Exploring the relationship between Elon Musk's tweets and Tesla stock price change using NLP techniques

Group 9 Edmund Lam, Peishan Li, Xinrun Shan, Jingru Tang

Equal contributions, names in alphabetical order

Abstract

Studies in the recently developing field of behavioral finance show that stock prices are driven by sentiment, and Twitter, as a prominent social media platform in today's world, is becoming increasingly popular for people to share their sentiments about stocks. Various research papers have attempted to demonstrate the potential connection between the mood of a CEO and the stock value of their company. In this group project, we investigate how the sentiment expressed by Tesla CEO Elon Musk on Twitter affected Tesla's stock price performance. Specifically, we analyzed the content of Musk's tweets and extracted the sentiments by using a set of text featurization and regression techniques. We hypothesized a correlation between the CEO's daily sentiment and the company's daily stock price movement. Data from 2021 did not show a significant correlation, and we could not conclude Tesla's stock prices were affected by Musk's tweets. We realize the fluctuation in the US stock is affected by multiple factors, and we acknowledge some limitations in this study that require further investigation in future research.

Introduction

Stock market prediction has been an active topic of research, and studies show stock market prices do not follow a random walk and can indeed be predicted to some degree (Gallagher and Taylor, 2002). Furthermore, behavioral finance evidence confirms that financial decisions can be emotion-driven because investors are rationally limited (Leitch and Sherif, 2017).

Recent studies have shown that social media sources can have an observable effect on investors' opinions towards financial markets, and researchers have begun to incorporate sentiment analysis in the process of stock price predictions (Wei and Wang, 2016). Nowadays, Twitter has become a popular platform where users share their opinions about stocks, financial markets, and related matters. Although opinions expressed on Twitter are often relevant and succinct because of the platform's character limit, they may have some impact on the price of stocks.

In this study, we investigate the connection between Elon Musk's Twitter and the stock value of Tesla. The primary analysis we used was sentiment analysis that could identify different tones in Elon's tweets throughout the year of 2021, and then we correlated them to the stock price of Tesla. In this paper, we first discuss how we generated the dataset and the work of data preprocessing, which filters out unnecessary information. Next, we analyze sentiment by constructing sentiment scores and categorizing Musk's tweets according to two different tones: positive and negative, which is done by 1) building a Lexicon Text Blob Model, and 2) using reference from a list of positive and negative words obtained from the sentiment dictionary of Hu and Liu (2004). We also identify emotional components that could be detected from each of Elon's tweets, and obtain the frequency of words that represent a certain emotion for each tweet. Then, we build linear regression and logistic regression models to quantitatively measure the relationship between the sentiment score and Tesla's stock price. Various graphs will be utilized for further illustration. For the result, nevertheless, we did not detect significant evidence that confirms our hypothesis that Musk's tweets can yield economically predictive values. We acknowledge that US stock markets are affected by individuals worldwide and multiple additional important factors. We end by discussing the limitations of our study.

Data

Yahoo Finance was used to source company stock price data, which we converted into returns following the formula as shown below:

$$\text{Stock Returns}(R_{i,t}) = \frac{Price_t - Price_{t-1}}{Price_{t-1}}$$

The following line graph illustrates the change in the daily closing price of Tesla stock throughout the year of 2021, which shows an obvious upward trend:

We extracted all the tweets Elon Musk posted in 2021 through the Twitter API. Only the tweets posted after the trading hour (4:00 p.m.) were analyzed because we believe those tweets will most affect the change in the next day's stock price. We then performed the preprocessing techniques to clean the data: all special characters and stop words were removed so that focus can be put on more important words; all words were converted into lower case because the same word with a capitalized first letter could be interpreted differently; all words were also 'lemmatized' so the different inflected forms of a word could be grouped together. The work of preprocessing ended off by applying and compiling all these transformations into a new data frame including 126 corpora. We then created a word cloud to visualize the frequency of words in Musk's tweets. In the graphic below, it is evident that positive words such as "great" and "good" were frequently used. This seems to correspond with the overall increasing trend of Tesla's share price.

Methodology

In this paper, we propose that the stock price of a company's market could be affected by the sentiment and emotions within public opinions of their leaders, and have selected Elon Musk and the Tesla stock market as our testing objectives. Therefore, we perform sentiment analysis, which deals with human languages with the help of data science techniques. We analyze the subjective feelings and emotions of Elon Musk's tweets, or how people echo from them. In the methodology section, we explain the two directions: The first direction classifies Elon's tweets into positive and negative, which is done by 1) building a Lexicon Text Blob Model, and 2) using reference from a list of positive and negative words obtained from the sentiment dictionary of Hu & Liu (2004). The second direction identifies which emotional components could be detected from each of Elon's tweets, and obtains the frequency of words that represent a certain emotion. For both directions, we create intuitive data visualizations to reflect the relationship between the sentiments and Tesla stock price changes, and build regression models to quantitatively measure the relationship as well.

1. Positive and negative sentiments and regression analysis

1) Lexicon TextBlob Model

TextBlob Model is used in our paper to work out the polarity and numerical sentiment scores of Elon Musk's tweets collected. TextBlob actively used NLTK to access the categorizations and other analyses of textual data. And for lexicon-based approaches, a sentiment or tone is defined by its semantic orientation and the intensity of each word in the sentence. Our research applies the built-in pre-defined dictionary classifying positive and negative words in Python ***(TextBlob(text).sentiment.polarity).*** After assigning each word in Elon Musk's tweets, final numerical sentiment scores are calculated by taking the average of all the sentiments in the bag of words for every single tweet. The range of the sentiment scores lies between -1 to +1, where -1 represents highly negative emotions, and +1 indicates robust positive tones contained in the tweet. And it is expected that the sentiment score will return zero if the tweet does not contain any words that have a polarity in the NLTK training set or because in our methodology, we used an equally-weighted average sentiment score over all the words in one tweet. This equally-weighted approach might lead to a limitation for our research that will be discussed in more detail in the following sections.

Now that we have numeric data for the tone of tweets, and the preprocessed daily stock price percentage changes, we built models to test the relationship between the two variables.

The first model is a simple linear regression model. The dependent variable is daily stock price percentage change, and the independent variable is the tone of the tweets (polarity), which equals 1 (positive), -1 (negative), or 0 (neutral). The statistical expression is:

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times Polarity + \varepsilon \ (1)$$

We also built a logistic regression model. The dependent variable is whether the stock price increases or decreases, and polarity remains as the independent variable. The formula is:

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times Polarity + \varepsilon \ (2)$$

in which the dependent variable is re-coded from $Daily\ stock\ price\ percentage\ change$, whose positive values indicate stock price increase, and negative values indicate stock price decrease, and the independent variables is re-coded from the original sentiment score, whose positive values indicate positive sentiment and +1 for $Polarity$, and vice versa.

2) Sentiment Dictionary of Hu & Liu (2004)

Hu and Liu (“Mining and Summarizing Customer Reviews”) provide a list of 6800 words that are positive and negative derived from *amazon.com* and other sources. The rate of occurrence of the pre-defined words provides information on the overall tone of each tweet. Specifically, a score of tone that equals 1 suggests polarity positive, and -1 polarity negative.

Similar to the Lexicon Text Blob Model, we built a simple regression model to test the relationship between the tone of a tweet and the stock price percentage change the day the tweet is sent out, as well as a logistic regression model that tests the effect of whether a tweet has a positive or negative sentiment, on whether the stock price increases or decreases.

The formula for the regression model is the same with that of the Lexicon Text Blob Model: the only difference lies in the actual values of sentiment scores due to different principles.

$$Daily\ stock\ price\ percentage\ change\ =\ \beta_0\ +\ \beta_1\ \times\ Polarity\ +\ \varepsilon\ (3)$$

The formula for the logistic regression model is:

$$Daily\ stock\ price\ changing\ direction\ =\ \beta_0\ +\ \beta_1 \times\ Polarity\ +\ \varepsilon\ (4)$$

in which the dependent variable is re-coded from $Daily\ stock\ price\ percentage\ change$, whose positive values indicate stock price increase, and negative values indicate stock price decrease, and the independent variables is re-coded from the original sentiment score, whose positive values indicate positive sentiment and +1 for $Polarity$, and vice versa.

