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Empirical Analysis in The Concept of Indian Financial Market Using Machine Learning

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Abstract

This study aims to examine the relationships among the constituents of the Indian stock market, specifically, to examine the relationship between the S&P BSE Oil & Gas index and four other sectors, such as, S&P BSE IT, S&P BSE energy, S&P BSE auto, and S&P BSE power are being specifically explored. The aim of this study is to understand the potential effects of variations in the BSE Oil & Gas index on these industries. For a variety of stakeholders, including investors, politicians, and market analysts, this study is vital because it offers critical insights into the economies that form the basis of India. With the help of various methodologies, this study examines historical stock price fluctuations by using statistical methods and data analysis, with a focus on time series modelling. In order to assess and comprehend the possible effects of changes in the Indian stock market, this study carefully looks at important financial indicators and pertinent market trends. Examining any asymmetries in these relationships will help determine if the oil and gas business experiences positive or negative shocks, and which ones have distinct effects on the various sectors under consideration. This study is one of various contributions into the global discourse on market interdependence that provides useful guidelines for the Indian stakeholder in handling their vital segments of the markets in India.

Keywords: Stock Markets, Forecasting, Multiple Regression, Anova, Arima, Correlation Matrix, Engle-Granger Test

1. Introduction

The level of stock market trading price today is one of the most important metrics for level trading activity, which depends on market dynamics at the same time and may include valuable insights about security. Each new piece of information forms, collectively with the prices and volumes, an aggregate of market information that makes a market. The sum of traders' reactions rather than an average belief of new information that may affect stock prices. Averaging prices often neutralizes differences in the price reactions of investors, but these differences are still available within trading volume. The prediction of what is currently happening in the stock market attracts many analysts and researchers. Stock market prediction has been a very big headache for many theories like Random walk theory, because it involves so many variables and datasets. The two economies differ by a wide margin, considering the time span to be very extensive. It acts as a weighing machine in long term economy. This implies that there are chances of predicting stock market moves in a long-term economy. Statistical tools and theory in stock price analysis and forecasting applied in this paper. To begin with, we present a brief overview of different Indian stock markets within the concept of Indian Financial Market. Afterwards, we direct our attention towards some of the successes recorded during research work relating to stock analysis and projection.

This study seeks to examine empirically how oil price stocks relate with prices of other stock markets. The role of oil and gas price stock market is playing very important in the Indian stock market, unlike most of the European countries. With respect to Indian economy, the case is very interesting on the issue of market risks. Market risk has been defined as the risk inherent in investments decreasing in value caused by changes in market factors. The term refers to the institution's exposures to price volatilities in markets, such as movements in money cost, forex rate, stock and product rate. Market risk entails the probability that there will be decrease in the value of an institution's proprietary trading holdings in equity, debt, FX and commodity. Also, the market risk can result from investment or guarantee of minimum return that is not hedged in the management of clients' moneys within financial institution. Banks also face a certain variety of market risks because they take financial instruments susceptible to the price fluctuations as collateral for the loans. The most prominent case of a failed market risk management in recent times is the collapse of Bear Sterns which is an American bank that has heavy participation in proprietary trading and came crumbling down at the beginning of the global fiscal crisis of 2008. The US fed bailout of LTCM was in response to severe loss realized during the 1998 emerging market crisis related to 'zero risk' derivative contracts. Nevertheless, the most prominent incident should have been the closure of Barings

Bank which happened in 1995 as it had existed for one hundred years and was a banker to the royal family.

As observed by Brown and Yucel, 2002, researches have shifted from a general analysis to a more detailed relationship analysis between the oil price and a country's macroeconomic performance. Most of this research looks at how the price of crude oil affects gross domestic product or gross national product and the relevant channel impacts the macro economy. The recent global financial crises have highlighted growing inter-connectivity of market, its complexity and volatility, which went against common belief. Therefore, the significance of market risk management goes upwards in future. Market risk is one of the most difficult risks to manage. A bank will know the extent of loss it may suffer as a result of market volatility to prevent traders from taking large positions with the aim of meeting profit objectives. Given that no one possesses a crystal-ball type of knowledge, statistics will be used to give us an estimate of downside market volatility. From historical volatility data and market rates we can derive variance/covariance parameters that are required to estimate the maximum potential downside loss at a chosen statistical confidence limit.

