



SOCIAL MEDIA AND THE STOCK MARKETS: AN EMERGING MARKET PERSPECTIVE

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Abstract: There are numerous studies that have explored the impact of social media on stock market performance, but there is little such evidence from emerging markets. Many multinational banks and other financial conglomerates from developed countries are now expanding their operations into emerging markets known for their rapid growth. Companies from developed countries prefer to use social media to connect with their stakeholders. This can be challenging as emerging markets are very different from developed markets in terms of infrastructure and stock market development. The study conducts sentiment analysis of tweets about Indian companies included in the Nifty 50 or industry indices over a period of 15 months. Granger causality test results show that Twitter sentiment has a significant relationship with indices related to banking and financial sector of Indian stock market. Impulse response function results show that the impact of negative sentiment on index returns lasts longer than the impact of positive sentiment. This study will help companies to effectively utilize social media for information sharing and dissemination in new environments.

Keywords: Emerging markets, Sentiment analysis, Social media, Twitter, Indian stock market, Market efficiency, Impulse response.

Introduction

Nowadays, more and more people use various online news channels, blogs, virtual communities, social media networking websites such as Facebook and Twitter to stay updated on important events around the world and share their feelings and opinions on various expressive themes (Kapoor et al., 2017). The vast amount of data available on the Internet is used by companies to understand their stakeholders better and manage risks (Lahey, 2016). These vast amounts of information available on the Internet have attracted the attention of researchers in various ways, such as: B.: Researchers have analyzed the use of social media data by start-ups (Kim &

Choi, 2019), investigated the role of social media in promoting joint initiatives in temporary project organizations (Rimkunee & Zinkeviciute, 2014), investigated the application of social media in formulating marketing strategies (Ahmed et al., 2017; Klepek & Starjična, 2018), etc. Due to the ease of sharing information through social media, social media has now become a very popular communication channel. Researchers have studied various social media platforms such as Facebook (Siganos et al., 2014), Yahoo Messenger (Antweiler & Frank, 2004), and StockTwits (Oliveira et al., 2016) to determine their impact on stock market research. Twitter was chosen for this study because it is a popular social



media platform for sharing financial information and trading systems based on Twitter are also popular among investors (Sprenger et al., 2014). There is ample evidence that public opinion expressed on Twitter has significant predictive power for the development of stock market indicators (e.g., He et al., 2016; Liu et al., 2015; Risius et al., 2015). However, researchers in this field have mainly studied developed markets, and developing markets have yet to be fully explored, given the spread of information through social media (Agarwal et al., 2019). Studies on developing countries have mainly focused on testing only weak forms of market efficiency (e.g., Mobarek & Fiorante, 2014). Since the degree of irrationality of investor behavior and stock market inefficiency varies across countries (Chui et al., 2010), it is essential to investigate stock market behavior in emerging markets in light of information available through social media. Stock markets in developing countries are still not fully developed compared to developed countries (Claessens & Yurtoglu, 2013). Twitter is a popular social media platform with 330 million active users worldwide (Clement, 2019). Information on Twitter has proven to have a significant impact on financial markets. For example, in 2013, the US market fell by almost 1% within three minutes of a hoax report of a White House bombing from a hacked Associated Press Twitter account, resulting in huge losses (Selyukh, 2013). Twitter is an important social media platform for India. While Twitter does not release official figures, Taranjit Sinha (Head of India Operations at Twitter) revealed in an interview that India was Twitter's fastest growing market (in terms

of daily active users) in 2017. India as a market on Twitter has grown almost five times the global average (Chaturvedi, 2017). Moreover, there is some evidence to suggest that information on Twitter can affect Indian investors and markets. For example, the Securities and Exchange Board of India [SEBI] has warned investment advisors not to use Twitter to give stock market advice to investors to protect their interests (SEBI, 2018). Recently, Singapore Exchange's Nifty futures fell 200 points following Iran's missile attack on US military, but recovered 100 points after the US President's tweet curbed the possibility of escalating tensions between the US and Iran (ETMarkets.com, 2020). Moreover, India's Nifty stocks closed 1.58% higher following the US President's Twitter response (George, 2020).

