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RELATIONSHIP BETWEEN TWITTER SENTIMENTS AND STOCK MARKET RETURNS: AN EMPIRICAL ANALYSIS OF NIFTY FIFTY COMPANIES

Dr. Divya Verma
Assistant Professor, University School of Management Studies, Guru Gobind Singh Indraprastha University, Dwarka, New Delhi, INDIA, divya.ipu@gmail.com

Mr. Mohit Kumar
Student, University School of Management Studies, Guru Gobind Singh Indraprastha University, Dwarka, New Delhi, INDIA

Dr. Narender
Amity University, Haryana, email- narendervrm007@gmail.com

Deepti Sehrawat Verma
Ph.D Scholar, Central University of Haryana, Mahendragarh, Haryana.

ABSTRACT
Twitter has emerged as a popular social media channel. The present paper analyses the relationship between Twitter sentiments and CNX Nifty Index stock returns. Twitter sentiments were captured with R software's help for a period of 22 days for Indian benchmark Index Nifty which includes fifty blue-chip companies. The sentiments were classified as positive sentiments score, negative sentiments score and total tweets score. Also Overall Twitter Sentiment Score was computed which includes positive sentiments minus negative sentiments indicating the overall direction of investor sentiments. The relationship between stock returns and positive tweets, negative tweets and total tweets was analysed using correlation and the Granger causality test. The results show that there is a high degree of correlation between returns and tweets about companies with 28 per cent companies. Granger causality test shows that Indian benchmark index Nifty returns causes Twitter sentiments. Granger causality test shows that positive sentiments (55.5 per cent) and negative sentiments (44.4 per cent) about a company on Twitter causes stock returns. 61.5 per cent companies show that total Tweets score causes stock returns. The results also show that for 30.8 per cent companies overall Twitter sentiment score causes returns in the stock market. These results are useful for investors and companies to understand the role of investor sentiments reflected on Twitter which can impact market movement and can be used by companies and investors to maximize their returns in the market.

Introduction

Twitter is one of the biggest microblogging social networks established in 2006, allowing users to express their opinion in 280 characters about various issues on public and private feeds of people they follow (Nisar & Yeung, 2018). It had 325 million monthly active users worldwide in 2019. There are 49.35 million active Twitter users in the USA, followed by Japan, which is

39.85 million and 7.83 million active Twitter users in India as of 2019. It is highly convenient and accessible for users to respond and spread information immediately. Twitter is mostly seen as a medium to promoting such media products where instant success is essential like movies, music, launching new products. It is used to create awareness, seek advice, and form opinions by individuals and businesses (Atefeh, 2015). This real-time rich data can be useful for studying the individual behaviour, group behaviour and global patterns related to sentiments about any news, event, political issue, social issue, products etc. Data analytics is now possible to analyse the opinion, mood, and sentiments of people around the world on a real-time basis with no data collection cost. Social media data are majorly used for brand management, advertising, checking popularity, launching new products, guerilla marketing, designing policies and strategies.

Fama (1970) gave an efficient market hypothesis that assumes investors to be rational, and everyone has all information about the market. There are other classical finance approaches, namely fundamental and technical analysis, which provide tools to investors to make rational investment decisions. But in reality, it has been observed by behavioural scientists that investors are not perfect and are irrational while taking decisions. The classical finance models can predict stock prices and expected returns with a noise factor component, which is an unpredictable portion of the market (Bollen, Mao, & Zeng, 2011). This noise or unexplained market reactions were always a cause of concern for analysts as they cause market overreactions, underreaction, creation of bubbles, the setting of bullish and bearish phases in the market. The answer to these unexplained market reactions was given by behavioural finance experts, who emphasised studying human beings' behaviour while taking financial decisions (Bhatia, Mellers, & Walasek, 2019).

Behavioural finance explains that people make irrational decisions based on human emotions, mood, attitude, feelings, past experiences, intuition, sentiments and behavioural biases. Behavioural finance suggests that investment decisions are affected by various cognitive and emotional biases. Humans are emotional beings, and emotions influence their behaviour. As per the somatic marker hypothesis given by Neuroscientists, emotions play a crucial role in a human's ability to make fast and rational decisions in complex situations. Bhardwaj et al. (2015) explain that emotions and feelings influence rational decision-making in individuals which can happen consciously or unconsciously based on the somatic marker hypothesis. Thus, understanding human sentiments, mood, opinions about any stock, event, company or policy will be crucial as they will shape their decision (Sun, Chen, Liu and Hao, 2018). Apart from that, group behaviour of the public is also very important in deciding the market's direction. Emotional contagion is the tendency for two individuals or social groups to converge emotionally. This is possible through social networks like Twitter (Nagarajan & Gandhi, 2019). If there is a homogeneity of emotions on the social network in various groups, this can cause herd mentality in investment decisions. This can give a very relevant explanation to market crashes, boom phase, bear and bullish phase about some stocks or the overall market. There is evidence that if a social group is forming a strong opinion about the market, an individual investor's emotions are bound to influence it. Kurov, A. (2008) show that emotions expressed by others on Facebook influence our own emotions. Behavioural biases like availability bias, representativeness bias, and framing effect can emerge through Twitter, affecting individual behaviour and its relationship can be analysed.

Social media has become a medium to judge investors' mood, tastes, and sentiments and help get insights into individual behaviour. Twitter-based models can help build an aggregate opinion about the collective population (Bollen et al., 2011). Klibanoff et al. (1998) found that investor changes their behaviour as a reaction to any dramatic news. Mao et al. (2012) carried out volume analysis and compared the number of tweets on the S&P 500 with the movement of stock indicators and found that they are correlated and can be used to predict market movements. Rao and Srivastava (2012) did not find a significant causal relationship between the volume of tweets and stock market parameters. Oliveira, Cortez and Areal (2017) revealed that Twitter sentiments could predict stock returns. Tetlock (2007) explained that pessimistic sentiments impact returns after any negative information are known. Emotional outbursts on Twitter (Zhang, Fuehres, & Gloor, 2011; Nisar & Yeung, 2018) can also impact stock returns.

