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Twitter sentiments and stock indices returns with reference to nifty energy indices of India

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Abstract. *An attempt has been made in the study, to examine the correlation between Twitter Sentiments and Stock Indices Returns, with reference to Nifty Energy Indices. This study used daily time series data, for a period of five years from 01.01.2018 to 31.12.2022. The study found positive relationship between variables of twitter positive, negative sentiment and nifty energy indices but negative relationship was found between neutral sentiment and nifty energy indices. The findings of the study would be useful to the investors and other participants of stock market, understanding the influence of Twitter sentiment on the energy indices returns.*

Keywords: stock indicators, energy markets, growth.

JEL Classification: Q43.

Introduction

The market efficiency has been a controversial topic in the academic realm. There is an ongoing debate on the efficiency theory, which is a fundamental assumption on the operation of financial markets. There is a general consensus among researchers towards weak or semi-strong form efficiency (Dimson and Mussavian, 1998; Lim and Brooks, 2011). But, it is difficult to comprehend how information is disseminated among the investors and at exactly what speed. Twitter has become a strong tool to assess and pass the information when it is made available (Bartov et al., 2018). It is to be noted that there is strong relationship between stock markets and twitter data (Bollen et al., 2011). Besides, the twitter is considered as a close proxy for the propagation of publicly available information. The users generally share the information that is already known or they would share the ones the tweet had posted. Thus, twitter is a useful and powerful tool to share information and determine the stock market efficiency. In other words, this social media has now become an extremely popular communication channel as it is easy for the users to share the information over social media. The researchers have already examined various social media platforms such as Facebook, yahoo messenger, StockTwits (Siganos et al., 2014; Oliveira et al., 2016; Antweiler & Frank, 2004), for analysing their impact on the stock markets. Twitter has been chosen for studies as it is a favoured social media platform for sharing financial information, and the twitter based trading systems have also been popular among the investors (Sprenger et al., 2014). There have been plenty of evidences to indicate that the public sentiments, expressed on twitter possessed significant predictive power over that of other information on the performance of the stock market indicators (e.g. He et al., 2016; Liu et al., 2015; Risius et al., 2015). However, research on the stock markets and social media field has predominantly focused on the developed markets, leaving the developing economies' markets relatively uncharted in repect of the impact of information diffusion through social media (Agarwal et al., 2019). The research studies conducted in developing countries have primarily centered on examining weak-form market efficiency (Mobarek & Fiorante, 2014). There are varying degrees of irrational of investor behavior and market inefficiencies across countries (Chui et al., 2010). Hence it has become essential, on the part of researchers, to investigate how the stock markets in emerging economies respond to the information, disseminated through social media channels. Moreover, it is important to note that stock markets in developing countries are still in a state of evolution compared to their counterparts in developed nations (Claessens & Yurtoglu, 2013).

Twitter is a widely used online social media. The fast growth of twitter has drawn the attention of many researchers in different disciplines and policy makers. A recent study on the public mood clearly revealed that twitter is significantly correlated with the nifty energy index and thus, information through twitter can be used to forecast the changes in the nifty energy index, with a high degree of accuracy. In this paper, an attempt has been made to investigate the correlation between the daily number of tweets about stock market and nifty energy indices return in India.

Review of literature

This section presents a review of earlier papers and research works that focused on the relationship between investor sentiments and stock returns indicators.

Ting Yao et al (2017) investigated the impact of mechanism of investors' attention on crude oil prices. The investors' sentiments contributed to 15% of fluctuation of WTI crude oil price during the sample period. Dayong Zhang et al (2017) explored the extent to which oil prices and market fundamentals contributed to the variations in gas prices in Japan, United States and Germany. The prices of gas in America were less affected by supply and demand factors than the by prices in Japan and Germany. Mahmoud Qadan et al (2018) found investors' sentiment to exercise significant effect on the oil prices and volatility in the indices spills over. Ji, Qiang et al (2019) examined the dynamic directional information spillover of return and volatility between the fossil energy market and investors, sentiment towards renewable energy. Yan-Ran Ma et al (2019) investigated the inter-connectedness between WTI oil price returns and the returns of listed firms in the US energy sector. The idiosyncratic information was mostly independent of oil stocks but individual energy stock returns did respond to WTI price movements. Bernard Njindan Iyke et al (2021) examined *energy securities*, that contained valuable information, useful to predict the energy *stock returns*. Lu Wang et al (2021) examined the causality between the crude oil futures market and the investor sentiment under extreme shocks. According to Lu Wang, et al (2021), the crude oil futures market and investors sentiment' showed dynamic causality at different frequencies. Besides, the crude oil futures were strongly affected by negative extreme shocks than by positive extreme shocks. According to Gianluca Anese et al (2023), there was impact of investorb sentiments on the market, over a 20-min time frame. Dictionary-based sentiment provided meaningful results that outperformed those based on stock index returns.