2. Literature Review

The empirical analysis of the relationship between BSE Oil and Gas stocks and other BSE stocks is a multifaceted field that draws upon various perspectives and methodologies. These days number of papers dealing with volatility modelling have significantly increased and more sophisticated technique techniques are using. The general concept is to work better over high frequency time series in financial markets is Autoregressive Integrated Moving Average (ARIMA) or Generalized Autoregressive Conditional Heteroskedastic Models (GARCH) and their modifications (such as TGARCH, EGARCH etc.).

Several studies in modelling the stock market volatility both in developed and in developing countries. Many researchers investigated the performance of ARIMA models, GARCH models in explaining volatility of emerging stock markets. These models have been adopted by many studies in different area of econometrics with specific focus on analysis of financial time series. In this part, some latest econometric results on the conditional mean and volatility of the stock returns from developing economies' stock markets (both emerging and frontier) are presented.

Some notable studies include the weekday effect which is also known as the weekend or Monday effects. The literature has provided several approaches to day of the week effect study, ranging from simple OLS techniques to more advanced ones like ARIMA and GARCH models. However, some other researchers delved into the different causes of the day of the week effect. Financial literature suggests the co-movement is positive, i.e., the fact that higher volumes are likely to be correlated with either higher or lower changes in prices. Nevertheless, such a positive relation between volume and price change (daily return) is present in stock markets only, but not in future markets. A significant portion of the literature focused on the impact of oil prices on stock markets. Basher, Haug, and Sadorsky (2012) and Filis, Degiannakis, and Floros (2011) explored the dynamic correlation between stock markets and oil prices [1,2]. Narayan and Narayan (2010) specifically modelled the impact of oil prices on Vietnam's stock prices [3].

Regime-switching approaches were used by Aloui and Jammazi (2009), as well as, Kilian and Park (2009) to examine the dynamics between crude oil shock and stock market behavior [4,5]. Such studies are important because they explain what might happen to BSE Oil & Gas shares following a sharp change in oil price and how it correlates with other BSE stock indices. The study done by Hammoudeh et al. (2009) addressed volatility and shock spillovers among different equity sectors in the stock market of the gulf countries, giving a particular viewpoint for the influence of oil shocks on overall market behaviour in these countries [6]. Chan, Gup, and Pan (1992) offered one of the earliest insights about stock price movement in the major Asian markers and the US [7]. This research may not be directly about oil and gas but it builds awareness of cross-market interaction. Additionally, these results can serve as a yardstick for examining whether BSE Oil and Gas stocks respond in line with general market movements.

In 2006, Ang, Hodrick, Xing & Zhang's work on the cross-section of volatility and expected returns can serve as background for what may be relevant to the BSE context. It explains the market inefficiency factors and, perhaps premium risk that might impact the BSE Oil and Gas space. Ali (2020) conducted an empirical analysis on the perceptions of investors in the Amman Stock Exchange [8]. While this study is specific to the Jordanian market, it sheds light on the role of investor sentiment and perceptions in shaping stock market dynamics. Understanding investor behaviour is crucial when exploring the relationship between BSE Oil and Gas stocks and other BSE stocks. Examining investor sentiment within the Bombay Stock Exchange can provide valuable insights into the factors influencing trading patterns and stock price movements.

Iliyasu et al., 2019 looked at the stock market bubble contagion aspect during the Nigerian financial crisis [9]. This also provides a connection on how speculation bubbles and market sentiment influences stock markets. Such an analysis could be helpful to further improve our knowledge on how investors react during such events and the resulting implications to stock linkages. Mendoza et al. (2020) analysed impacts of the MILA (Mercado Integrado Latinoamericano) on Latin American stock markets [10]. The above study does not focus on BSE but demonstrates a regional view of market integration as well as their activities and dynamic correlations. Discussing regional market integration within the Indian subcontinent and the implications of these on the BSE Oil and gas sector as compared to the rest of sectors could prove to be an interesting line of research. Yousaf, Ali & Wong (2020), Volatility Spillovers between World Leading and Asian Stock Markets: An Empirical Analysis [11]. The study provides a glimpse of how global market dynamics impact the local and regional markets. This will help to understand how BSE Oil and Gas stocks operate within a wider framework.

Enriching the comprehension of the complex forces that shape the interrelationships between BSE oil and gas stocks in comparison to the rest BSE stocks, the perspective of this literature review incorporates these views points. Its further stresses upon the role played by investor behaviours, regional market integration and global effects in understanding of stock market interconnections.