After understanding the importance of Twitter as a tool to define public sentiment, the present study analyses the relationship between Twitter sentiments on Indian stock market returns. This study answers two questions: Is there any correlation between Twitter sentiments and returns of the Indian stock market? And second, whether Twitter sentiments comes first and later on stock prices changes or vice versa. The study attempt to analyse the lead-lag relationship between Twitter sentiments and stock prices. Twitter sentiments can be positive or negative, and they are formed after any event or News is shared about any company. Mood or sentiments of the public is defined as positive or negative based on Twitter feeds and then its relationship is studied with stock returns. The total Twitter score defines the volume of public sentiment about any company. Daily Twitter feeds related to the Nifty Index comprising of fifty companies have been taken, and its relationship is studied with stock price movements. This study is highly relevant in the Indian context as there are limited studies carried out on Indian companies. Another distinct feature of this study is that it not only captures responses from twitter as total tweet score but also analyses the negative tweet score, positive tweet score and their relationship with stock returns. Apart from that the Overall Twitter Sentiment score which evaluates the overall sentiments of investors, has also been used to analyse its movement with stock returns, with an assumption that the overall direction of sentiment may be impacting the stock returns. The study results will be useful for investors and analysts to understand the market sentiments as this will help them take care of the noise. In such a scenario, Twitter comes as a cost-effective and convenient source of stock market news and information to the retail investors, and they take their investment decisions based on corporate News shared on a real-time basis on Twitter. Apart from just getting first-hand information about stocks on Twitter, one also gets to know the opinion and public sentiment about an event. This helps investors take decisions that can help earn exceptional returns. Understanding positive public sentiments and negative sentiments on stock returns will also help the investors avoid behavioural biases and errors like herding, overreactions, and framing effect while taking investment decisions.

The paper is divided into five sub-sections: a review of literature, materials and methods, results, discussion, and conclusion.

Review of Related Literature

Social networks and micro-blogs have recently gained popularity and due to which sentiment analysis has become an efficient tool for everyday life. Economists and researchers have also tried their hands at it. Microblogging platforms like Twitter have proven to be an important source for opinion mining and sentiment analysis. Various researchers have carried out Twitter-based sentiment analysis studies in various countries, through different methods of compiling data. These are discussed hereunder.

Studies based on Sentiment Analysis

Tumarkin and Whitelaw (2001) attempted to predict stock prices using internet sentiment data. They tracked the financial forums available on the internet and tried to link the stock prices and information posted. They could not find a strong relationship between the two. This research study gained the interest of many economists and researchers. A similar kind of study was done by Antweiler and Frank (2004). They examined two message boards for 45 companies from Dow Jones Industrial Average with more than 1.5 million messages and found a statistically significant relationship. Chen et al. (2014) did a textual analysis of articles published on popular social media platforms for investors in the United States and found a strong relationship between them. The opinions and information had a strong impact in predicting stock returns. Tayal and Komaragiri (2009) examined the positive and negative impact of blog sentiment and Twitter on the prices of two companies' stocks, namely, Microsoft and Google. It was found that microblogs had more predictive power as compared to blogs. Si et al. (2013) used Twitter's REST API for data streaming and collected around 6 lacs tweets over 97 days, using keywords as symbols of the Standard & Poor's 100 stocks. They examined the tweets via sentiment analysis based on the topic using the Dirichlet Processes Mixture model. It was found that the prediction accuracy can be improved by Twitter's case based sentiment analysis. Sakaki et al. (2010) studied the real-time nature of Twitter by taking Twitter users as sensors of an earthquake and examining if their activity was able to detect earthquake shakes. It was found that they can promptly detect an earthquake and its location through a probabilistic spatiotemporal model and an algorithm analysing Tweets.

Zhang, et al. (2012) analysed the stock market using Twitter by classifying optimistic and pessimistic tweets. The results show that there were more optimistic tweets rather than pessimistic ones. Tweets have a positive correlation with VIX but are negatively related to Dow Jones and NASDAQ. Oh, C. and Sheng, O. (2011) analyses stock tweets and concluded that tweets have strong power to predict the future market directions. Liew, J. K. S., and Wang, G. Z. (2016) investigated the impact of Twitter on IPO prices and studied them for three days for IPOs for two years. Twitter sentiments have a direct effect on IPO prices on the first day. Pagolu et al. (2016) investigated the correlation between the stock prices of Microsoft and twitter opinions. Nguyen, et al. (2015) modelled Twitter sentiments to predict stock prices. Ranco et al. (2015) analysed Dow Jones Industrial Average (DJIA) 30 stocks using the Granger causality index and found a positive relationship between returns and twitter sentiments. Oliveira, Cortez and Areal (2013) found no association between stock return predictability and investor sentiment indicators.

Studies based on Volatility and Volume

Rao and Srivastava (2012) collected approximately 4 million tweets over 14 months ranging from June 2010 to July 2011 and examined the relationships between, trading volume, volatility and stock prices of NASDAQ-100, DJIA, and 13 other big cap technological stocks and Twitter sentiment. They used Naıve Bayesian classification to analyse the positive and negative impact of tweets. They suggested that market data and Twitter sentiment are strongly dependent on each other. De Jong, et al., (2017) analysed stock return volatility and Twitter sentiment on 13 days of data of the Dow Jones Industrial average. They found that the majority of tweets impact the stock market returns. Sprenger et al. (2014) studied around 250,000 Tweets related to stock every day in 2010 and used the Naive Bayesian classification method to sort the Tweets into three categories as buy, hold or sell signals. It was found that stock returns are strongly affected by Twitter sentiment effects. It was also found that Tweets volume can even predict the trading volume for the next day.

