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Modelling Market Indices, Commodity Market Prices and Stock Prices of Energy Sector using VAR with Variance Decomposition Model

Bharat Kumar Meher[1], Iqbal Thonse Hawaldar[2]*, Santosh Kumar[1], Abhishek Kumar Gupta[1]

[1]Darshan Sah College, Katihar (Under Purnea University), Bihar, India, [2]College of Business Administration, Kingdom University, Bahrain. *Email: i.hawaldar@ku.edu.bh

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ABSTRACT

The study aims to examine the existence of a correlation between the stock prices of the energy sector, commodities prices of the energy sector, and market indices. The study uses an empirical approach to develop various VAR (Vector Autoregression) with Variance Decomposition Models for each company under the energy sector indexed in NIFTY50 by considering daily prices for 3 years. For a comparative study, the data have been divided into two parts. The first part is considered pre-COVID era, i.e., from July 1, 2018, to December 31, 2019, and the second part is considered post-COVID era, i.e., from January 1, 2020, to June 30, 2021. While observing the estimates of VAR of different companies, it can be said that crude oil is significant in most of the models during pre-COVID whereas, during post COVID, lag term of crude oil and NIFTYENGERGY are significant. On the other hand, while observing the estimates of variance decomposition in all the VAR models, the first lag term of the particular company's share price is strongly endogenous. In comparison, the other independent variable, i.e., lag term of the price of crude oil and natural gas, values of NIFTY50 and NIFTY ENERGY are strongly exogenous to the stock prices of the energy sector.

Keywords: Vector Autoregression, VAR with Variance Decomposition, Market Index, NIFTY50, Nifty Energy, Commodity Market, COVID
JEL Classifications: C320, C53, C58, G1, G17

1. INTRODUCTION

Most investors, who need a handsome return on their investment, either invest in stock markets or commodities markets. Nowadays, apart from investing in stocks, investing in commodities has generated hefty returns and has become increasingly popular, despite the high risks associated with this type of investment due to the inherent volatility of commodity prices. Even most fund managers have started advising their clients to devote a share of their portfolios to commodity-related products as part of a long-term diversification strategy (Lombardi and Ravazzolo, 2013). In the same way, many investors and fund managers are also interested in investing in stocks linked to commodity-related products. Different factors influence or govern stock prices, i.e., Firm-Specific factors (like financial structure and market value determinants), Media and Investors' Sentiments, Customers Satisfaction, Macroeconomic Factors, and Commodities (Meijden, 2015). However, instead of taking these macro variables in determining the future prices of any stock, using only the past prices would be considered weak forecasting. Hence, it will be interesting to inculcate a few variables closely associated with the stock prices in the energy sector and formulate models to predict prices for shares of companies in the energy sector.

A study suggests that commodity prices are driven exogenously while considering the crude oil and natural gas price as associated variables. It is now widely acknowledged that this is not the case. Commodity price increases often come on the back of buoyant demand due to booming economic activity (Kilian, Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, 2009); (Kilian and Park, 2009). Moreover, considering the market index, many investors use the market index to predict the price movement of stocks. A study by (Chang, 2013), Regression Discontinuity and the Price Effects of Stock Market Indexing -NBER Working Paper No. 19290, found that the inclusion of stocks into indices affects the share prices. There might be possible that considering the values of two associated market indices, i.e., NIFTY50 and NIFTY ENERGY, the lagged values of market indices might affect the current stock prices. The study can make an important contribution in three ways. First, whether there exists a correlation between the stock prices and associated variables. Second, finding out how the associated variables, namely, the price of crude oil, natural gas, NIFTY50 and NIFTY ENERGY, help determine the stock prices of energy companies. Finally, a comparative study of the effects of associated variables during the pre- and post-COVID era has been reflected in this study.

