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Empirical Investigation into the Interlinkages Between the Price Movements of Energy Commodities and Stock Market in India

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Abstract

The present study is an attempt to empirically inquire into the behaviour of and integration between energy commodity prices and the benchmark index of the Indian securities market. For this, two prime energy commodities are considered, i.e., crude oil and natural gas and the Nifty 500, the broader market index of India's National Stock Exchange (NSE). The inquiry is based on data for the daily spot price (FUTCOM) of crude oils and natural gas in the evening session from January 1, 2017, to September 30, 2024, from the Multi Commodity Exchange of India and the daily close price of Nifty 500 index from the National Stock Exchange of India. Firstly, the series are tested for stationarity and transformed in the log return form. Next, a preliminary analysis is performed using graphical and descriptive methods. Then, the times series approach of the Vector Autoregressive (VAR) model, the Granger causality and the Johansen cointegration are applied to investigate the inter-relation among the three variables in the short and long run. The variables are found to be sensitive to external effects of the Covid-19 pandemic. Results establish bidirectional causality between the crude oil prices and the Nifty 500 index. Long-term equilibrium relationships among all three variables are discovered using the cointegration test. The study concludes that the connectedness among the trio variables is time-varying. The results have practical implications for the benefit of investors, traders, arbitrageurs, and managers in hedge and mutual funds, as they can consider the findings while designing and reframing risk management and hedging strategies. Similarly, the empirical results can benefit policymakers when drafting and designing policies governing the commodities and equity markets.

Keywords*: energy commodity, crude oil, natural gas, cointegration, stock market, causality*

1. Introduction

Crude oil and natural gas are the two prominent sources of energy that serve as a pivotal factor in an economy's development. Globally, India is the third largest oil-consuming country after the USA and China (Terra Nova, T. 2024). Further, it is experiencing a tremendous growth in consumption of energy from 26,822 Petajoules (PJ) in 2013-14 to 35,159 Petajoules (PJ) in 2022-23 (Provisional). Moreover, 6.48% of total energy consumption increased from 2021-22 to 2022-23 (Ministry of Statistics and Program Implementation, 2024). Natural gas consumption in India is also rapidly growing owing to population growth and economic development, reflecting a significant shift towards cleaner energy. India relies heavily on imports to fulfil its constantly growing oil and natural gas demand. India imports approximately 83% of its crude oil and 47% of its natural gas. Further, about 30% of India's total energy consumption is met by crude oil. The price of these two commodities is driven by the demand, supply and geopolitical factors that significantly impact other

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sectors of the economy. Crude oil and natural gas prices are subject to more significant uncertainty that might result in low investment, less production and reduced aggregate output. It affects the performance of various industries and sectors, ultimately affecting the stock market performance, a barometer of the economy. Thus, the volatility in oil and natural gas prices significantly impacts economic and financial structures and influences stock market returns. Hence, it is important to identify the underlying dynamics between the energy commodity and equity markets.

Many studies have shown that volatility in the prices of these commodities affects the financial market. Many traders dealing in the commodity markets shift to stock markets to hedge investment risks and optimize returns. There is growing interest among researchers in understanding the contagion and interconnection between the commodity and stock markets driven by increasing uncertainty in both sectors and the significance of these markets for portfolio diversification and hedging risk (Mensi W. et al., 2022).

Extensive literature is available on assessing the inter-relationship between the commodities and stock market as aggregate and at sectoral levels in developed and emerging economies, with a few studies covering Indian markets. We were motivated to identify how the securities market in India responds to price shocks, particularly in the two leading energy commodities, crude oil and natural gas, which play an important role in the development of the economy.

This study aims to assess the overall performance of the equity market and the energy commodity market. It will also examine the cointegration and causal effect between the price movements of two prime energy commodities, crude oil and natural gas, and the stock market, focusing on India.

The significance of this research lies in providing informed knowledge on the performance and interlinkages between the energy and equity markets in India to investors, portfolio managers, and policymakers with empirical evidence using Vector Autoregressive (VAR) model, cointegration, and causal methodologies on daily data spanning from January 2017 to September 2024, covering more than seven years that includes the periods before, during, and after COVID-19.

The contribution of our study can be summarised as follows. Initially, we provide the performance evaluation of the stock market by considering a broader benchmark index, i.e., the Nifty 500 index and the energy commodity market represented by crude oil and natural gas based on risk and return parameters. Then, considering the significance of the trio of crude oil, natural gas and equity investments for short-term (speculators and arbitrageurs) as well as long-term (mutual and hedge funds) investors, we build the cointegrating and causality models helpful in framing mixed assets portfolio and effectively hedging the risk in the financial market.

The structure of the paper is as follows: Section 2 provides a review of the relevant literature. Section 3 outlines the data used in the study. Section 4 details the research methodology. Section 5 presents the results along with a discussion. Lastly, Section 6 concludes the study, offering policy recommendations and suggesting directions for future research, followed by references and appendix section.

2. Literature Review

Many studies that focused on similar variables using various statistical techniques are reviewed to get the knowledge of existing literature of the interconnectedness of commodity and stock markets across nations. Anna Creti et al. (2013) identified that the correlations between the commodity and stock markets are highly volatile, especially from the financial crisis of 2007-08 onwards, which led to the growing financialization of commodity markets. They investigated the correlation between the price returns of 25 commodities and the stock market using GARCH methodology involving the study period from January 2001 to November 2011. Similar results were obtained by Marco J. L. et al. (2016), who examined the correlation between the returns from commodity and equity and its implications for asset allocation using the time-varying Bayesian Dynamic Conditional Correlation Model. They identified higher volatility between the two variables and concluded that joint modelling of equity and commodity prices yields accurate forecasts. Syzdykova, A. & Azretbergenova, G. (2024) examined the asymmetric effect of oil prices on exchange rates and stock market index returns in Kazakhstan by applying nonlinear ARDL cointegration technique over monthly data from January 2010 to February 2024. It was found that changes in oil prices, whether positive or negative, significantly affected the Kazakhstan stock exchange (KASE) returns and the exchange rates.

Numerous recent studies have examined spillover effects between the various sectors and markets. One such study by Elsayed, A.H. et al. (2020) analyzed the volatility spillover mechanism between the energy markets and stock prices of seven major global securities markets during 2000-2018 using time domain interlinkages techniques of Diebold and Yilmaz. They identified an insignificant contribution of volatility in the energy sector to the global securities market. In the clean energy market, the major transmitters of volatility were the returns from the World Stock Index and the World Energy Index. Further, their study identified a strong impact of the energy market on the global financial markets. Maghyereh, Aktham I., et al. (2016) explored the oil and equities directional connectedness using the implied volatility indexes, taking samples from the eleven global stock exchanges from 2008-2015. Their research established the bi-directional information spillovers between the two markets across the studied countries. However, the transmission from oil to equity markets significantly contributed to the linkages between the two.

