Social Media and Company's Stock Prices

Social Media and Business Analytics (Seminar)

Seminar Paper

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ABSTRACT

Twitter is an online social networking service with over 300 million monthly active users. This enormous amount of data available on social media platforms can be extracted and analyzed for various purposes. In this paper, we aim to investigate the relationship between sentiment analysis of Twitter data and stock market prices for five companies (Walmart, ExxonMobil, Apple, Berkshire Hathaway Inc., and Amazon) by scraping the Tweets extracted from Twitter based on company hashtags and using the twitter intelligence tool – twint. Sentiment analysis is applied to the extracted tweets and a correlation is analyzed between stock market movements of a company and sentiments in tweets. Elaborately, news and tweets in social media about a company would encourage decision of people to invest or not in the stocks of that company and as a result, the stock price of that company would increase or fall. At the end of the paper, it is shown that a none or very weak correlation exists between the rise and fall in stock prices with the public sentiments in tweets.

Keywords

Sentiment Analysis, Social Media, stock price, correlation, Twitter.

1. INTRODUCTION

Stock market prices are largely fluctuating and over the period it has been an active area for research. The efficient market hypothesis (EMH) states that financial market movements depend on various factors such as news, current events, and product releases and all these factors play a significant role in impacting the company's stock value (Fama, 1965). This hypothesis is accepted by several researchers as a model governing the markets in general, several others have attempted to extract patterns on how stock markets behave and respond to external factors (Mittal & Goel, 2012).

With the increase in access to social media, inputs in the form of public opinions have grown considerably over time. Social media is transforming into a public platform where public emotions on any topic can be shared or communicated, leading to an overall impact on public opinion. Twitter is one such platform that has gained a lot of attention in recent times.

Twitter with an active user base of more than 300 million monthly active users, is a 'microblogging' platform that enables modern-day users to send and receive short posts called tweets (Lin, 2019). Tweets can extend to a maximum of 140 characters long which include links to relevant websites and resources. It is a social media platform that is popular among students, companies, and the general public. Registered users of Twitter can read and post tweets via the internet, or mobile applications (Anon., 2020). With such a broad and impressive user base, it facilitates researchers in conducting studies on mining Twitter data to extract patterns and establish relations. Twitter is currently being used for daily conversations, sharing information, and reporting news (Lin, 2019).

In our paper, we deal with the topic of sentiment analysis of twitter data. Sentiment classification is the mode of judging opinion in a piece of text as positive, negative, or neutral. Many studies highlight how twitter is used as a major source for public-opinion analysis.

Asur & Huberman (2010) have explained in their paper, how they used twitter data to predict the box office collections in the domain of movie, before its release based on public sentiment as expressed on twitter platform. Aramaki, et al.(2011) have explained how twitter data is extracted and used for early prediction and identifying of flu outbreaks. Ruiz, et al. (2012) have used time-constrained graphs to study the problem of correlating the Twitter micro-blogging activity with changes in stock prices and trading volumes. Bordino, et al. (2012) have explained in their paper that trading volumes of stocks traded in NASDAQ-100 are correlated with their query volumes (i.e., the number of users requests submitted to search engines on the Internet).Gilbert & Karahalios (2010) have found out that an increase in expressions of anxiety, worry, and fear in weblogs predicts downward pressure on the S&P 500 index. Bollen, et al. (2011) have shown that public mood analyzed through twitter feeds is well correlated with Dow Jones Industrial Average (DJIA).

All these studies indicate that twitter can be used as a valuable source and a powerful tool for conducting studies and making predictions. Our paper addresses the following research question:

Does the sentiment analysis of Twitter data impact on the stock market prices of the corporate company?

The remaining paper is structured as follows. The introduction is followed up by Theoretical background and later by Methodology. The methodology section explains the data portion highlighting the data collection and pre-processing part. In the later sections, we present the results of our findings followed by the conclusion and scope for future research.

2. THEORETICAL BACKGROUND

The rising number of blogs in social media, opinion mining, and sentiment analysis has become very popular in recent times and there has been a significant amount of research being done in this particular field. The most well-known publication in this area is by Bollen, et al. (2011). The authors have used the Fuzzy neural network approach in which they investigate whether the collective sentiments of the public derived from twitter feeds are correlated to the value of the Dow Jones Industrial Index. Their final result shows that public mood states in twitter are strongly correlated with the Dow Jones Industrial Index. Dickinson & Hu (2015) in their paper have used n-gram and "word2vec" textual representation techniques alongside a random forest classification algorithm to predict the sentiment of tweets and later demonstrate a correlation between sentiment and stock prices of the company. The authors also mention in their study that further research on the correlation between sentiment and stock prices is justified. Dickinson & Hu (2015) have also have investigated the correlation of sentiments of the public with stock increase and decreases using the Pearson correlation coefficient for stocks. Teti, et al. (2019) have explained how social media is used as a tool to identify the relationships with stock prices by considering intervening variables as a part of their study to achieve the results. The methods proposed by these papers provide an interesting overview of sentiment analysis and how it can relate to the stock market.

In this paper, we took an inductive approach to identify the relations between sentiment polarity of twitter data and stock prices based on the sentiments extracted from twitter to find the correlation. The core contribution of our work is to use twitter intelligence tool – "twint" to scrape the data and "TextBlob" for sentiment analysis of twitter data. Finally, the correlation between twitter data and stock price is identified using the Pearson correlation coefficient. The following conceptual framework gives an overview of our seminar paper.