Ranco et al. (2015) applied the Karl Pearson correlation and Granger causality test on Twitter sentiments and stock market returns. Antweiler and Frank (2004) examined only 45 companies from Dow Jones Industrial Average, Tayal and Komaragiri (2009) examined two companies, namely, Microsoft and Google, Si et al. (2013) studied Standard & Poor's 100 stocks, Rao, and Srivastava (2012) analysed 13 techie stocks and Ranco G, Aleksovski D, Caldarelli G, Grčar M, Mozetič I (2015) studied 30 stocks from Dow Jones Industrial Average (DJIA).

Zhang et al. (2016) calculated the daily happiness sentiment and found that it granger-cause the changes in index return for the majority of stock markets. Guo and Li (2019) proposed a Twitter Sentiment Score (TSS model) using lexicon-based sentiment analysis using R. TSS's was found to perform better in an upward market than in a downward market. Shen (2018) have worked on daily happiness sentiment extracted from Twitter and investigate its association with the skewness of stock returns of 26 stock index returns. They concluded that the skewness near the highest happiness days is significantly larger than around the lowest happiness days. Li et al. (2017) investigated the lead lag relationship between local daily happiness sentiments and stock returns of cross listed companies in China and United States and found a bi-directional relationship with market variables. Zhang et al. (2018) found that interdependence exist between online twitter activities and stock market movement of America, Middle East and North Africa. The daily happiness sentiment (dhs) can Granger cause indexes returns in linear causality test, while the opposite direction is more prominent in nonlinear causality test. This indicates that using nonlinear causality test can give different results.

Materials and Methods

The study aims to analyse the relationship between Twitter sentiments and stock returns in the Indian stock market. This relationship is studied at two levels. One, is there any correlation between public Twitter sentiments and stock market returns of sample companies? Second, whether public sentiment on Twitter causes stock prices changes? Or is it stock market prices that change first and then the effect is discussed as positive or negative sentiments on Twitter by the public?

Data was collected for 22 days for all fifty companies comprising the CNX Nifty Index for a period from 21-10-2019 to 15-11-2019. Returns were calculated from closing share price data for Nifty 50 companies. For collecting sentiment data from Twitter following data mining methodology was followed.

The data was collected for CNX Nifty Index companies, comprising of 50 companies and benchmark index Nifty. CNX Nifty companies comprise 65 per cent of the total market capitalisation of the National Stock Exchange and include blue-chip companies. These companies are highly popular on Twitter. Data related to the daily closing price of Nifty 50 stocks were taken from the NSE website.

Web Mining

R programming has been used for data filtering, processing and analysis. Personal Twitter account was linked with R, and tweets are extracted with the help of the API. Programming packages including *twitteR, devtools, jsonlite, httr, stringr, ggplot2,* were installed in R-studio before collecting data. After installing the above packages in R, certain R programming functions like *searchtwitter, search_twitter_and_store* to extract tweets using certain keywords (includes the name of the company like *wipro, nifty, reliance, ongc)* with respect to required filters were used.

Data Processing

Initially tweets are collected in a list format, and they need to be filtered for duplicate tweets and then data has to be converted into a corpus for further analysis. Retweets were also removed as it also shows over-representation of a sentiment. For example, if a negative tweet is retweeted twice, with more than one tagged word, this can lead to overrepresentation and a bias towards negative sentiment in the data with an unknown multiplier effect (Nasir (2018)). So, for simplicity, retweets have been removed. This corpus is further processed for removing English connecting words, patterns, special symbols, removal of excess spaces, numbers, HTTP links etc. using *gsub* command. Work directories of R include positive and negative words which are stored in Opinion lexicons. The positive lexicons file include words like *awarded, affordable, convenient, satisfied, happy, successful, riskfree, outperform* etc. The negative lexicon file contains words like *abolishing, cheated, complaints, criticism, inconsistent* etc. To calculate the daily positive and negative scores each word was matched in the Wordbag. The total tweets score, positive sentiment score and negative sentiment score were collected for analysis purpose (Gakhar and Kundlia, 2020).

Sentimental Classification

Twitter sentiment has been defined as Twitter feeds of users about any company or the stock market. So, public Twitter sentiments can be classified as positive sentiments and negative sentiments. Positive sentiments are the total of positive tweets made by users during the sample period about the sample company. Negative sentiments are calculated from the total of negative feeds about a sample company. These both reflect the mood of the public. Total Tweets is the sum total of positive tweets, negative tweets and neutral tweets about a sample company. Thus total tweets score shows the volume of discussion about any company on Twitter. Overall Twitter Sentiment Score is calculated by subtracting positive minus negative sentiment scores. So, this figure indicates the overall positive or negative sentiments of investors.

The following hypotheses were tested.

H1: There is a significant correlation between Twitter sentiment and stock market indicators for a given day.

H2: Twitter sentiment causes stock market returns.

To analyse the data Automated Dicky Fuller Test, Cointegration Test, Correlation analysis (Alanyali 2013), Granger Causality Test has been conducted. ADF test is conducted to check the stationarity of the time series. For an understanding of the relationship between Twitter sentiments and stock prices, correlation analysis has been used, to measure linear dependence between two variables (Alanyali 2013). Johansen cointegration test is used when we want to study integration for long term association among variables through trace test. Granger causality is a way to investigate causality between two variables in a time series. A variable X is causal to variable Y if X is the cause of Y or Y is the cause of X. Granger causality is not testing a true cause-and-effect relationship; instead, it explains that if one variable precedes the other in time series (Leamer, 1985). Ranco (2015) and Tabari et al. (2018) have also used the Granger causality test to analyse the relationship between Twitter sentiments and stock prices.