The review of select literature has provided an overview of some empirical studies, already undertaken on the same lines of the present research. But only few studies focused on the relationship between twitter sentiment and energy stock returns. Hence this article proposes to investigate the correlation between Twitter Sentiments and Stock Returns, with reference to Nifty Energy Index in India.

3. Hypotheses of the study

For the purpose of this study, following three hypotheses were developed and tested.

H1 – There is normal distribution among the Twitter sentiments and Nifty Energy Index indicators;

H2 – There is stationarity among the Twitter sentiments and Nifty Energy Index indicators;

H3 – There is correlation between Twitter sentiments and Nifty Energy Index indicators.

4. Methodology of the study

4.1. Sample Selection

The information floated in the tweets regarding stock market operations, was selected and used for this study. For the purpose of this study, five nifty energy stock market indicators like, ADANIGREEN, BPCC, IOC, RELIANCE and POWERGRID were selected. The information, shared through the tweets, was classified into three categories, namely, positive, negative and neutral and all the three were used for the analysis during the study period.

4.2. Sources of Data

The present study fully depended on secondary data, regarding energy stock indices indicators and Twitter response. For the purpose of this study, the stock market information and energy stock indices were collected from yahoofinance.com (http://finance.yahoo.com/). The required data about twitter news feed were collected from Twitter data base (https://www.kaggle.com/).

4.3. Period of Study

This study covered a period of five years from 01.01.2018 to 31.12.2022.

4.4. Tools used in the Study

For the purpose of achieving the above objectives, the following tools were used for the analysis.

a) Descriptive Statistics (to find out the normal distribution of twitter sentiment and stock market indicator)

Mean

Mean depicts characteristics of the whole group in a single value. Its value lies somewhere between the two extremes i.e., minimum and maximum (Thomas K. Tiemann, 2010). Hence the mean is frequently referred to as a measure of central tendency and it is formulated as:

Mean $(\bar{x}) = \frac{\sum xi}{n}$

Where,
$\bar{x}$ = represents the mean;
$\sum =$ Symbol of Summation;
Xi = Value of the i^{th} item, I = 1,2,3 …..n, and
n = Total Number of items.

Standard Deviation

Standard Deviation measures the absolute dispersion or variability of distribution of the data. The greater value of standard deviation reveals the magnitude of the deviation from the mean value. It is also called as root mean square deviation (Thomas K. Tiemann, 2010). The standard deviation of a random variable X is defined as:

$$\sigma = \sqrt{E((X - E(X))^2} = \sqrt{E(X^2) - (E(X))^2} = \sqrt{Var\ (X)}$$

Where,
E (X) is the expected value of X and
Var (X) is the variance of X.

Skewness

Measures of skewness tell us the direction and the extent of skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution of data set is symmetric if it looks the same to the left and right of the centre point. Negative values for the skewness indicate that data are skewed left and positive values for the skewness indicate that data are skewed right. The skewness is calculated as follows:

$$\gamma 1 = \mu 3/\sigma 3$$

Where,
μ3 is the third movement about the mean;
σ is the standard deviation.

Kurtosis

Kurtosis measures the amount of peakedness of distribution. A flatter distribution than normal distribution is called platykurtic. A more peaked distribution than the normal distribution is referred to as leptokurtic. Between these two types of distribution, the distribution, which is normal in shape, is referred to as a mesokurtic distribution. A negative kurtosis value implies a platykurtic distribution and a positive kurtosis value indicates a leptokurtic distribution. The kurtosis is defined as:

$$\gamma 1 = \mu 4/\sigma 4$$

Where,
μ4 is the fourth movement about the mean;
σ4 is the standard deviation.

b) Unit Root Test

In statistics and econometrics, the Augmented Dickey Fuller Test is a test for a unit root in a time sample. It is an augmented version of the Dickey Fuller Test for a larger and more complicated set of time series models.

$$\Delta yt = \alpha + \beta t + \gamma yt - 1 + \delta 1 \Delta yt - 1 + \cdots + \delta \rho \Delta yt - p + \varepsilon t.$$

Where,
α is a constant;
β the coefficient on a time trend and
p the leg order of the autoregressive process.

c) Correlation Analysis

To know the relationship between the twitter sentiment and stock market indicator, correlation is used with following equation:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n(\sum x^2 - (\sum x)^2 (n \sum y - (\sum y)^2)}}$$

Where,
N = Number of observations;
$\sum x =$ Dependent variables and
$\sum y =$ Independent variables.