The following are the main contributions of this article to the existing literature: a. We provide a comprehensive overview of how Twitter information impacts stock markets in developing countries using evidence from India. b. To the best of our knowledge, this is the first time to investigate the impact of Twitter sentiment on broad market indexes and indices of different sectors of a country's economy. c. We study the impact of positive and negative sentiments on stock markets (broad market index and sectoral indexes) of developing countries. In this study, sentiment analysis was conducted using VADER on tweets about Indian companies that are part of the Nifty50 national broad market index and 11 other industry indexes of the Indian economy. This tool is specifically designed to capture sentiment (expressed through emoticons, acronyms, and abbreviations) in a



microblogging-like context. Further, each tweet is classified as positive or negative. Stock market data was used for the same indexes. Various statistical tests are then performed to determine the relationship between Twitter sentiment and stock market indices. The results were confirmed using a vocabulary-based sentiment analysis approach. This paper is divided into six sections. Section 1 describes the literature available in the field and highlights gaps in the existing literature. Section 2 describes the data and methodology used for the sentiment analysis and stock market indices calculations used in this paper. Section 3 presents the results of contemporaneous correlation and Granger causality between Indian stock market index and Twitter sentiment. Section 4 details the impact of the impulse response function on Twitter used in the empirical analysis and explains how this affects the results obtained. Section 5 tests the robustness of the sentiment analysis process and results. Section 6 discusses the results of the paper with practical implications and suggestions for future research. The last section concludes the study.

1. Literature review

The efficient market hypothesis states that stock prices cannot be predicted because they already fully reflect all relevant market information (Fama, 1965). However, this theory has been modified to introduce three levels of market efficiency based on the "relevant information" that should be reflected in the market price of a stock: moderate efficiency (all public information) and strong efficiency (all relevant public and private information) (Malkiel and Fama, 1970).

In the era of big data, using social media information to predict stock prices has been widely studied. Many researchers have investigated the role of Twitter information in financial markets (e.g., Bollen et al., 2011; Tetlock, 2007). Zherdev et al. (2014) showed that positive and negative sentiments can be extracted from Twitter and significantly predict the future price of the S&P500 index. Studies have shown that negative sentiments expressed on Twitter have a significant impact on company-specific stock prices (He et al., 2016; Risius et al., 2015). Liu et al. (2015) Identify homogeneous groups Analyze stock prices of companies whose stock prices fluctuate based on Twitter-based metrics such as number of tweets and number of followers. The Daily Happiness Index (created by sentiment analysis of 10% of all Twitter messages) is widely used to examine the impact of social media on financial markets. Zhang et al. (2016) find that online sentiment derived from the Twitter Happiness Index has significant predictive power for stock market performance metrics (index returns and range-based volatility) across 11 developed countries. (2017) investigated the relationship between stock markets and the Twitter Happiness Index in 10 developed countries. The authors found that high-returning stocks were more affected by investor sentiment than low-returning stocks. Recently, Zhang et al. (2018) investigated the impact of Twitter sentiment on index returns in 40 countries across four regions: the Americas, Europe, Asia Pacific, and the Middle East and North Africa. They observed the interaction between online activity on Twitter and stock market trends. Leitch and Sherif (2017) developed a Twitter

sentiment score to predict corporate stock returns, and many recent studies have also found that user-generated content on social media has a significant impact on stock market movements (Fan et al., 2020a, 2020b; van Dieijen et al., 2020).

According to the World Federation of Exchanges (WFE), the National Stock Exchange of India (NSE) was the second-largest stock exchange in the world by stock trading volume in 2018 (National Stock Exchange [NSE], 2019). (2015) demonstrated techniques that can be used for sentiment analysis of live server data from Indian stock exchanges; however, none of these techniques were implemented in the study. An event study collected tweets about demonetization, a major event in the Indian economy, and investigated whether public sentiment expressed on Twitter influenced the movement of the Indian stock market (Mohan & Kar, 2017), but found no significant relationship. Nayak et al. (2016) attempted to predict the Indian stock market based on Twitter sentiment

using the machine learning technique Support Vector Machine. However, they did not discuss the statistical significance of the results. No previous studies have compared the impact of negative and positive public opinion expressed on Twitter on the Indian stock market. Several other studies have shown that information from the Internet does not have significant predictive power for investor sentiment. b. Kim and Kim (2014), who used messages posted on the Yahoo Finance message board. The sentiment of the messages used in this study was classified into one of five categories that the message board explicitly offered to retail investors: “strong buy”, “buy”, “hold”, “strong sell”, and “sell”.