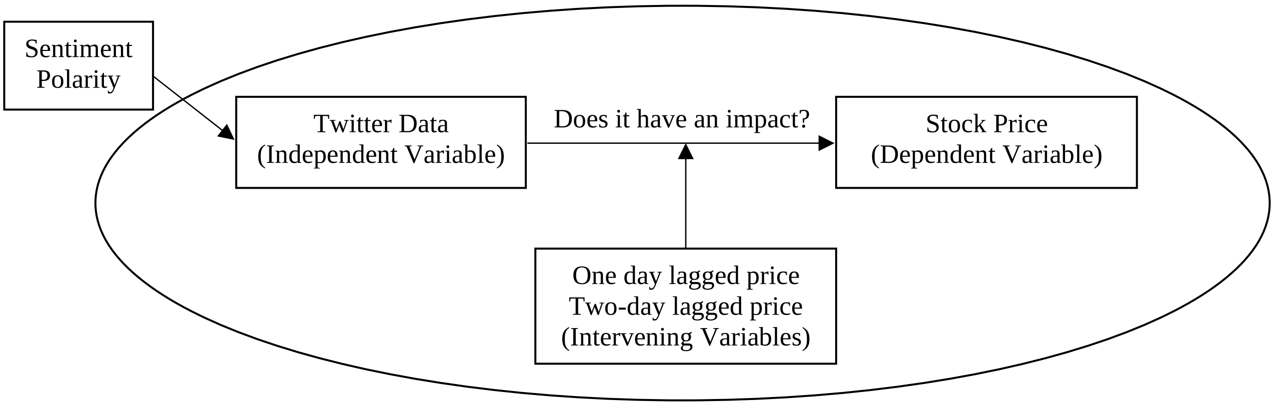

Figure 1: Conceptual Framework

3. METHODOLOGY

This section describes the process of data collection and the methodology followed to answer our research question.

3.1 Approach

The approach followed for the study is shown in a general framework schematized in Figure 1. Twitter data are collected and studied in parallel with the stock price data. Later, both the data are normalized on one common scale and further correlation analysis is performed to identify if tweets sentiments have an impact on the stock market prices for an individual company.

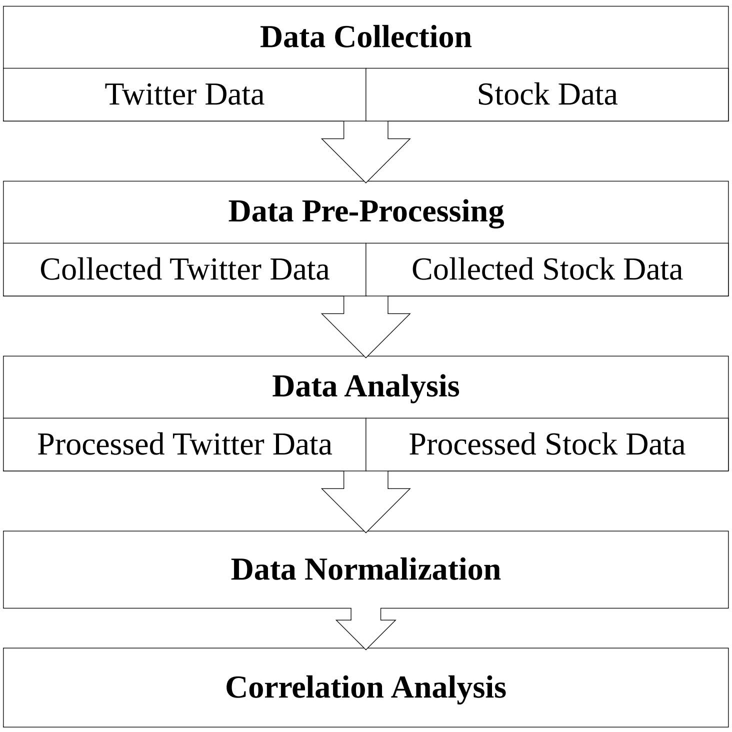

Figure 2: Approach towards study

3.2 Data Collection

Twitter data for five different companies namely Walmart, ExxonMobil, Apple, Berkshire Hathaway Inc., and Amazon, from December 1st, 2019 to December 31st, 2019 were considered for the study. The year 2020 is the year in which Corona Pandemic occurred. The sole reason for choosing December 2019 being, it was the latest month available for our study before the Corona pandemic crisis. Choosing sample space post corona would give us unusual data as the stock market would have been affected due to the pandemic. The companies were chosen based on the largest revenue generated by US companies (Dhiraj, 2019). Tweets were extracted from Twitter using Twint. Twint is an advanced Twitter scraping tool, which allows users to scrape Tweets from Twitter profiles without using Twitter's API (Poldi, 2019). The tweets were collected and filtered using keywords # WMT, # XOM, # AAPL, # BRK, and # AMZN. In total, 71311 English Tweets were extracted of which 3604 mentioned Walmart, 3108 ExxonMobil, 35640 Apple, 4620 Berkshire Hathaway Inc., and 24339 were about Amazon. The tweets were extracted in such a way that they represent the sentiment of the public on a specific company. The study focused on collecting data for various companies rather than choosing abundant data for a specific company. Stock opening and closing prices for the same sample space and period were obtained from Yahoo! Finance (Finace, 2020).

3.3 Variables

The motive of our study is to find if sentiment analysis of twitter data has an impact on the stock market prices of the corporate company. To arrive at the conclusion, we have considered sentiment polarity of twitter data as an independent variable and stock price as the dependent variable. All the variables are collected during daily market activity. Moreover, according to the study, the relationship with social media sentiment is expected to vary with time. Due to this factor, two more variables are considered as intervening variables, such as

- One-day lagged price
- Two day lagged price

3.4 Data Preprocessing

Tweets, which are extracted from Twitter data consists of many acronyms, emoticons, special characters and URL. In our study, such attributes, which are present in Twitter data, are not relevant and they may hinder our further analysis. Hence, to represent the correct sentiment of the public, tweets were pre-processed. Furthermore, to reduce dimensionality and simplify the inputs, text information has to be cleaned of noises, images, punctuations, and any insignificant terms required for sentiment analysis. To achieve this step, we used the Python programming language.

Stock prices data collected are not completely understandable, since the stock market does not function during weekends and public holidays. The data, which was collected from Yahoo! Finance, had to be pre-processed to become suitable for further reliable analysis. To fill the missing values, a simple statistical function was adopted. If the value that is missing is y, the previously known value is xprevious and the next known value is xnext, then the value y will be as follows:

$$y = (\text{xprevious} + \text{xnext})/2$$

This approximation works most of the time very well except in cases of unexpected rapid rise and fall of the stock prices (Kordonis, et al., 2016).