To understand the impact of COVID-19, Lucey, Brian and Ren, Boru (2023) examined dynamic connectedness between the sustainability indices, equities and energy assets employing the CAViaR-TVP-VAR technique on daily data about the period October 14, 2014 – August 14, 2022. They observed that total risk connectedness was at a medium level. COVID-19 also had a mild effect in the short run. Another research by Hanif W. et al. (2023) evaluated the time-frequency dependence and risk connectivity between the green stocks and oil shocks by applying wavelet coherence and frequency connectedness analysis. Their study discovered tighter dependency relationships between the two variables at mid and long-term scales. Lead lag patterns were mixed and time-varying. They further noticed a substantially significant risk spillover from the oil market in the green stock market. They also concluded that various global crises, viz., the Great Recession, the oil price collapse and the COVID-19 pandemic, significantly enhanced the magnitude of risk spillovers.

Mensi W. et al. (2022) examined the interlinkages between the sectoral markets and crude oil and gold in the USA to comprehend the impact of oil prices on various sectoral markets. They also studied the implications of their connectedness on portfolio management using Diebold and Yilmaz (2012) and Barunik and Krehlik's approaches. They discovered that gold, oil, financials, utilities, communications services and health care were the net recipients of the spillover effects, and the rest of the sectors were the net contributors irrespective of the frequencies. Furthermore, a reduced spillover effect was observed when gold and oil were included in the sector portfolio.

In India, Shahani, R. et al. (2023) investigated the cointegrating behaviour of crude oil and natural gas in the Indian commodity market using daily returns from April 1, 2017, to March 31, 2022. Based on ARDL (with structural break) and nonlinear ARDL methods, their study evidenced the long-run cointegration for natural gas only and not for crude oil. Further, they found that natural gas, concerning crude in the short run, was inelastic while highly elastic in the long run. There was no asymmetric impact of crude on natural gas in the short run, whereas, in the long run, it was found only at a 10% significant level. Furthermore, the negative and significant Error Correction term (using VECM) for natural gas reflected the stable movement from short-run disequilibrium to long-run equilibrium, though the speed of adjustment was 3 percent per period. Another study by Bhullar Pritpal et al. (2024) investigated the volatility spillover between the energy commodities, viz. oil and natural gas and the stock indices, including India, USA and Japan, during 2001-2023 using DCC-GARCH models. They found strong interdependence between the crude oil and all the stock indices under study compared to natural gas.

Thus, body of literature has discussed the association between the various commodities and equity markets by applying numerous techniques, viz. correlation, GARCH model, wavelet analysis, and so on, across developed and emerging economies, including India. However, scant literature is available in the Indian context. Thus, there is scope of research to assess the commodity and equity market nexus. This study is one-step addition to the empirical evidence on it in the Indian context.

3. Data

The data for this study is sourced from the Multi Commodity Exchange (MCX) India and the National Stock Exchange (NSE) India databases. From the NSE, daily closing prices for the Nifty 500 Index are obtained. From the MCX, spot market prices for crude oil (per barrel) and natural gas (per Metric Million British Thermal Unit, mmBtu) are used. All values are reported in Indian Rupees (INR). The analysis period spans from January 2017 to September 2024, using daily price data for all series, though data is only available for business days, excluding weekends and national holidays. It results in three-time series with irregular intervals.

4. Methodology

The Time series data is analyzed using Graphical, Descriptive and econometric methods. Time plots are made to represent data graphically in order to understand the trends over the period. The original data series were checked for stationarity as a pre-condition for time series analysis. Stationarity implies that the mean and variance remain constant over time. Additionally, the covariance between two time periods depends solely on the interval between them, rather than the specific times at which it is calculated (Enders, 2004). The original series were transformed into log return series to make the data stationary and the analysis more meaningful. Log returns possess multiple advantages over simple returns. They can be easily summed over multiple periods, which allows for straightforward calculations of cumulative returns across different time frames. The distribution tends to be more symmetrically distributed, providing advantages for statistical analysis. The descriptive statistics are analyzed for absolute values and log return values.

Stationarity testing is performed using the Augmented Dickey-Fuller (ADF) test. The ADF test is a unit root test whose null hypothesis is the presence of a unit root, which is non-stationarity.

A Vector Autoregression (VAR) model is employed to capture the dynamic interactions among multiple time series variables. Unlike univariate models that analyze a single time series, the VAR model examines the interdependencies by treating all variables in the system as endogenous (dependent on each other) (Enders, 2004). Further, the causal effects are checked using the Granger Causality test. Following that, the long-run relationship is checked using the Johansen Cointegration test.

The analysis is performed using the latest version of the statistical software R. R is an open-source program for statistical analysis and visualization.

5. Results

Figure 1 below shows the line plots of the series. Panel A shows the Nifty 500 closing prices; the series was stable below Rs. 10,000 before 2020.

[1] *A barrel (BBL) equals 42 US gallons or 159 litres.*
[2] *A Metric Million British Thermal Unit (mmBtu) is commonly used to measure energy value, particularly for natural gas.*