Analysis and Interpretation

This section discusses the relationship between Twitter sentiment score and returns of Nifty fifty companies. Overall Twitter Sentiment Score is calculated by subtracting positive minus negative sentiment scores. So, this figure indicates the overall positive or negative sentiments of investors. A positive score shows an overall positive sentiment that prevails, and a negative score shows an overall negative sentiment trend about a company. Table 1 shows the average overall Twitter Sentiment score and stock returns. Further, the correlation has been carried out between Overall Twitter sentiment score and returns to know that overall sentiments are correlated with companies' returns. It is found that 14 companies have high degree of correlation with Overall Twitter sentiment score i.e. 28 per cent of the sample companies. Kotak Mahindra Bank, Axis Bank, Bajaj Finance, Eicher Motors, Bharat Petroleum Corp Ltd., Grasim Industries Ltd. and Hindustan Petroleum Corporation Limited

Table 1: Summary Statistics of Overall Twitter Sentiment Score and Stock Returns

Companies	Overall Twitter Sentiment Score		Returns		Correlation
	Mean	Std. Dev	Mean Returns	Std. Dev	
Adani Ports and Special Economic Zone Ltd.	-0.8568	10.863	-0.1400	0.013	-0.1872
Asian Paints Ltd.	0.1429	1.552	0.0106	0.021	-0.3647
Axis Bank Ltd.	49.4286	364.384	0.0051	0.004	**0.8017**
Bajaj Auto Ltd.	0.4286	4.656	-0.0003	0.000	0.1746
Bajaj Finance Ltd.	10.1429	8.425	0.0003	0.000	**0.5563**
Bajaj Finserv Ltd.	-1.4286	24.442	0.0003	0.002	-0.1171
Bharat Petroleum Corporation Ltd.	-0.1429	1.552	0.0206	0.007	**0.5124**
Bharti Airtel Ltd.	-19.5714	128.085	-0.0003	0.006	-0.1729
Bharti Infratel Ltd.	0.3896	6.402	-0.8700	0.009	0.1995
Cipla Ltd.	-2.1429	46.624	-0.0037	0.001	0.3257
Coal India Ltd.	-2.0000	8.418	-0.0017	0.005	0.3344
Dr. Reddys Laboratories Ltd.	-6.8571	45.743	0.0008	0.006	-0.2249
Eicher Motors Ltd.	-0.8571	9.311	0.0104	0.013	**0.6535**
GAIL (India) Ltd.	-0.5714	23.730	-0.0126	0.019	0.3857
Grasim Industries Ltd.	-0.5714	3.812	-0.0079	0.009	**0.7364**
HCL Technologies Ltd.	1.8571	26.101	-0.0065	0.005	0.3620

HDFC Bank Ltd.	9.4286	132.267	0.0025	0.004	-0.3199
Hero MotoCorp Ltd.	1.0000	10.863	0.0041	0.007	**-0.5869**
Hindalco Industries Ltd.	3.1429	6.402	-0.0061	0.000	0.3141
Hindustan Petroleum Corporation Ltd.	-0.1429	1.552	0.0169	0.015	**0.5028**
Hindustan Unilever Ltd.	0.2857	3.104	0.0077	0.007	-0.2590
Housing Development Finance Corporation Ltd.	9.7143	115.469	0.0044	0.005	**-0.5604**
ICICI Bank Ltd.	-34.1429	399.005	0.0079	0.001	-0.4421
Indiabulls Housing Finance Ltd.	-0.5714	6.207	-0.0046	0.006	**-0.5266**
Indian Oil Corporation Ltd.	-0.1429	1.552	0.0114	0.013	0.4788
IndusInd Bank Ltd.	-1.4286	15.518	0.0041	0.003	0.2542
Infosys Ltd.	33.4286	383.015	-0.0024	0.001	0.1946
ITC Ltd.	11.7143	127.250	-0.0016	0.004	0.3488
JSW Steel Ltd.	1.4286	15.518	-0.0029	0.007	-0.0583
Kotak Mahindra Bank Ltd.	-1.1429	2.587	0.0056	0.002	**0.8306**
Larsen & Toubro Ltd.	5.2857	87.274	0.0042	0.004	**-0.6754**
Mahindra & Mahindra Ltd.	3.7143	159.916	-0.0024	0.005	0.1596
Maruti Suzuki India Ltd.	2.2857	14.907	0.0094	0.003	**-0.5240**
NTPC Ltd.	-1.2857	103.674	-0.0003	0.008	-0.2343
Oil & Natural Gas Corporation Ltd.	0.8571	0.990	0.0031	0.001	-0.4823
Power Grid Corporation Of India Ltd.	1.0000	9.150	-0.0008	0.001	-0.0112
Reliance Industries Ltd.	-36.2857	256.903	-0.0010	0.003	-0.0604
State Bank Of India	-144.00	881.505	-0.0005	0.006	-0.0946
Sun Pharmaceutical Industries Ltd.	1.1429	12.415	-0.0188	0.013	0.3600
Tata Consultancy Services Ltd.	2.0000	11.808	-0.0051	0.003	0.3487
Tata Motors Ltd.	-23.7143	202.793	-0.0113	0.005	0.1332
Tata Steel Ltd.	-2.4286	33.585	0.0040	0.001	-0.2337
Tech Mahindra Ltd.	-1.1429	97.312	0.0050	0.011	-0.4439
Titan Company Ltd.	0.8571	19.268	0.0144	0.010	**-0.5127**
Ultratech Cement Ltd.	0.2857	3.104	0.0075	0.006	-0.3961
UPL Ltd.	6.4720	12.415	0.4400	0.001	**0.5673**
Vedanta Ltd.	2.1567	1.552	-0.5000	0.013	**0.5645**

Wipro Ltd.	-16.8571	306.339	-0.0009	0.009	0.2023
Yes Bank Ltd.	6.4286	40.071	-0.0060	0.004	0.4460
Zee Entertainment Enterprises Ltd.	0.2532	40.071	-0.1000	0.007	0.3047

have a high degree of a positive correlation between Overall Twitter Sentiment score and returns. Figure 1 summarizes company-wise correlation between sentiments and returns. Out of the sample 50 companies, 27 companies have positive overall Twitter sentiment score which is 54 per cent. The mean returns are positive for 24 companies i.e. 48 per cent of the sample companies.