Many journal articles examined how various macroeconomic factors affected equity prices Islam et al., in their work, concentrated on Bangladesh, explaining how the link between macroeconomic factors and stock market returns is maintained. Sachdeva, Bhullar and Gupta (2021) took it one step further by analysing co-integration between the Indian and global capital markets [12]. Such research is instrumental in the analysis of how macroeconomic conditions affect the relationship between BSE Oil and Gas shares versus other BSE shares.

However, there is one new study conducted by Ullah, Zhao, Kamal, and Zheng (2020), which focused on the relationship between military, defence and stock market development in China [13]. Though unrelated in regards to oil itself, this research emphasizes the need for multi-tiered economic analysis of trends in the UAE's economic and security environment. Understanding the complex relations within the BSE Oil and Gas stocks in comparison with other BSE stocks can be ensured by the reviewed articles. The interaction between general market dynamics, macroeconomic factors, and oil specific shocks shape such a relationship. This can be a subject for future research about their dynamics involving the situation of Bombay Stock Exchange and the distinct properties of oil and gas sector. Furthermore, it would be beneficial to incorporate the most recent studies as well as relevant up-to-date data to update the analysis for the present day's markets.

3. Analysis

S&P BSE Oil & Gas price has been chosen as response variable because India imports 82% of its oil needs and aims to bring that down to 67% by 2022 by replacing it with local hydrocarbon exploration, renewable energy, and indigenous ethanol fuel. India was the second top net crude oil (including crude oil products) importer of 205.3 Mt in 2019. By March 2021, domestic crude oil production output fell by 5.2% and natural gas production by 8.1% in FY21 as producers extracted 30.4917 Mt of crude oil and 28.67 BCM of natural gas in the fiscal year. In August 2021, crude oil production decreased by 2.3%, but there was a 20.23% increase in homegrown natural gas. The data used in here are historical stock prices of BSE Oil and Gas. BSE IT, BSE Energy, BSE Auto and BSE Power, imported from BSE website. Using various packages in R-Programming. Basically, the data consists of Open, High, Low, Close. Here Daily Return prices is used to keep things simple and hence our model will be univariate time series. Daily Return calculated on Closed prices in MS-Excel. Data from 1st-April-2010 to 1st –August-2022 has been used or equivalent to 3064 trading days. On the first step we have to check the descriptive analysis of all stock indices.

STATISTICS	DAILY RETURN OIL&GAS	DAILY RETURN IT	DAILY RETURN ENERGY	DAILY RETURN AUTO	DAILY RETURN POWER
Mean	0.000310657	0.000649054	0.000498182	0.000536743	0.000226376
Standard Error	0.000250123	0.00024331	0.000281286	0.000247914	0.000237781
Median	0.000450728	0.000624498	0.000564593	0.000779515	0.000761982
Standard Deviation	0.013842898	0.013465852	0.015567576	0.013720639	0.013159864
Sample Variance	0.000191626	0.000181329	0.000242349	0.000188256	0.000173182
Kurtosis	7.606191156	7.026114789	20.46344162	7.253347841	3.662072864
Skewness	-0.54566448	-0.383637563	-0.441121811	-0.176516069	-0.314387963

Table 1: Descriptive Statistics

The table presents key statistical measures describing the daily return patterns of various sectors from April 1, 2010, to August 1, 2022. Notable metrics include the mean, representing the average daily return for each sector, with Oil & Gas exhibiting a mean of 0.000310657. Standard deviation and variance indicate the degree of volatility and spread in the daily return values, where Energy stands out with a high standard deviation of 0.015567576 and a variance of 0.000242349. Median values offer insights into central tendencies less influenced by extreme values, such as the daily return for Auto with a median of 0.000779515. Additionally, kurtosis and skewness unveil distribution characteristics; Energy displays a substantial kurtosis of 20.46344162, suggesting heavy-tailedness, while Oil & Gas exhibits a negative skewness of 0.54566448, indicating a left-skewed distribution. These statistics collectively provide a comprehensive overview of the risk, return, and distribution characteristics of the sectors during the specified timeframe.

A multivariate regression analysis was conducted to examine the potential impact of changes in BSE Oil & Gas stock prices on BSE IT, BSE Auto, BSE Energy, and BSE Power. This statistical approach was selected because of its capability to simultaneously assess the relationships between a single independent variable and multiple dependent variables. The decision to employ a multivariate regression model was based on the recognition of its capacity to capture and analyze the potential intricate interactions and dependencies among the various sectors, allowing for a comprehensive understanding of the interplay between BSE Oil & Gas stock prices and the performance of BSE IT, BSE Energy, BSE Auto, and BSE Power.