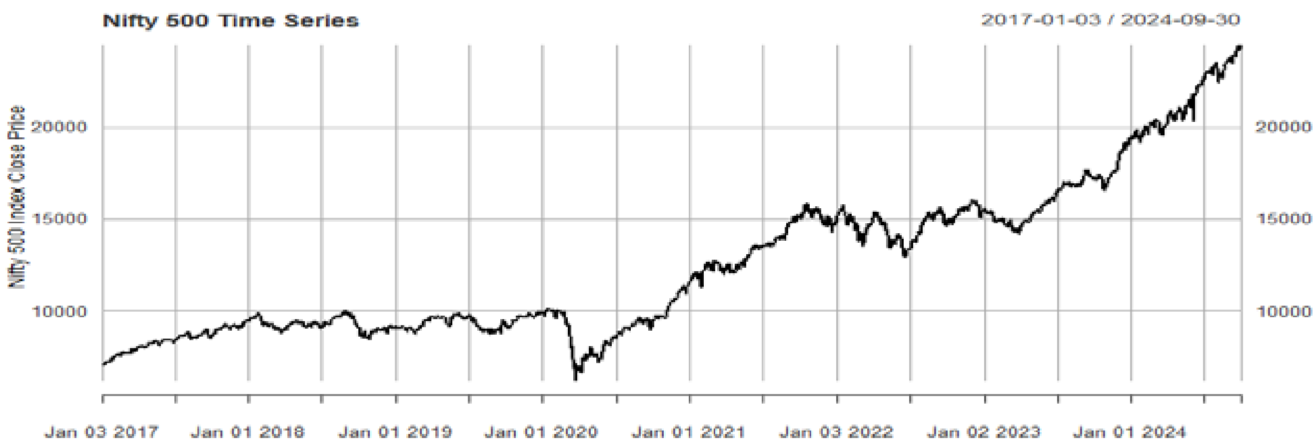
After that, it witnessed a sharp decline in 2020, attributed to the COVID-19 pandemic. The series started rising in value and stabilized for 2022. In 2023, the series started rising till 2024 and reached above Rs. 24,000. The series showcases the significant growth of the Indian stock market during the period under consideration, thereby showcasing the robust growth of the economy.

Panel B shows the line plot of crude oil spot price series. The series depicts a fluctuating trend, which is rising overall. The series also dropped significantly in 2020, around the time lockdowns were announced in the nation as a preventive measure for the pandemic. Till 2022, the series increased rapidly above Rs. 8000, thereafter noting a decline coming down to Rs. 6000.

Panel C shows the natural gas spot price series. The series was stable with minor fluctuations until the middle of 2021, after which it observed peaks. The series stabilized at its original level after 2022.

Figure 1: Line Plots of actual series

Panel a) Nifty 500 Closing Price (Rs.)



Source: Authors' computation

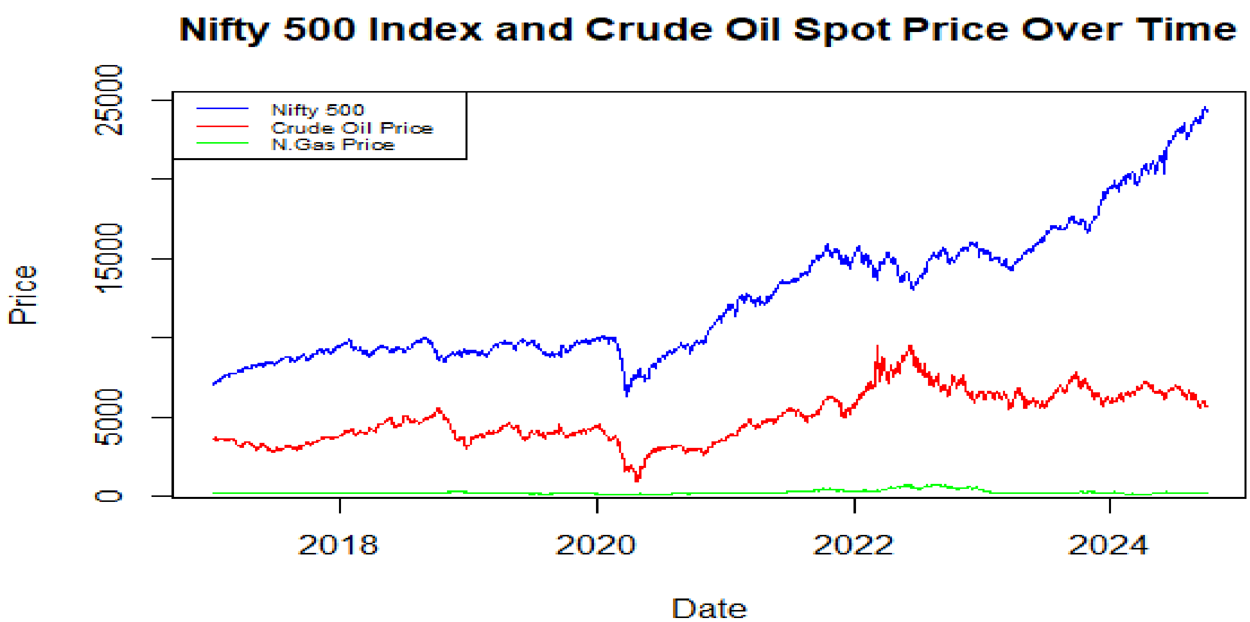
Panel b) Crude Oil Spot Price (Rs.)

Source: Authors' computation

Panel c) Natural Gas Spot Price (Rs.)

Source: Authors' computation

Figure 2: Line plots of all series



Source: Authors' own computation

Figure 2 provides us with a comparative view of the three series. It displays that the Benchmark Index, Nifty 500, holds the highest value, followed by Crude oil price in the spot market, and natural gas price takes the lowest value. Moreover, it can be observed that the Nifty 500 and crude oil prices followed similar trends until 2022. However, post 2022, the Nifty 500 value has increased, whereas Crude oil prices have decreased slightly, indicating the growth of the stock market.

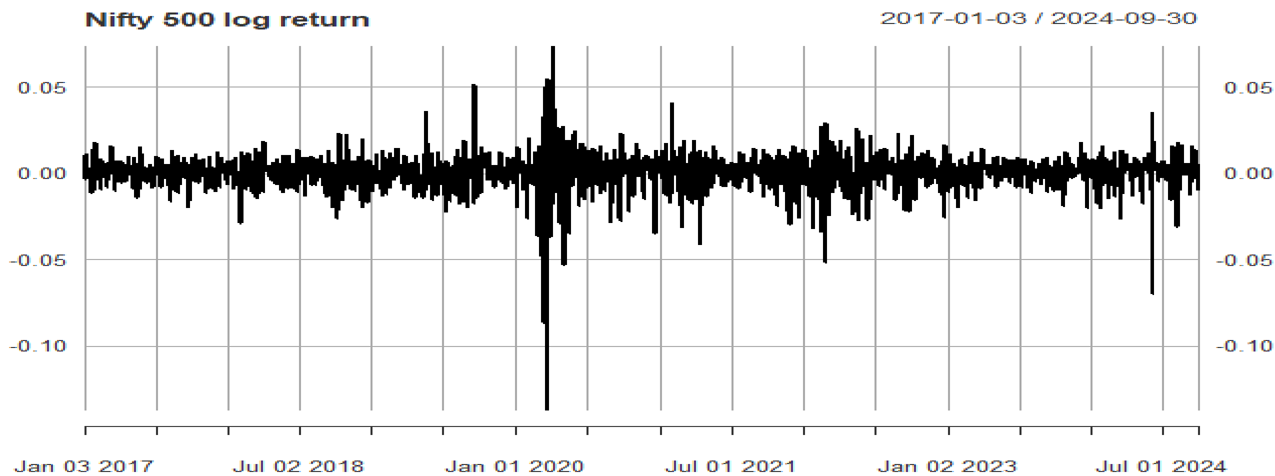
5.1 Checking for Stationarity

After plotting the series, it was observed that they showed trends that indicated non-stationarity, as it did not revert back to the mean. It is tested for using the formal testing procedure of the unit root test. It is one of the commonly used methods for assessing stationarity. The presence of a unit root signifies that the data series is non-stationary. The stationarity of the series was evaluated using the formal ADF test, which confirmed that the series was non-stationary.