This study seeks to answer the research question: How does the information over Twit-ter influence the Indian stock markets? For this, the following hypothesis are proposed as shown in Table 1.

Table 1. Table of hypotheses

| | |
|----------------|--|
| H ₁ | There is no relation between returns of NIFTY50 and positive Twitter Sentiment. |
| H ₂ | There is no relation between returns of index Nifty Auto and positive Twitter Sentiment. |
| H ₃ | There is no relation between returns of index Nifty Pharma and positive Twitter Sentiment. |
| H ₄ | There is no relation between returns of index Nifty Bank and positive Twitter Sentiment. |
| H ₅ | There is no relation between returns of index Nifty PSU Bank and positive Twitter Sentiment. |
| H ₆ | There is no relation between returns of index Nifty Private Bank and positive Twitter Sentiment. |
| H ₇ | There is no relation between returns of index Nifty Realty and positive Twitter Sentiment. |
| H ₈ | There is no relation between returns of index Nifty FMCG and positive Twitter Sentiment. |

| | |
|-----------------|--|
| H ₉ | There is no relation between the returns of index Nifty Media and positive Twitter Sentiment. |
| H ₁₀ | There is no relation between the returns of index Nifty Metals and positive Twitter Sentiment. |
| H ₁₁ | There is no relation between the returns of index Nifty IT and positive Twitter Sentiment. |
| H ₁₂ | There is no relation between the returns of index Nifty Financial Services and positive Twitter Sentiment. |
| H ₁₃ | There is no relation between returns of NIFTY50 and the negative Twitter Sentiment. |
| H ₁₄ | There is no relation between returns of index Nifty Auto and negative Twitter Sentiment. |
| H ₁₅ | There is no relation between returns of index Nifty Pharma and negative Twitter Sentiment. |
| H ₁₆ | There is no relation between returns of index Nifty Bank and negative Twitter Sentiment. |
| H ₁₇ | There is no relation between returns of index Nifty PSU Bank and negative Twitter Sentiment. |
| H ₁₈ | There is no relation between returns of index Nifty Private Bank and negative Twitter Sentiment. |
| H ₁₉ | There is no relation between returns of index Nifty Realty and negative Twitter Sentiment. |
| H ₂₀ | There is no relation between returns of index Nifty FMCG and negative Twitter Sentiment. |
| H ₂₁ | There is no relation between returns of index Nifty Media and negative Twitter Sentiment. |
| H ₂₂ | There is no relation between returns of index Nifty Metals and negative Twitter Sentiment. |
| H ₂₃ | There is no relation between the returns of index Nifty IT and negative Twitter Sentiment. |
| H ₂₄ | There is no relation between the returns of index Nifty Financial Services and negative Twitter Sentiment. |

Data and methodology

This paper investigates relationship between the information on the Twitter and the Indian stock markets. This study extracts two different kind of information

Collection of social media data

The daily stock market data is collected from the NSE website (NSE, 2019). All the market indices are rebalanced semi-annually and additional reconstitution of the indices also takes place in case any of

from the twitter: a) optimistic public sentiments, b) pessimistic public sentiments. The daily Twitter data and the stock market data has been collected for the period of 15 months (i.e. 1, Aug 2017 to 10, Nov 2018).

the constituent companies undergoes a scheme of arrangement for corporate events such as merger, suspension, spin-off, etc. The Twitter data as well as the stock market data has been collected carefully, taking care of all the

inclusions/exclusions

done

intheindicesduringthesampleperiod.