3.5 Sentiment and Stock Analysis

In Sentiment analysis, we focus on finding the polarity of the given text. We have used TextBlob a package in Python to do the same. The sentiment property of TextBlob returns two values namely Polarity and subjectivity. Polarity refers to the sentiment orientation (positive, negative, neutral) in the text. Subjectivity is opinions that describe people's feelings towards a specific subject or topic. Since subjectivity is not relevant for our study, we have only considered polarity (Jain, 2018).

Stock analysis is done by computing the percentage change in stock price (PCT_{change}). It is calculated by subtracting the opening stock price of the given day with the closing stock price and dividing it from the opening stock price. If the sign is negative, that means that the price is decreased. If the sign is positive, it indicates that the price is increased over time. If the closing stock price is considered as "close'' the opening stock price as "open", then the formula is as follows (Kordonis, et al., 2016):

$$PCT_{\ change} = 100 * \frac{close - open}{open}$$

3.6 Data Normalization

Normalization refers to rescaling numeric attributes onto one common scale between 0 and 1 (Anon., 2020). In our study, both dependent and independent variables are normalized so that we could compare them for further analysis. To achieve this step, we tabulated and normalized data in Excel. The following formula was used to convert an array of data to a normalized value (Glen, 2020).

$$X_{new} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

- X_{new} – New Normalized value
- X_{max} – The maximum value in the dataset
- X_{min} – The minimum value in the dataset
- X– Variable

3.7 Correlation Analysis

The correlation (r) calculates the strength of the linear relationship between two variables (Mindrila & Balentyne, 2013). In our study, the two variables involved are public sentiment and stock price. Once the normalization value was derived for each company, correlation analysis was carried out for the same. Pearson's Correlation Coefficient method was adopted to demonstrate a connection between the two variables. According to the study, the relationship with social media sentiment is expected to vary with time, as a result, correlation analysis was also carried out on intervening variables, namely one-day and two lag price. The values were plotted on the scatterplot and this significantly made it possible to evaluate the relationship between price and sentiment for each company. A sampling of these calculations and charts are explained in the next section.

The formula used for calculation is as follows:

Pearson r:

$$r = \frac{1}{n-1} \sum \left(\frac{x_i - \bar{x}}{S_x} \right) \left(\frac{y_i - \bar{y}}{Sy} \right)$$

- x_i and y_i are dependent and independent variables
- S_x and S_y are Standard deviations of x and y respectively
- $\bar{x}$ and $\bar{y}$ are mean of x and y respectively

- r is always a number between -1 and 1.
- $r > 0$ indicates a positive association.
- $r < 0$ indicates a negative association.
- Values of r near 0 indicate a very weak linear relationship.
- The strength of the linear relationship increases as r moves away from 0 toward -1 or 1.
- The extreme values r = -1 and r = 1 occur only in the case of a perfect linear relationship (Mindrila & Balentyne, 2013).

Our study results are interpreted based on the following table (Mindrila & Balentyne, 2013)

Absolute Value of r	**Strength of Relationship**
$r < 0.3$	None or very weak
$0.3 < r < 0.5$	Weak
$0.5 < r < 0.7$	Moderate
$r > 0.7$	Strong

Table 1: Correlation Analysis

Once the correlation (r) was calculated as explained above, we then determined whether the correlation between variables is significant or not (p-value). The value of p for which a correlation will be considered statistically significant is called the alpha level and, in our study, we have considered alpha level as 0.05. Correlations are considered statistically significant if the p-value is lower than 0.05 (Mindrila & Balentyne, 2013).

4. RESULTS AND DISCUSSIONS

This section describes the results obtained through the methodologies described in the previous section. For our study and evaluation purposes, a total of 71311 tweets were collected tweets from five different companies namely Walmart, ExxonMobil, Apple, Berkshire Hathaway Inc., and Amazon. Tweets between December 1st, 2019 to December 31st, 2019 were collected. The following table indicates the overall tweet volume extracted for each company and the graph gives an overview of the tweets collected daily for five individual companies.

Companies	Overall Tweets
Walmart	3604
ExxonMobil	3108
Apple	35640
Berkshire Hathaway Inc.	4620
Amazon	24339