2. Emotions and regression analysis

We identify 8 different emotions from Elon Musk's tweets, including anger, anticipation, disgust, fear, sadness, sadness, surprise, trust as well as 2 sentiments, which are positive and negative. To do this, we use the NRC Word-Emotion Association Lexicon (Mohammad, 2010), which could be obtained in the *tidytext* package in R.

The first set of models are linear regression models, where we test the relationship of the daily stock price percentage change and the percentage change in frequency of emotional words for each tweet (which is calculated by the count of emotion or sentiment words in the tweet, divided by the count of all words in the tweet, then taking logarithm). The formulas are:

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ angry\ words) + \varepsilon \quad (5)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ anticipation\ words) + \varepsilon \quad (6)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ disgust\ words) + \varepsilon \quad (7)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ fear\ words) + \varepsilon \quad (8)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ joy\ words) + \varepsilon \quad (9)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ sadness\ words) + \varepsilon \quad (10)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ surprise\ words) + \varepsilon \quad (11)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ trust\ words) + \varepsilon \quad (12)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ positive\ words) + \varepsilon \quad (13)$$

$$Daily\ stock\ price\ percentage\ change = \beta_0 + \beta_1 \times log(Frequency\ of\ negative\ words) + \varepsilon \quad (14)$$

For robustness check, we built a multi-regression model with all the emotion and sentiment frequency changes as independent variables. The formula is:

$$\begin{aligned} Daily\ stock\ price\ percentage\ change = {} & \beta_0 + \beta_1 \times log(Frequency\ of\ angry\ words) \\ & + \beta_2 \times log(Frequency\ of\ anticipation\ words) + \beta_3 \times log(Frequency\ of\ disgust\ words) \\ & + \beta_4 \times log(Frequency\ of\ fear\ words) + \beta_5 \times log(Frequency\ of\ joy\ words) \\ & + \beta_6 \times log(Frequency\ of\ sadness\ words) + \beta_7 \times log(Frequency\ of\ surprise\ words) \\ & \beta_8 \times log(Frequency\ of\ trust\ words) + \beta_9 \times log(Frequency\ of\ positive\ words) \\ & + \beta_{10} \times log(Frequency\ of\ negative\ words) + \varepsilon \quad (15) \end{aligned}$$

For data visualization of this section, we plot out the data points, with the frequency change of emotion or sentiment words on the x-axis, and the percentage change of Tesla stock price on the y-axis. We also plot a smoothed linear regression line in each graph to reflect the regression relationship.

The second set of models are logistic regression models. The dependent variable is re-coded into binary format, with a value that equals to 1 representing a stock price increase, -1 representing a stock price decrease, and 0 representing no changes. The independent variables are kept as the numeric values (log form of the frequencies). The formulas are:

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(\ Frequency\ of\ angry\ words) + \varepsilon \quad (16)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(\ Frequency\ of\ anticipation\ words) + \varepsilon \quad (17)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ disgust\ words) + \varepsilon \quad (18)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ fear\ words) + \varepsilon \quad (19)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ joy\ words) + \varepsilon \quad (20)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ sadness\ words) + \varepsilon \quad (21)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ surprise\ words) + \varepsilon \quad (22)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ trust\ words) + \varepsilon \quad (23)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(Frequency\ of\ positive\ words) + \varepsilon \quad (24)$$

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times log(\ Frequency\ of\ negative\ words) + \varepsilon \quad (25)$$

Similarly, the multi-regression model is expressed as:

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times Frequency\ of\ angry\ words$$
$$+ \beta_2 \times Frequency\ of\ anticipation\ words + \beta_3 \times Frequency\ of\ disgust\ words$$
$$+ \beta_4 \times Frequency\ of\ fear\ words + \beta_5 \times Frequency\ of\ joy\ words$$

$$+ \beta_6 \times Frequency\ of\ sadness\ words + \beta_7 \times Frequency\ of\ surprise\ words$$
$$\beta_8 \times Frequency\ of\ trust\ words + \beta_9 \times Frequency\ of\ positive\ words$$
$$+ \beta_{10} \times Frequency\ of\ negative\ words + \varepsilon \quad (26)$$

For data visualization, we try a different way of plotting, by calculating the word frequency for tweets associated with stock price increase & decrease separately, and filter out DataFrames with only words contained in the dictionary of each emotion or sentiment category. The matrix we use is tf_idf, which combines the term frequency (TF) and the inverse document frequency (IDF) into a single numerical value. It decreases the weight for commonly used words and increases the weight for words that are not used very much in a collection of documents. A version of formula is: $TF/IDF = Term\ Frequency \times Inverse\ Term\ Frequency$;

$w_{t,d} = (1 + logtf_{t,d}) \times log_{10}(\frac{N}{df_t})$.

Results

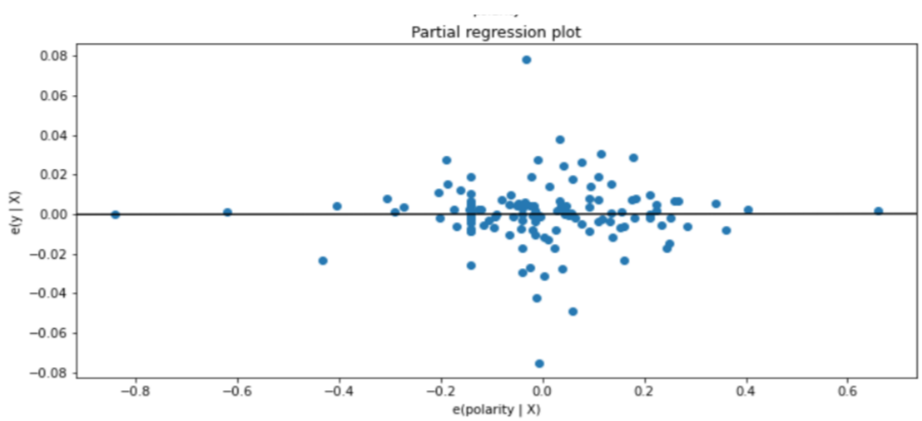
1. Relationship between Polarity Scores of Elon Musk's tweets and Tesla's Stock Price Changes

1) Linear Regression Models:

Linear Regression Model is firstly tried to explore the statistical relationship between Polarity of Elon Musk’s tweets and Tesla’s Stock Price Changes. The dependent variable is the numerical daily stock price change, and the independent variable is the dummy variable representing the Polarity of Elon Musk’s tweets, where +1 indicates Positive Tone,-1 indicates Negative Tone and 0 means Neutral tone.

$$Daily\ stock\ price\ percentage\ change\ =\ \beta_0\ +\ \beta_1\ \times\ Polarity\ +\ \varepsilon\ (1)$$

The coefficients of the linear regression model using the sample dataset is shown below. The coefficient on the independent variable $Polarity$ is 0.0002 with p-value equals to 0.975, indicating the coefficient is not statistically significant, no obvious significant relationship between tones of Elon Musk’s tweets and Tesla’s Stock Price Changes is discovered.