Collectionofstockmarketdata

The NSE website provides daily stock market statistics (NSE, 2019). Half-yearly rebalancing of all market indices takes place, and extra reconstitutions of the index also happen if any of the covered firms go through an adjustment program for corporate events like spin-offs, suspensions, or mergers. With careful consideration to all inclusions and exclusions in the indexes produced throughout the sample period, data from Twitter and the stock market were gathered. Other well-known online sources of social media information, such as Facebook, Instagram, and Snapchat, are excluded from this analysis for three reasons, whereas the Twitter platform was

especially chosen for it. As a result of limitations put in place after the Cambridge Analytica controversy early in 2018, data cannot be downloaded from Facebook (Gonzalez, 2018). Furthermore, prior research has indicated that viewpoints shared on Facebook, Twitter, and stock discussion boards

Analysisandresults

Contemporaneouscorrelation

This section explores the contemporaneous effect of public sentiments as expressed on the Twitter on the Indian equity market indicators. The results of the same have been depicted in Tables 2 and 3

Table 2. Kendall correlation coefficients between Avg_Pos and Indian Stock market indicators

| Index | StockMarketIndicators | |
|----------------------------|-----------------------|------------|
| | Ret | Rv |
| NiftyAuto | .043 | -.002 |
| NIFTYBank | -.021 | -.006 |
| NIFTYFinancialService s | -.021 | .192* * |
| NIFTYFMCG | .002 | .048 |
| NIFTYIT | -.031 | .015 |
| NIFTYMedia | .026 | .028 |
| NIFTYMetals | -.013 | -.013 |
| NIFTYPharma | -.064 | .036 |
| NIFTYPSUBANK | -.038 | -.019 |
| NIFTYPvtBank | .002 | .228* * |
| NIFTYRealty | -.076 | .028 |
| NIFTY50 | .050 | .166* * |

Table 3. Kendall correlation coefficients between Avg_Neg and Indian Stock market indicators

| Index | StockMarketIndicators | |
|------------------------|-----------------------|--------|
| | Ret | Rv |
| NiftyAuto | -.058 | .023 |
| NIFTYBank | -.001 | .193** |
| NIFTYFinancialServices | -.043 | -.024 |
| NIFTYFMCG | -.042 | -.013 |
| NIFTYIT | .037 | .051 |
| NIFTYMedia | -.059 | -.033 |
| NIFTYMetals | - .112* | -.008 |
| NIFTYPharma | .047 | -.114* |
| NIFTYPSUBANK | .060 | -.037 |
| NIFTYPvtBank | .110* | .017 |
| NIFTYRealty | .082 | -.007 |
| NIFTY50 | -.011 | .026 |

Table 2 and Table 3 clearly show that the correlation between the returns from the Nifty 50 and the Twitter sentiments is insignificant. The returns for the Metals and the Private Banks sector are also found to be correlated to the negative sentiments derived from the Twitter messages. Hence we fail to accept the hypothesis H_{18} and H_{22} .

Table 4. Table depicts the outcome of the Granger-causality test between the *Open-to-closer* returns and the sentiment indicators *Avg_Neg* and *Avg_Pos*. The table displays the F-statistics and the critical values are put in the parenthesis. * represents the statistical significance at 5% level

| Index | Null: Avg_Pos does not cause Ret | Null: Ret does not cause Avg_Pos | Null: Avg_Neg does not cause Ret | Null: Ret does not cause Avg_Neg |
|--------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| NIFTYAuto | (3.095)3.906 | (2.0252)3.906 | (0.290)3.906 | (1.2216)3.906 |
| NIFTYBank | (4.645)*3.906 | (2.0007)3.906 | (5.628)*3.906 | (2.1253)3.906 |
| NIFTY Financial Services | (4.303)*3.906 | (0.1333)3.906 | (6.233)*3.906 | (3.534)3.906 |
| NIFTYFMCG | (3.011)3.906 | (0.4527)3.906 | (1.017)3.906 | (2.1504)3.906 |

| | | | | |
|------------------|-------------------|-------------------|-------------------|---------------------|
| | 6 | 6 | 6 | 6 |
| NIFTYIT | (0.1807)3.90 6 | (0.6324)3.90 6 | (0.192)3.90 6 | (1.1083)3.90 6 |
| NIFTYMedia | (5.538)*3.90 6 | (1.27)3.906 | (2.316)3.90 6 | (2.6826)3.90 6 |
| NIFTYMetal | (2.998)3.90 6 | (1.6235)3.90 6 | (2.201)3.90 6 | (1.1670)3.90 6 |
| NIFTYPharma | (1.9424)3.90 6 | (0.1088)3.90 6 | (1.665)3.90 6 | (0.3402)3.90 6 |
| NIFTYPSUBBank | (2.112)3.90 6 | (0.0948)3.90 6 | (2.253)3.90 6 | (5.2236)*3.90 06 |
| NIFTYPrivateBank | (4.721)*3.90 6 | (0.9989)3.90 6 | (4.838)*3.90 6 | (1.786)3.90 6 |
| NIFTYRealty | (0.787)3.90 6 | (1.6672)3.90 6 | (0.880)3.90 6 | (0.2265)3.90 6 |
| NIFTY50 | (2.931)3.90 6 | (0.6998)3.90 6 | (1.0680)3.90 6 | (0.7180)3.90 6 |