Table 2: Overall Tweet volume for each company

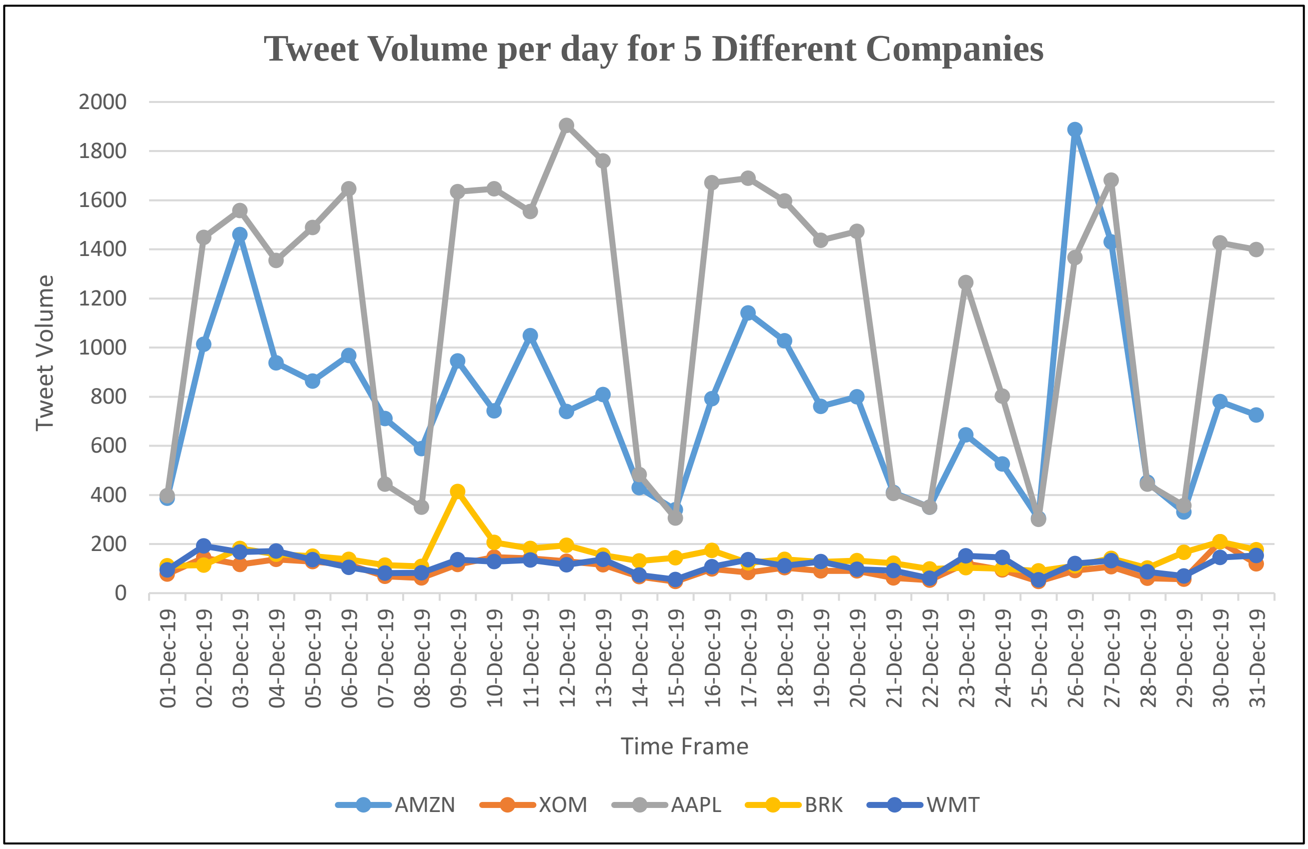

Figure 3: Tweet Volume per day for 5 Different Companies

It is noted from the above graph that the tweet volume during weekends and holidays is considerably low when compared to the remaining days as the stock market is closed during weekends and holidays. It is interesting to observe that the companies which we have considered for our study have a wide range of tweet volume as shown in the above table. Sentiment and stock analysis are performed on the sample space, the analyzed data is later normalized, i.e. data from sentiment and stock analysis are normalized onto one common scale. Correlation analysis is performed to observe the relationship between sentiment and stock price. Besides, correlation values (r) are shown between sentiment and stock price returns for the same day (No Lag), stock price returns after one day (One day lagged price), and stock price returns after two days (Two days lagged price) respectively. To find the strength of the linear correlation between sentiment and stock price, Pearson's Correlation Coefficient method was adopted. The sentiments were used as "X" values and stock prices were used as "Y" values. Correlation coefficients that are statistically significant at $p < 0.05$ were also computed.

It must be noted that in our paper, we have explained the process and methodology followed for each company by showing graphs only for "No Lag" but the same approach has been followed to compute the correlation for "one day lag" and "Two-day lag" stock prices. The results have been tabulated, which gives an overview of the correlations obtained for every intervening variable. These results are highlighted in the respective result sections of the company.

4.1 Walmart

In total, 3604 tweets mentioning Walmart were collected for our study. The number of average tweets per day was 116. Figure 4 indicates an overview of the results obtained for Walmart - "No lag". Table 3 below gives an overview of the correlation obtained between the sentiment and stock price for each day considered and the stock price returns for the same day (No lag), one day (One day lagged price) and two days (Two days lagged price) after the tweets were made on twitter. As it can be seen, all the correlations are none or very weak ($r < 0.3$). The table also indicates that none of the outcomes are statistically significant at $p < 0.05$.