5. Result and discussion

Normality (Descriptive Statistics) of the Twitter Sentiment and Nifty Energy Index

Table 1 shows the results of descriptive statistics, for twitter sentiment data and stock market indicators, during the study period from 01.01.2018 to 31.12.2022. It is evident that the summary statistics, namely, minimum, maximum, mean, standard deviation, skewness, and kurtosis, was used to analyse the sample variables during the study period. It is clear from the Table that the positive tweets (14.96), negative tweets (5.86), neutral tweets (27.87), ADANIGREEN (462.200), BPCC (262.850) IOC (47.700) RELIANCE (875.748) and POWERGRID (108.112) scored positive mean values, during the study period. Similarly, the ADANIGREEN (606.323) reported the highest value of standard deviation in daily returns. The analysis of skewness revealed that both positive and negative values for all sample variables, namely, positive tweets (4.798), negative tweets (11.382), neutral tweets (10.804), ADANIGREEN (-0.963), BPCC (0.415) IOC (0.277) RELIANCE (-0.2778) and POWERGRID (0.454) were recorded during the study period. The analysis of skewness and kurtosis of the stock market indices and twitter sentiment indicated that there was non-symmetric distribution of data, with fat tails, as compared with normal distribution. In short, the distribution of return data, for all the sample indices, was normal. Hence the Hypothesis *(H1) - There is normal distribution among the Twitter sentiments and Nifty Energy Index indicators*, was rejected.

Table 1. *Normality (Descriptive Statistics) of Twitter Sentiment and Nifty Energy Index indicators during the study period from 01.01.2018 to 31.12.2022*

	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
Twitter Sentiment						
Twitter Positive Sentiment	0	8	14.96	23.596	4.798	31.889
Twitter Positive Sentiment	0	12	5.86	15.211	11.382	192.355
Twitter Neutral Sentiment	0	15	27.87	44.207	10.804	189.568
Nifty Energy Index Indicators						
ADANIGREEN	462.200	2970.500	1898.108	606.323	-0.963	0.223
BPCC	262.850	544.600	389.933	58.475	0.415	-0.750
IOC	47.700	113.133	75.548	14.737	0.277	-0.579
RELIANCE	875.748	2819.850	1979.036	506.004	-0.278	-1.313
POWERGRID	108.112	245.150	168.105	34.948	0.454	-1.138

Stationarity (Unite Root Test) for Twitter sentiments and Nifty Energy Index Indicators

Augmented Dickey_Fuller Test (ADF)) was used to examine the stationarity among the sample Twitter sentiments and Nifty Energy Index indicators. The results of the Augmented Dickey Fuller Test (ADF), for daily closing values for Twitter sentiments and Nifty Energy Index indicators, during the study period from 01.01.2016 to 31.01.2020 are shown in Table-2. The analysis of results of ADF was made at three significant levels, namely, 1%, 5% and 10%. The probability values (p-values), for all the sample variables, were nearly zero. The statistical values, using ADF test for all the sample variables, were -8.036 for positive tweets, -7.241 for negative tweets, -6. 881 for Neutral tweets, -4.630 for ADANIGREEN, -2.333 for BPCC, -1.521 for IOC, -1.758 for RELANCE, -1.491 for POWERGRID during the study period. These values were less than that of test critical values at 1%, 5% and 10% levels of significance. The ADF Tests clearly revealed that the data of all sample variables attained stationarity. Hence, the Hypothesis *(H2) – There is stationarity among the Twitter sentiments and Nifty Energy Index indicators,* was rejected.

Table 2. *Stationarity (Unite Root Test) for Twitter Sentiment and Nifty Energy Index Indicators during the study period from 01.01.2018 to 31.12.2022*

Variable	t-Statistics	P value
Twitter		
Twitter Positive Sentiment	-8.036	0.000
Twitter Positive Sentiment	-7.241	0.000
Twitter Neutral Sentiment	-6.881	0.000
Nifty Energy Indicators		
ADANIGREEN	-4.630	0.000
BPCC	-2.333	0.000
IOC	-1.521	0.000
RELIANCE	-1.758	0.000
POWERGRID	-1.491	0.000
Test critical values		
1% level	-3.436	
5% level	-2.864	
10% level	-2.568	

Relationship between Positive Sentiment of Twitter and Nifty Energy Index Indicators