Table 5. The table depicts the outcome from the Granger-causality test between the volatility (Range-based) and the positive and negative sentiment indicators. The tables shows the F-statistics and values in the parenthesis are the critical. **represents the statistical significance at 1% level

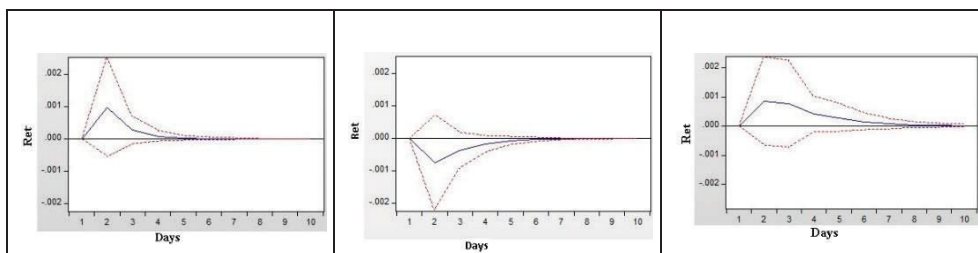
| Index | Null: Avg_Posd oes not causeRang e_v | Null: Range_vd oes not causeAvg _Pos | Null: Avg_Negd oesnotcaus eRange_v | Null: Range_vd oes not causeAvg _Neg |
|--------------------------------|--|--|---|--|
| NIFTYAuto | (1.544)3.90 6 | (7.2785)** 6.803 | (0.303)3.90 6 | (1.4133)3.90 6 |
| NIFTYBank | (0.572)3.90 6 | (0.3952)3.90 6 | (0.0614)3.90 6 | (1.9452)3.90 6 |
| NIFTY FinancialS ervices | (0.0085)3.90 6 | (0.0162)3.90 6 | (0.00502)3.9 06 | (3.664)3.90 6 |
| NIFTYFMCG | (0.258)3.90 6 | (1.5992)3.90 6 | (0.283)3.90 6 | (1.0615)3.90 6 |
| NIFTY IT | (6.949)3.90 6 | (0.4421)3.90 6 | (1.168)3.90 6 | (0.001)3.90 6 |
| NIFTYMedia | (1.4404)3.90 6 | (1.3720)3.90 6 | (0.491)3.90 6 | (1.6385)3.90 6 |

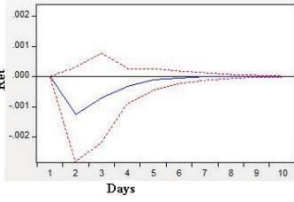
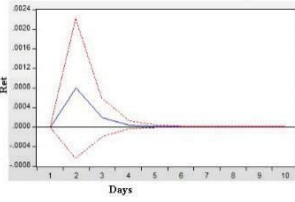
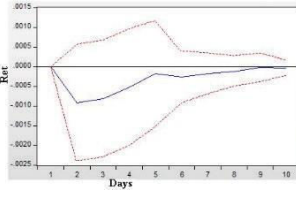
| | | | | |
|----------------------|-------------------|-------------------|-------------------|-------------------|
| NIFTYMetal | (1.842)3.90 6 | (1.6222)3.90 6 | (1.555)3.90 6 | (2.3322)3.90 6 |
| NIFTYPharm a | (0.5576)3.90 6 | (0.1501)3.90 6 | (2.763)3.90 6 | (0.4744)3.90 6 |
| NIFTYPSUB ank | (1.712)3.90 6 | (0.1833)3.90 6 | (0.779)3.90 6 | (2.4894)3.90 6 |
| NIFTYPrivate Bank | (0.444)3.90 6 | (2.6658)3.90 6 | (0.492)3.90 6 | (1.852)3.90 6 |
| NIFTYRealty | (2.172)3.90 6 | (6.7960)3.90 6 | (1.629)3.90 6 | (2.6142)3.90 6 |
| NIFTY50 | (0.215)3.90 6 | (0.0106)3.90 6 | (0.0910)3.90 6 | (1.8157)3.90 6 |