2. LITERATURE REVIEW

Many existing studies have explored the relationship between commodity prices, stock prices, indices, and some macroeconomic factors. Some of the important studies are reviewed in this section. In a study Lombardi and Ravazzolo (2013) examined the correlation between commodity and stock returns and found an increase in the correlation between equity and commodity prices. They also found that joint modelling commodity and equity prices produce more accurate point and density forecasts. Similarly, a paper explored the implications of feedback within noisy rational expectations setting with incumbent publicly traded firms and privately held new entrants. In this setting, the equilibrium relation between stock prices, future dividends, and aggregate output depends on these firms' strategic environment (Subrahmanyam and Titman, 2013). Again, a study used the Granger Causality test and Variance Decomposition under the VAR environment to understand whether stock indices influence oil prices in India and China or not. The results reveal that Sensex does granger cause oil prices in India, whereas oil prices in India do not granger cause Sensex. In China, the SSE Composite index also causes oil prices, whereas oil prices do not granger cause the SSE Composite Index (Makhija and Raghukumari, 2016). Furthermore, a paper studies the correlation of 16 agricultural prices with stock market dynamics. With the possible role of financial and macroeconomic factors in driving this time-varying relation, along with the reasons for the positive correlation between agricultural commodities and stocks in recent years. The correlation between agricultural prices and stock market returns tends to increase during periods of financial turmoil. The impact of financial turmoil on the correlation gets stronger as the share of financial investors in agricultural derivatives markets rises. The findings suggest that the influence of financial shocks on agricultural prices should decrease as global financial tensions settle down. Nevertheless, as long as agricultural markets are "financialised", they might rise again when it is less needed, i.e., in the presence of new financial turmoil (Girardi, 2014). Similar to that, a study by Meijden, 2015 showed relations between the firm's stock as the dependent variable and the agricultural commodities like Milk, Eggs, Sugar, Soybeans, Wheat, Oats, Barley, Rye Wheat, as well as the additional exogenous factors (crude oil prices, AEX and Debt-to-Equity ratios), as independent variables with appropriate lag order using an OLS model. Meijden found that the econometric analyses showed a poor correlation or no correlation between the stocks and commodities (Meijden, 2015). There is a bidirectional causal relationship between crude oil and Malaysia stock market index, while there is a unidirectional causal relationship between crude oil and China stock market index (Keong et al., 2014). A high negative correlation has existed between stock and commodity prices over the past 140 years. Moreover, the two markets have alternated in price leadership with 29–32-year cycles (Zapata et al., 2012). Furthermore, a study used the data on gold prices, stock exchange and oil prices from 1991 to 2016 and found a long-run relationship between gold and stock prices and between oil and stock prices but the too weak correlation in the short-run. The authors concluded that investors should invest in gold because a hike in inflation reduces the real value of money. People seek to invest in alternative investment avenues like gold to preserve the value of their assets and earn additional returns (Kousar and Batool, 2019). Rossi (2012) investigates the relationship between commodity prices and the prices of other assets equity markets, by focusing on small open economies with a large export share of primary commodities, such as Australia, Canada, Chile, New Zealand, and South Africa and found that global commodity prices and equity markets are positively correlated with lagged equity values. Rossi found that the time series properties of commodity prices have, however, drastically changed since the 2000s, and commodity prices have become more correlated with equity markets around the same time (Rossi, 2012). Few recent studies, like a study, examined time-scale connectedness between returns on African stock markets and commodities across the energy, agriculture, metals, and beverage markets with wavelet-based coherency, wavelet multiple cross-correlation analysis, and wavelet-based Sharpe ratio and generalised Sharpe ratio diversification analysis (Boako and Alagidede, 2020). A recent study explored the impact of the COVID-19 pandemic on the dynamic connectedness among gold, oil and five leading stock markets by applying a new DCC-GARCH connectedness approach. We find stronger connectedness between these markets during the COVID-19 pandemic than pre-pandemic. We also find gold is a receiver of shocks from the five stock markets during this pandemic, whereas oil is a net transmitter of shocks (Benlagha and Omari, 2021). Again, a study represents the asymmetric volatility on prices of Crude Oil and Natural Gas during the pandemic (Meher, Hawaldar, Mohapatra, & Sarea, 2020). Similarly, a recent study depicts the leverage effect of COVID-19 on the stock price volatility of energy companies in India using GJR-GARCH and EGARCH models with high-frequency data (Meher et al., 2021). Hawaldar (2016) and Iqbal (2015) tested cross sectional verification of portfolio returns. Iqbal (2014) and Iqbal et al. (2007) found out the earning announcement affects stock returns and stock market is not efficient in semi strong form of efficient market hypothesis. The findings of Spulbar et al. (2022) confirmed the presence of the leverage effect during the sample period in Japan stock market. The empirical results identified the presence of high volatility in Japan stock market during COVID 19.

The existing studies were not enough to show the interrelationship between the prices of commodities, values of indices, and stock prices of the energy sector. Moreover, some of the studies which have been done were not considering the pandemic COVID-19 period. Hence, this paper is an innovative attempt to study the impact of prices of commodities under the energy sector, NIFTY and NIFTY ENERGY, on the stock prices of India's energy sector during COVID. Moreover, such impact has been studied during pre and post covid periods. The study makes a vital contribution to revealing the correlation between the stock prices, commodity prices, and market and thematic Index of the energy sector in India. Moreover, the study also provides valuable information on investing stocks of energy companies by using the lagged terms of associated variables, i.e., commodity prices of energy sector, market, and energy thematic index during the pre and post COVID era.

3. DATA AND METHODOLOGY

The present work uses an empirical approach to develop various VAR (Vector Autoregression) with Variance Decomposition Models for each company in the energy sector. VAR is a forecasting algorithm that can be used when two or more time series influence each other. In other words, the relationship between the time series involved is bi-directional. The purpose of these models is to predict the prices of stocks of energy companies using the lag terms of the price of the stock itself, the price of crude oil, natural gas, values of NIFTY50 and NIFTY ENERGY index as regressors. The estimates of variance decomposition of VAR models for each company could show the impact of each lagged variable term on the stock price. The study considered only those energy companies that are listed

Table 1: Estimates of vector autoregression of BPCL during pre and post COVID era