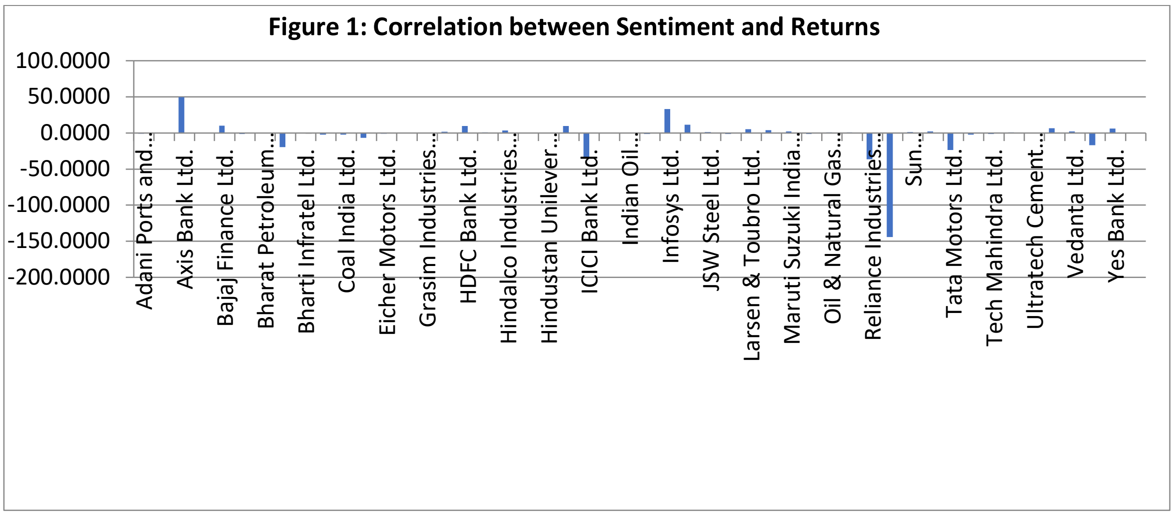

Figure 1: Correlation between Sentiment and Returns

Table 2 shows correlation analysis between stock return and Overall Twitter sentiment scores. There is a high degree of a positive correlation between returns of 12 companies (24 per cent) and positive tweets score. A sample word cloud of terms used in tweets about Nifty is shown in Figure 2.

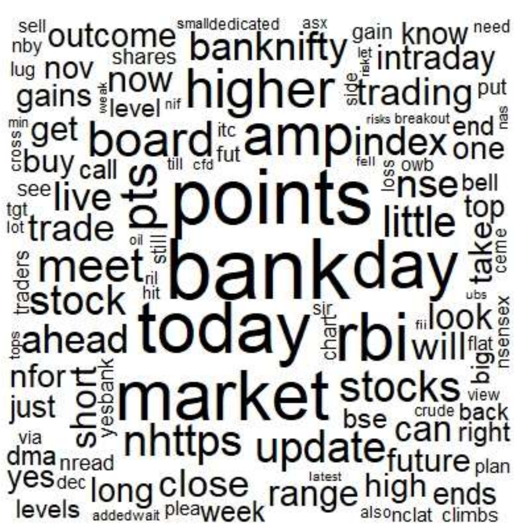

Figure 2: Wordcloud for Nifty

There is a high degree of a correlation between the return of 12 companies (24 per cent) and negative tweets score on Twitter. The total tweet score and returns are highly correlated for 14 companies out of the sample 50 companies (28 per cent).

Table 2: Correlation Results of Returns with Tweets Score

Name of the company	Total tweets score	Positive sentiments score	Negative Sentiments score
Adani Ports and Special Economic Zone Ltd.	-0.0588	0.0552	0.0482
Asian Paints Ltd.	-0.287	-0.4285	-0.1545
Axis Bank Ltd.	**0.5233**	0.435	**0.5832**
Bajaj Auto Ltd.	**0.6008**	**0.6256**	0.2692
Bajaj Finance Ltd.	0.4635	**0.525**	0.353
Bajaj Finserv Ltd.	0.0347	-0.0363	-0.2555
Bharat Petroleum Corporation Ltd.	-0.0315	**-0.6271**	**0.9299**
Bharti Airtel Ltd.	0.0194	0.1169	-0.3139
Bharti Infratel Ltd.	**-0.6434**	**-0.9516**	**-0.7633**
Cipla Ltd.	-0.0496	0.0188	0.3916
Coal India Ltd.	-0.1052	0.4934	**0.5095**
Dr. Reddys Laboratories Ltd.	0.1639	0.0827	0.4204
Eicher Motors Ltd.	0.3795	0.1201	0.1342
GAIL (India) Ltd.	0.129	0.4952	0.142
Grasim Industries Ltd.	**-0.9304**	-0.3376	**-0.9037**
HCL Technologies Ltd.	-0.282	0.2932	-0.4513
HDFC Bank Ltd.	**0.9232**	**0.6536**	**0.8506**
Hero MotoCorp Ltd.	**0.6238**	0.3534	0.2147
Hindalco Industries Ltd.	0	0.2346	0.032
Hindustan Petroleum Corporation Ltd.	0.1847	0.1931	0.1038
Hindustan Unilever Ltd.	**0.6367**	**-0.6329**	-0.4194
Housing Development Finance Corp Ltd.	**0.8291**	0.0452	**0.5579**
ICICI Bank Ltd.	0.1542	0.1256	-0.016
Indiabulls Housing Finance Ltd.	**0.6362**	0.4736	-0.2521
Indian Oil Corporation Ltd.	**-0.5792**	-0.2157	-0.4661
IndusInd Bank Ltd.	0.4484	0.1643	0.0704
Infosys Ltd.	0.4333	-0.0547	0.2325
ITC Ltd.	0.1995	**-0.6863**	-0.2684
JSW Steel Ltd.	0.3471	**0.8488**	-0.2861
Kotak Mahindra Bank Ltd.	0.2766	0.3826	0.3729
Larsen & Toubro Ltd.	0.289	0.4014	0.1361
Mahindra & Mahindra Ltd.	-0.0697	0.4737	-0.4876
Maruti Suzuki India Ltd.	**0.5979**	-0.0488	0.2389
NTPC Ltd.	-0.003	0.0454	-0.0268