Sentiment Analysis: Linear Regression

	Dependent variable: DailyChange
Polarity	0.0002 (0.008)
Constant	0.002 (0.002)
Observations	126
R2	0.00001
Adjusted R2	-0.008
Residual Std. Error	0.016 (df = 124)

F Statistic	0.001 (df = 1; 124)
Note:	*p<0.1; **p<0.05; ***p<0.01

A similar regression analysis was conducted using results from the Hu & Liu Dictionary (2004) as the independent variable. The coefficient on Polarity was -0.002 with a p-value of 0.323. The coefficient and the p-value suggest that there is no statistically significant or meaningful relationship between Polarity and Daily Stock Price Change.

$$Daily\ stock\ price\ percentage\ change\ =\ \beta_0\ +\ \beta_1\ \times Polarity\ +\ \varepsilon\ (3)$$

Sentiment Analysis: Linear Regression

	Dependent variable:
	DailyChange
Polarity	-0.002
	(0.002)
Constant	0.002
	(0.002)
Observations	113
R2	0.009
Adjusted R2	-0.0001
Residual Std. Error	0.015 (df = 111)
F Statistic	0.985 (df = 1; 111)
Note:	*p<0.1; **p<0.05; ***p<0.01

2) Logistic Regression Models

For the Logistic Regression Model, the dependent variable is re-coded into binary format: where +1 represents a stock price increase, -1 represents a stock decrease and

0 means the stock price remains at the same level. Independent variable, dummy variable representing Polarity of Elon Musk's tweets, remains the same in the logistic regression model.

$$Daily\ stock\ price\ changing\ direction = \beta_0 + \beta_1 \times Polarity + \varepsilon \quad (2)$$

The coefficients of the logistic regression model using the sample dataset is shown in the table below. The coefficients on the independent variable $Polarity$ now become more negative and more robust than the coefficient attained in the linear regression model. However this negative relationship is still not statistically significant as p-value is 0.476. Therefore, according to the result of the logistic regression model, we could not conclude a robust statistical relationship between the tones of Elon Musk's tweets and Tesla's stock price changes.

Sentiment Analysis: Logistic Regression

	Dependent variable: Direction
Polarity	-0.727 (1.019)
Constant	0.658*** (0.238)
Observations	126
Log Likelihood	-82.432
Akaike Inf. Crit.	168.865
Note:	*p<0.1; **p<0.05; ***p<0.01

A logistic regression was also conducted using results from the Hu & Liu Dictionary as the independent variable in place of the TextBlob Model. The coefficient on Polarity was -0.231 with a p-value of 0.454. Again there is little evidence of a significant or meaningful relationship between tone and direction of price change.

Sentiment Analysis: Logistic Regression

	Dependent variable:
	Direction
Polarity	-0.231
	(0.308)
Constant	0.555**
	(0.216)
Observations	113
Log Likelihood	-74.785
Akaike Inf. Crit.	153.570
Note:	*p<0.1; **p<0.05; ***p<0.01

2.Statistical Result of Each Emotion’s Influence on Tesla's Stock Price Changes

1) Linear Regression Model Results:

Results for equation (5) to (14) are displayed in the table below. The dependent variable is daily stock price change, and the independent variable is the change in frequency of words of a certain emotion or sentiment category.

Emotion Analysis: Simple Linear Regression Result

	Dependent variable:									
	DailyChange									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
angryf	-0.004									
	(0.029)									
anticipationf		0.040								
		(0.025)								
disgustf			-0.056							
			(0.035)							
fearf				-0.010						
				(0.027)						
joyf					0.008					
					(0.026)					
sadnessf						0.009				
						(0.045)				
surprisef							0.005			
							(0.027)			
trustf								-0.003		
								(0.024)		
positivef									0.010	
									(0.019)	
negativef										0.003
										(0.021)
Constant	0.002	-0.0005	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	122	122	122	122	122	122	122	122	122	122
R2	0.0002	0.021	0.021	0.001	0.001	0.0003	0.0000	0.0002	0.002	0.0002
Adjusted R2	-0.008	0.013	0.013	-0.007	-0.008	-0.008	-0.008	-0.008	-0.006	-0.008
Residual	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016

Std. Error (df = 120)										
F Statistic (df = 1; 120)	0.019	2.567	2.599	0.129	0.086	0.041	0.0003	0.019	0.272	0.022

===

Note: *p<0.1; **p<0.05; ***p<0.01

In terms of coefficients, the change in frequency of anticipation, joy, sadness, surprise, positive and negative emotions have a positive sign, and angry, disgust, fear, trust frequency changes have a negative sign. Although the direction of the relationship mostly fits with our intuitions (relatively positive emotions and sentiment are related to stock price increase, and vice versa), none of the relationships are statistically significant.

We now run a multiple regression, with the frequency change of all emotional and sentiment words as independent variables respectively. The result is displayed in the table below.

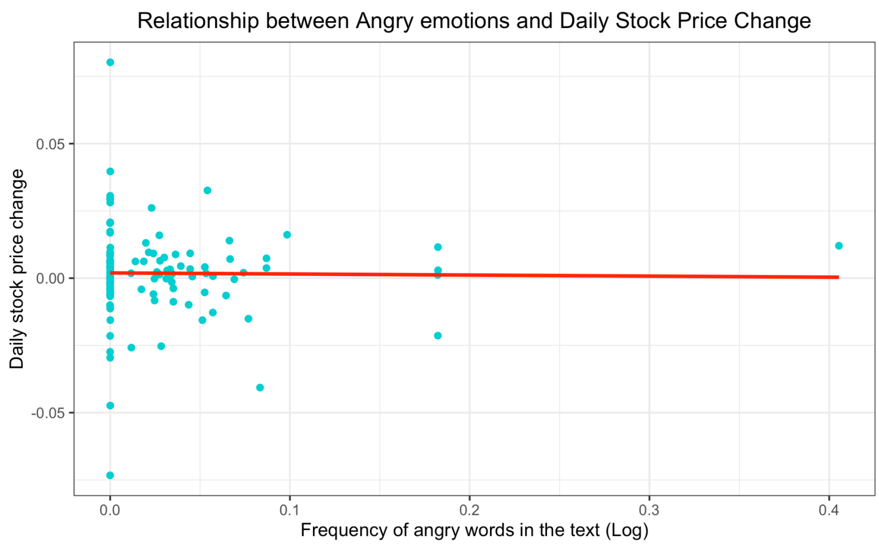
Emotion Analysis:
Multilinear Regression Result

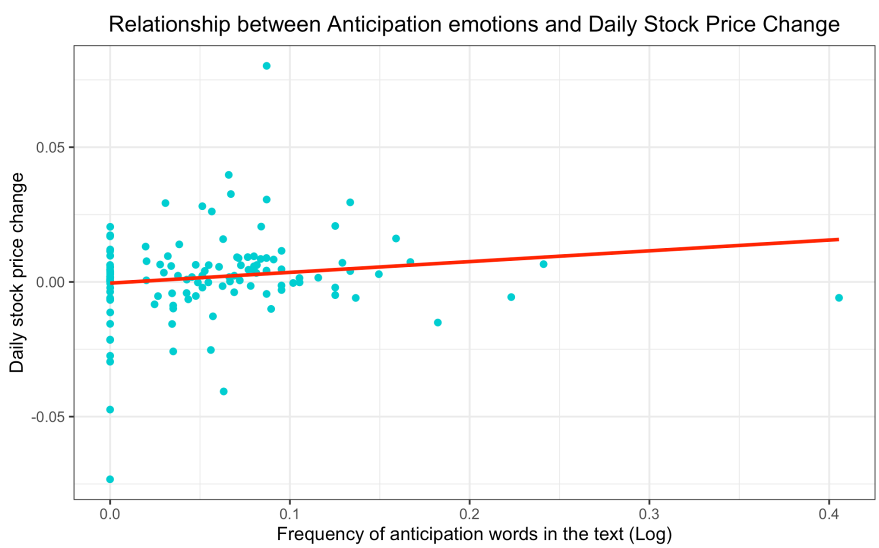
	Dependent variable: DailyChange
angryf	0.003***
	(0.001)
anticipationf	-0.004**
	(0.002)
disgustf	0.0001
	(0.001)
fearf	-0.0001
	(0.001)