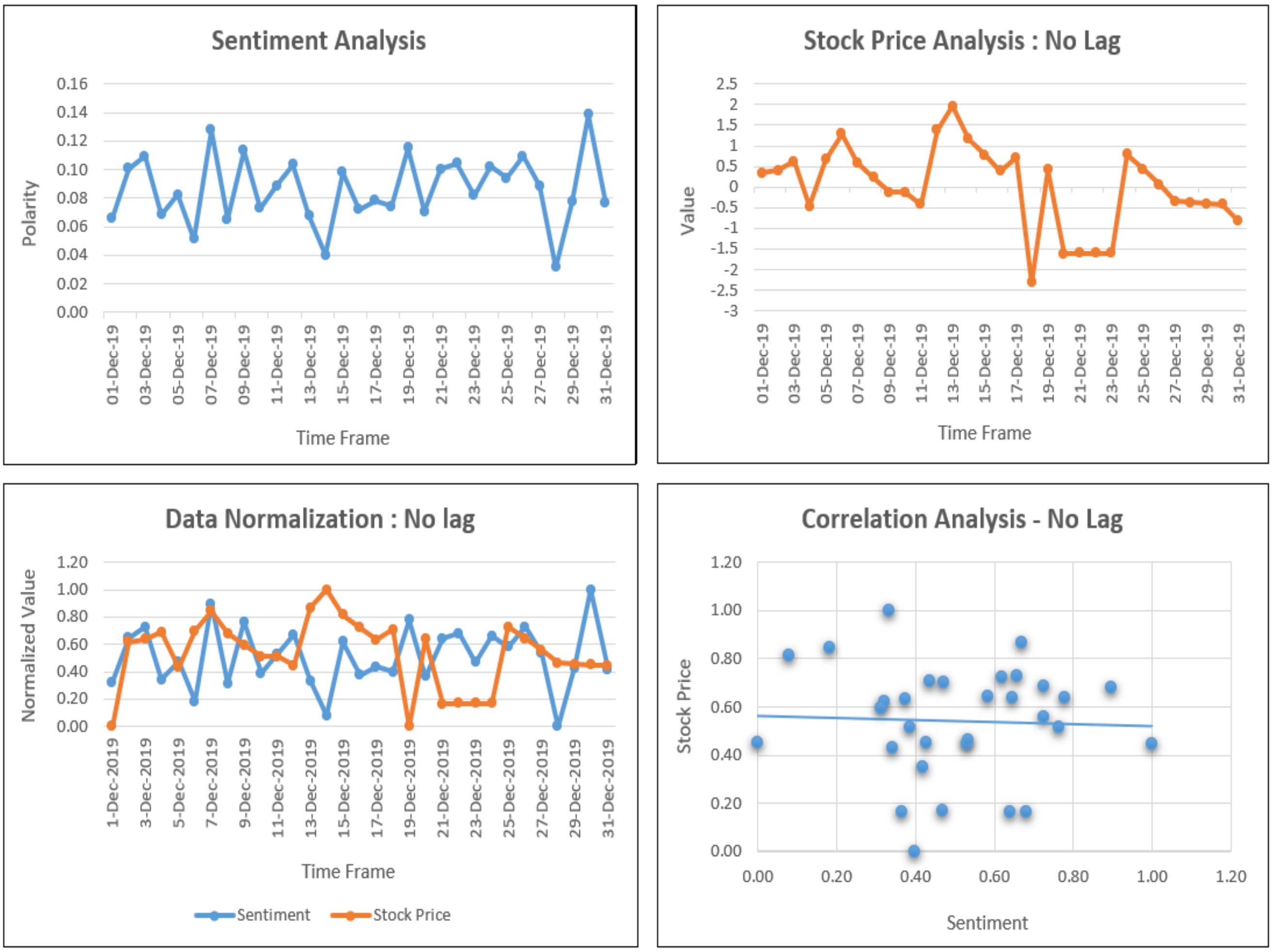

Figure 4: Walmart Results-No Lag

	Correlation Value (r)	p value	Significance Level
No Lag	-0.04	0.81	Not Significant
1 Day Lagged Price	-0.19	0.31	Not Significant
2 Day Lagged Price	-0.09	0.63	Not Significant

Table 3: Correlation between sentiment and stock prices - Walmart

4.2 ExxonMobil

In total, 3108 tweets mentioning ExxonMobil were collected for our study. The number of average tweets per day was 100. Figure 5 indicates an overview of the results obtained for ExxonMobil - "No lag". Table 4 below gives an overview of the correlation obtained between the sentiment and stock price for each day considered and the stock price returns for the same day (No lag), one day (One day lagged price) and two days (Two days lagged price) after the tweets were made on twitter. As it can be seen, all the correlations are none or very weak ($r < 0.3$). The table also indicates that none of the outcomes are statistically significant at $p < 0.05$.

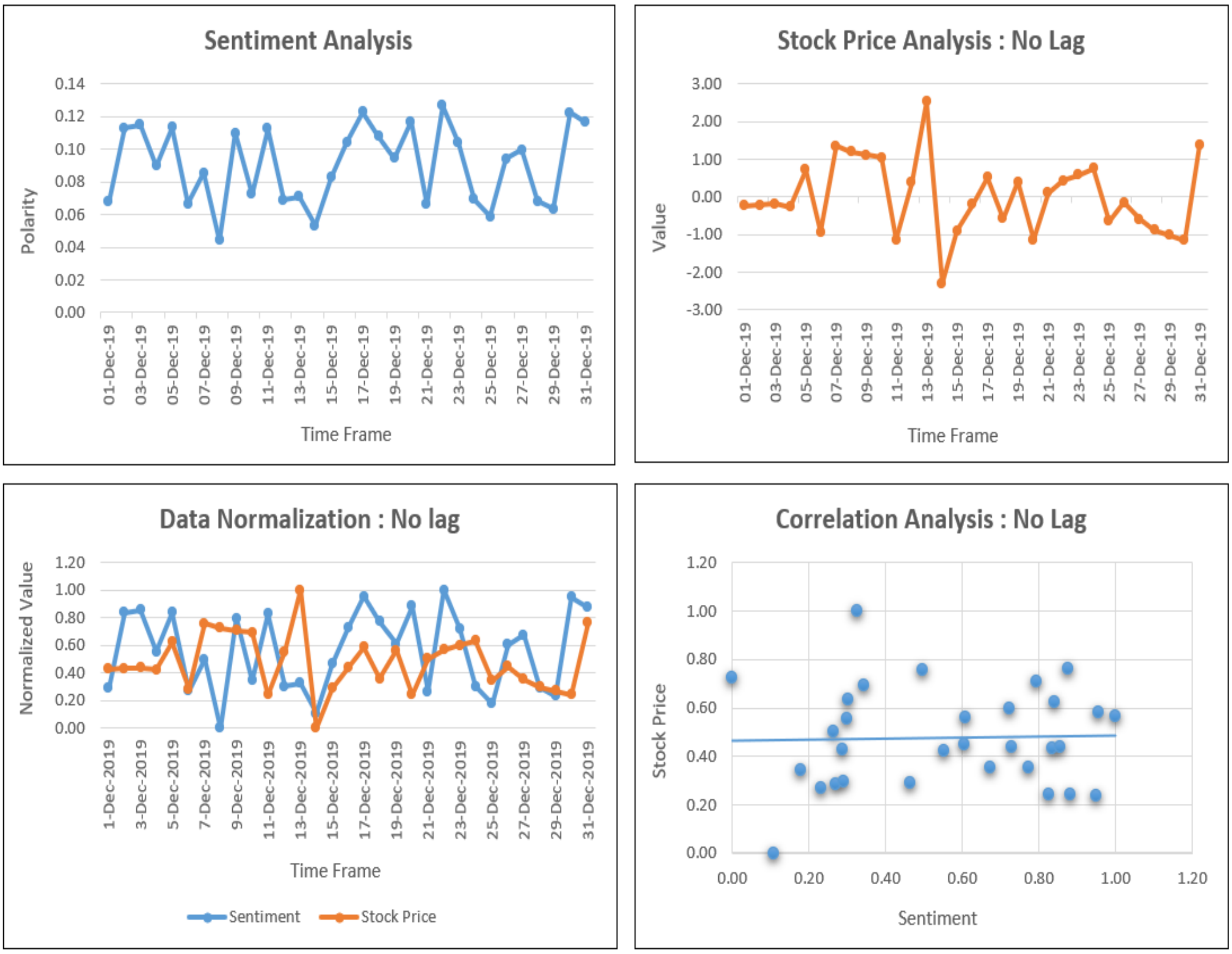

Figure 5: Exxon Mobil Results-No Lag

Intervening Variables	Correlation Value (r)	p value	Significance Level
No Lag	0.04	0.84	Not Significant
1 Day Lagged Price	0.09	0.61	Not Significant
2 Day Lagged Price	0.05	0.77	Not Significant

