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Performance of the Indian Stock Market and Sentiment Among Investors on Twitter

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ABSTRACT

This study examines the association between investor sentiment on Twitter and the performance of the Indian stock market. Utilizing daily time series data spanning eight years, from January 1, 2015, to December 31, 2022, the research employs Descriptive Statistics, Correlation Matrix, VAR models, Granger-causality tests, and Quantile Regression Analysis to explore these relationships. The analysis reveals that while Twitter sentiment correlates with certain stock market variables, there is no significant autoregressive or causal relationship between sentiment and market performance. Specifically, the VAR models indicate that Twitter sentiment does not influence stock returns or trading volumes dynamically. Furthermore, Granger-causality tests show no causal link between Twitter sentiment and stock returns or volumes. However, the Quantile Regression Analysis uncovers significant relationships between Twitter sentiment and stock returns at various quantiles, suggesting that sentiment provides valuable insights into stock returns. These findings hold practical implications for researchers, investors, and market participants, highlighting the role of social media sentiment in understanding market dynamics. The study contributes to financial literature by demonstrating that while there is a correlation between Twitter sentiment and market performance, there is no dynamic or causal relationship, thereby providing a nuanced understanding of investor sentiment's impact on the Indian stock market.

Keywords: Twitter sentiment, Indian stock market, Investor sentiment, Social media and finance

Introduction

The Efficient Market Hypothesis (EMH) argues that the long-term fluctuations in the stock prices could be explained by the interaction of information and previous prices **(Fama, 1970).** But later, the researcher started to wonder that the price fluctuations might also be caused by the rational and behavioral components of investors **(Menkhoff, 1998).** The behavior of investor components of investors are typically referred to as "Investors Sentiment" or "Investors Mood." According to the finance literature, measuring the investors sentiment or investor mood and stock market return are strongly correlated. **(Lee, Jiang, & Indro, 2002; Brown & Cliff, 2005; Baker & Wurgler, 2006, 2007)** clearly provided a summary of significant and noteworthy discoveries on the correlation between investors' sentiment and various empirical models on the behavior of individual, corporates, and stock market. Most studies solely employed the opinion polls and market factors to quantify the investors' sentiments. So, it is critical to employ novel methods for capturing the investors' sentiment or investors mood **(Brown & Cliff, 2005; Baker & Wurgler, 2006).** Over the past few years, several scholars have focused on using online activities to gather information about investors' sentiment. This approach captures the investor sentiment instantly and answers the criticisms **(Klibanoff, Lamont, and Wizman (1998).** Besides, social networks are used as they are the quickest and most effective techniques to gauge the attitude or mood of investors. Now-a-days, one of the most important sources to find market information is Twitter. stated that Twitter has become a significant one because of the large number of investors, financial experts upload their entities, and news profiles on twitter, besides, all of them frequently make updates on the market developments in twitter also. **Klibanoff, et al., (1998)** suggested that the volume of tweets and the emotion of investors derived from Twitter could be utilized to predict the q2, **Mao, et al., (2011)** indicated that the majority of research on investor sentiment found online only examined developed markets. Regarding investors' online activities and how they affect emerging market stock prices, there is a research void in the global literature. Though their information environments are more precarious, emerging markets concentrate on the more serious issues related to information asymmetry**, Mao, et al., (2011)** The purpose of this study is to ascertain the relationship between trading volume and return on the Indian stock market and the emotions of investors on Twitter. By looking at trading volumes and stock market returns this study would focus on the investors sentiment that may favorably correlate with stock market fluctuations. This relationship, which may change throughout time, would be particularly significant in the current economic factors.

Review literature and Development of hypotheses

The following are the brief review of selected studies.