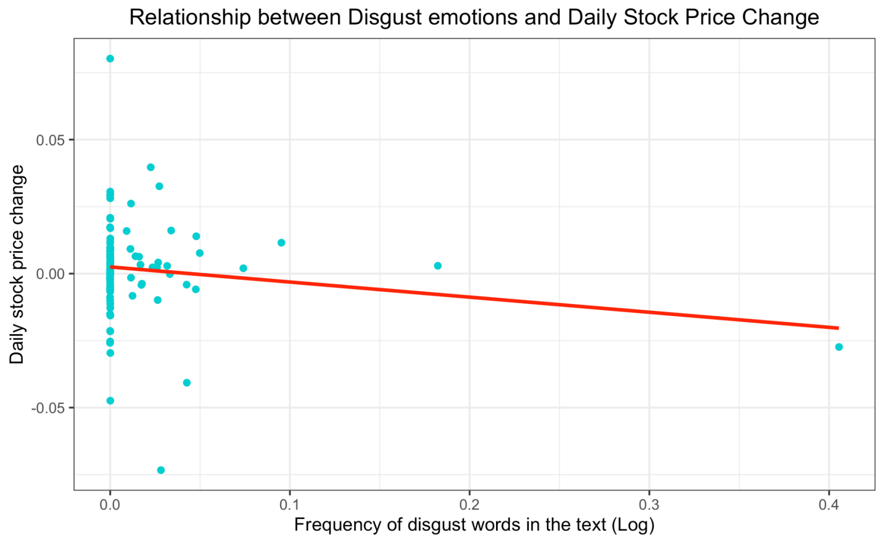
joyf	-0.001
	(0.002)
sadnessf	0.0002
	(0.001)
surprisef	0.0003
	(0.001)
trustf	-0.002
	(0.002)
positivef	0.007***
	(0.002)
negativef	-0.003*
	(0.002)
Constant	0.001
	(0.003)
Observations	122
R2	0.144
Adjusted R2	0.067
Residual Std. Error	0.016 (df = 111)
F Statistic	1.866* (df = 10; 111)
Note:	*p<0.1; **p<0.05; ***p<0.01

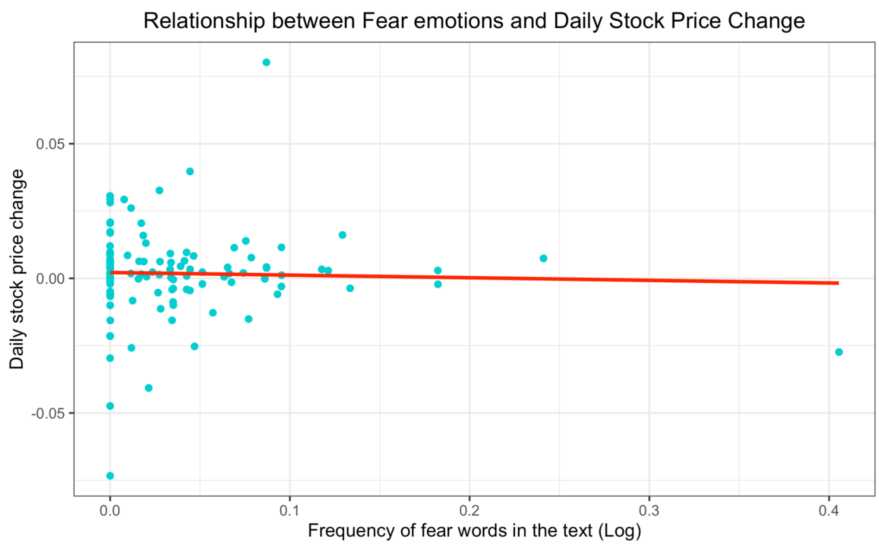
This suggests that under multiregression, only the frequency change of angry, anticipation, positive and negative words within the tweet could have a statistically significant effect on the stock price percentage change on that day. 1% increase of angry word frequency leads to 0.003 increase in stock price percentage change, keeping other factors fixed; 1% increase of angry word frequency leads to 0.004 decrease in stock price percentage change, keeping other factors fixed; 1% increase of positive word frequency leads to 0.007 increase in stock price percentage change, keeping other factors fixed; an 1% increase of negative word frequency leads to 0.003 decrease in stock price percentage change, keeping other factors fixed. Positive and negative word frequency changes seem to have a more intuitive effect on the stock price, while angry and anticipation words have quite the opposite effect as we've expected.

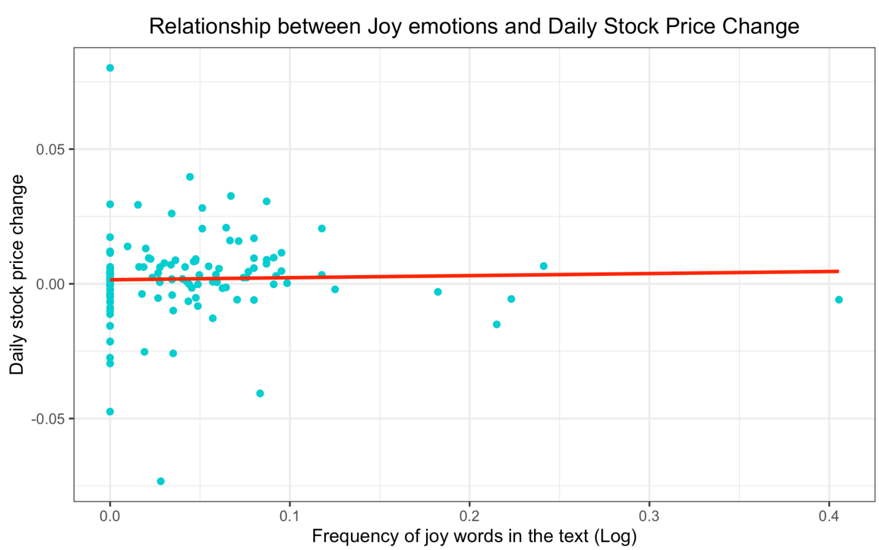
The visualizations of the relationships are shown in the graphs below. The red lines in the graphs are smoothed using the *lm* method.

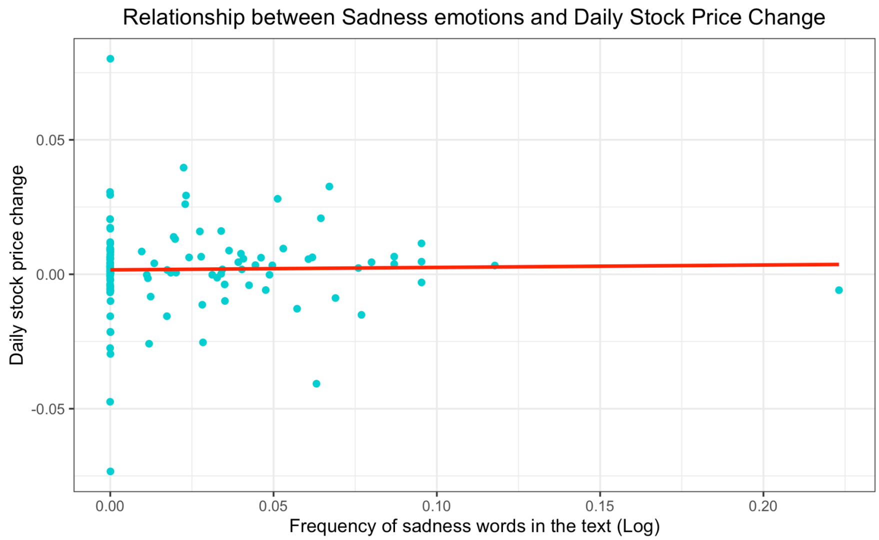




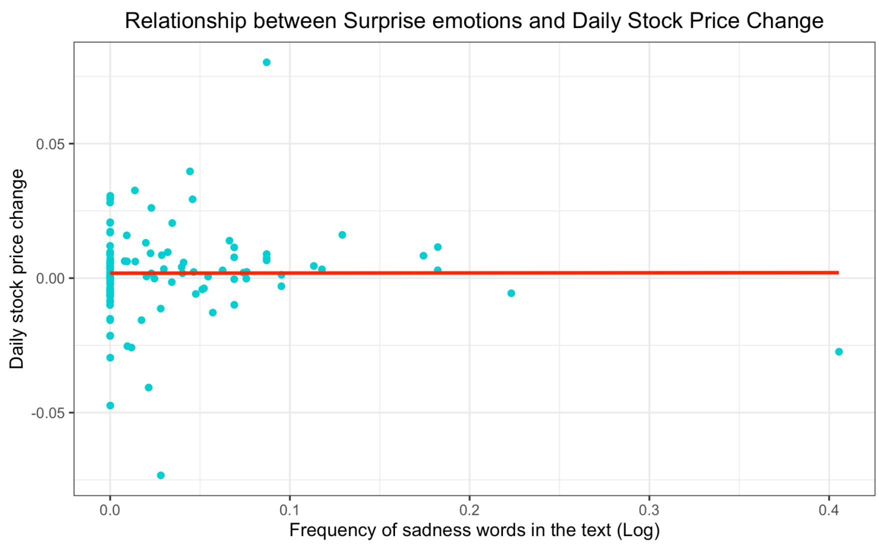

Relationship between Disgust emotions and Daily Stock Price Change
Daily stock price change
Frequency of disgust words in the text (Log)
0.05
0.00
-0.05
0.0
0.1
0.2
0.3
0.4