The series was then transformed into a log return form to perform the analysis further. The log return series were found to be stationary, reverting to the mean (see Figure 2). The ADF test also confirms this (Table A2).

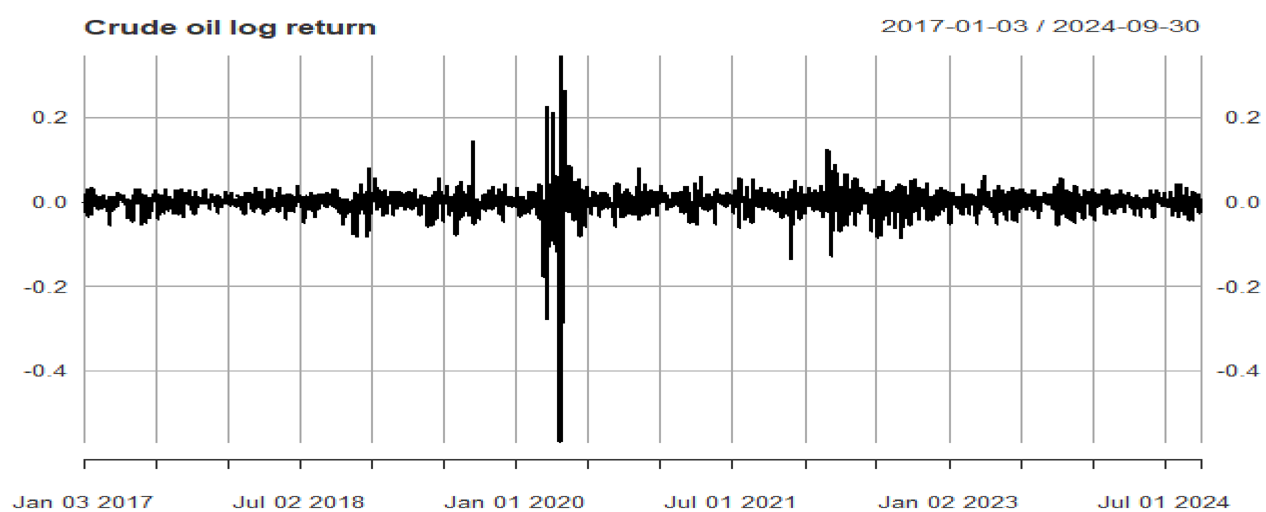
Figure 3: Line Plots of Log returns

Panel a) Nifty 500 Index



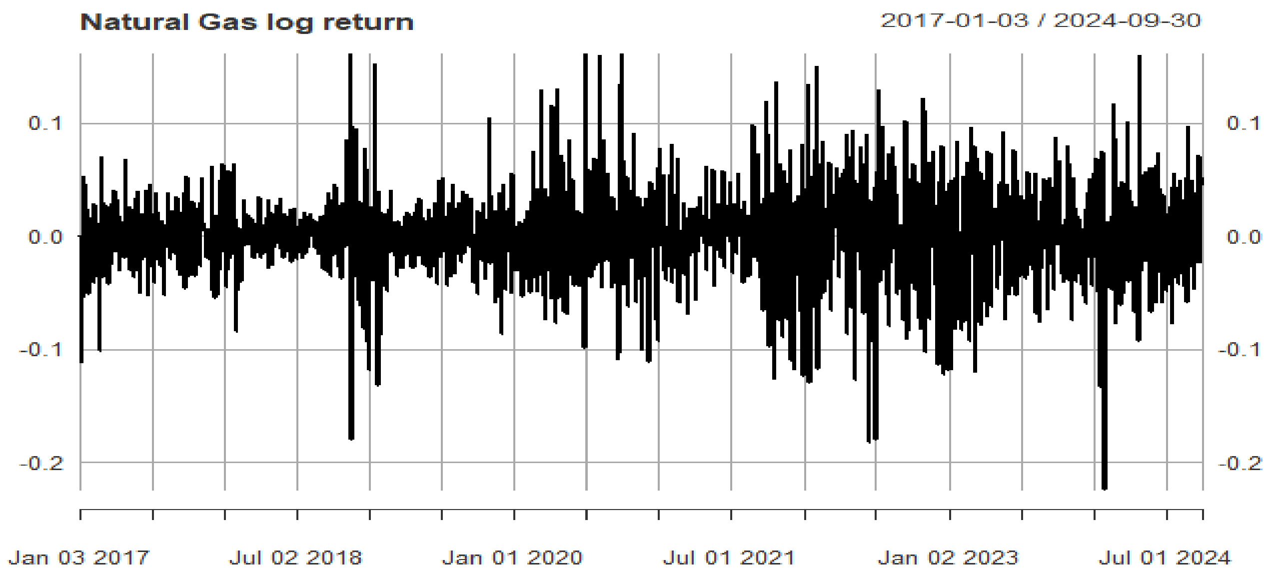
Source: Authors' own computation

Panel b) Crude Oil Spot Price



Source: Authors' computation

Panel c) Natural Gas Spot Price



Source: Authors' computation

5.2 Descriptive Statistics

Descriptive statistics are discussed for both the actual and the series with log differencing transformations. The actual series is important as it depicts the overall trends in the variables during the time period. Log return series are also discussed as analysis is based on them.

Table 1 showcases the descriptive statistics of the actual series. The actual series, Nifty 500, shows a mean of Rs. 12,572 with a standard deviation of Rs. 4,237. The minimum value of the series is Rs. 6,243, and the maximum value is Rs. 24,497. Series is slightly positively skewed with a skewness of 0.84. The kurtosis of the distribution is -0.18.