By employing a multivariate regression framework, the analysis aimed to determine whether discernible and simultaneous effects on the stock prices of BSE IT, BSE Energy, BSE Auto, and BSE Power were induced by fluctuations in BSE Oil & Gas stock prices. This methodological choice enables a more nuanced exploration of the relationships between the variables of interest, considering the joint dynamics that may exist among the diverse sectors under investigation. Additionally, the estimation of coefficients for each sector through the multivariate regression analysis sheds light on the magnitude and direction of the potential influence of changes in BSE Oil & Gas stock prices on each of the respective sectors, contributing to a comprehensive understanding of the broader market dynamics.

Now, to formally test the hypothesis regarding the impact of changes in BSE Oil & Gas stock prices on BSE IT, BSE Energy, BSE Auto, and BSE Power, individual hypotheses for each sector can be formulated and tested using the estimated coefficients from the multivariate regression model. Therefore, consider the Null Hypothesis ($\boldsymbol{H_0}$): There is no significant effect of changes in BSE Oil & Gas stock prices on BSE IT stock prices, and Alternative Hypothesis ($\boldsymbol{H_1}$): There is a significant effect of changes in BSE Oil & Gas stock prices on BSE IT stock prices. By performing multivariate regression analysis,

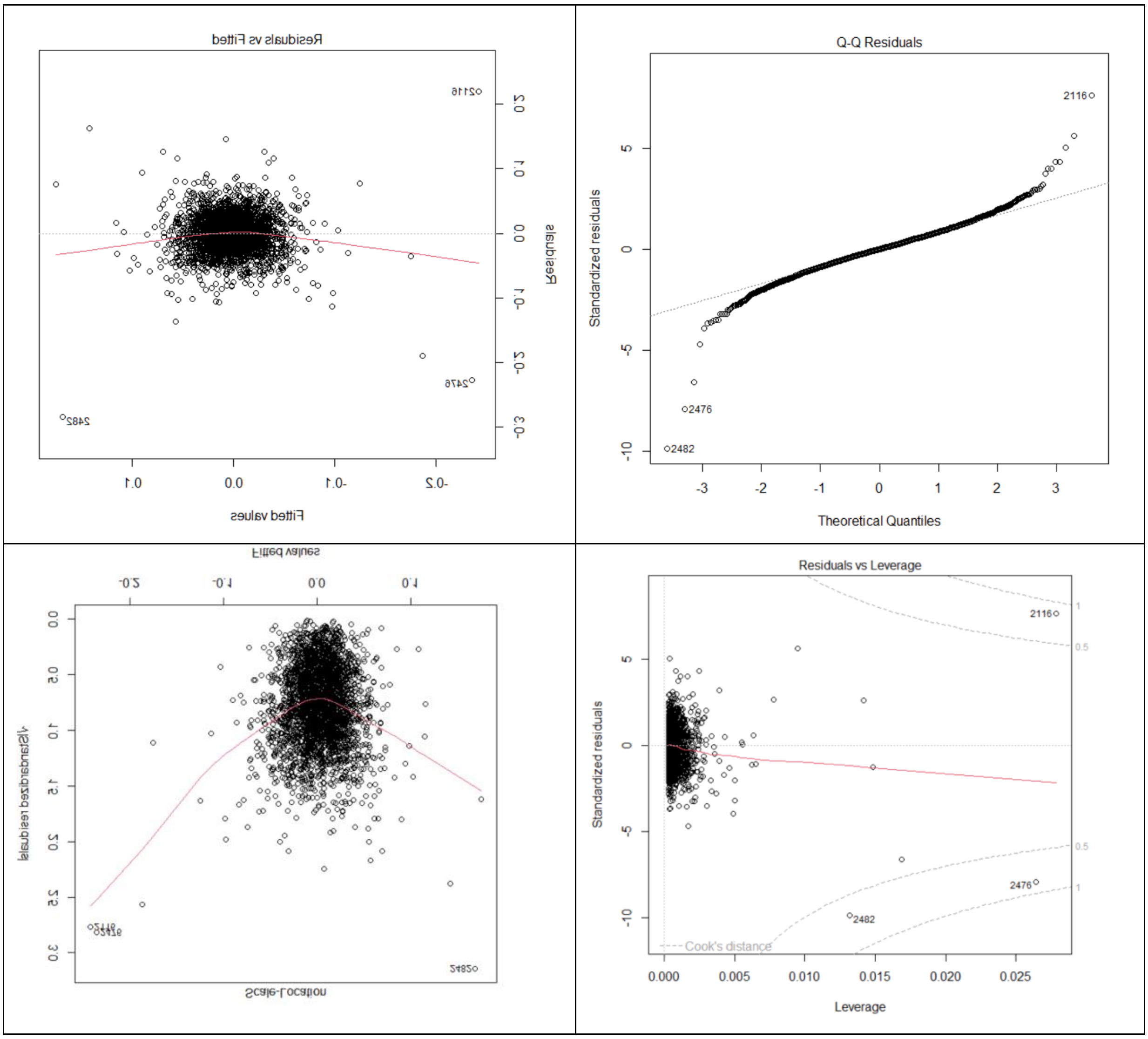

Figure 1: Linearized Model

The regression residuals were calculated and observed, representing the differences between the observed and predicted values, providing insights into the unexplained variation within the model. These residuals serve as a measure of the model's accuracy, indicating areas where the model may deviate from actual outcomes, contributing to the evaluation of predictive performance.