Vojtech fiala, et al, (2011) studied the impact of economic agents' attitude on the stock returns for the stocks of Apple and Microsoft. The counts of tweets with positive and negative sentiment were produced. **Hana Alostad and Hasan Davulcu (2012)** analyzed twitter users' talks about investing advice and stock market news. The study demonstrated that information indicated by breaking tweet volumes increased the hourly directional prediction accuracies. According to **Thomas Renault.et.al (2012),** the social media platforms could assist the investors in gathering and disseminating the stock market information. The study discovered that an abnormally high volume of social media communications was linked to a significant price gained on the event day. **Mavrodiev, P., & Perony, N. (2014)** examined how investor's use the SM and how these platforms affect the market volatility index (a measure of volatility on the Chicago Board of Options Exchange). **Juan Pineiro-Chousa,et.al (2016)** investigated how social media affected stock volatility and used an intelligence algorithm to build a model. It was found that social factors, like the heightened attention to a stock's volatility, matter more than the public consensus. According to **Xianjiao wu, et.al (2017)** the internet usage had a direct impact on the stock market's dynamics. Social media was a great instrument for manipulating the stock market because of its potential power, especially in the age of online disinformation. In the words of **Mattias Erlingsson (2021),** The impact of traditional media and news coverage on stock volatility and turnover was studied by the researchers. It has been demonstrated that social media coverage foresaw rises in volatility and turnover. **Shailendra Kumar (2021)** investigated how sentiment in tweets from Twitter affected stock price forecasting. The future price of an interested stock using historical stock data, sentiment analysis of news headlines, and twitter tweets was forecasted. **Mohamed Reda Bouadjenek,et. al (2023)** proved that the data shared on various SM platforms can be used to forecast a number of different characteristics of stock market performance. Based on the above, the hypothesis (H1) as follows is developed

H1. A positive and dynamic relationship exists between stock market performance and investor sentiment on Twitter.

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Kaushik, et al (2017) looked closely at how top Indian publicly traded companies used social media and how such news affected their stock prices. **Mazboudi, M., & Khalil, S. (2017)** analyzed the relationship between X activity, quantified by the number of followers and tweets, and stock returns, volume, and volatility among the top 82 ASX-listed firms. **Daifeng li, et. al (2019)** explained some of the irrational behaviors connected to financial decisions. According to **Sitong chen.et.al (2019),** the stock price movement of the Shanghai Composite Index is predicted using seven distinct data mining approaches. **Padhanarath, et.al (2019)** studied the connection between the stock prices and online comments. **Fronzetti colladon A & Scettri G (2019)** examined how employees communicate within an intranet social network, providing innovative measures of semantic **Garrett, L. (2020)]** addressed the issue of market reaction based on data from social media and the internet. The news media reflections on the internet and social media could be used to make short-term investing decisions. According to. The research findings reveal a significant Granger causality relationship between the number of tweets on a given day and the closing price of the FTSE MIB **Arianna Lazzini (2021)].** Hence, the hypothesis(H2) is developed as follows for testing H2. Investor sentiment on Twitter is positively correlated with stock market returns in India and accounts for a portion of these returns

Methodology

Sample Selection

India's stock market is primarily represented by two key indicators: the Sensex of the BSE and the Nifty of the NSE. This study focuses on these two major indicators. The data from tweets related to stock market activities were collected and analyzed.

Sources of Data

This study relied entirely on secondary data concerning stock indices and Twitter responses. Data for the stock market indicators, including the Sensex of the BSE and the Nifty of the NSE, were used. Market information, such as share prices, was sourced from Yahoo Finance (http://finance.yahoo.com/). Twitter news feed data were obtained from the Twitter database (https://www.kaggle.com/).

Period of the Study

This study analyzed data over eight years, from January 1, 2015, to December 31, 2022.

Models

This section outlines the method for estimating the dynamic relationships between stock performance and Twitter activity

Rationale for panel VAR

Vector Autoregression (VAR) offers several advantages over other research models. Firstly, VAR can handle biases such as endogeneity, autocorrelation, and reverse causality **(Luo et al., 2013).** By incorporating lagged variables, VAR enables the analysis of various time-dependent relationships.

Test for Granger Causality

According to the specified equation and the test results of stationarity, there may be granger causality between the interactions of stock performance and twitter. Granger causality tests first tests for each variable individually and then for all the variables jointly.