Table 3 presents the results of correlation analysis, for positive sentiment of twitter and nifty energy index indicators, during the study period from 01.01.2018 to 31.12.2022. For the purpose of this study, a variable, namely, twitter positive sentiment was considered as independent variable while five nifty energy index indicators, namely, ADANIGREEN, BPCC, IOC, RELIANCE and POWERGRID were used as the dependent variables. There was a positive correlation between twitter positive sentiment and nifty energy index returns, as evident from values (Pearson correlation matrix) of 0.243 for ADANIGREEN, 0.115 for BPCC, 0.262 for RELIANCE and 0.252 for POERGRID, at 99% confidence level (i.e., p value was less than 0.01). The overall analysis showed that the indicator namely, twitter positive sentiment had reported positive relationship with nifty energy indices (dependent variables). Hence the hypothesis *(H3) – There is correlation between Twitter Positive sentiment and Nifty Energy Index indicator*, was accepted. It was evident from the analysis that the variable, namely, twitter positive sentiment on IOC, had not realized correlation, at both confidence levels (i.e., p value of 0.01 and 0.05). In other words if a firm has a high number of retail investors, the proportion of positive messages on Twitter about its stock index performance, would increase the value of the stock in the market.

Table 3. *The Results of Correlation between Twitter Positive Sentiment and Nifty Energy Index during the study period from 01.01.2018 to 31.12.2022*

		Twitter Positive Sentiment	Nifty Energy Index Indicators				
			ADANIGREEN	BPCC	IOC	RELIANCE	POWERGRID
Twitter Positive Sentiment	Pearson Correlation	1	0.243**	0.115**	0.031	0.262**	0.258**
	Sig. (2-tailed)		0.000	0.000	0.328	0.000	0.000
Nifty Energy Index Indicators							
ADANIGREEN	Pearson Correlation	0.243**	1	-0.118	0.376**	-0.775**	0.156*
	Sig. (2-tailed)	0.000		0.065	0.000	0.000	0.014
BPCC	Pearson Correlation	0.115**	-0.118	1	-0.015	-0.387**	-0.442**
	Sig. (2-tailed)	0.000	0.065		0.634	0.000	0.000
IOC	Pearson Correlation	0.031	0.376**	-0.015	1	-0.358**	0.158**
	Sig. (2-tailed)	0.328	0.000	0.634		0.000	0.000
RELIANCE	Pearson Correlation	0.262**	-0.775**	-0.387**	-0.358**	1	0.740**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
POWERGRID	Pearson Correlation	0.258**	0.156*	-0.442**	0.158**	0.740**	1
	Sig. (2-tailed)	0.000	0.014	0.000	0.000	0.000	

**. Correlation is significant at 0.01 level (2-tailed).

*. Correlation is significant at 0.05 level (2-tailed).

Relationship between Twitter Negative Sentiment and Nifty Energy Index Indicators

The general indicator of stock market (correlation matrix) was used to find out the relationship between Twitter Negative Sentiment and Nifty Energy index indicators. As stated earlier, the variable, namely, twitter negative sentiment was employed as the independent variable while five nifty energy index indicators, namely, ADANIGREEN, BPCC, IOC, RELIANCE and POWERGRID, were used as dependent variables. The results of correlation analysis, in respect of twitter negative sentiment and nifty energy returns during the study period from 01.01.2018 to 31.12.2022, are given in Table 4. There was positive correlation between twitter negative sentiment and nifty energy indices, as evident from the recorded with Pearson correlation matrix value of 0.317 for ADANIGREEN, 0.143 for RELIANCE and 0.158 for POERGRID, at 99% confidence level (i.e., p value was less than 0.01). The overall analysis found that the indicator, namely, twitter positive sentiment had reported relationship with nifty energy index (dependent variables). Hence, the hypothesis *(H3) – There is correlation between twitter negative sentiment and nifty energy index indicators*, was not rejected. It was evident from the analysis that the two sets of variables, namely, Twitter negative sentiment and BPCC and twitter negative sentiment and IOC had not realized correlation, at both confidence levels (i.e., p value of 0.01 and 0.05). But the stock return and percentage of negative tweets were positively correlated and the increase in negative emotion was linked to a decrease of returns in the market.