Oil & Natural Gas Corporation Ltd.	-0.1533	-0.4512	-0.2574
Power Grid Corporation Of India Ltd.	0.2003	0.3458	0.4281
Reliance Industries Ltd.	**0.6973**	**0.694**	**0.7593**
State Bank Of India	0.1388	0.0361	-0.0184
Sun Pharmaceutical Industries Ltd.	-0.4575	-0.4308	**-0.5177**
Tata Consultancy Services Ltd.	-0.2264	-0.1631	0.1458
Tata Motors Ltd.	**0.5129**	**0.7306**	0.0909
Tata Steel Ltd.	0.2987	**0.577**	0.7216
Tech Mahindra Ltd.	-0.4433	0.3012	**-0.8958**
Titan Company Ltd.	-0.2429	-0.2512	-0.137
Ultratech Cement Ltd.	-0.2007	-0.2178	-0.227
UPL Ltd.	**0.7833**	**0.8092**	**-0.7354**
Vedanta Ltd.	0.2491	0.0298	-0.104
Wipro Ltd.	0.0127	0.2852	-0.3581
Yes Bank Ltd.	-0.4706	-0.2534	**-0.5156**
Zee Entertainment Enterprises Ltd.	0.2495	0.2266	0.1251

Positive sentiment score of 24 per cent companies is highly correlated with stock returns, and negative sentiment score of 22 per cent companies are highly correlated with their stock returns. The company-wise movement of positive sentiments, negative sentiments along with total tweet score is shown in Figure 3.

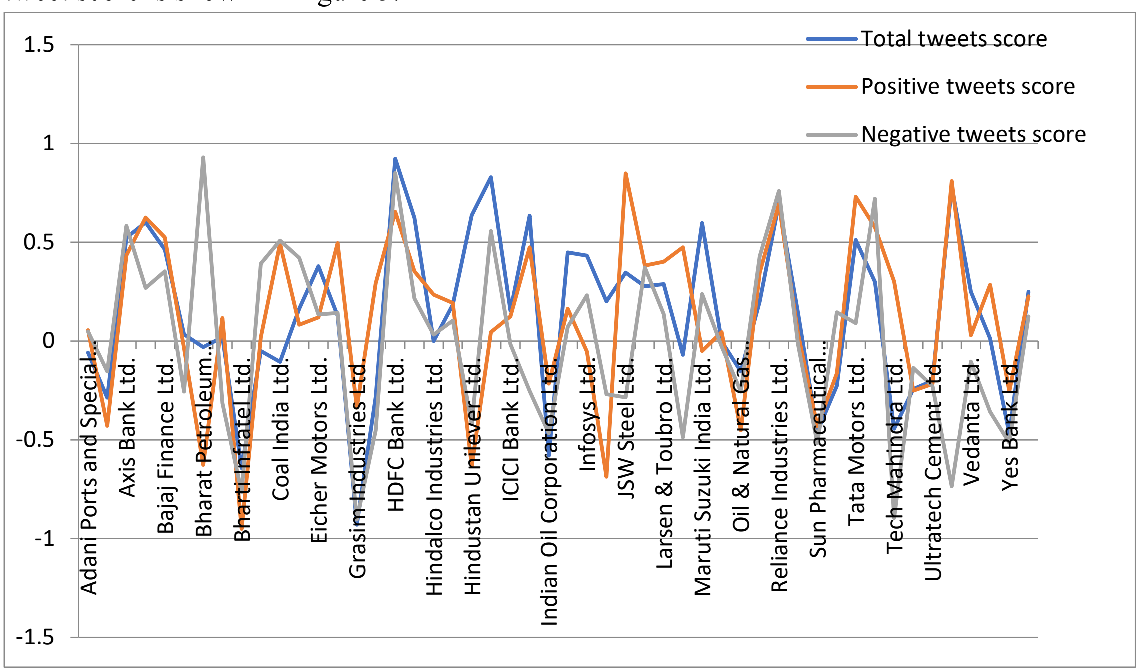

Figure 3: Correlation between Total Tweets, Positive and Negative Tweets of Nifty Companies

The above analysis shows that many companies have shown positive or negative relation between Twitter sentiment scores and stock returns. So, there exist some significant relationship between the two variables which will be analysed in the following discussion.

Table 3 explains the relation between positive tweets score and stock returns. Only 18 percent companies (9 companies) have shown a directional relationship between stock returns and positive tweets score. The relationship direction goes from positive tweets score to returns for 55.5 per cent companies. The returns of the Nifty Index granger cause positive sentiments on Twitter.