Vector autoregression estimates										
Sample (adjusted): 7/04/2018 to 12/31/2019 and 1/01/2020 to 6/29/2021										
Included observations: 390 after adjustments in Pre COVID and 390 after adjustments in Post COVID										
Standard errors in ( ) and t-statistics in [ ]										
	Pre COVID					Post-COVID				
	DBPCL	DCOIL	DN50	DNGAS	DNIFEN	DBPCL	DCOIL	DN50	DNGAS	DNIFEN
DBPCL(−1)	0.041919	0.419228	−0.519628	−0.001987	−0.616326	−0.010539	−0.414808	−0.056527	0.014610	0.312830
	(0.06368)	(0.61255)	(0.62899)	(0.04942)	(1.26972)	(0.07283)	(0.97225)	(1.24185)	(0.04567)	(1.76203)
	[0.65830]	[0.68440]	[−0.82614]	[−0.04021]	[−0.48540]	[−0.14471]	[−0.42665]	[−0.04552]	[0.31990]	[0.17754]
DCOIL(−1)	−0.019932	−0.068696	−0.135565	−0.000416	−0.194234	0.007860	−0.299400	0.144582	−0.004279	0.322936
	(0.00536)	(0.05152)	(0.05290)	(0.00416)	(0.10679)	(0.00375)	(0.05004)	(0.06392)	(0.00235)	(0.09070)
	[−3.72172]	[−1.33341]	[−2.56260]	[−0.10007]	[−1.81883]	[2.09665]	[−5.98277]	[2.26187]	[−1.82035]	[3.56064]
DN50(−1)	0.006388	−0.078398	0.030075	0.002476	−0.043919	0.008631	−0.000656	0.101745	0.005013	0.015914
	(0.00758)	(0.07291)	(0.07486)	(0.00588)	(0.15112)	(0.00496)	(0.06618)	(0.08453)	(0.00311)	(0.11994)
	[0.84287]	[−1.07534]	[0.40173]	[0.42090]	[−0.29062]	[1.74104]	[−0.00992]	[1.20363]	[1.61260]	[0.13269]
DNGAS(−1)	0.018887	−0.026421	−0.493590	−0.160199	−1.082827	−0.042370	−0.009508	0.998998	−0.018660	1.515387
	(0.06518)	(0.62696)	(0.64378)	(0.05058)	(1.29959)	(0.08135)	(1.08603)	(1.38719)	(0.05101)	(1.96825)
	[0.28978]	[−0.04214]	[−0.76670]	[−3.16720]	[−0.83321]	[−0.52083]	[−0.00875]	[0.72016]	[−0.36578]	[0.76992]
DNIFEN(−1)	0.001607	0.030679	0.054284	−0.000871	0.143537	−0.007229	0.040134	−0.125672	−0.003775	−0.083244
	(0.00417)	(0.04012)	(0.04119)	(0.00324)	(0.08316)	(0.00403)	(0.05386)	(0.06880)	(0.00253)	(0.09762)
	[0.38526]	[0.76472]	[1.31774]	[−0.26903]	[1.72607]	[−1.79158]	[0.74509]	[−1.82659]	[−1.49200]	[−0.85273]
C	0.216316	−1.939717	3.120139	−0.130181	5.622537	−0.080565	3.027069	8.845265	0.310092	9.545602
	(0.46983)	(4.51952)	(4.64081)	(0.36462)	(9.36829)	(0.51559)	(6.88309)	(8.79180)	(0.32332)	(12.4745)
	[0.46041]	[−0.42919]	[0.67233]	[−0.35703]	[0.60017]	[−0.15626]	[0.43978]	[1.00608]	[0.95910]	[0.76521]
R−squared	0.049435	0.011161	0.030492	0.026342	0.024185	0.023824	0.087242	0.028259	0.016420	0.037687
Adj. R−squared	0.037058	−0.001715	0.017868	0.013664	0.011480	0.011113	0.075357	0.015606	0.003613	0.025157
Sum sq. resids	32967.91	3050633.	3216571.	19855.53	13107660	39525.70	7044332	11492878	15542.80	23137494
S.E. equation	9.265740	89.13112	91.52314	7.190766	184.7553	10.14552	135.4423	173.0011	6.362078	245.4667
F−statistic	3.994093	0.866839	2.415457	2.077799	1.903482	1.874305	7.340579	2.233382	1.282124	3.007737
Log likelihood	−1418.629	−2301.505	−2311.834	−1319.754	−2585.785	−1454.005	−2464.696	−2560.149	−1272.001	−2696.596
Akaike AIC	7.305789	11.83336	11.88633	6.798737	13.29121	7.487206	12.67023	13.15974	6.553852	13.85946
Schwarz SC	7.366807	11.89438	11.94734	6.859755	13.35222	7.548224	12.73125	13.22076	6.614870	13.92048
Mean dependent	0.301667	−1.779487	3.765513	−0.110000	6.743077	−0.064872	2.669231	9.179487	0.300769	10.10500
S.D. dependent	9.442350	89.05481	92.35196	7.240403	185.8250	10.20236	140.8534	174.3670	6.373603	248.6138
Determinant resid covariance (dof adj.)			2.84E+15			2.26E+16				
Determinant resid covariance			2.63E+15			2.09E+16				
Log likelihood			−9690.543			−10094.99				
Akaike information criterion			49.84894			51.92302				
Schwarz criterion			50.15403			52.22811				
Number of coefficients			30			30				

under NIFTY50. The NIFTY 50 is a benchmark Indian stock market index representing the weighted average of 50 of the largest Indian companies listed on the National Stock Exchange. Similar NIFTY Energy sector Index includes companies belonging to Petroleum, Gas, and Power sectors. The Index comprises 10 companies listed on the National Stock Exchange of India (NSE). The data relating to closing prices of stocks, daily closing prices of crude oil, daily closing prices of natural gas, values of the NIFTY50 Index, and values of NIFTY ENERGY have been downloaded from investing.com. Two different estimates of VAR models with Variance Decomposition have been calculated for each company, i.e., one for the pre-COVID period and another one for post-COVID and a comparison has been made.

The variance decomposition estimate could show how much each variable affects the stock prices in terms of percentage for a short-term period of 10 days. For the application of VAR with the Variance Decomposition model, the closing values and prices are differentiated once to convert the non-stationary data into stationary, and ADF (Augmented Dickey-Fuller Test) has been employed to examine whether the data is stationarity in nature. The study considers the secondary data of daily closing prices of stocks of energy companies, crude oil, and natural gas and values of NIFTY50 and NIFTYENERGY for the period ranging from July 1, 2018, to June 30, 2021. For comparative study, the data has been divided into two parts. The first part is considered to pre the covid era, i.e., from July 1, 2018, to December 31, 2019, and the second part is considered post covid era, i.e., from January 1, 2020, to June 30, 2021. Formulate models of selected commodities, E-Views 10 has been used.

4. RESULTS, ANALYSIS AND DISCUSSION

Vector Autoregression with Variance Decomposition model has been applied with 5 variables, the formula of which are mentioned below:

$$lnCOMP_t = a + \sum_{i=1}^{k}\beta_i lnCOMP_{t-i} + \sum_{j=1}^{k}\varphi_j lnCrudeoil_{t-j}$$
$$+\sum_{m=1}^{k}\varnothing_m lnNaturalgas_{t-m} + \sum_{p=1}^{k}\vartheta_p lnNIFTY50_{t-p}$$
$$+\sum_{q=1}^{k}\beta_q lnNIFTYENERGY_{t-q} + u_{1t}$$

Where

a is the intercept

$lnCOMP_t$ is the natural log of the current stock price of a particular company

$lnCOMP_{t-i}$ is the natural log lag value of the stock price of a particular company

$lnCrudeoil_{t-j}$ is the natural log of lag term of crude oil price

$lnNaturalgas_{t-m}$ is the natural log of lag term of natural gas price

$lnNIFTY50_{t-p}$ is the natural log of lag term of NIFTY50

$lnNIFTYENERGY_{t-q}$ is the natural log of lag term of NIFTYENERGY

u_{1t} is the error term.

Apply VAR, log returns have been calculated for the stock prices of all the companies, prices of energy commodities, and values of indices taken into this study to make all the data stationary. After making all the data stationary, the VAR equation for each company has been estimated. Then the lag length criterion was examined and found that the lag length criterion should be one for all the formulated models.