Relationship between Fear emotions and Daily Stock Price Change
Daily stock price change
Frequency of fear words in the text (Log)
0.05
0.00
-0.05
0.0
0.1
0.2
0.3
0.4

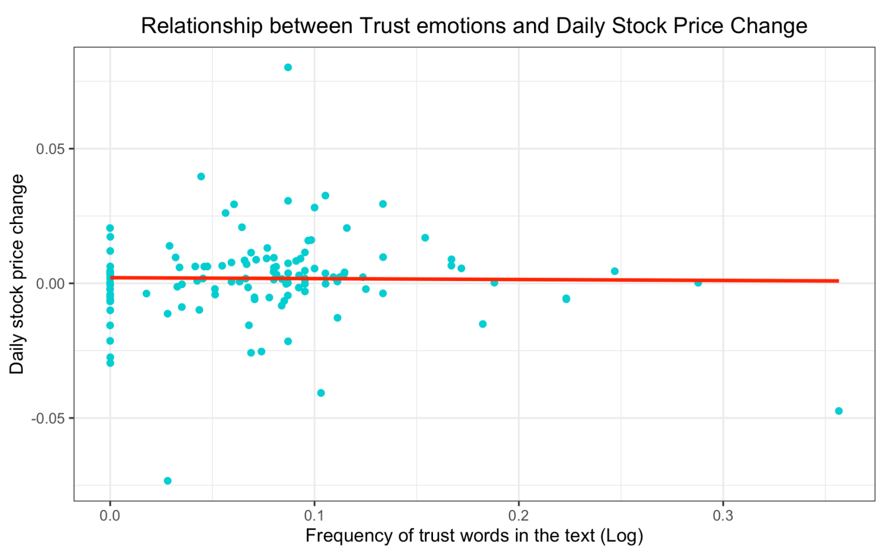

Relationship between Joy emotions and Daily Stock Price Change
Daily stock price change
Frequency of joy words in the text (Log)
0.05
0.00
-0.05
0.0
0.1
0.2
0.3
0.4



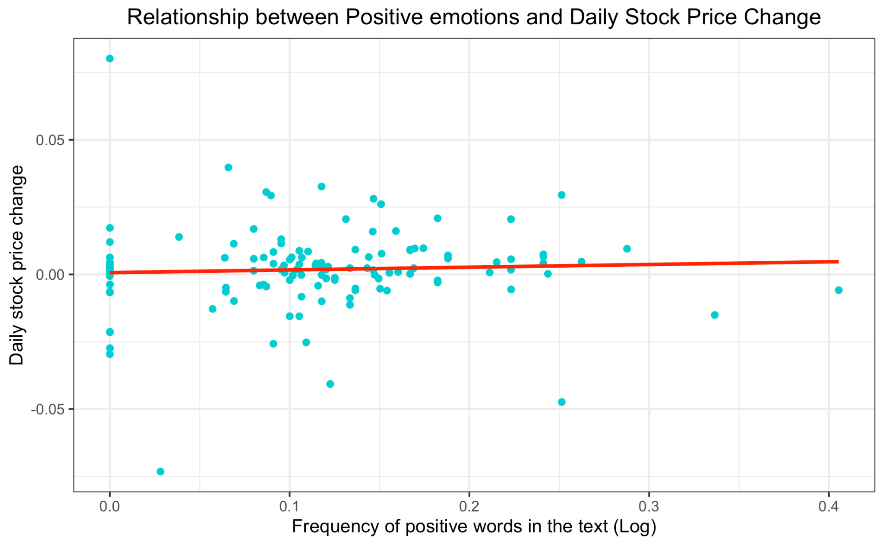
Relationship between Sadness emotions and Daily Stock Price Change
Daily stock price change
0.05
0.00
-0.05
0.00
0.05
0.10
0.15
0.20
Frequency of sadness words in the text (Log)

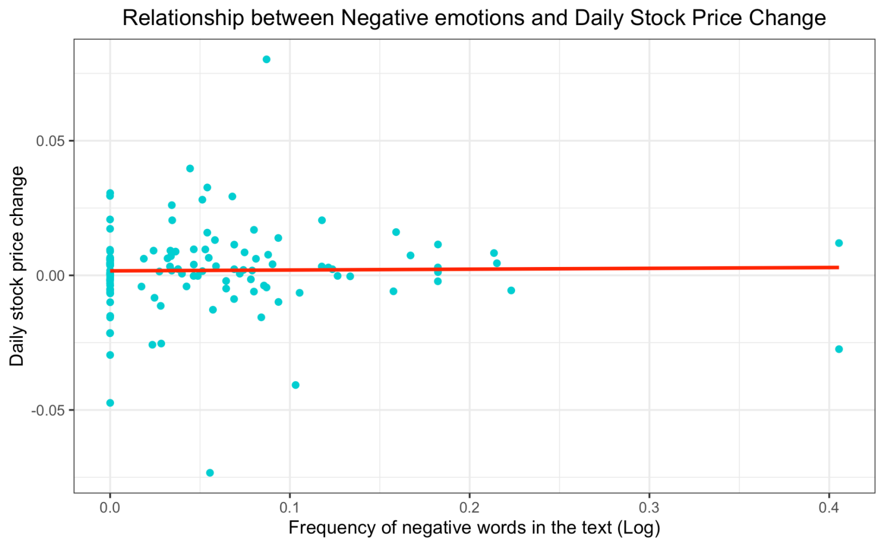


Relationship between Surprise emotions and Daily Stock Price Change
Daily stock price change
0.05
0.00
-0.05
0.0
0.1
0.2
0.3
0.4
Frequency of sadness words in the text (Log)



Relationship between Trust emotions and Daily Stock Price Change
Daily stock price change
0.05
0.00
-0.05
0.0
0.1
0.2
0.3
Frequency of trust words in the text (Log)





2) Logistic Regression Model Results:

Results for equation (16) to (25) are shown below. Similar to linear regression, logistic regression with only one emotion or sentiment included does not generate statistically significant results.

Emotion Analysis: Simple Logistic Regression Result

==

Dependent variable:

DailyChange

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
angryf	3.059									
	(4.203)									
anticipationf		-0.861								
		(3.144)								
disgustf			-3.194							
			(4.512)							
fearf				-1.791						
				(3.355)						
joyf					-1.917					
					(3.233)					
sadnessf						0.316				
						(5.643)				
surprisef							0.425			
							(3.437)			
trustf								2.479		
								(3.192)		
positivef									2.483	
									(2.502)	
negativef										-0.252
										(2.614)
Constant	0.461**	0.587**	0.575***	0.600***	0.622***	0.530**	0.524**	0.356	0.248	0.551**
	(0.213)	(0.262)	(0.195)	(0.222)	(0.237)	(0.225)	(0.214)	(0.296)	(0.343)	(0.237)
Observations	122	122	122	122	122	122	122	122	122	122
Log	-80.021	-80.280	-80.053	-80.176	-80.143	-80.316	-80.310	-80.006	-79.814	-80.313

Likelihood
Akaike Inf. Crit
164.043 164.561 164.105 164.352 164.285 164.632 164.620 164.011 163.628 164.626
===
Note: *p<0.1; **p<0.05; ***p<0.01

The result for logistic multiregression (equation (26)) is displayed in the table below.

