0.996    | 0.4005 |
| NSE – Nifty        | Gold                 | 0.9025   | 0.4449 |

Scale 5 (32-64 weeks)

| Dependent Variable | Independent Variable | F - stat | Prob.  |
|--------------------|----------------------|----------|--------|
| Crude              | NSE – Nifty          | 0.9623   | 0.4248 |
| NSE – Nifty        | Crude                | 0.306    | 0.8208 |
| Gold               | NSE – Nifty          | 1.6423   | 0.203  |
| NSE – Nifty        | Gold                 | 0.5822   | 0.6318 |

Scale 6 (64-128 weeks)

| Dependent Variable | Independent Variable | F - stat | Prob.  |
|--------------------|----------------------|----------|--------|
| Crude              | NSE – Nifty          | 1.8376   | 0.2185 |
| NSE – Nifty        | Crude                | 1.5133   | 0.2838 |
| Gold               | NSE – Nifty          | 1.3021   | 0.3389 |
| NSE – Nifty        | Gold                 | 0.3033   | 0.8224 |
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With the help of Haar a trous wavelet transform, we decompose the original time-series into different scales. There are seven scales all together, being decomposed. We then study the Granger Causalities for the two different pairs viz. NSE-Nifty & Crude and NSE-Nifty & Gold. We have checked it by virtue of F-test. as seen from the tables, we could only find a relationship for the scale of 2-4 weeks; 4-8 weeks and 16-32 weeks. For the 2-4 weeks scale, we could see NSE-Nifty granger cause Crude at 1% level of significance. For the scale of 4-8 weeks, NSE-Nifty granger cause Crude at 10% level of significance. For the 16-32 weeks Crude Granger cause NSE-Nifty at 5% level of significance. For other pairs there are no granger causal relations.

Unlike a number of nexuses as reported for the Chinese Market [19], as such here for the Indian markets, we are unable to find a large number of such nexuses.

3.8 Fourier Transform

We performed the Fourier Transform (Fig. 4) for a range of frequencies in 0-500 (week)$^{-1}$ range inorder to detect any latent frequency present therein for the NSE-Nifty data. Unfortunately there is no frequency detected. As seen from the graph, it is highest for $\omega = 0$ (zero). As for explanation, 1 (week)$^{-1}$ is defined as one cycle per week.

3.9 Wavelet Coherence

Wavelet Coherence works on a similar motive as that of a correlation method. We performed the Cross Wavelet Coherence Test [62] for NSE-Nifty & Gold, then NSE-Nifty & Crude and Multiple Wavelet Coherence[62] for all the three. We have a heat map which indicates the amount of coherence between the participating time-series. Wavelet coherence graph of both NSE-Nifty & Gold and NSE-Nifty & Crude have been studied. Horizontal axis depicts the time in multiple of 50 weeks whereas vertical axis depicts the time-period. We should note here, the unit of frequency used was "1/week" earlier. But now onwards for Wavelet Analysis we shall use the term week (always written in italics) to mean the frequency.

For the NSE-Nifty & Gold nexuses (Fig. 5), we can see that in shorter time-periods there is no indication of coherence for all the time from November 1995 to August 2018. From 400 weeks to 800 weeks for the low frequency zones of 64-128 week; 0 week to almost 800 weeks in the low frequency zones of 128-256 week; and for initial few weeks of the data in all frequency levels, we get relatively better coherence for NSE-Nifty & Gold. But still there are small patches of absence of high power levels in many inbetween cases.

Regarding crude oil (Fig. 6), there was initially no coherence for any of the low frequency zones. But from 2003, the wavelet coherence gradually increased, though it is not the best but still better.

It now appears from our studies that, there is coherence for low frequencies (64-128 week and 128-256 week), but no coherence for high frequencies (2-4 week, 4-8 week, 8-16 week, 16-32 week and 32-64 week). For the initial few weeks in all frequencies; and in the 400-800 weeks in the low frequency zones of 64-128 week; we get relatively better coherence as far as the NSE-Nifty & Oil is concerned. For the NSE-Nifty, Gold and Oil multiple coherence test, we get a higher coherence in the initial few weeks in all the frequency zones. Later on, during 400-800 weeks in the frequency zones of 6-7 week approximately, we get a good coherence. Thus for long term traders they can include gold and/or crude in their portfolio along with NSE-Nifty index in order to decrease the risk(volatility) of the portfolio for Indian Market. But for short term traders, it is advisable, not to include all the three in their portfolio.

4 Conclusions

In this paper, we undertook a research based on the time domain, frequency domain and again on joint time-frequency domain for the three variables Crude, Gold and NSE-Nifty. The correlation tests indicate a good correlation on some particular time interval. The ANNOVA table indicates good regression but with a positive serial correlation. Cointegration tests show that there is no relation among the three time-series data. We then perform the Fourier Transformation for frequency domain and get no corresponding frequencies for the time series. Granger Causality Tests were performed. We did not find any economically viable causal relationships for any pairs with the help of
Figure 4: Fourier Transform for a range of frequencies in 0 to 500 (week)⁻¹ in order to detect any latent frequency present therein for the NSE-Nifty data. (There is no frequency detected)
Granger Causality Tests. For joint time-frequency domain we perform the Continuous Wavelet Coherence tests to determine the coherence between the two pair of time series. With respect to the correlations, we find that the pairs; NSE-Nifty & Gold and NSE-Nifty & Crude are not correlated till first 200 weeks. But after 200 weeks till 700 weeks there is a very high correlation (more than 0.80 for both the pairs of time-series). This is basically a structure broken point. But after that, till August, 2018; we can not see any such correlation between the two pairs. Next we find an adjusted R-squared equal to 0.848, but the DW test shows a value of 0.7, which indicates positive serial correlation. Cointegration test shows no indication of any relationships between the three time-series data. Fourier Transform shows no presence of frequencies for the NSE-Nifty data. We find three Granger causal relations for different frequencies, but they are unidirectional. We then execute the Continuous Wavelet Transform to detect the coherence test. A lot of coherence has been established for different time-zones at different frequencies. So we get to know, the otherwise relationships which had high serial-correlation, no Cointegration relationships and very few irrelevant Granger Causal relationships.
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Summary of Analysis

| Correlation Tests: As such no great Correlation found for the entire period except from 200th week to 700th week |
|-------------------------------------------------------------|
| Regression Analysis: Error Terms positively Correlated       |
| ADF, PP, KPSS Tests: Found the three data-sets are integrated of order one. |
| Johansen Co-integration Test: No cointegration exists between the three data-sets |
| Fourier Test: No hidden frequency detected                   |
| Granger Causality on Discrete Wavelet Transform: No economically viable cause-effect relations detected |
| Continuous Wavelet Transform: Some great coherence values are found corresponding to some particular frequencies |

Figure 6: NSE-Nifty-Crude Wavelet Coherence. Here the Period (along vertical axis) is in week, and Time (along horizontal axis) is in week. The vertical scale on the right side is the normalized colour coded value of Power in the power spectrum.
Figure 7: NSE-Nifty-Crude Multiple Wavelet Coherence. Here the Period (along vertical axis) is in week, and Time (along horizontal axis) is in week. The vertical scale on the right side is the normalized colour coded value of Power in the power spectrum.

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