2. Impulseresponse

The Impulse Response Function (IRF) is used to examine the response of a variable to a unit shock (one standard deviation) in another variable. To assess the influence of the Twitter information on the returns from the Indian equity markets, IRFs are computed on the basis of the VAR (Vector Autoregression) system parameters. Following Deng et al. (2018) IRFs have been used in this study, to perform a detailed sector analysis and look deeper into studying the influence of twitter on the equity markets over time. Following (Trusov et al., 2008), the IRFs are shown graphically so as to get a visual impression of the dynamic inter-relationships among the stock market returns and the public sentiment indicators derived from the Twitter for the sectorial indices NIFTY Private Bank, NIFTY Financial

Services and NIFTY Bank. These sectors are specifically chosen as it is evident from the Table 5 that the optimistic and the pessimistic public sentiments can granger-cause the returns of the sectorial indices related to the banking and financial services industry i.e. NIFTY Bank, NIFTY Financial Services, and the NIFTY Private Bank. Other sectors cannot be analyzed using IRFs because there is no evidence of causality between their returns and the Twitter information. The results are displayed in Table 6 (Figure 1 to Figure 6). Other sectors cannot be analyzed Table 6. This table shows the graphical representation of the IRFs applied to dynamic interrelationships among the stock market returns and the public sentiment indicators derived from the Twitter for the sectorial indices NIFTY Private Bank, NIFTY Financial services and NIFTY Bank



| | | |
|--|--|--|
| <p>Figure1. Depicts the response of Ret to a unit shock in Avg_Pos, computed for the index NIFTY Private Bank</p> | <p>Figure2. Depicts the response of Ret to a unit shock in Avg_Neg, computed for the index NIFTY Private Bank</p> | <p>Figure3. Depicts the response of Ret to a unit shock in Avg_Pos, computed for the index NIFTY Financial services</p> |
|  |  |  |
| <p>Figure4. Depicts the response of Ret to a unit shock in Avg_Neg, computed for the index NIFTY Financial Services</p> | <p>Figure5. Depicts the response of Ret to a unit shock in Avg_Pos, computed for the index NIFTY Bank</p> | <p>Figure6. Depicts the response of Ret to a unit shock in Avg_Neg, computed for the index NIFTY Bank</p> |

using IRFs because there is no evidence of causality between their returns and the Twitter information.

It is observed in section 4.b. that the movement of the indices related to the banking and financial services sectors is significantly influenced by the public sentiments (either the optimistic or the pessimistic) expressed on the Twitter. The IRF helps in providing a detailed sector analysis. A comparison based on the influence of the positive and the negative sentiments on the returns, is provided in Figure 1 to Figure 6. The sectors NIFTY Private Bank, NIFTY Financial services and NIFTY Bank are chosen for making the comparisons. The stock market returns (Ret) for the sectors and the sentiment indicators (both positive and negative) have been confirmed for the stationarity properties (through the ADF and KPSS test).

Figure 1 and Figure 2 show that the impact of the positive and the negative

sentiments on the returns of the NIFTY Private Bank is significantly different from zero only for a period of 3 days and 4 days, respectively. The Figure 3 and Figure 4 suggest that the impact of the positive and the negative sentiments on the returns of the NIFTY Financial services is significant for a period of 6 days and 4 days, respectively. The impact of the positive and the negative sentiments on the returns of the NIFTY Bank is observed for a period of 3 and 8 days respectively, as shown in the Figure 5 and Figure 6.

Kendall correlations, which quantify the contemporaneous effect of the polarity scores on the stock market indicators are calculated for Nifty 50 and each of the 11 sectorial indices. Table 7 provides the results. The results confirm our previous results (using VADER) that the sentiments extracted using the financial context dictionary do not exhibit any significant correlation.

relationwiththestockmarketindicators.B
utthesectorialindexofNIFTYFinancialS
ervicesexhibits

asmallbutsignificantcorrelationwiththe
publicsentiments expressedonTwitter.