Table 4: Correlation between sentiment and stock prices – Exxon Mobil

4.3 Apple

In total, 35640 tweets mentioning Apple were collected for our study. The number of average tweets per day was 1150. Figure 6 indicates an overview of the results obtained for Apple - "No lag". Table 5 below gives an overview of the correlation obtained between the sentiment and stock price for each day considered and the stock price returns for the same day (No lag), one day (One day lagged price) and two days (Two days lagged price) after the tweets were made on twitter. As can be seen, all the correlations are none or very weak ($r < 0.3$). The table also indicates that none of the outcomes are statistically significant at $p < 0.05$.

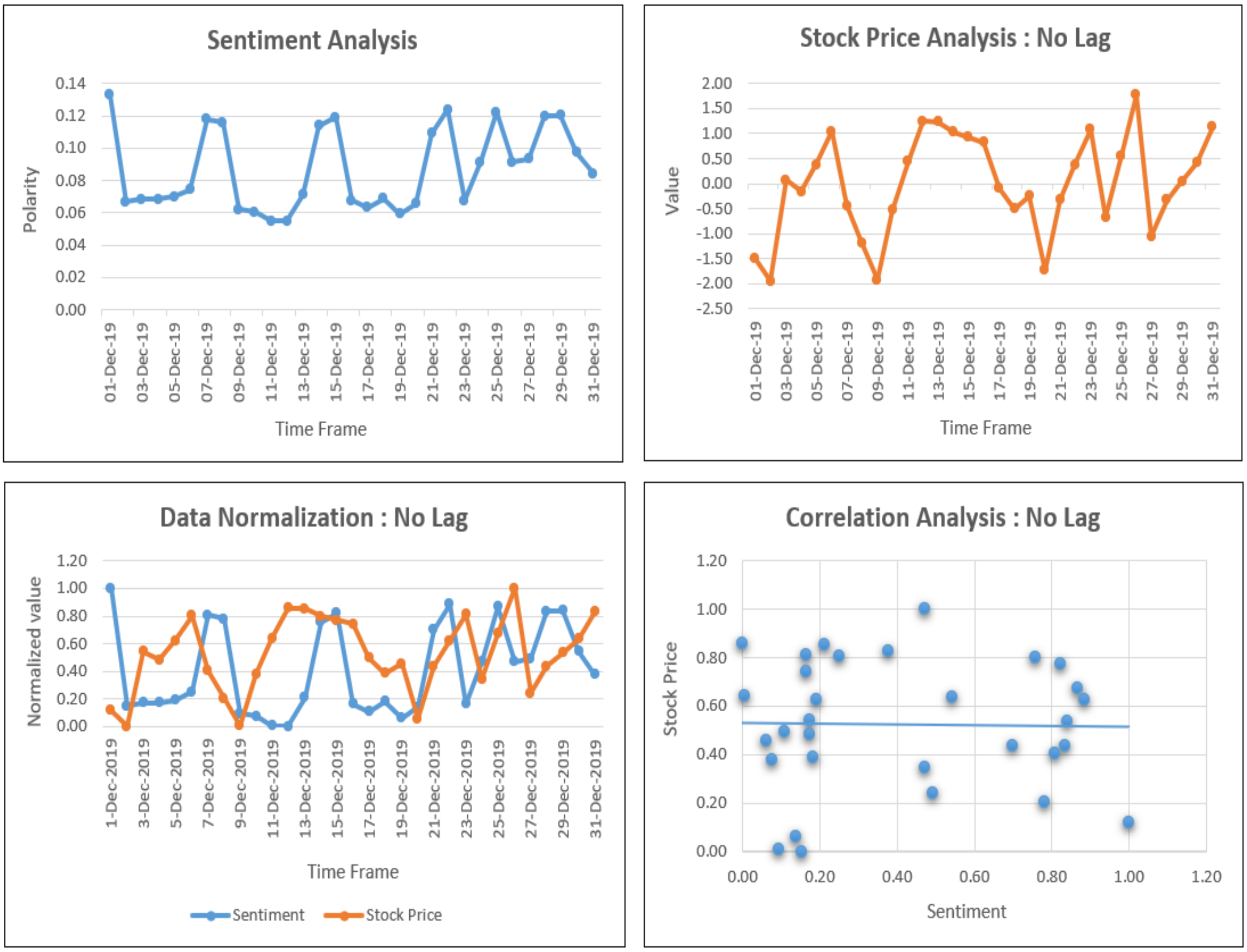

Figure 6: Apple results-No Lag

Intervening Variables	Correlation Value (r)	p value	Significance Level
No Lag	-0.02	0.91	Not Significant
1 Day Lagged Price	-0.03	0.86	Not Significant
2 Day Lagged Price	-0.18	0.32	Not Significant

Table 5: Correlation between sentiment and stock prices – Apple

4.4 Berkshire Hathaway Inc.

In total, 4620 tweets mentioning Berkshire were collected for our study. The number of average tweets per day was 149. Figure 7 indicates an overview of the results obtained for Berkshire - "No lag". Table 6 below gives an overview of the correlation obtained between the sentiment and stock price for each day considered and the stock price returns for the same day (No lag), one day (One day lagged price) and two days (Two days lagged price) after the tweets were made on twitter. As it can be seen, all the correlations are none or very weak ($r < 0.3$) except for two days lagged price. The table also indicates that none of the outcomes are statistically significant at $p < 0.05$ expect for two days lagged price.