4.1. Bharat Petroleum Corporation Limited (BPCL)

BPCL operated in the petroleum industry in India and was incorporated on November 3, 1952, as a private limited company with the name Burmah Shell Refineries Ltd. The company operates in a single segment - Refinery and Marketing activities, including the downstream petroleum sector. They are also engaged in the Exploration and Production of Hydrocarbons (E&P). BPCL regularly imports their LPG requirements from the Middle East. BPCL is a public sector undertaking with the Government of India holding a 54.93% stake as of September 30, 2017. During 2001-02, the company commissioned the Gas Turbine and Heat Recovery Steam Generator project at Rs. 1750 million. There is a high possibility that during the COVID, the company's share price might be affected.

Table 1 depicts the coefficients, standard error and t-statistics of the VAR model that constitute closing prices of a share of BPCL, closing prices of crude oil, closing prices of natural gas, closing values of NIFTY 50 Index, and closing values of NIFTYENERGY Index during Pre and Post COVID era. The values mentioned in the parentheses () are the standard errors, and the values mentioned in square brackets are the t-statistics. During the Pre COVID era,

Table 2: Estimates of variance decomposition for BPCL

Variance decomposition of DBPCL												
Sample (adjusted): 7/04/2018 to 12/31/2019 & 1/01/2020 to 6/29/2021												
Included observations: 390 after adjustments in Pre COVID and 390 after adjustments in Post COVID												
Period	S.E.	Pre COVID					Post COVID					DCOIL
		DBPCL	DN50	DNGAS	DNIFEN	DCOIL	S.E.	DBPCL	DN50	DNGAS	DNIFEN	
1	9.265740	100.0000	0.000000	0.000000	0.000000	0.000000	10.14552	100.0000	0.000000	0.000000	0.000000	0.000000
2	9.501817	96.30246	0.254311	0.001057	0.064016	3.378158	10.25803	98.02808	0.350556	0.027299	0.593789	1.000276
3	9.503462	96.26916	0.282070	0.004153	0.064010	3.380604	10.26756	97.84700	0.350712	0.028960	0.594473	1.178857
4	9.503473	96.26899	0.282164	0.004154	0.064098	3.380596	10.26848	97.82940	0.350812	0.029225	0.594370	1.196192
5	9.503474	96.26898	0.282164	0.004155	0.064100	3.380599	10.26859	97.82738	0.350821	0.029256	0.594358	1.198184
6	9.503474	96.26898	0.282164	0.004155	0.064100	3.380599	10.26860	97.82715	0.350822	0.029260	0.594356	1.198409
7	9.503474	96.26898	0.282164	0.004155	0.064100	3.380599	10.26860	97.82713	0.350822	0.029260	0.594356	1.198435
8	9.503474	96.26898	0.282164	0.004155	0.064100	3.380599	10.26860	97.82712	0.350822	0.029260	0.594356	1.198437
9	9.503474	96.26898	0.282164	0.004155	0.064100	3.380599	10.26860	97.82712	0.350822	0.029260	0.594356	1.198438
10	9.503474	96.26898	0.282164	0.004155	0.064100	3.380599	10.26860	97.82712	0.350822	0.029260	0.594356	1.198438

the first lag term of the price of crude oil is highly significant, whereas the coefficients of the first lag term of the price of a share of BPCL and values of the NIFTY50 Index are less significant. On the other hand, the other lag variables like natural gas prices and values of NIFTYENERGY index are not significant at all. When it comes to Post COVID era, the first lag term of the price of crude oil, lag values of NIFTY50, and NIFTYENERGY index is highly significant.

In contrast, the coefficients of the first lag term of the price of a share of BPCL and values of the NIFTY50 Index are less significant. Moreover, the independent variables can be explained by only 4.94% of the dependent variable, due to which the model formulated above cannot be considered as much dependable. On the other hand, the lag price of natural gas is not significant. The succeeding table represents the variance decomposition results for the price of BPCL.

Table 2 represents the percentage of forecast error variance for 10 days which is considered a short-run period. In the short run, on day 1, 100% of the forecast error variance in the price of BPCL is explained by the variable itself, which means other variables in

Table 3: Estimates of vector autoregression of ONGC during pre and post COVID era