Table 4. *The Results of Correlation between Twitter Negative Sentiment and Nifty Energy Index Indicators during the study period from 01.01.2018 to 31.12.2022*

		Twitter Negative Sentiment	ADANIGREEN	BPCC	IOC	RELIANCE	POWERGRID
Twitter Negative Sentiment	Pearson Correlation	1	0.317**	0.057	0.013	0.143**	0.158**
	Sig. (2-tailed)		0.000	0.072	0.690	0.000	0.000
Nifty Energy Index Indicators							
ADANIGREEN	Pearson Correlation	0.317**	1	0.118	0.376**	0.775**	0.156*
	Sig. (2-tailed)	0.000		0.065	0.000	0.000	0.014
BPCC	Pearson Correlation	0.057	0.118	1	-.015	-0.387**	-0.442**
	Sig. (2-tailed)	0.072	0.065		0.634	0.000	0.000
IOC	Pearson Correlation	0.013	0.376**	-0.015	1	-0.358**	0.158**
	Sig. (2-tailed)	0.690	0.000	0.634		0.000	0.000
RELIANCE	Pearson Correlation	0.143**	0.775**	-0.387**	-0.358**	1	0.740**
	Sig. (2-tailed)	0.000	.000	0.000	0.000		0.000
POWERGRID	Pearson Correlation	0.158**	0.156*	-0.442**	0.158**	0.740**	1
	Sig. (2-tailed)	0.000	0.014	0.000	0.000	0.000	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Relationship between Twitter Neutral Sentiment and Nifty Energy Index Indicators

Table 5 shows the results of correlation analysis for twitter neutral sentiment and nifty energy index indicators, during the study period from 01.01.2018 to 31.12.2022. The variable, namely, twitter neutral sentiment was considered as the independent variable while five nifty energy index indicators, namely, ADANIGREEN, BPCC, IOC, RELIANCE and POWERGRID, were considered dependent variables for the purpose of this study. There was negative correlation between twitter neutral sentiment and nifty energy returns, as evedint from Pearson correlation matrix value of 0.-129 for ADANIGREEN, -0.159 for IOC, and -0.217 for POERGRID at 99% confidence level (i.e., p value was less than 0.01). The overall analysis revealed that the indicators of twitter neutral sentiment had reported positive relationship with nifty energy index. But two variable sets such as twitter neutral sentiment and BPCC and twitter neutral sentiment and RELIANCE, had not realized correlation, at both confidence levels (i.e., p value of 0.01 and 0.05) during the study period. Hence the hypothesis *(H3) – There is correlation between Twitter neutral sentiment indicators and Nifty Energy Index indicators*, was not rejected.

Table 5. *The Results of Correlation between Twitter Neutral Sentiment and Nifty Energy Indicators during the study period from 01.01.2018 to 31.12.2022*

Twitter Neutral Sentiment			Nifty Energy Indicators				
			ADANIGREEN	BPCC	IOC	RELIANCE	POWERGRID
Twitter Neutral Sentiment	Pearson Correlation	1	-0.129**	0.009	-0.159**	-0.039	-0.127**
	Sig. (2-tailed)		0.000	0.779	0.000	0.218	0.000
Nifty Energy Index Indicators							
ADANIGREEN	Pearson Correlation	-0.129**	1	-0.006	0.048	-0.149**	-0.084**
	Sig. (2-tailed)	0.000		0.845	0.129	0.000	0.008
BPCC	Pearson Correlation	0.009	-0.006	1	-0.015	-0.387**	-0.442**
	Sig. (2-tailed)	0.779	0.845		0.634	0.000	0.000
IOC	Pearson Correlation	-0.159**	0.048	-0.015	1	-0.358**	0.158**
	Sig. (2-tailed)	0.000	0.129	0.634		0.000	0.000
RELIANCE	Pearson Correlation	-0.039	-0.149**	-0.387**	-0.358**	1	0.740**
	Sig. (2-tailed)	0.218	.000	0.000	0.000		0.000
POWERGRID	Pearson Correlation	-0.127**	-0.084**	-0.442**	0.158**	0.740**	1
	Sig. (2-tailed)	0.000	0.008	0.000	0.000	0.000	

6. Conclusion

The present study examined the relationship between Twitter sentiments and the Nifty energy index indicators in the stock market. Its aim was to findout whether there was correlation between Twitter sentiments (positive, negative, and neutral) as expressed in tweets and the movements of the Nifty Energy Index indicators. There has been an ongoing debate on the market efficiency in the financial markets and the role of Twitter as a tool to assess the information being disseminated among the investors. The real-time twitters and its role on the information exchange, makes it a potential proxy for analysing the stock market efficiency. The correlation analysis found positive relationship between sample variables of twitter such as positive, negative sentiment and nifty energy indicators namely, ADANIGREEN, BPCC, IOC, RELIANCE and POWERGRID. This study suggests that the managers of social media should carefully monitor social media, at different intervals of time, for predicting the stock market by investors.

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