Min	1Q	Median	3Q	Max
-0.284887	-0.016322	0.000462	0.016962	0.219325

Table 2: Residuals

Coefficients	Estimate	Standard Error	t-value	P(>|t|)
(Intercept)	0.0013141	0.0005253	2.502	0.0124
Daily Return Oil & Gas	1.9193349	0.0379412	50.587	<2e-16e

Table 3: T-Statistics

	Values	Degrees of Freedom (DF)
Residual Standard Error	0.02906	3061
Multiple R-Squared	0.4553	-
Adjusted R-Squared	0.4552	-
F-Statistics	2559 (on 1 and 3061)	1 and 3061
p-value	<2.2e-16	-

Table 4

The residuals from the multivariate regression analysis exhibited a range from -0.284887 to 0.219325, with quartiles indicating a relatively small spread. In Table 3, the t-statistics for the coefficients revealed that the intercept had an estimated value of 0.0013141 with a standard error of 0.0005253, resulting in a t-value of 2.502 and a statistically significant p-value of 0.0124. The coefficient for Daily Return Oil & Gas was estimated to be 1.9193349, accompanied by a standard error of 0.0379412, yielding a substantial t-value of 50.587 and an extremely low pvalue of <2e-16. The residual standard error, indicative of the model's goodness of fit, was 0.02906 with 3061 degrees of freedom. The multiple R-squared was 0.4553, suggesting that the model explains a significant proportion of the variance, while the adjusted R-squared remained consistent at 0.4552. The F-statistic, assessing the overall significance of the model, was 2559 with a p-value of < 2.2e-16, indicating a highly significant relationship between the independent variable and the dependent variables.