Vector autoregression estimates										
Sample (adjusted): 7/04/2018 to 12/31/2019 and 1/01/2020 to 6/29/2021										
Included observations: 390 after adjustments in Pre COVID and 390 after adjustments in Post COVID										
Standard errors in ( ) and t-statistics in [ ]										
	Pre COVID					Post-COVID				
	DONGC	DN50	DNGAS	DNIFEN	DCOIL	DONGC	DN50	DNGAS	DNIFEN	DCOIL
DONGC (−1)	0.049066	3.127328	−0.103731	−1.988294	1.116572	−0.219275	−7.417220	0.121831	−14.70805	5.276568
	(0.06570)	(2.12403)	(0.16712)	(4.29611)	(2.07298)	(0.07074)	(4.86308)	(0.17928)	(6.88039)	(3.81115)
	[0.74688]	[1.47236]	[−0.62071]	[−0.46281]	[0.53863]	[−3.09960]	[−1.52521]	[0.67954]	[−2.13768]	[1.38451]
DN50(−1)	0.000864	0.025908	0.002475	−0.048093	−0.075527	0.000102	0.097613	0.005131	0.008308	0.000547
	(0.00231)	(0.07458)	(0.00587)	(0.15085)	(0.07279)	(0.00122)	(0.08413)	(0.00310)	(0.11903)	(0.06593)
	[0.37472]	[0.34738]	[0.42182]	[−0.31882]	[−1.03761]	[0.08321]	[1.16029]	[1.65435]	[0.06980]	[0.00830]
DNGAS(−1)	0.007126	−0.520131	−0.159566	−1.078164	−0.028097	−0.008703	0.904711	−0.017160	1.344522	0.060455
	(0.01988)	(0.64263)	(0.05056)	(1.29981)	(0.62719)	(0.02009)	(1.38118)	(0.05092)	(1.95412)	(1.08242)
	[0.35849]	[−0.80937]	[−3.15583]	[−0.82948]	[−0.04480]	[−0.43318]	[0.65503]	[−0.33699]	[0.68804]	[0.05585]
DNIFEN (−1)	0.000979	0.009182	7.49E−05	0.145105	0.031892	0.000871	−0.070816	−0.004295	0.037866	−0.011535
	(0.00131)	(0.04229)	(0.00333)	(0.08554)	(0.04128)	(0.00101)	(0.06953)	(0.00256)	(0.09837)	(0.05449)
	[0.74805]	[0.21710]	[0.02250]	[1.69627]	[0.77263]	[0.86129]	[−1.01856]	[−1.67557]	[0.38495]	[−0.21171]
DCOIL (−1)	0.001237	−0.137096	−0.000195	−0.184884	−0.074593	0.003904	0.153574	−0.004516	0.338074	−0.302832
	(0.00163)	(0.05267)	(0.00414)	(0.10653)	(0.05141)	(0.00092)	(0.06341)	(0.00234)	(0.08971)	(0.04969)
	[0.75958]	[−2.60285]	[−0.04707]	[−1.73544]	[−1.45107]	[4.23264]	[2.42194]	[−1.93173]	[3.76840]	[−6.09402]
C	−0.078264	3.512648	−0.144487	5.309615	−1.759094	−0.050440	8.088123	0.314884	7.956254	3.830695
	(0.14354)	(4.64077)	(0.36514)	(9.38654)	(4.52925)	(0.12719)	(8.74364)	(0.32235)	(12.3707)	(6.85231)
	[−0.54525]	[0.75691]	[−0.39571]	[0.56566]	[−0.38839]	[−0.39656]	[0.92503]	[0.97685]	[0.64315]	[0.55904]
R-squared	0.017413	0.034221	0.027314	0.024131	0.010702	0.063993	0.034082	0.017374	0.048859	0.091232
Adj. R-squared	0.004619	0.021646	0.014649	0.011424	−0.002179	0.051837	0.021538	0.004613	0.036507	0.079430
Sum sq. resids	3065.260	3204198.	19835.71	13108391	3052048.	2417.744	11425264	15528.52	22870163	7017059.
S.E. equation	2.825323	91.34696	7.187176	184.7605	89.15179	2.505964	172.2673	6.350892	243.7274	135.0042
F-statistic	1.361039	2.721324	2.156607	1.899095	0.830824	5.264361	2.716904	1.361444	3.955439	7.730107
Log likelihood	−955.4255	−2311.082	−1319.559	−2585.796	−2301.595	−910.9830	−2565.059	−1274.582	−2700.737	−2469.756
Akaike AIC	4.930387	11.88247	6.797739	13.29126	11.83382	4.690450	13.15120	6.550294	13.84520	12.66371
Schwarz SC	4.991405	11.94349	6.858756	13.35228	11.89484	4.751351	13.21210	6.611195	13.90610	12.72462
Mean dependent	−0.074103	3.765513	−0.110000	6.743077	−1.779487	−0.028389	9.087084	0.298465	10.01074	2.828645
S.D. dependent	2.831871	92.35196	7.240403	185.8250	89.05481	2.573554	174.1529	6.365589	248.3019	140.7080
Determinant resid covariance (dof adj.)		2.46E+14	3.54E+14			1.40E+15				
Determinant resid covariance		2.28E+14	3.28E+14			1.30E+15				
Log−likelihood		−9213.491				−9577.165				
Akaike information criterion		47.40252	47.76584			49.14151				
Schwarz criterion		47.70761	48.07093			49.44602				
Number of coefficients		30	30			30				

the model, i.e., price of crude oil, natural gas, values of NIFTY50 and NIFTYENERGY Index do not have any strong influence on the stock price of BPCL. On day 2, the lag one term of the stock price of BPCL is strongly endogenous to the price of BPCL as it has an impact of 96.30%. In contrast, the lag one terms of other variables, i.e., price of crude oil, natural gas, NIFTY50 and NIFTYENERGY index values, are strongly exogenous as these variables are together affecting only 3.70% of the price of BPCL. Similarly, even in the remaining 8 past days, the lag prices are more influencing the current price of BPCL, whereas the other variables have the least impact.

4.2. Oil and Natural Gas Corporation Limited (ONGC)

Maharatna ONGC is India's largest crude oil and natural gas Company, contributing around 71% to Indian domestic production. Crude oil is the raw material used by downstream companies like IOC, BPCL, HPCL, and MRPL to produce petroleum products like Petrol, Diesel, Kerosene, Naphtha, and Cooking Gas LPG. The company has a unique distinction of being a company with in-house service capabilities in all areas of Exploration and Production of oil and gas and related oil-field services. Winner of the Best Employer award, this public sector enterprise has a dedicated team of around 28,500 professionals who toil round the clock in challenging locations.

Table 3 depicts the VAR model's coefficients, standard error and t-statistics that constitute closing prices of a share of ONGC, closing prices of crude oil, closing prices of natural gas, closing values of NIFTY 50 Index, and closing prices of natural gas values of NIFTYENERGY Index during Pre and Post COVID era. The values mentioned in the parentheses () are the standard errors, and the values mentioned in square brackets [ ] are the t-statistics. During the Pre COVID era, none of the variables is significant. Whereas, during Post COVID era, the first lag term of price ONGC and crude oil is highly significant. Moreover, the independent variables can explain only 6.4% of the dependent variable; hence the model is unreliable. The succeeding table represents the Variance Decomposition Results for the price of ONGC.

Table 4 reveals the percentage of forecast error variance for 10 days which is considered a short-run period. In the short run, on day 1, 100% of forecast error variance in the price of ONGC is explained by the variable itself, which means other variables in the model, i.e., price of crude oil, natural gas, values of NIFTY50 and NIFTYENERGY Index do not have any influence on the stock price of ONGC. On day 2, the lag one term of the stock price of ONGC is strongly endogenous to the price of ONGC as it has an impact of 99.40%. In contrast, the first lag terms of other variables, i.e., price of crude oil, natural gas, NIFTY50 and NIFTYENERGY index values, are strongly exogenous as these variables affect only 0.60% of the price of ONGC. Similarly, even in the remaining 8 past days, the lag prices are more influencing the current price of ONGC, whereas the other variables have the most negligible impact. As far as post-COVID is concerned, the first lag term of ONGC has an impact of 99.37%, and the first lag terms of other variables affect 0.63% only.