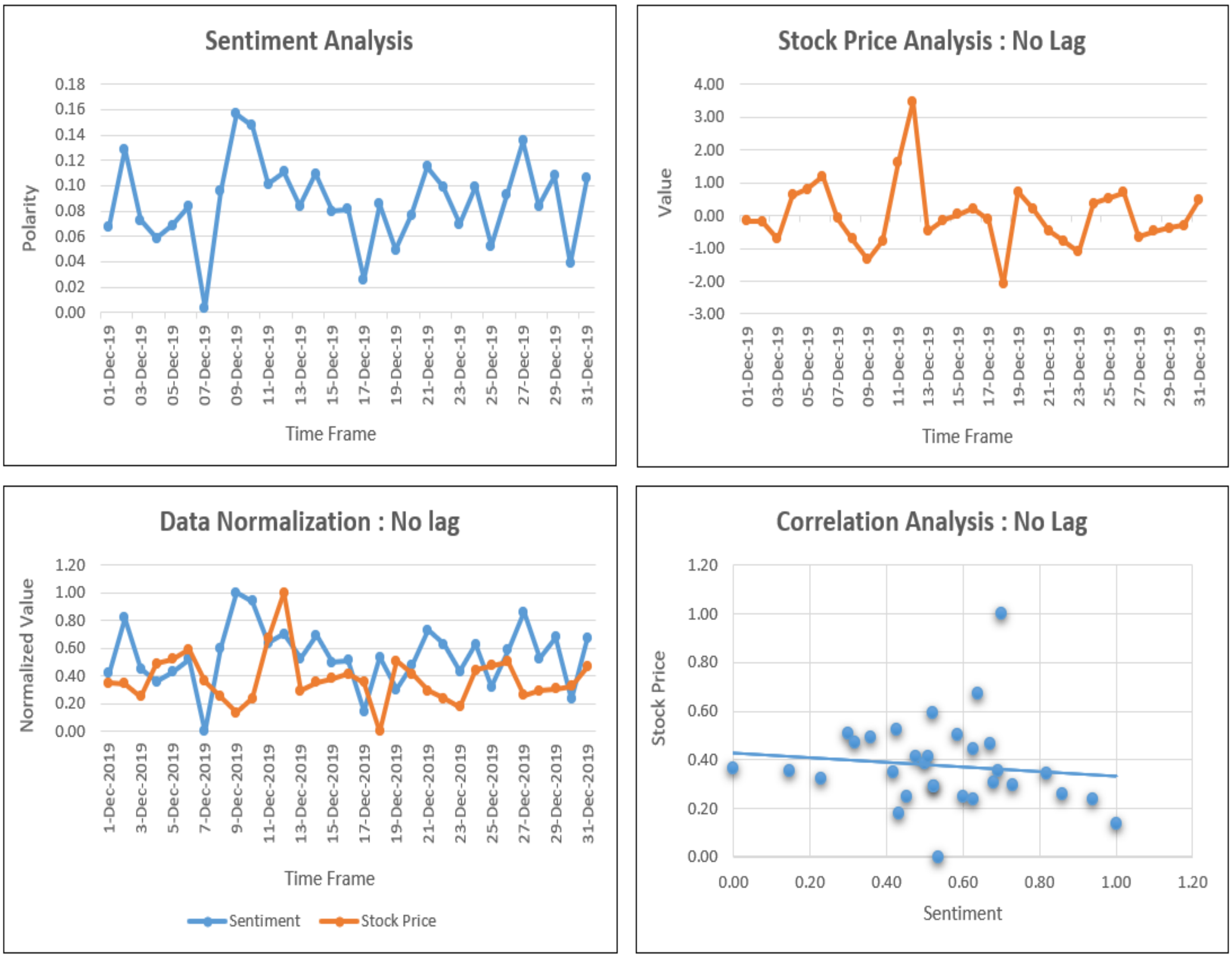

Figure 7: Berkshire Hathaway Inc. Results-No Lag

Intervening Variables	Correlation Value (r)	P value	Significance Level
No Lag	-0.11	0.54	Not Significant
1 Day Lagged Price	0.06	0.75	Not Significant
2 Day Lagged Price	0.40	0.02	Significant

Table 6: Correlation between sentiment and stock prices – Berkshire Hathaway Inc.

4.5 Amazon

In total, 24339 tweets mentioning Amazon were collected for our study. The number of average tweets per day was 785. Figure 8 indicates an overview of the results obtained for Amazon - "No lag". Table 7 below gives an overview of the correlation obtained between the sentiment and stock price for each day considered and the stock price returns for the same day (No lag), one day (One day lagged price) and two days (Two days lagged price) after the tweets were made on twitter. As it can be seen, all the correlations are none or very weak ($r < 0.3$). The table also indicates that none of the outcomes are statistically significant at $p < 0.05$.