Table 7. Kendall correlation coefficients. * represents the statistical significance at 5% level

| Index | Ret | Range _v |
|--------------------------|-----------------|-------------|
| NIFTY Auto | 0.119 | 0.065 |
| NIFTY Bank | – 0.084 | 0.119 |
| NIFTY FMCG | – 0.067 | – 0.012 |
| NIFTY Financial Services | – 0.133 * | 0.041 |
| NIFTY IT | 0.072 | – 0.050 |
| NIFTY Media | – 0.066 | – 0.093 |
| NIFTY Metal | – 0.019 | 0.068 |
| NIFTY Pharma | – 0.092 | 0.129 |
| NIFTY PSUBank | – 0.075 | 0.108 |
| NIFTY Private Bank | – 0.058 | 0.032 |
| NIFTY Realty | – 0.021 | 0.065 |
| NIFTY 50 | – 0.081 | 0.008 |

Discussion

The present paper investigates in detail how the Twitter information influences the performance of the equity markets of a developing economy, with the evidences from Indian stock markets. VADER sentiment Analyzer has been used to extract the

optimistic and the pessimistic public sentiments from the Twitter data.

The findings of this paper reveal that the impact of the Twitter information on the performance of the broad indices of the Indian equity markets is not significant. The robust

ness of the result has been confirmed by using another algorithm (Loughran & McDonald, 2011) for the sentiment analysis. This suggests that the results are indifferent towards the use of different sentiment analysis techniques and there exists no significant correlation between the Twitter sentiments and the broad market indices (Nifty 50) of the Indian stock markets. This might be attributed to the fact that in the developing countries, the use of information and Communication Technologies, especially the social media platforms is still in the emerging state as compared to the developed countries (Ilavarasan et al., 2018). Some of the reasons attributed to it are the affordability of devices, differential penetration rates, regulatory framework, etc.

This paper also explores the influence of Twitter information on the various economic sectorial indices of the Indian economy. The results show that these sectorial indices related to the bank and financial sector (NIFTY Private Bank, NIFTY Financial services, and NIFTY Bank) show a small but significant relationship with the Twitter information. A small but significant correlation between the NIFTY Financial services and the Twitter sentiments is also confirmed using the financial context lexicon (Loughran & McDonald, 2011). The Granger causality tests also reveal the bi-directional causality between the returns from these sectorial indices and the positive and negative sentiments on the Twitter. The impulse response function indicates that the influence of

the negative information on the stock market returns, persists for a longer period as compared to the influence of the positive information. The results obtained are interesting since only Banking and financial industry stocks have a significant relationship with Twitter sentiment, unlike other markets where all sectors are influenced by social networks' sentiment. The emerging economies offer attractive markets to the businesses in the developed economies, but they are still in the developing stage. The business strategies that work in the developed countries (such as using social media for information dissemination) might not be as successful in the developing countries (Ilavarasan et al., 2018).

This study provides an answer to the research question raised in this study. The correlation coefficients in Table 2 and Table 3 clearly show that the Twitter information has no significant influence on the NIFTY 50. However, the Metals and the Private Banks sectors' returns are found to be significantly correlated to the negative sentiments derived from the Twitter information. Similarly, the results from the Granger causality tests suggest that the positive and negative public opinion on Twitter can cause the returns of these sectorial indices NIFTY Bank, NIFTY Financial Services, and the NIFTY Private Bank only. Hence we fail to accept the hypotheses H₄, H₆, H₁₂, H₁₆, H₁₈, H₂₂, and H₂₄. On the basis of these results, the answer to the research question would be that the Twitter information influences Indian stock market to some degree and the impact of positive and negative sentiments differs in lag as

wellastheparticularindexesit influences.

Since the results from the Banking and Financial services sector show that there exists a significant relationship between the social media information and their stock market performance, indices related to these sectors are analyzed further for quantifying such effects. Therefore IRFs have been used for further analysis. The results depicted by the eIRFs answer the research question raised by the hypothesis H_3 in detail. It is clearly suggested (as shown in the Figure 1 to Figure 6) that in the sectors NIFTY Private Bank and NIFTY Bank, the influence of the pessimistic sentiments on the stock market performance lingers for a longer period of time as compared to the influence of the optimistic sentiments. So, the paper is interesting because of its results and also because it is the first paper that analyses the impact of Twitter on the various economic sectors of Indian markets. This study also provides further evidence to suggest that the rate of adoption of social media information is different for different economic sectors.