Table 3: Granger Causality Test Results of Positive Sentiments Score and Returns

COMPANIES		F-Statistic	Prob.
CNX Nifty Index	return to positive_tweets	13.3031	**0.0322**
	positive_tweets to returns	0.0889	0.9171
HUL	return to positive_tweets	40.596	**0.0238**
	positive_tweets to returns	238.182	**0.0042**
HDFC Bank Ltd.	return to positive_tweets	0.01483	0.9142
	positive_tweets to returns	12.9809	**0.0591**
Infosys Ltd.	return to positive_tweets	0.98881	0.4248
	positive_tweets to returns	33.3699	**0.0287**
Wipro Ltd.	return to positive_tweets	1.16595	0.3931
	positive_tweets to returns	9.18888	**0.0538**
Sun Pharmaceutical Industries Ltd.	return to positive_tweets	9.92222	**0.0477**
	positive_tweets to returns	3.056	0.2225
GAIL (India) Ltd.	return to positive_tweets	123.161	**0.008**
	positive_tweets to returns	0.1458	0.7393
Titan Company Ltd.	return to positive_tweets	18.0834	**0.0511**
	positive_tweets to returns	2.05873	0.2878
Tech Mahindra Ltd.	return to positive_tweets	35.7582	**0.0268**
	positive_tweets to returns	0.00029	0.988
Dr. Reddys Laboratories Ltd.	return to positive_tweets	0.70031	0.4907
	positive_tweets to returns	113.975	**0.0087**

Table 4 depicts granger causality results for negative tweet score and stock returns. Out of 50 sample companies, nine companies which is 18 percent of the sample shows significant results which have been reported here. Returns significantly cause negative sentiments on Twitter for Maruti Suzuki Ltd., Titan Company Ltd., Tata Steel Ltd., Hindalco, Tata Motors Ltd., and Dr. Reddys Laboratories Ltd. With respect to granger causality results 44.4 per cent companies show that negative twitter sentiments lead the stock market returns.

Table 4: Granger Causality Test Results of Negative Sentiments Score and Returns

COMPANIES		F-Statistic	Prob.
CNX Nifty Index	return to negative_tweets	0.9463	0.4801
	negative_tweets to returns	1.4849	0.3562
HDFC Bank Ltd.	return to negative_tweets	4.94734	0.1561
	negative_tweets to returns	13.135	**0.0684**
Maruti Suzuki India Ltd.	return to negative_tweets	8.93073	**0.0561**

	negative_tweets to returns	1.42071	0.3555
Titan Company Ltd.	return to negative_tweets	9.97528	**0.0473**
	negative_tweets to returns	0.91764	0.4392
Vedanta Ltd.	return to negative_tweets	0.67766	0.4969
	negative_tweets to returns	11.6428	**0.0562**
Tata Steel Ltd.	return to negative_tweets	32.271	**0.0296**
	negative_tweets to returns	20.8264	**0.0448**
Hero MotoCorp Ltd.	return to negative_tweets	0.87469	0.4484
	negative_tweets to returns	34.3469	**0.0279**
Hindalco Industries Ltd.	return to negative_tweets	21.7173	**0.0431**
	negative_tweets to returns	0.05229	0.8404
Tata Motors Ltd.	return to negative_tweets	26.7381	**0.0354**
	negative_tweets to returns	6.13667	0.1316
Dr. Reddys Laboratories Ltd.	return to negative_tweets	110.512	**0.0089**
	negative_tweets to returns	0.93846	0.4349

Table 5 discusses Granger causality results between a total number of Twitter sentiment (positive plus negative score) score and stock market return. The total tweets score shows a number of times a company is mentioned on Twitter. The analysis of Nifty shows that Nifty returns granger cause a total number of times Nifty tweets appears on Twitter. 61.5 per cent companies show that total Tweets score causes stock returns. Stock returns causes total tweets score for 38.4 per cent of companies. These results are similar to Zhang et al. (2018).

Table 5: Granger Causality Test Results of Total Tweet Score and Returns

COMPANIES		**F-Statistic**	**Prob.**
CNX Nifty Index	total_tweets to returns	9.9457	0.7875
	return to total_tweets	20.7172	**0.0486**
HDFC Bank Ltd.	total_tweets to returns	10.7331	**0.0419**
	return to total_tweets	2.31229	0.2677
Indian Oil Corporation Ltd.	total_tweets to returns	1.48298	0.3475
	return to total_tweets	23.1809	**0.0405**
Mahindra & Mahindra Ltd.	total_tweets to returns	22.4513	**0.0418**
	return to total_tweets	0.07408	0.811
Titan Company Ltd.	total_tweets to returns	1.03856	0.4154
	return to total_tweets	111.645	**0.0088**
Grasim Industries Ltd.	total_tweets to returns	17.4901	**0.0527**
	return to total_tweets	1.1267	0.3997
Dr. Reddys Laboratories Ltd.	total_tweets to returns	28.1048	**0.0338**
	return to total_tweets	8.70E-05	0.9934
Zee Entertainment Enterprises Ltd.	total_tweets to returns	11.92644	**0.0299**
	return to total_tweets	0.2887	0.6448
Hero MotoCorp Ltd.	total_tweets to returns	4.0637	0.1814
	return to total_tweets	15.60378	**0.0141**
Tata Steel Ltd.	total_tweets to returns	0.86725	0.45

	return to total_tweets	51.37713	**0.0146**
Sun Pharmaceutical Industries Ltd.	total_tweets to returns	2.25424	0.2721
	return to total_tweets	6.68986	**0.0122**
Oil & Natural Gas Corporation Ltd.	total_tweets to returns	21.36317	**0.0264**
	return to total_tweets	1.07634	0.4085
Kotak Mahindra Bank Ltd.	total_tweets to returns	13.58188	**0.0198**
	return to total_tweets	1.38425	0.3604
Reliance Industries Ltd.	total_tweets to returns	40.06437	**0.0181**
	return to total_tweets	0.0073	0.9397

Table 6 analyses the direction of the relationship between overall Twitter sentiments score and stock returns. Out of 50 sample companies, 13 stocks have shown some relationship between the overall Twitter sentiment score and companies' return. The granger causality results show that Nifty returns are causing the overall tweet sentiment score about Nifty on Twitter. Return significantly cause overall sentiment score on Twitter for 69.2 per cent companies.