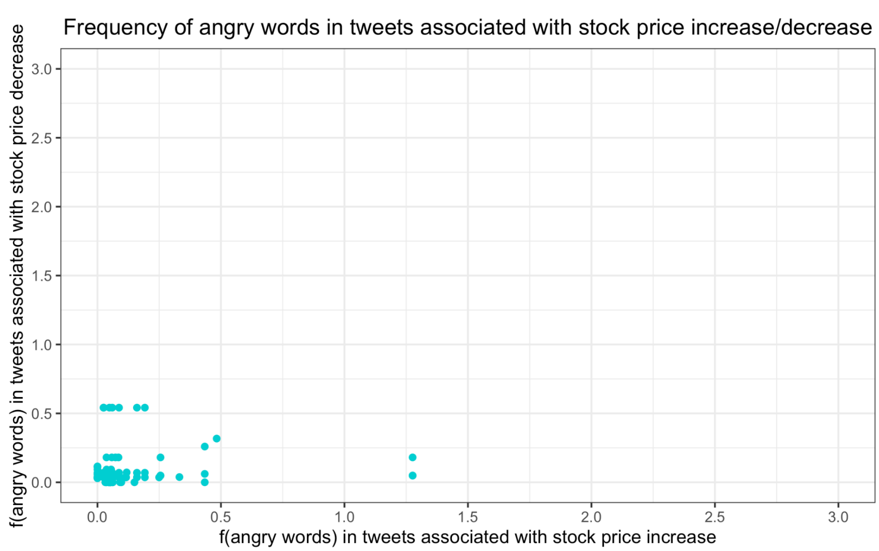
Emotion Analysis:
Multi-logistic Regression Result

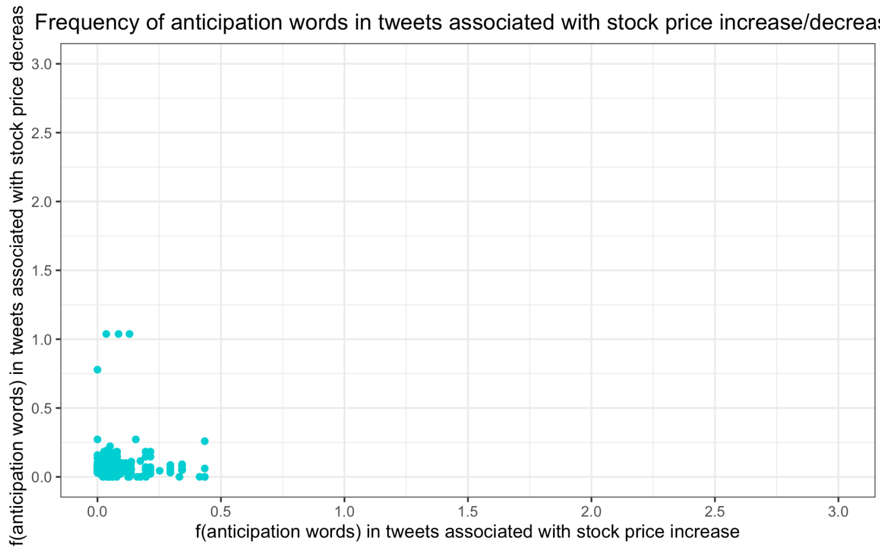
	Dependent variable: Direction
angryf	5.647
	(5.067)
anticipationf	-2.380
	(4.909)
disgustf	-7.209
	(8.111)
fearf	-5.451
	(5.794)
joyf	-11.350*
	(6.498)
sadnessf	4.862
	(7.987)
surprisef	12.813*
	(7.398)
trustf	2.327
	(4.224)
positivef	7.348*
	(3.848)
negativef	-2.879
	(5.006)
Constant	-0.043
	(0.446)
Observations	122
Log Likelihood	-75.710
Akaike Inf. Crit.	173.421

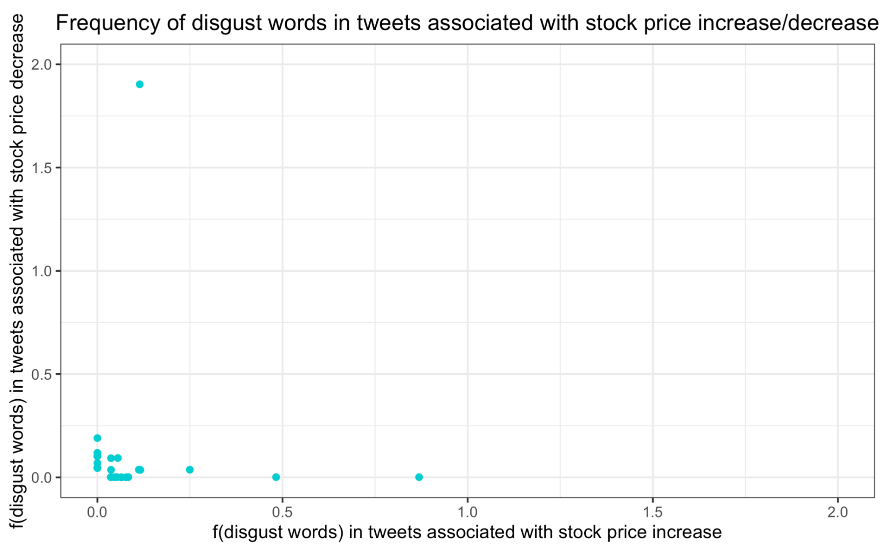
Note: *p<0.1; **p<0.05; ***p<0.01

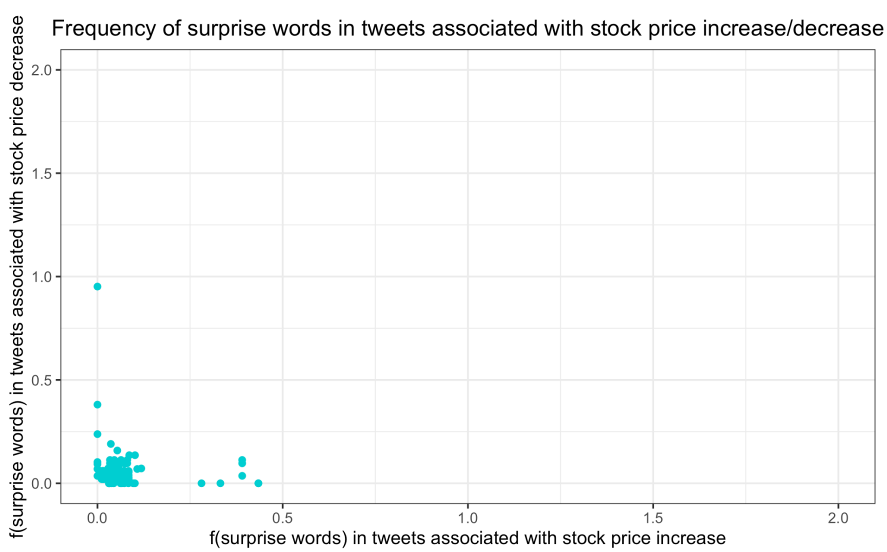
This result suggests that keeping other factors fixed, the percentage change of frequency of joy words significantly decreases logit of daily stock price percentage change by 11.350, the percentage change of frequency of surprise words significantly increases logit of daily stock price percentage change by 12.813, and the percentage change of frequency of positive words significantly increases logit of daily stock price percentage change by 7.348, while the other emotions and sentiment do not have a statistically significant influence.