The crude oil price series shows a mean of Rs. 4,964, with a standard deviation of Rs. 1,617. The minimum value is Rs. 887, and the maximum value is Rs. 9,510. Series is slightly positively skewed, with a skewness of 0.31. The kurtosis of the distribution is -0.65.

The natural gas spot price averaged Rs. 244, with a standard deviation of Rs. 124. The series' minimum value is Rs 111, and its maximum value is Rs. 773. Series is highly positively skewed, with a skewness of 2.14. The distribution is peaked, with a high kurtosis of 4.16.

Table 1: Descriptive Statistics of Actual values of series

Descriptive Statistics of Absolute values			
	Nifty 500	**Crude Oil Price**	**Natural Gas Price**
Source	NSE India	MCX India	MCX India
Unit	Rs./ INR	Rs. /INR	Rs./INR
Mean	12572	4964	244.4
SD	4236.87	1616.67	124.44
Min	6243	887	111.2
Max	24497	9510	773.1
Range	18253.9	8623	661.9
1st Quartile	9151	3688	179.7
Median	10697	4664	200
3rd Quartile	15280	6324	245.5
Skewness	0.84	0.31	2.14
Kurtosis	-0.18	-0.65	4.16
Observations	1933	1933	1933

Source: Authors' computation

Table 2 presents the descriptive statistics for the log return values of the series. The average return of 0.00064 is provided by the Nifty 500 series, which is the highest. Crude oil has shown an average return of 0.00023 over the period in consideration. Natural gas shows a negative return with a minimal magnitude. The risk, measured by the standard deviation, is also lowest for the Nifty 500, followed by crude oil. The highest risk is associated with Natural gas. Risk to return reward, measured by the Coefficient of Variation (CV), is also the lowest for the Nifty 500. These characteristics make the Indian stock market a better investment avenue than these commodities.

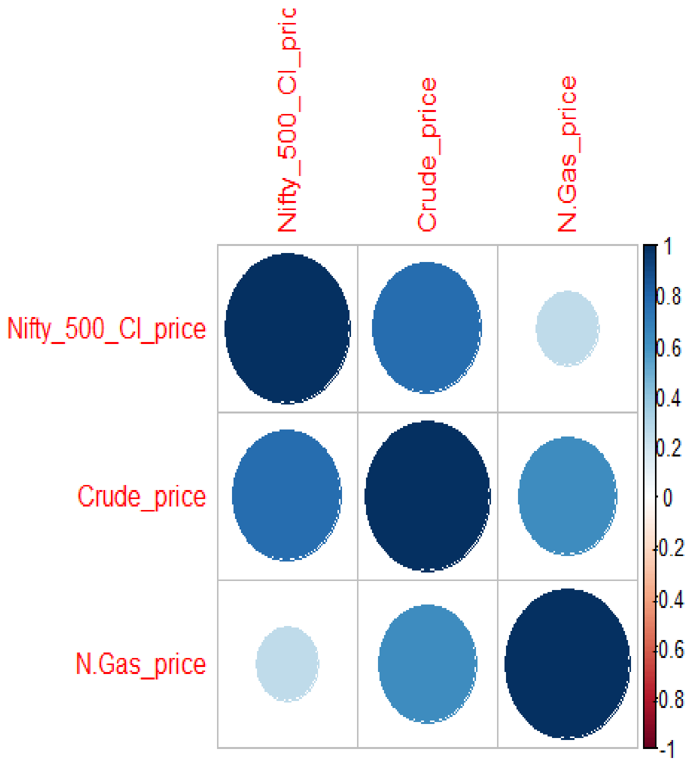
Table 2: Descriptive Statistics of Log Return values of series

Descriptive Statistics of Log return values			
	Nifty 500	**Crude Oil Price**	**Natural Gas Price**
Mean	0.00064	0.00023	-0.00002
SD	0.01000	0.03000	0.04000
Coefficient of Variation	15.55694	129.87013	-1860.46512
Range	0.21000	0.92000	0.39000

Source: Authors' computation

5.3 Correlation analysis

Figure 4: Correlation plot



Source: Authors' computation

The correlation plot reveals the degree and direction of association between variables. In our case, the series are positively associated. The Nifty 500 index and Crude oil have a 0.76 association. The natural gas price and Crude oil price have a 0.62 association. The Nifty 500 index and natural gas prices have a low association 0.26.

5.4 Econometric Analysis

R suggested models with different lag lengths based on four criteria. The four criteria choose the lags to minimize the function laid down. The Schwarz Criterion (SC) suggested the model with two lags, also known as the Bayesian Information Criterion (BIC).

The first model with 2 lags was selected to keep it simple and retain degrees of freedom. The model was then checked using a diagnostic check.

5.4.1 Diagnostic Check

A stability check and autocorrelation test were performed as diagnostic checks. The VAR model with two lags, as Schwarz Criterion (SC) suggested, is stable but has autocorrelated residuals. Hence, another model with five lags was considered, as suggested by Hannan Quinn's (HQ) criterion. This model is also found to be stable and does not have the problem of autocorrelated residuals.

Stability Check

The stability test for VAR models is based on the eigenvalue stability condition. Checks roots of the characteristic polynomial to evaluate whether the system satisfies the stationarity condition. This test ensures that all roots of the characteristic polynomial are strictly within the unit circle in the complex plane (i.e., their moduli are less than 1). A stable VAR model indicates that the dynamic relationships among the variables are well-behaved over time without exhibiting explosive or non-stationary behaviour.

Our model is found to be stable.

Figure 5: Stability Test Result

```
> stability_check2 <- roots(var_model2)
> print(abs(stability_check2))
 [1] 0.7356676 0.7356676 0.6642790 0.6061909 0.5786935 0.5786935 0.5756241
 [8] 0.5756241 0.5644191 0.5644191 0.5334809 0.5334809 0.5147053 0.4514878
[15] 0.4514878
> # Check if all roots are within the unit circle
> if (all(abs(stability_check2) < 1)) {
+   cat("The VAR model is stable.\n")
+ } else {
+   cat("The VAR model is unstable.\n")
+ }
The VAR model is stable.
```

Source: Authors' computation

Residual Autocorrelation Test

To assess the adequacy of the estimated Vector Autoregression (VAR) model, the residuals were tested for autocorrelation by using the Portmanteau test. This test evaluates whether the model's residuals exhibit white noise, a crucial assumption for the validity of VAR models.

The Portmanteau test assesses the null hypothesis that the residuals have no autocorrelation up to a specified lag, with the alternative hypothesis indicating the existence of autocorrelation. The test statistic is calculated as a function of the sum of squared residual autocorrelations and follows a chi-squared (χ^2) distribution under the null hypothesis.