4.3. Reliance Petroleum

Reliance Petroleum is an Indian petroleum company specialising in oil and energy, owned by Mukesh Ambani of Reliance Industries Limited (RIL), one of India's largest private sector companies.

Table 5 depicts the coefficients, its standard error and t-statistics of the VAR model that constitutes closing prices of a share of BPCL, closing prices of crude oil, closing prices of natural gas, closing values of NIFTY 50 Index, and closing values of NIFTYENERGY Index during Pre and Post COVID era. The values mentioned in the parentheses () are the standard errors, and the values mentioned in square brackets [ ] are the t-statistics. During the Pre COVID era, the first lag term of the price of crude oil was highly significant, whereas the coefficients of the first lag term of the price of a share of BPCL and values of NIFTY50 Index were less significant. On the other hand, the other lag variables like natural gas prices and values of NIFTYENERGY index are not significant at all. When it comes to Post COVID era, the first lag term of the price of crude oil, lag values of NIFTY50 and NIFTYENERGY Index, is highly significant. In contrast, the coefficients of the first lag term of the price of a share of BPCL and values of the NIFTY50 Index are less significant.

Moreover, the independent variables can explain only 4.94% of the dependent variable, due to which the model formulated above cannot be considered dependable. On the other hand, the

Table 4: Estimates of variance decomposition for ONGC

	Variance decomposition of ONGC											
	Sample (adjusted): 7/04/2018 to 12/31/2019 & 1/01/2020 to 6/29/2021											
	Included observations: 390 after adjustments in Pre COVID and 390 after adjustments in Post COVID											
	Pre COVID						Post COVID					
Period	S.E.	DONGC	DN50	DNGAS	DNIFEN	DCOIL	S.E.	DONGC	DN50	DNGAS	DNIFEN	DCOIL
1	2.825323	100.0000	0.000000	0.000000	0.000000	0.000000	2.505964	100.0000	0.000000	0.000000	0.000000	0.000000
2	2.849586	99.40000	0.304829	0.042317	0.106975	0.145878	2.578376	95.53450	0.440803	0.003150	0.147591	3.873955
3	2.850224	99.37034	0.308227	0.047270	0.117833	0.156334	2.588690	94.80868	0.474647	0.003448	0.150849	4.562380
4	2.850228	99.37008	0.308348	0.047287	0.117945	0.156337	2.590123	94.70653	0.478340	0.003460	0.150964	4.660711
5	2.850229	99.37007	0.308349	0.047291	0.117947	0156342	2.590321	94.69235	0.478802	0.003468	0.150980	4.674399
6	2.850229	99.37007	0.308349	0.047291	0.117947	0.156342	2.590349	94.69040	0.478864	0.003469	0.150982	4.676288
7	2.850229	99.37007	0.308349	0.047291	0.117947	0.156342	2.590352	94.69013	0.478872	0.003469	0.150982	4.676549
8	2.850229	99.37007	0.308349	0.047291	0.117947	0.156342	2.590353	94.69009	0.478873	0.003469	0.150982	4.676585
9	2.850229	99.37007	0.308349	0.047291	0.117947	0.156342	2.590353	94.69009	0.478874	0.003469	0.150982	4.676590
10	2.850229	99.37007	0.308349	0.047291	0.117947	0.156342	2.590353	94.69008	0.478874	0.003469	0.150982	4.676590

Table 5: Estimates of vector autoregression of reliance petroleum during pre and post COVID era