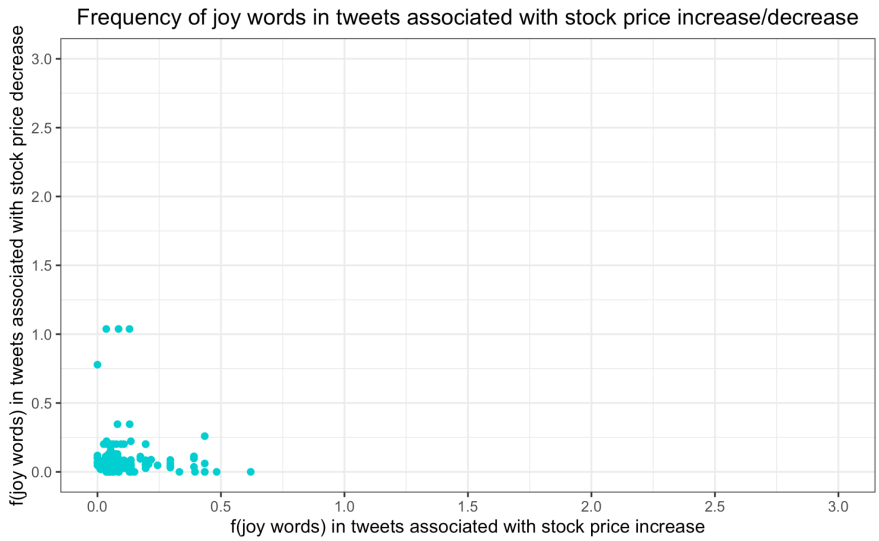
The data visualizations in this section reflect the difference in occurrence of emotion and sentiment words in tweets that are associated with a stock price increase or decrease that day. Specifically, each point in the graph represents a word that could reflect a certain emotion/sentiment, and the location (x-axis and y-axis value) represents frequency of the word in stock price increase/decrease texts.

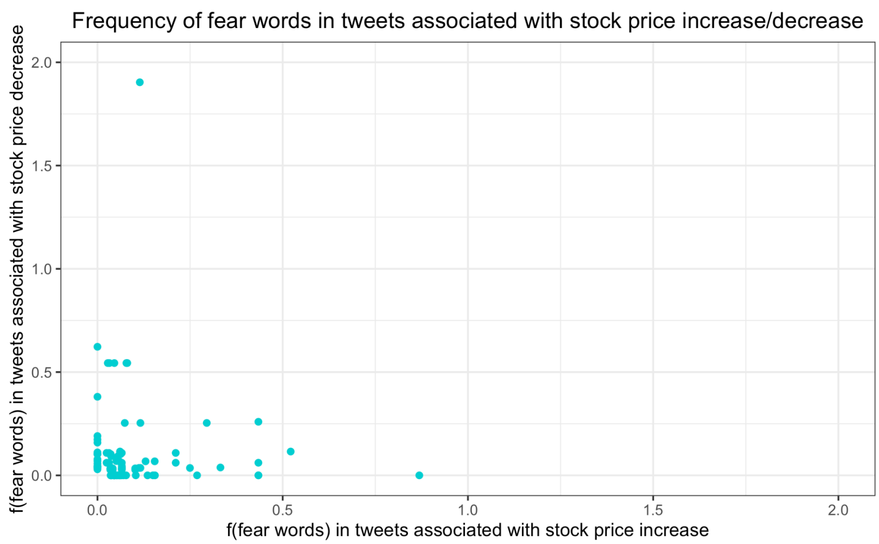


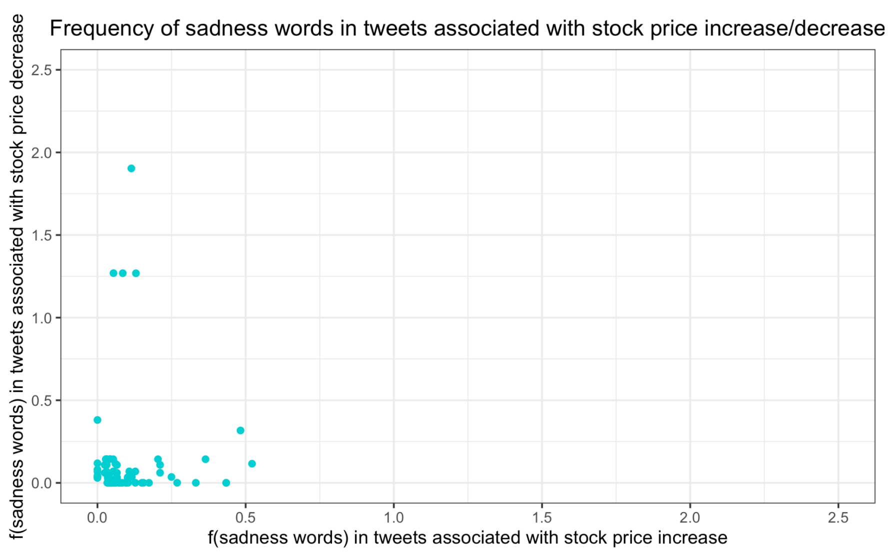

Frequency of anticipation words in tweets associated with stock price increase/decreas
f(anticipation words) in tweets associated with stock price decreas
f(anticipation words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0
2.5
3.0

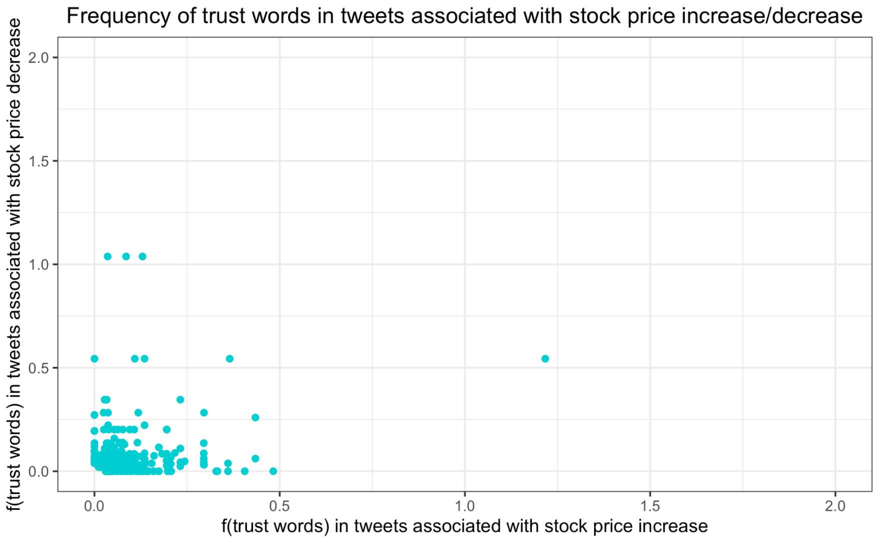

Frequency of disgust words in tweets associated with stock price increase/decrease
f(disgust words) in tweets associated with stock price decrease
f(disgust words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0

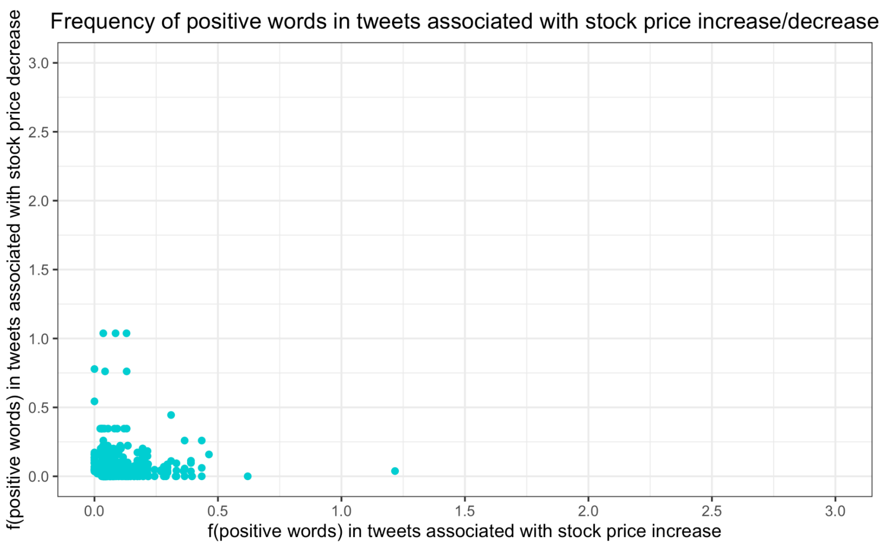

Frequency of surprise words in tweets associated with stock price increase/decrease
f(surprise words) in tweets associated with stock price decrease
f(surprise words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0