For this analysis, the test was conducted for up to 12 lags using the asymptotic version of the Portmanteau test. The test results include the chi-squared statistic, degrees of freedom, and the associated p-value. A p-value exceeding 0.05 suggests that the null hypothesis cannot be rejected, indicating that the residuals are uncorrelated and that the model is adequately specified. Conversely, a p-value of 0.05 or lower would indicate significant residual autocorrelation, necessitating a re-evaluation of the model specification.

The model with two lags is found to have auto-correlated residuals with a p-value of approximately zero. Models with higher numbers of lags, 5 (suggested by HQ criteria) and 7 (suggested by AIC and FPE criteria) lags, were also checked, but the autocorrelation problem remained. The reason for this might be that the number of variables under consideration is not enough to explain each other, as some macroeconomic and global factors and governance-related factors also affect our variables.

Hence, a model with 5 lags is considered to conduct the study. A drawback is that the results of the Granger causality test based on this model may be biased.

Figure 5: Autocorrelation test: VAR model with five lags

```
> print(autocorr_test)

        Portmanteau Test (asymptotic)

data:  Residuals of VAR object var_model2
Chi-squared = 136.51, df = 63, p-value = 2.397e-07

$serial

        Portmanteau Test (asymptotic)

data:  Residuals of VAR object var_model2
Chi-squared = 136.51, df = 63, p-value = 2.397e-07


>   cat("No significant autocorrelation in residuals (p-value =", autocorr_test$serial$p.value,
").\n")
No significant autocorrelation in residuals (p-value = 2.396967e-07 ).
```

Source: Authors' computation

5.4.2 VAR Model with five lags

The following is the table for the model with five lags. The model is found to be stable, but its residuals show autocorrelation. This model was suggested by the Hannan-Quinn (HQ) Criterion.

Table 3: VAR Model estimation results

```
Estimated coefficients for equation Crude_Return:
==================================================
Call:
Crude_Return = Nifty_500_Return.l1 + Crude_Return.l1 + N.Gas_Return.l1 + Nifty_500_Return.l2 +
Crude_Return.l2 + N.Gas_Return.l2 + Nifty_500_Return.l3 + Crude_Return.l3 + N.Gas_Return.l3 + N
ifty_500_Return.l4 + Crude_Return.l4 + N.Gas_Return.l4 + Nifty_500_Return.l5 + Crude_Return.l5
+ N.Gas_Return.l5 + const

Nifty_500_Return.l1     Crude_Return.l1     N.Gas_Return.l1 Nifty_500_Return.l2
       0.1157528607        0.0214911793        0.0005797115        0.0978987041
    Crude_Return.l2     N.Gas_Return.l2 Nifty_500_Return.l3     Crude_Return.l3
      -0.1167176477       -0.0059791624       -0.0780075786       -0.0495371358
    N.Gas_Return.l3 Nifty_500_Return.l4     Crude_Return.l4     N.Gas_Return.l4
      -0.0037455495       -0.1447788153        0.1210396784        0.0046219840
Nifty_500_Return.l5     Crude_Return.l5     N.Gas_Return.l5               const
       0.3104544454        0.0257427404       -0.0253615148        0.0005241040

Estimated coefficients for equation N.Gas_Return:
==================================================
Call:
N.Gas_Return = Nifty_500_Return.l1 + Crude_Return.l1 + N.Gas_Return.l1 + Nifty_500_Return.l2 +
Crude_Return.l2 + N.Gas_Return.l2 + Nifty_500_Return.l3 + Crude_Return.l3 + N.Gas_Return.l3 + N
ifty_500_Return.l4 + Crude_Return.l4 + N.Gas_Return.l4 + Nifty_500_Return.l5 + Crude_Return.l5
+ N.Gas_Return.l5 + const

Nifty_500_Return.l1     Crude_Return.l1     N.Gas_Return.l1 Nifty_500_Return.l2
       0.0723348098        0.0017029589       -0.0582488004        0.0123801692
    Crude_Return.l2     N.Gas_Return.l2 Nifty_500_Return.l3     Crude_Return.l3
       0.0742712367       -0.0322804062       -0.0835535682       -0.0369274026
    N.Gas_Return.l3 Nifty_500_Return.l4     Crude_Return.l4     N.Gas_Return.l4
       0.0481661082        0.0287579864       -0.0305494858        0.0160044131
Nifty_500_Return.l5     Crude_Return.l5     N.Gas_Return.l5               const
       0.0993599606       -0.1032775170       -0.0208872880        0.0008079393
```

Source: Authors' computation

The Vector Autoregression (VAR) analysis with five lags reveals complex dynamic relationships between the Nifty 500 index, crude oil, and natural gas returns. For the Nifty 500 returns equation, we observe that its own first lag has a negative coefficient (-1.706), while the second lag shows a positive effect (0.0374), suggesting short-term mean reversion in stock market returns. The impact of crude oil returns on the Nifty 500 is relatively modest, with the first lag showing a negative coefficient (-0.1283) and the second lag displaying a positive coefficient (2.28), indicating a volatile transmission mechanism from oil markets to stock returns. All subsequent variables have a positive effect; only lag 5 of crude and natural gas have a negative impact.

In the crude oil returns equation, we find significant feedback effects from the stock market, with the first leg of Nifty 500 returns showing a positive coefficient (0.1157) and the impact being stronger (0.31) at the 5th lag. It suggests that stock market movements have a substantial bi-directional relationship with crude oil returns. The own-lag effects for crude oil are relatively small, with the first lag showing a positive coefficient (0.0214) and the second lag of crude oil lag showing a similar magnitude but a negative coefficient (-0.1167). Subsequent lags show diminishing effects. The impact of natural gas is comparatively smaller as its coefficients are small.

For natural gas returns, the results indicate moderate sensitivity to stock market movements, with the first leg of Nifty 500 returns showing a positive coefficient (0.0723). The own-lag effects for natural gas are notably negative for the first lag (-0.0582), suggesting mean-reverting behaviour in natural gas prices. The relationship between crude oil and natural gas appears relatively weak, with small coefficients across different lags.

These findings suggest that while significant interconnections exist between Indian stock markets and energy commodities, the relationships are complex and time-varying. Compared to natural gas, the stronger bidirectional relationship between stock markets and crude oil highlights the importance of oil prices for Indian financial markets.