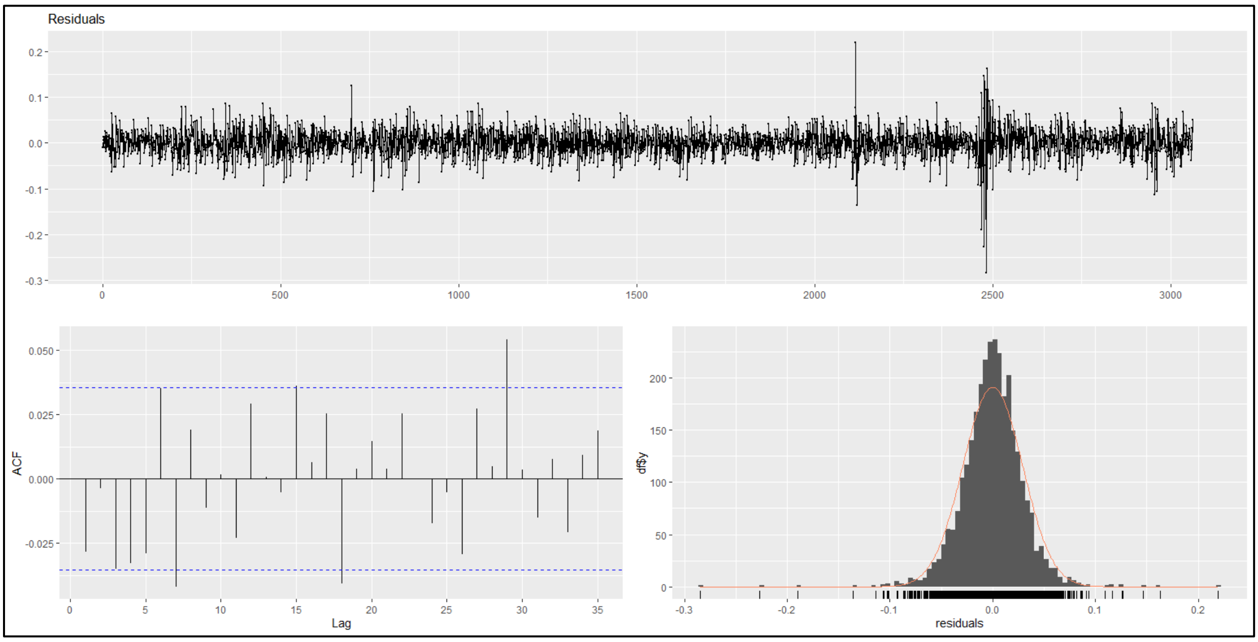

Figure 2: Residuals and ACF

ANOVA is conducted to assess the overall statistical significance of the multivariate regression model. By employing ANOVA, the aim is to determine whether there is a significant relationship between the independent variable and the dependent variables collectively, providing a comprehensive evaluation of the model's overall explanatory power.

	Degrees of Freedom (DF)	Sum of Squares	Mean Sum of Squares	F-Values	P(>F)
Daily Return Oil & Gas	1	2.1615	2.16153	2559	<2.2e-16
Residuals	3061	2.5855	0.00084		

Table 5: Anova Table

The ANOVA model results indicate that the degrees of freedom for Daily Return Oil & Gas are 1, with a corresponding sum of squares of 2.1615 and a mean sum of squares of 2.16153. The Fvalue is 2559, revealing a highly significant relationship (p-value < 2.2e-16) between Daily Return Oil & Gas and the dependent variables. The residuals, with 3061 degrees of freedom, exhibit a sum of squares of 2.5855 and a mean sum of squares of 0.00084. The collective analysis supports the statistical significance of the multivariate regression model.

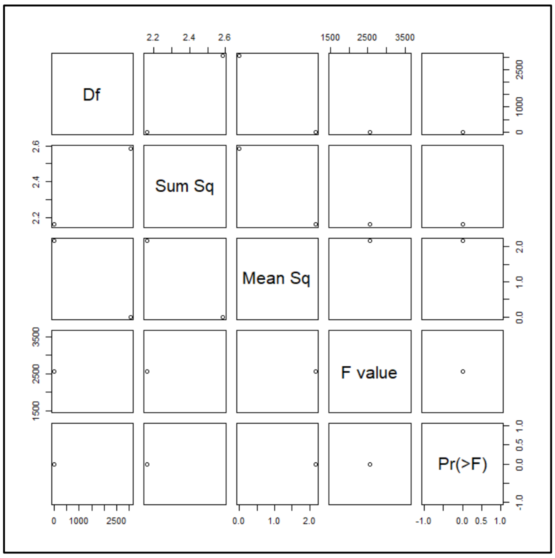

Figure 3

An ARIMA model is being employed to analyze BSE Oil & Gas, driven by the rationale that it offers a robust framework for time series forecasting by capturing the autocorrelation and seasonality patterns in the data. The utilization of an ARIMA model enables the examination of historical stock prices in a dynamic temporal context, facilitating the identification of trends and patterns over time. This approach is chosen to provide a comprehensive understanding of the underlying temporal dynamics inherent in BSE Oil & Gas, allowing for informed predictions and insights into potential future stock price movements based on historical patterns within the time series data.

σ^2	log-likelihood	AIC	AICc	BIC
0.0001917	8763.11	17524.22	17524.21	17518.19

Table 6: ARIMA (0,0,0) with Zero Mean

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training Set	0.0003106569	0.01384412	0.0101703	100	100	0.7236787	0.0003665078

Table 7: Training set error measures

The ARIMA (0,0,0) model with zero mean yielded a variance (□2) of 0.0001917. The loglikelihood was 8763.11, resulting in an AIC of 17524.22, AICc of 17524.21, and BIC of 17518.19. In Table-7, the training set error measures indicated a mean error (ME) of 0.0003106569, a root mean squared error (RMSE) of 0.01384412, and a mean absolute error (MAE) of 0.0101703. The mean percentage error (MPE) and mean absolute percentage error (MAPE) were both 100%. The mean absolute scaled error (MASE) was 0.7236787, and the firstorder autocorrelation coefficient (ACF1) was 0.0003665078. These results contribute to the evaluation of the ARIMA model's performance on the training dataset.