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Results Discussion

Dynamic Relationship between market performance and Twitter sentiment

Table 1 presents the results of descriptive statistics for investor sentiment on Twitter and stock market performance in India. The summary statistics used for the analysis include minimum, maximum, mean, median, and standard deviation **(Dyliane Mouri Sliva de Souza and Orleans Silva Martins 2022)**.. The table shows that the mean values for positive tweets (4.111), negative tweets (27.986), BSE Return (3.817595), BSE Volume (4,714,308), NSE Return (0.007236), and NSE Trading Volume (4,518.750) were positive during the study period. The NSE volume exhibited the highest standard deviation (25,503.21), indicating high variability associated with the positive performance of the Indian stock market and Twitter sentiment, and reflecting a non-symmetric distribution of return data during the study period. Table 2 displays the correlation matrix used to determine the relationship between Indian stock market performance and investor sentiment on Twitter from January 1, 2015, to December 31, 2022. For this study, two variables of Twitter sentiment (positive sentiments and negative sentiments) were considered independent variables, while four stock market variables (NSE Returns, BSE Returns, Volume of NSE, and Volume of BSE) were the dependent variables. The results indicate a positive correlation between Twitter sentiment and stock market performance. Positive sentiments recorded significant values of 0.116 with BSE Return, 0.021 with BSE Volume, 0.023 with NSE Return, and 0.142 with NSE Volume during the study period. Negative Twitter sentiment also showed significant values of 0.019 with BSE Return, 0.007 with BSE Volume, 0.002 with NSE Return, and 0.142 with NSE Volume at a 95% confidence level. Overall, the analysis found that Twitter sentiment had a significant relationship with three out of the four dependent stock market variables.

Table -1 Results Descriptive statistics

Variable	BSE Return	BSE Volume	NSE Return	NSE Volume	Twitter Positive Sentiment	Twitter Negative Sentiment
Mean	3.817595	4714308	0.007236	4518.750	27.98611	4.111111
Median	0.170059	284600.0	0.003500	282.0000	26.00000	2.000000
Maximum	90.25000	1.3308	0.124000	205754.0	209.0000	44.00000
Minimum	-0.999617	189300.0	-0.092000	4.000000	0.000000	0.000000
Std. Dev.	14.02081	22178.01	0.046306	25503.21	25.91236	6.045731
Probability	0.000000	0.000000	0.680137	0.000000	0.000000	0.000000

Sources: Data collected from http://finance.yahoo.com/ & https://www.kaggle.com/ and Computed SPSS 20.0

Table -2 Results Correlation

Variable		Twitter Positive Sentiment	Twitter Negative Sentiment	NSE Return	NSE Volume	BSE Return	BSE Volume
Twitter Positive Sentiment	Pearson Correlation	1					
	Sig. (2-tailed)						

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Twitter Negative Sentiment	Pearson Correlation	0.028	1				
	Sig. (2-tailed)	0.000					
NSE Return	Pearson Correlation	-0.116	-0.019	1			
	Sig. (2-tailed)	0.000	0.000				
NSE Volume	Pearson Correlation	0.021	0.007	-.017	1		
	Sig. (2-tailed)	0.000	0.000	.858			
BSE Return	Pearson Correlation	-0.023	-0.002	-.032	-.031	1	
	Sig. (2-tailed)	0.031	0.000	.730	.233		
BSE Volume	Pearson Correlation	0.142	-0.048	.050	-.029	-.059	1
	Sig. (2-tailed)	0.052	0.000	.679	.808	.621	

Sources: Data collected from http://finance.yahoo.com/ & https://www.kaggle.com/ and Computed SPSS 20.0

It was hypothesized that the relationship between Twitter sentiment and the performance of the Indian stock market was dynamic. They used VAR models with up to two lags to analyze the relationship between Twitter sentiment, stock returns, and market volume. The results of the VAR models, shown in Table 3, indicate that Twitter positive sentiment explained the performance of the stock market through NSE Volume at lag 1 and lag 2 ($P > 0.05$), which was statistically significant. However, BSE Return, BSE Volume, and NSE Return at lag 1 and lag 2 were not statistically significant. **Table 4** presents the results of the Granger causality test between Twitter sentiment and the performance of the Indian stock market during the study period. According to the table, there is no causal relationship between Twitter sentiment and stock returns or volume. However, the lagged values for trading volume and returns ($P < 0.05$) were not statistically significant. Consequently, Hypothesis 1, which posited a positive and dynamic association between stock market performance and investor sentiment on Twitter, was not confirmed.