5.4.3 Granger Causality Test Results

It is important to note that the Granger causality test is designed to identify linear causal relationships, which implies that the detected causality is based on the predictive ability of one variable in relation to another within the framework of a linear model.

The test results reveal significant causal relationships among the variables under consideration (refer to Table A4). Crude oil prices have a statistically significant causal effect on the Nifty 500 index and natural gas prices (p-value < 0.01). Similarly, the Nifty 500 index demonstrates a statistically significant causal effect on crude oil and natural gas prices (p-value < 0.01). However, natural gas prices do not exhibit a statistically significant causal effect on the Nifty 500 index or crude oil prices (p-value = 0.65).

5.4.4 Johansen cointegration test

An enquiry into the long-term relationship among the variables is made using the Johansen cointegration test. "According to Engel and Granger (1987), if the variables are found to be cointegrated, they would not drift apart over time, and the long-run combination amongst the non-stationary variables can be established." The test results reveal a significant long-term equilibrium relationship among natural gas prices and the Nifty index (Table A5, panel a). The test identifies two cointegrating relationships, as the trace statistic for $r = 0$ is 1614.13, far exceeding the critical value of 24.60 at the 1% significance level, and for $r \leq 1$, it is 738.23, also well above the critical value of 12.97. The first cointegrating vector indicates that a unit increase in natural gas prices corresponds to a 1.189-unit decrease in the Nifty index in the long run. The adjustment coefficients show that natural gas prices exhibit a stronger correction mechanism with a loading value of -1.001, compared to the Nifty index's weaker adjustment at 0.0816. These findings confirm a robust cointegrating relationship, highlighting the interdependence of energy prices and stock market movements.

The test confirms a long-term equilibrium relationship between crude oil prices and the Nifty index, suggesting that changes in crude oil prices significantly influence stock market movements (refer to Table A5, panel b). The test indicates the presence of at least one cointegrating relationship, demonstrating that these variables move together over the long term despite short-term fluctuations. The cointegrating vectors reveal that an increase in crude oil prices is associated with a decrease in the Nifty index, highlighting the inverse relationship between energy prices and market performance. The loading matrix suggests that crude oil prices dominate in correcting deviations from the equilibrium while the stock market adjusts more slowly. These findings underline the critical impact of global energy price dynamics on financial markets.

The test indicates a significant long-term relationship among natural gas and crude oil prices (Table A5, panel c). The test results confirm at least one cointegrating vector, suggesting that these energy commodities are closely tied in their long-term price movements. The coefficients in the cointegrating relation highlight that a change in crude oil prices has a measurable impact on natural gas prices, reflecting the interdependence of these energy markets. As revealed by the loading matrix, the adjustment speeds show that crude oil prices play a larger role in correcting deviations from the equilibrium, while natural gas prices adjust more slowly. These findings underscore the integrated nature of energy markets and the influence of crude oil prices on related energy commodities.

Hence, all the series are cointegrated and showcase a long-term relationship.

6. Conclusion and Policy Recommendations

The study's main objective was to check the interaction between the Indian stock market and commodity market, taking values of a benchmark index, Nifty 500, from NSE and two important energy sector commodities, crude oil and natural gas, from MCX. This study provides compelling evidence of the intricate relationships between India's stock market and key energy commodities. The empirical analysis reveals several crucial findings. First, both markets demonstrated significant vulnerability to external shocks, as evidenced by the sharp declines during the COVID-19 pandemic. Second, the analysis through the risk-return framework depicts nifty 500 as the best investment avenue with minimal risk and high return. Crude oil can be seen as a possible avenue. Natural gas cannot be seen as a potential commodity for investment due to the negative average returns offered during the last 7-8 years.

Third, the Granger causality tests establish bidirectional causality between crude oil prices and the Nifty 500 index, while natural gas prices do not show a causal influence on the Nifty 500 and Crude Oil prices. Fourth, the Johansen cointegration analysis confirms the existence of long-term equilibrium relationships among all three variables, highlighting their fundamental interconnectedness in the Indian financial system. The inverse relationship between energy prices and market performance is found to exist.

These findings put forward important implications for policymakers, regulators, and market participants. From a risk management perspective, there is a clear need to establish an integrated market monitoring system that tracks real-time correlations between energy commodities and stock market movements. This should be complemented by early warning systems for potential market disturbances based on commodity price volatility. The government should also strengthen its strategic petroleum reserves management to buffer against external shocks.

On the regulatory front, we recommend implementing mandatory disclosure requirements for listed companies regarding their commodity price exposure. It should include standardized reporting formats for commodity risk assessment and specialized regulatory guidelines for companies with significant exposure to energy commodities. The strong interconnection between markets suggests that regulatory bodies should adopt a more coordinated approach to oversight.

Market infrastructure development is another crucial area for improvement. Creating specialized derivative instruments would enable better hedging of commodity-related risks, while improved price discovery mechanisms for energy commodities would enhance market efficiency. The market infrastructure should be enhanced to facilitate seamless integration between commodity and stock markets, reducing cross-market transactions and information flow friction.

Information dissemination and education also require significant attention. Regulatory bodies should create dedicated channels for disseminating commodity market information to stock market participants. It should be supported by comprehensive educational programs focusing on the interconnections between commodity and equity markets. Enhanced transparency and understanding enable market participants to make well-informed investment choices and more effectively manage their exposure to risk.

The present study limits the analysis to include only two energy commodities and a benchmark index from NSE. This limitation can be addressed by including certain control variables to capture the effects of macroeconomic and global factors. Future research can explore the impact of other commodities on the behaviour of stock market using a different benchmark index, like Sensex from the Bombay Stock Exchange and investigate the transmission mechanisms through several commodity price shocks affecting the Indian economy. Such research would further enhance understanding of these complex market dynamics and help in developing more effective policy responses.