The residuals from the ARIMA (0,0,0) model with zero mean were subjected to the Ljung-Box test. The test statistic (Q*) was calculated as 24.997 with degrees of freedom (df) equal to 10, resulting in a p-value of 0.005352. These results indicate that the null hypothesis of no autocorrelation in the residuals is rejected, suggesting the presence of significant autocorrelation. The model degrees of freedom were 0, and a total of 10 lags were employed in the analysis, contributing to the assessment of the model's adequacy in capturing the temporal dependencies within the residual series.

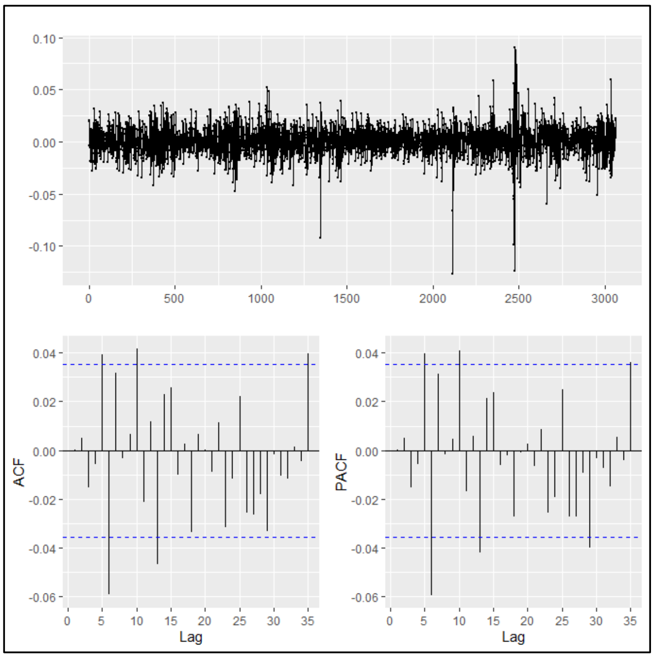

Figure 4: Residuals, ACF and PACF

A correlation matrix has been employed to establish relationships among variables. By calculating pairwise correlations, the magnitudes and directions of associations between variables are analysed, allowing for the identification of potential patterns or dependencies. The correlation matrix provides a comprehensive overview of the interconnections within the dataset, informing subsequent analyses.

	Daily Return Oil & Gas	**Daily Return IT**	**Daily Return Energy**	**Daily Return Auto**	**Daily Return Power**
Daily Return Oil & Gas	**1.0000000**	0.3253991	0.3176172	0.6147757	0.6692878
Daily Return IT	0.3253991	**1.0000000**	0.1822027	0.3826873	0.3155402
Daily Return Energy	0.3176172	0.1822027	**1.0000000**	0.2771632	0.2131833
Daily Return Auto	0.6147757	0.3826873	0.2771632	**1.0000000**	0.6363551
Daily Return Power	0.6692878	0.3155042	0.2131833	0.6363551	**1.0000000**

Table 8: Correlation Matrix

The partial correlation matrix reveals that Daily Return Oil & Gas has a strong positive relationship with Daily Return Power (correlation coefficient = 0.6692878) and Daily Return Auto (correlation coefficient = 0.6147757). Additionally, a moderate positive correlation exists with Daily Return IT (correlation coefficient = 0.3253991) and Daily Return Energy (correlation coefficient = 0.3176172). These findings suggest potential interdependencies among the variables, providing insights into the directional associations in the dataset.

The Engle-Granger test is utilized to examine cointegration among lagged variables, enabling the investigation of long-term relationships within time series data. This test, embedded within the Johansen procedure, facilitates the identification of meaningful connections that persist over time. By assessing eigenvalues, test statistics, and critical values, the Engle-Granger test provides a rigorous framework to infer the existence of cointegration, offering insights into the enduring relationships among variables without imposing stringent assumptions on the data.