Research implications

This research has both practical and theoretical implications. Most of the research that investigates the association between the Internet information and stock markets is concentrated

on the developed countries (Agarwal et al., 2019). This may be attributed to the fact that the developing economies pose an entirely different set of challenges e.g. stock markets of the emerging economies are not fully devel-

oped (Claessens & Yurtoglu, 2013). This study shows that the Indian stock markets are not efficient with regards to the information available on Twitter. It shows that the information on the internet does not get automatically reflected in the stock prices. Some possible reasons for this might be that the accessibility/affordability of the devices is still an issue. It also shows that the informational efficiency with respect

to the information over the social media, is quite different for the different economic sectors. It also provides information as to how the positive and negative information impacts the various sectors of a country.

This study also has some managerial implications. The business managers can focus on specialized media channels to reach out to various stakeholders as the mass communication channels (popular social media) do not seem to have any significant influence on the broad market indices. This paper also suggests that the social media adoption rate for NIFTY Private Bank and NIFTY Bank is higher than other sectors. Therefore, the business managers or the social media managers might consider using Twitter to disseminate more positive information and limit the negative content to build a positive image and thus use Twitter as an effective channel to reach out to their potential investors in two sectors (NIFTY Private Bank and NIFTY Bank).

Conclusions

The paper concludes that the Twitter information has an exceedingly small but significant relationship with the stock market

etperformanceofthesectorialindicesrelate
dtotheBankingand Financial services, in
the developing countries. This also
reveals that the social
mediacanbeusedasaneffectivetooldfordiss
eminatingusefulinformationtotheinvesto
rsinthesectors. These new mass media
channels might also be considered for
retail marketing andrelationship building
with the retail customers. However, this
relationship is not present inthe other
economic sectors as well as the over
market index (Nifty50). This study
empha-sizes a need to investigate and
collect concrete evidences to understand
the reasons behindthis. The results
indicate that the negative twitter content
has a long-lasting effect on
thestockmarketsthanthepositivecontent.
Thissuggeststhatthesocialmediamanager
sshouldcarefully monitor their social
media content for any negative content.
Also, future researchshould focus on
examining the reasons for the
insignificant correlation between the
overallperformance of the market and
the social media content through a
detailed analysis of
thetradingbehavioroftheretailinvestorsint
hedevelopingcountries.Thebehavioralas
pectsof using social media information
by the investors still need to be
explored. Future studiescan also explore
whether there is any inclination towards
the country-specific
informationchannelsontheinternet.Forthi
s,thefinancialmarketsoftheotherdevelopi
ngcountriesandtheinformationavailableo
ntheirhomegrownsocialmediaplatformsc
anbestudied.

The findings of this research have a
few limitations too. Firstly, it is limited
to the studyof the Indian stock markets.
The stock markets of the other emerging

economies might
alsobeexplored.Secondly,itonlyexplorest
hesubjectthroughamacrolevelstudyandad
etailed

study at the micro level might help to
understand the behavior of the stock
markets of theemerging economies in
light of the information available on the
social media. Finally,
thisstudyislimitedtotheinformationavailab
leontheTwitterwhileoothermediachannelsc
ouldalsobeexploredinfuturestudies.

Further research could attempt to enlighten
us on the underlying reasons to
understandwhythestockmarketsoftheemerg
ingeconomiesbehavedifferentlyfromthesto
ckmarketsof the developed countries. A
study gathering the viewpoints of the
investors regarding theinformation
available through the social media might
also help in furthering the
knowledgeinthisfield.Futurestudiescanalso
explorewhetherthereisapreferencefortheho
megrownsocialmediaplatformsovertheglob
allypopularsocialmediaplatformsamongthe
investors.This study focuses only on the
equity markets, while other financial
markets such as deriva
tivesmarketscanalsobeincludedinfurtherstu
dies.Astudycomprisingofacomparisonof
the influence of information from different
social media platforms on different
financialmarketscanbedoneinfutureresearc
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