Vector Autoregression Estimates										
Sample (adjusted): 7/04/2018 to 12/31/2019 and 1/01/2020 to 6/29/2021										
Included observations: 390 after adjustments in pre COVID and 390 after adjustments in post COVID										
Standard errors in ( ) and t-statistics in [ ]										
	Pre COVID					Post-COVID				
	DNRPET	DN50	DNGAS	DNIFEN	DCOIL	DNRPET	DN50	DNGAS	DNIFEN	DCOIL
DNRPET (−1)	0.102401	−0.079894	0.010913	0.317660	−0.306315	0.094225	−0.038109	−0.012248	−0.094021	0.083340
	(0.09843)	(0.45163)	(0.03545)	(0.91107)	(0.43945)	(0.07556)	(0.34253)	(0.01258)	(0.48602)	(0.26820)
	[1.04038]	[−0.17690]	[0.30784]	[0.34867]	[−0.69704]	[1.24711]	[−0.11126]	[−0.97337]	[−0.19345]	[0.31074]
DN50(−1)	−0.006069	0.024793	0.002671	−0.042251	−0.081268	0.004469	0.102382	0.005296	0.018565	−0.003334
	(0.01641)	(0.07529)	(0.00591)	(0.15188)	(0.07326)	(0.01870)	(0.08476)	(0.00311)	(0.12027)	(0.06637)
	[−0.36986]	[0.32929]	[0.45200]	[−0.27819]	[−1.10932]	[0.23905]	[1.20786]	[1.70081]	[0.15436]	[−0.05024]
DNGAS (−1)	−0.169717	−0.501081	−0.160117	−1.087644	−0.024035	0.256397	0.992034	−0.020254	1.507087	−0.004851
	(0.14041)	(0.64429)	(0.05057)	(1.29971)	(0.62691)	(0.30615)	(1.38795)	(0.05099)	(1.96934)	(1.08676)
	[−1.20869]	[−0.77772]	[−3.16614]	[−0.83684]	[−0.03834]	[0.83748]	[0.71475]	[−0.39725]	[0.76527]	[−0.00446]
DNIFEN (−1)	0.003156	0.047316	−0.002008	0.094438	0.073012	−0.022199	−0.123287	−0.002074	−0.064462	0.019564
	(0.01266)	(0.05809)	(0.00456)	(0.11719)	(0.05652)	(0.01523)	(0.06907)	(0.00254)	(0.09800)	(0.05408)
	[0.24928]	[0.81451]	[−0.44041]	[0.80588]	[1.29170]	[−1.45714]	[−1.78502]	[−0.81736]	[−0.65779]	[0.36177]
DCOIL(−1)	−0.013656	−0.130050	−0.000524	−0.192427	−0.068889	0.045258	0.144806	−0.004417	0.320590	−0.296439
	(0.01153)	(0.05291)	(0.00415)	(0.10673)	(0.05148)	(0.01399)	(0.06343)	(0.00233)	(0.09001)	(0.04967)
	[−1.18435]	[−2.45808]	[−0.12609]	[−1.80297]	[−1.33818]	[3.23453]	[2.28277]	[−1.89551]	[3.56187]	[−5.96830]
C	1.187002	3.154670	−0.139782	5.305680	−1.645896	1.364264	8.875120	0.307823	9.455547	3.156670
	(1.01581)	(4.66106)	(0.36585)	(9.40258)	(4.53529)	(1.93680)	(8.78059)	(0.32255)	(12.4586)	(6.87517)
	[1.16853]	[0.67681]	[−0.38207]	[0.56428]	[−0.36291]	[0.70439]	[1.01077]	[0.95433]	[0.75896]	[0.45914]
R-squared	0.020774	0.028848	0.026578	0.023896	0.011206	0.035470	0.028285	0.018580	0.037702	0.087039
Adj. R-squared	0.008024	0.016203	0.013903	0.011186	−0.001669	0.022911	0.015632	0.005801	0.025172	0.075151
Sum sq. resids	153032.4	3222025.	19850.72	13111552	3050494	559163.7	11492569	15508.68	23137139	7045900
S.E. equation	19.96302	91.60071	7.189894	184.7828	89.12909	38.15960	172.9987	6.355091	245.4648	135.4574
F-statistic	1.629322	2.281358	2.096933	1.880122	0.870367	2.824295	2.235503	1.453921	3.008964	7.321859
Log likelihood	−1717.976	−2312.164	−1319.707	−2585.843	−2301.496	−1970.656	−2560.144	−1271.573	−2696.593	−2464.739
Akaike AIC	8.840905	11.88802	6.798495	13.29150	11.83331	10.13670	13.15971	6.551654	13.85945	12.67046
Schwarz SC	8.901922	11.94904	6.859513	13.35252	11.89433	10.19771	13.22073	6.612672	13.92047	12.73147
Mean dependent	1.378599	3.765513	−0.110000	6.743077	−1.779487	1.507607	9.179487	0.300769	10.10500	2.669231
S.D. dependent	20.04359	92.35196	7.240403	185.8250	89.05481	38.60441	174.3670	6.373603	248.6138	140.8534
Determinant resid covariance(dof adj.)		5.81E+15				3.00E+17				
Determinant resid covariance		5.38E+15				2.77E+17				
Log likelihood		−9830.056				−10598.94				
Akaike information criterion		50.56439				54.50738				
Schwarz criterion		50.86948				54.81246				
Number of coefficients		30				30				

lag price of natural gas is not significant. The succeeding table represents the Variance Decomposition Results for the price of Reliance Petroleum.

Table 6 reveals the percentage of forecast error variance for 10 days which is considered as short run period. In the short run, in day 1, 100% of forecast error variance in price of Reliance Petroleum is explained by the variable itself, which means other variables in the model i.e. price of crude oil, natural gas, values of NIFTY50 and NIFTYENERGY index do not have any influence on the stock price of Reliance Petroleum. In day 2, the lag one term of stock price of Reliance Petroleum is strongly endogenous to price of Reliance Petroleum as it has an impact of 99.14%, whereas the first lag terms of other variables i.e., price of crude oil, natural gas, values of NIFTY50 and NIFTYENERGY index are strongly exogenous as these variables are together affecting

Table 6: Estimates of variance decomposition for reliance petroleum

Variance decomposition of reliance petroleum												
Sample (adjusted): 7/04/2018 to 12/31/2019 & 1/01/2020 to 6/29/2021												
Included observations: 390 after adjustments in Pre COVID and 390 after adjustments in Post COVID												
Period	Pre COVID						Post COVID					
	S.E.	DRPET	DN50	DNGAS	DNIFEN	DCOIL	S.E.	DRPET	DN50	DNGAS	DNIFEN	DCOIL
1	19.96302	100.0000	0.000000	0.000000	0.000000	0.000000	38.15960	100.0000	0.000000	0.000000	0.000000	0.000000
2	20.17250	99.14267	0.022780	0.436450	0.044717	0.353384	38.78173	96.87263	0.034108	0.304711	0.421435	2.367121
3	20.17387	99.14109	0.023116	0.437539	0.044853	0.353403	38.84680	96.54957	0.037058	0.307730	0.423144	2.682496
4	20.17391	99.14090	0.023121	0.437704	0.044853	0.353418	38.85375	96.51506	0.037351	0.308080	0.423190	2.716319
5	20.17391	99.14090	0.023121	0.437705	0.044853	0.353418	38.85453	96.51117	0.037389	0.308115	0.423174	2.720155
6	20.17391	99.14090	0.023121	0.437705	0.044853	0.353418	38.85462	96.51074	0.037393	0.308119	0.423172	2.720578
7	20.17391	99.14090	0.023121	0.437705	0.044853	0.353418	38.85463	96.51069	0.037393	0.308119	0.423172	2.720625
8	20.17391	99.14090	0.023121	0.437705	0.044853	0.353418	38.85463	96.51069	0.037393	0.308119	0.423172	2.720630
9	20.17391	99.14090	0.023121	0.437705	0.044853	0.353418	38.85463	96.51068	0.037393	0.308119	0.423172	2.720630
10	20.17391	99.14090	0.023121	0.437705	0.044853	0.353418	38.85463	96.51068	0.037393	0.308119	0.423172	2.720631

only 0.86% on the price of Reliance Petroleum. Similarly, even in the remaining 8 past days, the lag prices are more influencing the current price of Reliance Petroleum whereas the other variables have least impact. As far as post COVID is concerned the first lag term of Reliance Petroleum has an impact of 96.87% and first lag terms of other variables are together affecting 3.13% only.