Table 6: Granger Causality Test Results of Overall Twitter Sentiments Score and Returns

COMPANIES		**F-Statistic**	**Prob.**
Infosys Ltd.	OverallTweet_Sentiment to returns	96.3743	**0.0102**
	Returns to OverallTweet_sentiments	17.3448	**0.0531**
Maruti Suzuki India Ltd.	OverallTweet_Sentiment to returns	0.03448	0.8698
	Returns to OverallTweet_sentiments	8.92589	**0.0961**
Oil & Natural Gas Corporation Ltd.	OverallTweet_Sentiment to returns	0.81712	0.4614
	Returns to OverallTweet_sentiments	9.41322	**0.0918**
Titan Company Ltd.	OverallTweet_Sentiment to returns	3.7432	0.1927
	Returns to OverallTweet_sentiments	24.2792	**0.0388**
Dr. Reddys Laboratories Ltd.	OverallTweet_Sentiment to returns	461.85	**0.0022**
	Returns to OverallTweet_sentiments	8.19446	0.1034
HDFC Bank Ltd.	OverallTweet_Sentiment to returns	55.08105	**0.0152**
	Returns to OverallTweet_sentiments	0.69545	0.4921

State Bank Of India	OverallTweet_Sentiment to returns	0.59683	0.5206
	Returns to OverallTweet_sentiments	30.85692	**0.0188**
Wipro Ltd.	OverallTweet_Sentiment to returns	1.05354	**0.0412**
	Returns to OverallTweet_sentiments	11.39792	**0.0358**
Indian Oil Corporation Ltd.	OverallTweet_Sentiment to returns	65.30078	**0.0128**
	Returns to OverallTweet_sentiments	0.01941	0.902
Bajaj Finance Ltd.	OverallTweet_Sentiment to returns	2.60E-05	0.9964
	Returns to OverallTweet_sentiments	13.88728	**0.0187**
Sun Pharmaceutical Industries Ltd.	OverallTweet_Sentiment to returns	2.16091	0.2794
	Returns to OverallTweet_sentiments	24.66	**0.0163**
Bharti Airtel Ltd.	OverallTweet_Sentiment to returns	0.43918	0.5757
	Returns to OverallTweet_sentiments	16.91282	**0.0119**
CNX NIFTY INDEX	OverallTweet_Sentiment to returns	0.12773	0.755
	Returns to OverallTweet_sentiments	36.29375	**0.0128**

The results show that for 30.8 per cent companies overall Twitter sentiment score causes returns in the stock market. These results are similar to Zhang et al. (2018).

Conclusion

The Twitter posts include both positive and negative sentiments shown by Indian investors about companies. Further correlation has been carried out between overall Twitter sentiment score and returns to know whether overall sentiments are correlated with companies' returns. It is found that Overall Twitter sentiment score is correlated with stock returns for 28 per cent of the sample companies. The total tweet score and returns are highly correlated for 28 per cent companies. Positive sentiment score of 24 per cent companies is highly correlated with stock returns, and negative sentiment score of 22 per cent companies are highly correlated with their stock returns. Kotak Mahindra Bank, Axis Bank, Bajaj Finance, Eicher Motors, Bharat Petroleum Corp Ltd., Grasim Industries Ltd. and Hindustan Petroleum Corporation Limited have a high degree of a positive correlation between overall Twitter sentiment score and returns. The returns of the Nifty Index granger cause positive sentiments on Twitter. The analysis of Nifty shows that Nifty returns granger cause a total number of times Nifty tweets appears on Twitter. The granger causality results also show that Nifty returns are causing the overall Twitter sentiment score about Nifty on Twitter. This indicates that Indian benchmark index Nifty returns causes Twitter sentiments not vice versa. The individual company analysis shows that Twitter sentiments does influence the stock returns. The relationship direction goes from positive tweets score to returns for 55.5 per cent companies. 61.5 per cent companies show that total Tweets score causes stock returns. 44.4 per cent companies show that negative twitter sentiments lead the stock market returns. The results also show that for 30.8 per cent companies overall Twitter sentiment score causes returns in the stock market. This indicates that Twitter sentiments play an important role in movement of stock prices of companies, and both companies and investors can watch the sentiments based on tweets to maximize their returns in the market. This also indicates that market is moving in the direction of achieving strong form of efficiency with all the publically available information getting reflected in the stock prices. There are some limitations to this study, like the sample size used by the study was just 22 days, by increasing the sample time frame, more depth of the market can be checked. Also the study has used linear causality test, the results might have been tested by employing non-linear causality test, which would have justified the robustness of the results. This leaves us with the scope of including these in the future studies on the similar area along with testing the models in other countries as well.

Investor sentiments are very relevant for companies, portfolio managers and the overall market. The study has shown that investor sentiments captured through Twitter have an impact on stock returns. This study has given useful insights on Twitter use for capturing investor sentiment as it is otherwise challenging to capture sentiments in a disguised way from investors. Even companies can gauge their share price direction from the Twitter sentiments of the investors. Asset and mutual fund managers can design their social media marketing strategy around this theme.

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