Table-3 VAR models

variables		Twitter positive Sentiment	Twitter Negative Sentiment
BSE_ Return(lag-1)	Coefficient	0.114988	-0.037427
	Probability	(0.21124)	(0.05146)
	t- stat.	[0.54435]	[-0.72727]
BSE_ Return (lag-2)	Coefficient	0.111558	0.036653
	Probability	(0.21951)	(0.05348)
	t- stat.	[0.50821]	[0.68537]
BSE_Volume (lag-1)	Coefficient	-2.52E-07	-1.71E-07
	Probability	(3.0E-07)	(7.4E-08)

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	t- stat.	[-0.83297]	[-2.31610]
BSE_Volume(lag-2)	Coefficient	9.29E-08	1.03E-07
	Probability	(2.2E-07)	(5.3E-08)
	t- stat.	[0.42392]	[1.93573]
NSE_ Return (lag-1)	Coefficient	-14.54332	0.719639
	Probability	(69.4365)	(16.9164)
	t- stat.	[-0.20945]	[0.04254]
NSE_ Return (lag-)	Coefficient	134.7851	33.29875
	Probability	(65.8564)	(16.0442)
	t- stat.	[2.04665]	[2.07543]
NSE_volume(lag-2-1)	Coefficient	-6.93E-05	2.11E-05
	Probability	(0.00012)	(3.0E-05)
	t- stat.	[-0.56171]	[0.70163]
NSE_volume(lag-2)	Coefficient	5.90E-05	-1.25E-05
	Probability	(0.00012)	(3.0E-05)
	t- stat.	[0.47999]	[-0.41735]
C		19.01884	2.298952
		(6.90184)	(1.68146)

Sources: Data collected from http://finance.yahoo.com/ & https://www.kaggle.com/ and Computed SPSS 20.0

Table 4. Granger-causality

Hypothesis:	**F-Statistic**	**Prob.**	**Results**
BSE_Return does not Granger Cause Twitter Positive Sentiment	0.16329	0.8494	Rejected
Twitter Positive Sentiment does not Granger Cause BSE_Return	1.04321	0.3527	Rejected
BSE_Volume does not Granger Cause Twitter Positive Sentiment	2.13466	0.1265	Rejected
Twitter Positive Sentiment does not Granger Cause BSE_Volume	68.0072	1.0916	Rejected
NSE Return does not Granger Cause Twitter Positive Sentiment	0.99162	0.3742	Rejected
Twitter Positive Sentiment does not Granger Cause NSE Return	0.57660	0.5635	Rejected
NSE_Volume does not Granger Cause Twitter Positive Sentiment	0.25378	0.7759	Rejected
Twitter Positive Sentiment does not Granger Cause NSE_VOLUME	0.88296	0.4139	Rejected
BSE_Return does not Granger Cause Twitter Negative Sentiment	0.59849	0.5499	Rejected
Twitter Negative Sentiment does not Granger Cause BSE_Return	0.36992	0.6909	Rejected
BSE_Volume does not Granger Cause Twitter Negative Sentiment	0.08921	0.9148	Rejected

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Twitter Negative Sentiment does not Granger Cause BSE_Volume	0.20852	0.8123	Rejected
NSE Return does not Granger Cause Twitter Negative Sentiment	1.01319	0.3664	Rejected
Twitter Negative Sentiment does not Granger Cause NSE Return	0.14661	0.8638	Rejected
NSE_Volume does not Granger Cause Twitter Negative Sentiment	0.51115	0.6000	Rejected
Twitter Negative Sentiment does not Granger Cause NSE_VOLUME	0.09167	0.9124	Rejected