Eigenvalues (λ)	0.3638889	0.3440681	0.3336721	0.3189697	0.3007063

	test	**10pct**	**5pct**	**1pct**
$\boldsymbol{r \leq 4}$	1094.87	6.50	8.18	11.65
$\boldsymbol{r \leq 3}$	2270.75	15.66	17.95	23.52
$\boldsymbol{r \leq 2}$	3513.13	28.71	31.52	37.22
$\boldsymbol{r \leq 1}$	4804.25	45.23	48.28	55.43
$\boldsymbol{r = 0}$	6188.99	66.49	70.40	78.80

Table 10: Trace Statistics (Johansen Procedure)

In the presented results, the Engle-Granger test yields a substantial test statistic of 6188.99, surpassing critical values and leading to the rejection of the null hypothesis of no cointegration. This outcome signifies the presence of robust long-term relationships among the lagged variables. The accompanying eigenvectors and loading matrix further illuminate the specific nature of these relationships and the respective contributions of each variable. Such findings contribute valuable information for a nuanced understanding of the dataset, aiding in subsequent analyses of the interdependencies among the time series variables.

4. Conclusion

Significant relationships between BSE Oil & Gas and critical sectors—BSE IT, BSE Energy, BSE Auto, and BSE Power—were found in the context of a multimodal data science analysis that included multiple linear regression, ANOVA, ARIMA, correlation matrix, and the EngleGranger cointegration test. The identification of meaningful coefficients in the regression models revealed significant relationships and offered a data-driven understanding of the complex ways in which variations in BSE Oil & Gas affect the performance dynamics of BSE IT, BSE Energy, BSE Auto, and BSE Power.

By using ARIMA for time series analysis, BSE Oil & Gas's temporal subtleties were revealed, revealing observable patterns and trends that inform predictive modelling. Using sophisticated statistical methods, the correlation matrix firmly confirmed the favourable connections that have been consistently seen between BSE Oil & Gas and BSE IT, BSE Energy, BSE Auto, and BSE Power. These correlations, which are critical to data science analytics, revealed coordinated movements between industries and provided stakeholders with crucial information for navigating intricate financial environments. When the Engle-Granger test was conducted in a data-driven environment, it confirmed the continuous cointegration, indicating long-lasting linkages between variables. The cointegration hypothesis overruled the null hypothesis, highlighting a common long-term trajectory for BSE Oil & Gas and the industries under investigation. In data science interpretations, the loading matrix and eigenvectors are essential tools that offer detailed insights into specific weights and relations, enriching our comprehension of the cointegrating structure. These information-pushed insights assist us higher understand marketplace dynamics and offer stakeholders with useful facts to make clever choices in the constantly changing monetary panorama.

For enhanced precision and a deeper exploration of the intricate dynamics within the financial datasets, additional sophisticated tests such as Autoregressive Conditional Heteroskedasticity (ARCH), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and Granger causality tests can be considered. The incorporation of ARCH ,GARCH and many more models, common in data science methodology, would allow for a more granular examination of volatility patterns and conditional heteroskedasticity in the time series data. Furthermore, delving into Granger causality tests can provide valuable insights into the directional causality between BSE Oil & Gas and other sectors, adding another layer of understanding to the complex relationships identified in the current analyses. Beyond traditional statistical methods, the integration of advanced techniques, including neural networks, presents an avenue for comprehensive exploration, facilitating the identification of intricate patterns and non-linear relationships that might elude more conventional approaches.

The consideration of these advanced data science methodologies could contribute to a more holistic and precise comprehension of the intricate interdependencies within the financial markets under investigation.

Further Scope of the Research

This paper consists of 3063 days of data and forecasts them to find the association between five various stock markets. Other researchers can go for further statistical modelling by using various statistical tools and techniques.

Limitations of the Study

Stock market analysing may face a strong challenge to predicting the future stock market and it is a foolish game for traders and investors for a short-term period. But if they want to predict for long term period it may be profitable. And, it also depends on analysts to guess the proper strategy and use proper deep learning tools to examine the nature and predict the future outcome.

Ethical Standards

This stock market analysis was conducted with unwavering adherence to ethical principles. By maintaining the highest standards of research integrity, valuable insights were aimed to be contributed to the field of financial analysis, and the trust of the readers and the wider research community was upheld.

Fundings

Author did not receive any fundings for support for this work.

Declaration of Interest

No conflict of interest is declared by the author

Data Sharing Statement

The dataset is available in BSE official website.

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