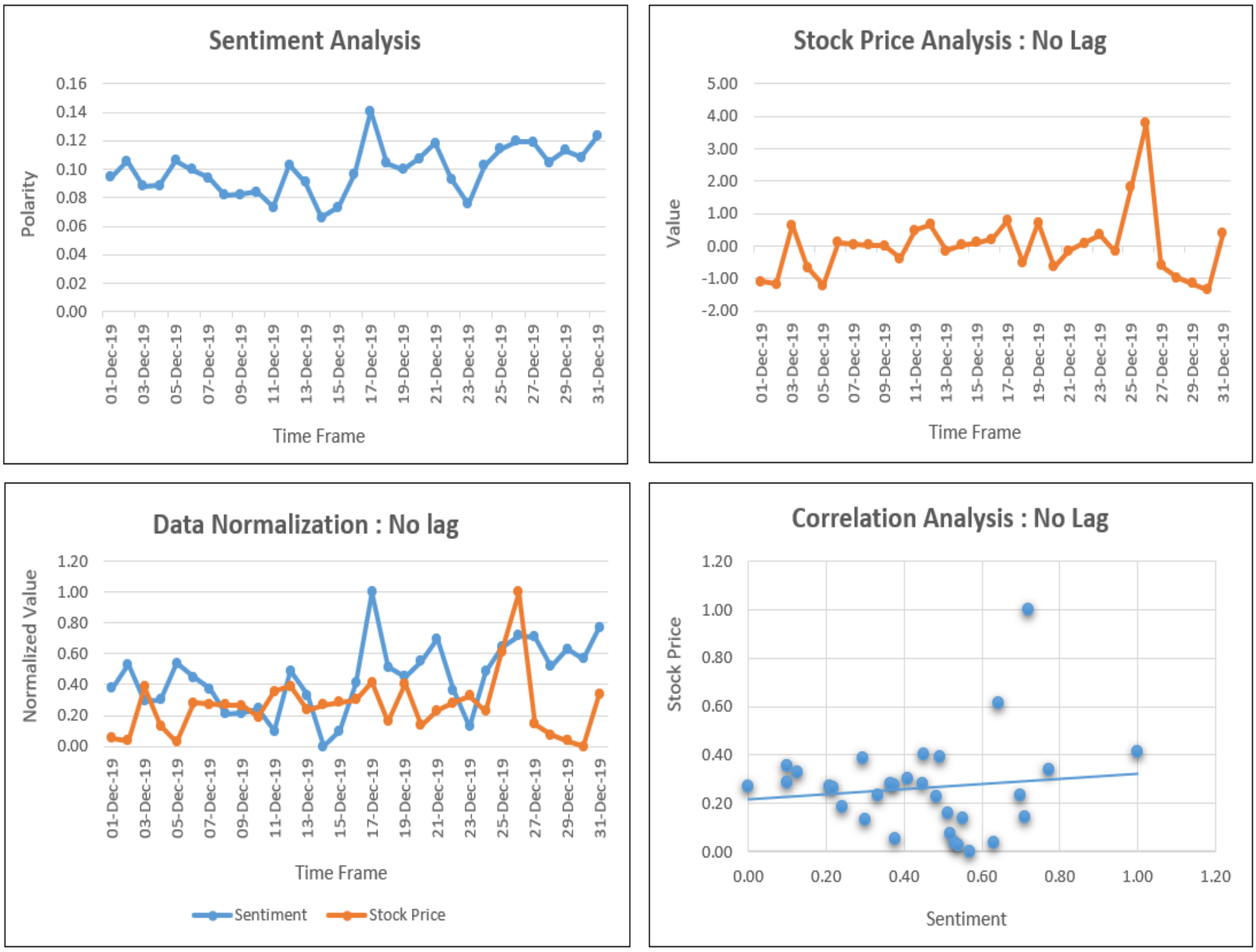

Figure 8: Amazon Results-No Lag

Intervening Variables	Correlation Value (r)	P value	Significance Level
No Lag	0.12	0.51	Not Significant
1 Day Lagged Price	0.00	0.99	Not Significant
2 Day Lagged Price	-0.15	0.41	Not Significant

Table 7: Correlation between sentiment and stock prices – Amazon

5. CONCLUSION

In this paper, we have investigated whether the sentiment analysis of twitter data has an impact on the stock prices of the corporate company. To answer our research question, data for the stock price and public sentiment for the five companies (Walmart, ExxonMobil, Apple, Berkshire Hathaway Inc., and Amazon) were obtained from Yahoo! Finance and Twitter respectively. A common feature for all five companies which we analyzed was that the correlations between sentiments and their stock returns were either none or very weak. Concerning the statistically significant correlations (p-value), it is also observed that none of the companies had a statistically significant relationship with the variables. Hence, on the whole, we would like to conclude by answering our research question, that sentiment analysis has a none or very weak impact on the stock prices of the corporate companies we have selected. The following tables give an overview of the correlation values and the statistical significance of correlation coefficients for each company. Furthermore, it is worth mentioning that our study and analysis is bound to certain limitation and we believe that there are many areas in which this work could be expanded in the future. Limitations and future research related to our study are highlighted in the next section.

	Walmart	**ExxonMobil**	**Apple**	**Berkshire Hathaway Inc.**	**Amazon**
No Lag	None or very weak	None or very weak	None or very weak	None or very weak	None or very weak
1 Day Lagged Price	None or very weak	None or very weak	None or very weak	None or very weak	None or very weak
2 Day Lagged Price	None or very weak	None or very weak	None or very weak	Weak	None or very weak

Table 8: Correlation Overview for 5 Companies

	Walmart	**ExxonMobil**	**Apple**	**Berkshire Hathaway Inc.**	**Amazon**
No Lag	Not Significant	Not Significant	Not Significant	Not Significant	Not Significant
1 Day Lagged Price	Not Significant	Not Significant	Not Significant	Not Significant	Not Significant
2 Day Lagged Price	Not Significant	Not Significant	Not Significant	Significant	Not Significant

Table 9: Statistical Significance overview for 5 Companies

6. LIMITATIONS AND FUTURE RESEARCH

The study we have presented has been limited to five companies for 31 days. The results have been inferred based on only 31 days of tweets and hence the results must be regarded as indicative rather than conclusive. The results cannot be generalized for the entire population as the polarity may vary with different tools. In our study, we have considered only twitter data for analyzing people's sentiment, which may be biased because not all the people who trade in stocks share their opinions on twitter. Finally, in our study, we have considered the only polarity of the tweets from English speaking people and not on public emotions.

Our study does not acknowledge some important factors, which will form the basis of future research. First, it is noted that the dataset we have considered is limited and hence we can consider a wider range of companies over a longer period to obtain more reliable results. Indeed, with a bigger data set, we may be able to infer whether or not sentiment plays a lager predictive role for certain stocks. Furthermore, it is worth mentioning that for our future study we can consider various variables such as public emotions along with the polarity of tweets. It is possible to obtain a higher correlation if the actual mood is studied. An additional step for future research is performing causality analysis on the sample space such that we identify the cause of the correlation and deliver more accurate results.

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