Sources: Data collected from http://finance.yahoo.com/ & https://www.kaggle.com/ and Computed SPSS 20.0

5.2 Association between market returns and investors sentiment

Table 5 presents the estimated quantile regression results at five different quantiles (q.10, q.25, q.50, q.75, q.90) during the study period to analyze the relationship between stock market returns and investor sentiment on Twitter. The 5-factor model results, incorporating Twitter sentiment, are shown. The results indicate that positive sentiment on Twitter does not significantly affect stock market returns at the median quantile (q.50) and the upper quantile (q.90). Furthermore, negative sentiment on Twitter does not have a discernible impact on BSE stock returns at the median quantile (q.50). However, the analysis identifies a positive and significant association between stock returns and Twitter sentiment at the lower quantiles (q.10, q.25) and the upper quantile (q.75). This suggests that investor sentiment on Twitter provides valuable insights into stock returns, aligning with previous research findings. These results demonstrate that there is a significant relationship between sentiment and stock returns, even in the Indian market. Therefore, Hypothesis 2, which posits that Twitter sentiment explains part of stock returns, is confirmed.

Table-5 Quantile regression

Variable	**q.10**	**q.25**	**q.50**	**q.75**	**q.90**
Twitter Positive Sentiment					
BSE Return	0.082**	0.796**	0.528**	0.575**	0.057
	0.005	0.003	0.000	0.020	0.072
NSE Return	0.616**	0.043	.0761**	0.376**	0.013
	0.025	0.189	0.000	0.000	0.690
Twitter Negative Sentiment					
BSE Return	0.772**	0.316**	0.064	0.479**	0.143**
	0.012	0.000	0.384	0.000	0.000
NSE Return	0.801**	0.886**	0.726**	0.711**	0.158**
	0.000	0.043	0.000	0.000	0.000
c	0.018**	3.242	7.545	0.778	10.89
	0.000	0.0019	0.000	0.438	0.000

Sources: Data collected from http://finance.yahoo.com/ & https://www.kaggle.com/ and Computed SPSS 20.0

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Practical implications.

The study's analysis has significant policy implications for researchers, investors, and stakeholders. First, researchers can use our measures to quantify market sentiments and incorporate social media trends into their studies, enhancing explanatory power. Second, although the relationship was expected to be dynamic, the autoregressive analysis using VAR models with up to two lags did not confirm a dynamic relationship between Twitter sentiment, returns, and market volume. Third, the Granger causality test found no causal relationship between Twitter sentiment and stock returns or volume. Fourth, the quantile analysis demonstrated a relationship between sentiment and returns, which was also observed in the Indian market. This suggests that investor sentiment on Twitter can provide valuable insights into stock returns.

Conclusion

The analyses suggest a positive and significant relationship between the performance of the Indian stock market and investor sentiment on Twitter. Although the study aimed to identify a dynamic relationship between these two phenomena, the findings did not fully confirm this expectation. **Autoregressive Analysis**: The VAR models did not establish a dynamic relationship between Twitter sentiment and market variables. **Granger Causality Test**: No causal relationship was found between Twitter sentiment and stock returns or trading volume. **Quantile Regression Analysis**: The relationship between sentiment and returns was significant at various quantiles, indicating that investor sentiment on Twitter can provide valuable insights into stock returns, particularly during specific market conditions. Despite the absence of a clear dynamic or causal relationship, the positive correlation between Twitter sentiment and market performance indicates that investor sentiment plays a role in market movements. The interaction among investors on Twitter appears to be associated with increases in market returns. When trading volume increases, Twitter sentiment tends to become more positive, and this sentiment correlates strongly with market performance. This study contributes to the financial literature by expanding upon earlier findings and demonstrating similar results observed in other markets. It addresses gaps in the literature by showing the effects of investors' online activities on the Indian market. Additionally, the study highlights the potential for investors to achieve abnormal returns based on insights from Twitter sentiment, especially during periods of poor market performance.This research is valuable for market participants, suggesting that monitoring Twitter sentiment can be a useful tool for making informed investment decisions.

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