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Appendix

Table A1: Data Series in Absolute Numbers

	Date	Nifty_500_Cl_price	Crude_price	N.Gas_price
1	2017-01-02	7002.5	3651	253.1
2	2017-01-03	7028.7	3651	253.1
3	2017-01-04	7030.7	3563	226.5
4	2017-01-05	7106.9	3631	222.7
5	2017-01-06	7083.1	3644	221.9
6	2017-01-09	7085.1	3669	223.2
7	2017-01-10	7132.2	3543	211.6
8	2017-01-11	7214.1	3459	223.1
9	2017-01-12	7231.8	3565	220.0
10	2017-01-13	7228.3	3609	230.5
11	2017-01-16	7247.9	3573	233.3
12	2017-01-17	7243.6	3573	233.3
13	2017-01-18	7269.0	3571	232.2
14	2017-01-19	7287.7	3470	224.3
15	2017-01-20	7202.7	3502	229.6

Table A2: Data series in Log Return Values

	dataactual.Date	Nifty_log_ret	Crude_log_ret	N.Gas_log_ret
1	2017-01-03	3.734539e-03	0.0000000000	0.0000000000
2	2017-01-04	2.845072e-04	-0.0243982160	-0.1110397226
3	2017-01-05	1.077987e-02	0.0189052058	-0.0169193707
4	2017-01-06	-3.354478e-03	0.0035738870	-0.0035987443
5	2017-01-09	2.823224e-04	0.0068371660	0.0058414006
6	2017-01-10	6.625755e-03	-0.0349453195	-0.0533705305
7	2017-01-11	1.141770e-02	-0.0239942959	0.0529224015
8	2017-01-12	2.450524e-03	0.0301845239	-0.0139925551
9	2017-01-13	-4.840907e-04	0.0122666718	0.0466233161
10	2017-01-16	2.707895e-03	-0.0100251466	0.0120743166
11	2017-01-17	-5.934514e-04	0.0000000000	0.0000000000
12	2017-01-18	3.500410e-03	-0.0005599104	-0.0047261098
13	2017-01-19	2.569265e-03	-0.0286910747	-0.0346146277
14	2017-01-20	-1.173204e-02	0.0091796399	0.0233542229
15	2017-01-23	5.510495e-03	0.0342441543	-0.0509265910

Table A3: Augmented Dickey-Fuller (ADF) Test Results

```
        Augmented Dickey-Fuller Test

data:  datalogret$Nifty_log_ret
Dickey-Fuller = -11.373, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary

        Augmented Dickey-Fuller Test

data:  datalogret$Crude_log_ret
Dickey-Fuller = -12.176, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary

        Augmented Dickey-Fuller Test

data:  datalogret$N.Gas_log_ret
Dickey-Fuller = -11.668, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary
```

Table A4: Granger's Causality test results

```
> print(grangertest_crude_to_nifty_gas$Granger)

        Granger causality H0: Crude_Return do not Granger-cause Nifty_500_Return
        N.Gas_Return

data:  VAR object var_model2
F-Test = 5.7046, df1 = 10, df2 = 5733, p-value = 1.451e-08

> print(grangertest_nifty_to_crude_gas$Granger)

        Granger causality H0: Nifty_500_Return do not Granger-cause Crude_Return
        N.Gas_Return

data:  VAR object var_model2
F-Test = 3.4834, df1 = 10, df2 = 5733, p-value = 0.0001376

> print(grangertest_gas_to_crude_nifty$Granger)

        Granger causality H0: N.Gas_Return do not Granger-cause Nifty_500_Return
        Crude_Return

data:  VAR object var_model2
F-Test = 0.77126, df1 = 10, df2 = 5733, p-value = 0.6569
```

Table A5: Johansen Cointegration test results

Panel a) Natural Gas and Nifty 500 Index

```
Test type: trace statistic , without linear trend and constant in cointegration

Eigenvalues (lambda):
[1] 0.3648115 0.3178480 0.0000000

Values of teststatistic and critical values of test:

            test 10pct  5pct  1pct
r <= 1 |  738.23  7.52  9.24 12.97
r = 0  | 1614.13 17.85 19.96 24.60

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

                     timeseries_n.gas_re.l2 timeseries_Nifty_re.l2
timeseries_n.gas_re.l2           1.000000e+00             1.00000000
timeseries_Nifty_re.l2          -1.189063e+00            13.29157659
constant                         5.503856e-05            -0.01005018
                        constant
timeseries_n.gas_re.l2  1.0000000
timeseries_Nifty_re.l2 -0.9685869
constant                8.0383949

Weights W:
(This is the loading matrix)

                    timeseries_n.gas_re.l2 timeseries_Nifty_re.l2
timeseries_n.gas_re.d           -1.00165328            -0.08639188
timeseries_Nifty_re.d            0.08167139            -0.06653928
                          constant
timeseries_n.gas_re.d -2.435938e-20
timeseries_Nifty_re.d  5.785462e-21
```

Panel b) Crude oil and Nifty 500 Index

```
Test type: trace statistic , without linear trend and constant in cointegration

Eigenvalues (lambda):
[1] 4.050380e-01 3.126414e-01 5.551115e-17

Values of teststatistic and critical values of test:

            test 10pct  5pct  1pct
r <= 1 |  723.56  7.52  9.24 12.97
r = 0  | 1725.72 17.85 19.96 24.60

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

                       timeseries_crude_re.l2 timeseries_Nifty_re.l2
timeseries_crude_re.l2           1.000000e+00            1.000000000
timeseries_Nifty_re.l2          -1.037431e+00           10.449226592
constant                        -6.454950e-06           -0.008000836
                        constant
timeseries_crude_re.l2  1.000000
timeseries_Nifty_re.l2 -7.358074
constant               54.168231

Weights W:
(This is the loading matrix)

                      timeseries_crude_re.l2 timeseries_Nifty_re.l2
timeseries_crude_re.d            -1.04801233            -0.07725963
timeseries_Nifty_re.d             0.08608218            -0.08434812
                         constant
timeseries_crude_re.d 2.67560e-21
timeseries_Nifty_re.d 1.51703e-21
```

Panel c) Natural gas and Crude Oil

```
Test type: trace statistic , without linear trend and constant in cointegration

Eigenvalues (lambda):
[1] 4.029607e-01 3.563966e-01 1.110223e-16

Values of teststatistic and critical values of test:

            test 10pct  5pct  1pct
r <= 1 |  850.50  7.52  9.24 12.97
r = 0  | 1845.94 17.85 19.96 24.60

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

                       timeseries_n.gas_re.l2 timeseries_crude_re.l2
timeseries_n.gas_re.l2            1.000000000            1.000000000
timeseries_crude_re.l2           -3.072654751            0.376549965
constant                          0.001469408           -0.001049497
                         constant
timeseries_n.gas_re.l2 1.00000000
timeseries_crude_re.l2 0.04575895
constant               8.22144132

Weights W:
(This is the loading matrix)

                      timeseries_n.gas_re.l2 timeseries_crude_re.l2
timeseries_n.gas_re.d             -0.1400168             -0.9523032
timeseries_crude_re.d              0.3245633             -0.3247392
                          constant
timeseries_n.gas_re.d 6.428159e-21
timeseries_crude_re.d 1.035276e-20
```