5. CONCLUSION

From the above results and discussion of Estimates of Vector Autoregression of selected eight companies, it has been found that only the coefficient of crude oil price is significant while regressing on stock prices of BPCL during pre-COVID. In contrast, during post COVID era the coefficient of crude oil price is more significant, followed by NIFTYENERGY and NIFTY50. In the case of ONGC, none of the coefficients of independent variables was significant in pre-pandemic. However, the coefficient of the lag term of crude oil price followed by the first lag term of ONGC stock price is significant during the post-pandemic. Similarly, while regressing the stock prices of Reliance Petroleum, none of the coefficients of the independent variables is significant during pre-COVID. However, during the post-pandemic era, only the coefficient of the lag term of crude oil price is significant.

On the other hand, while observing the estimates of variance decomposition in all the VAR models, the first lag term of the particular company's share price is strongly endogenous. However, the other independent variable, i.e., lag term of the price of crude oil and natural gas, values of NIFTY50 and NIFTYENERGY are strongly exogenous to the stock prices of the energy sector. Even though specific results have been accomplished as set out by the initial research objectives, the study still has some limitations that can be a manoeuvre by further studies or developed further for more comprehensive contributions. The study's main limitations include that the study is limited to 3 years, i.e., from July 1, 2018, to June 30, 2021. The first 18 months are considered pre covid era, i.e., from July 1, 2018, to December 31, 2019, and the next 18 months are considered post covid era, i.e., from January 1, 2020, to June 30, 2021. It would be challenging to forecast a case of any change in India's phase in the stock market by using the framed models. Furthermore, the study considered only three selected companies in the energy sector based on market capitalisation in NIFTY Energy, India. It does not reflect any trend of other companies of India under NIFTY Energy or any other country.

REFERENCES

Benlagha, N., Omari, S.E. (2021), The connectedness of stock markets with gold and oil: New evidence from COVID-19 pandemic. Finance Research Letters, 46, 102373.

Boako, G., Alagidede, I.P. (2020), Commodities Price Cycles and their Interdependence with Equity Markets in Africa. POLICY BRIEF, Working Paper 738.

Chang, Y.C. (2013), Regression Discontinuity and the Price Effects of Stock Market Indexing. Working Paper 19290 of National Bureau of Economic Research. Available from: https://www.nber.org/system/files/working_papers/w19290/revisions/w19290.rev0.pdf

Girardi, D. (2014), Food prices and wall street explaining the time-varying relation between agricultural prices and stock market dynamics. Quaderni Del Dipartimento di Economia Politica E Statistica, 1(1), 1-32.

Hawaldar, I.T. (2016), The cross-sectional variations in portfolio returns: Evidence from Bahrain bourse. British Journal of Economics, Finance and Management Sciences, 12(2), 1-11.

Iqbal, T.H. (2014), Seasonal analysis of abnormal returns after quarterly earnings announcements. International Journal of Accounting and Financial Reporting, 4(2), 501-519.

Iqbal, T.H. (2015), Empirical testing of capital asset pricing model on Bahrain bourse. Asian Journal of Finance and Accounting, 7(2), 107-119.

Iqbal, T.H., Mallikarjunappa, T., Nayak, P. (2007), Stock price adjustments to quarterly earnings announcement: A test of semi-strong form of efficiency. Gyan Management, 1(2), 25-42.

Keong, C.M., Huee, F.L., Mei, L.M., Wern, O.S., May, Y.P. (2014), Relationship between Commodities Market and Stock Market: Evidence from Malaysia and China. Malaysia: Faculty of Business and Finance.

Kilian, L. (2009), Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053-1069.

Kilian, L., Park, C. (2009), The impact of oil price shocks on the u. s. Stock market. International Economic Review, 50(4), 1267-1287.

Kousar, A.S., Batool, S.A. (2019), Impact of gold and oil prices on the stock market in Pakistan. Journal of Economics, Finance and Administrative Science, 25, 279-294.

Lombardi, M., Ravazzolo, F. (2013), BIS Working Papers No 420 On the correlation between commodity and equity returns: Implications for portfolio allocation. Monetary and Economic Department, 420, 1-32.

Makhija, H., Raghukumari, P.S. (2016), A study on impact of oil prices on emerging market stock indices. IOSR Journal of Economics and Finance, 6(2), 35-40.

Meher, B.K., Hawaldar, I.T., Gil, M.T., Dum, D.Z. (2021), Measuring leverage effect of Covid-19 on stock price volatility of energy companies using high-frequency data. International Journal of Energy Economics and Policy, 11(6), 489-502.

Meher, B.K., Hawaldar, I.T., Mohapatra, L., Sarea, A.M. (2020), The impact of COVID-19 on price volatility of crude oil and natural gas listed on multi commodity exchange of India. International Journal of Energy Economics and Policy, 10(5), 1-10.

Meijden, A.V. (2015), Agricultural Commodity Prices and the Stock Market: Testing for Price Relationships between Agricultural Commodities and Food Corporations' Shares using Statistical Analysis. Netherlands: MSc Thesis Chair Group Business Economics. p1-45.

Rossi, B. (2012), The Changing Relationship Between Commodity Prices and Equity Prices in Commodity Exporting Countries. Spain: ICREA-UPF, BGSE and CREI. p1-43.

Spulbar, C., Birau, R., Trivedi, J., Hawaldar, I.T., Minea, E.L. (2022), Testing volatility spillovers using GARCH models in the Japanese stock market during COVID-19. Investment Management and Financial Innovations, 19(1), 262-273.

Subrahmanyam, A., Titman, S. (2013), Financial market shocks and the Macroeconomy Avanidhar. Review of Financial Studies, 26(11), 1-49.

Zapata, H.O., Detre, J.D., Hanabuchi, T. (2012), Historical performance of commodity and stock markets. Journal of Agricultural and Applied Economics, 44(3), 339-357.

APPENDIX

C	Constant
S.E	Standard error
DN50	Natural log returns of NIFTY50
DNIFEN	Natural log returns of NIFTYENERGY
DCOIL	Natural log returns of crude oil price
DNGAS	Natural log returns of natural gas price
DBPCL	Natural log returns of stock prices of bharat petroleum corporation
DONGC	Natural log returns of stock prices of ONGC
DRPET	Natural log returns of stock prices of reliance petroleum