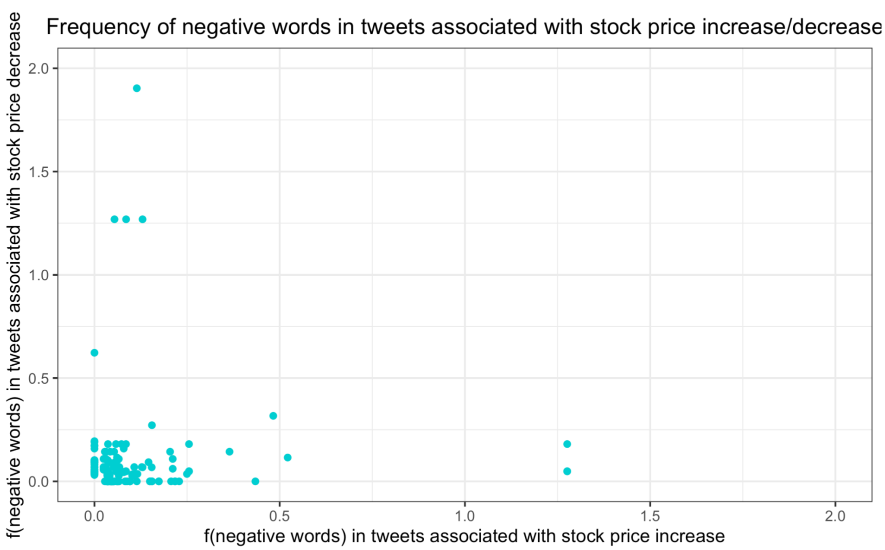

Frequency of joy words in tweets associated with stock price increase/decrease
f(joy words) in tweets associated with stock price decrease
f(joy words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Frequency of fear words in tweets associated with stock price increase/decrease
f(fear words) in tweets associated with stock price decrease
f(fear words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0


Frequency of sadness words in tweets associated with stock price increase/decrease
f(sadness words) in tweets associated with stock price decrease
f(sadness words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0
2.5


Frequency of trust words in tweets associated with stock price increase/decrease
f(trust words) in tweets associated with stock price decrease
f(trust words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0


Frequency of positive words in tweets associated with stock price increase/decrease
f(positive words) in tweets associated with stock price decrease
f(positive words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Frequency of negative words in tweets associated with stock price increase/decrease
f(negative words) in tweets associated with stock price decrease
f(negative words) in tweets associated with stock price increase
0.0
0.5
1.0
1.5
2.0

Conclusions

The analyses presented above attempted to identify relationships between characteristics of Elon Musk's tweets and price changes in Tesla's stock price. Several methods were used to test the predictive value of variables derived using sentiment analysis and emotion analysis on both the magnitude and direction of daily price change. The TextBlob Lexicon Model and the sentiment dictionary of Hu and Liu (2004) were used to create two different measures of sentiment, which were both found to have no significant relationship with the two dependent variables.

The NRC Word-Emotion Association Lexicon (Mohammad, 2010) was used to determine the emotional content of each tweet, providing measures of 8 different emotions in addition to positivity and negativity. With respect to the magnitude of price changes, the simple linear regressions did not reveal any significant relationships. Considering all of these variables together in a multilinear regression on the other hand found a significant relationship between angry, anticipation, positive, and negative with the price change. For positivity and negativity, the direction of influence seems consistent with intuition (positive sentiment with positive influence and vice versa), but for the emotion of anger and anticipation, the relationship seems contrary to the original hypothesis. Similarly, the logistic regressions conducted using each variable alone found no significant relationships. The multi-logistic analysis found effects for joy, surprise, and positivity at a $p<0.1$ significance level. Intuitively one would expect the direction of the effects of these emotions to be the same, but while surprise and positivity predict an increase in logit of an increase in price, joy predicts a decrease in logit of an increase in price. It is interesting to note that the effect of disgust was significant in predicting the magnitude but not the direction of the daily price change, considering the fact that direction is derived from the magnitude. Overall, while there is some evidence that characteristics of Elon Musk's use of language in his tweets have predictive value on Tesla's stock price on the following day, the results from the above analyses suggest that these effects are limited at best considering the coefficients, the p-values, as well as the R^2 values of the models.

Given the widely-known difficulties in predicting financial markets, as well as in predicting future events in general, these results should not be surprising. There are a large number of factors that may affect a company's stock price at any given time, and these effects are also not necessarily constant over time. On the other hand, there can also be countless factors that determine what Elon Musk, or any other CEO, is tweeting on any given day, and the content of his tweets may or may not be perceived as relevant signals by investors, since he is well-known for his somewhat erratic behavior on Twitter. Musk himself has said, "So the statements that I make, are they materially different from random movements of the stock that might happen anyway? I don't think so."

Nonetheless, while we have not been able to identify significant results in our analyses, this does not necessarily rule out a possible relationship between Musk's tweets and Tesla's stock price. It is difficult to ignore events such as TSLA falling 7% after Elon Musk asked his followers if he should sell 10% of his stake in Tesla. There are several limitations to our study and improvements that can be made in the future that can be tested should one believe this relationship to truly be significant.

Limitations

Firstly, our research is limited by the data that we decided to use for analysis. We only considered tweets from 2021, and only examined the effects of tweets during certain hours. Through this process of selection we only had a sample size of 126; extending our analyses to a greater sample may allow us to capture more signals in the inherently noisy financial data. Tweets during other hours may be significant to the stock's price and can be included in the future. Furthermore, in terms of our dependent variables, there are other features of stock prices beyond daily price change that may be of interest to investors, such as volatility, and different features can be examined in different timeframes, perhaps in an hourly manner.

In terms of our methodology, we used an equally-weighted average approach to calculate sentiment scores over all the words in one tweet. This could limit the model's ability to explore the actual tones contained in the tweet when both positive and negative words are included in one tweet at the same time like ‘happy’ and ‘but’. Further improvements on sentiment score calculation methods for these types of tweets improve the performance of the TextBlob Lexicon Model. While we tested two different methods of calculating sentiment, there are still many others that may perform better in our task, such as VADER, AFINN, or SentiWordNet.

Furthermore, in addition to sentiment and emotion, we can consider other methods of analysing the language used in each tweet. Our methods reduced each tweet to one or few variables, which may have resulted in a significant loss of information in the process. This also limited the complexity of the models we used to fit the data. More complex ways of representing the content of each tweet in higher dimensions, perhaps with the use of embeddings, may retain more relevant information and granularity in the data.

Finally, our analyses also largely ignored the component of time beyond calculating the daily change dependent variable, considering each tweet and price change as independent observations. This is a major limitation as variables such as stock price, or price changes, may depend on past observations and show characteristics such as momentum which may be relevant to our analyses. There can also be possible effects of temporal features in the tweets that we neglected. For instance, if a CEO maintains a long period of positive tweets, the possible effect of a positive tweet would likely diminish over time. In contrast, strong positive sentiment after a long period of negativity may have a greater impact.

References

Gallagher, L. A., & Taylor, M. P. (2002). Permanent and Temporary Components of Stock Prices: Evidence from Assessing Macroeconomic Shocks. *Southern Economic Journal,* 69(2), 345–362. https://doi.org/10.2307/1061676

N. Janardhan, Nandhini Kumaresh(2019). A Comprehensive Study on Lexicon Based Approaches for Sentiment Analysis

Hu, M., & Liu, B. (2004). *Mining and summarizing customer reviews.* KDD 04.

Leitch, D., & Sherif, M. (2017). Twitter mood, CEO succession announcements and stock returns. *J. Comput. Sci.* 21, 1–10. http://dx.doi.org/10.1016/j.jocs.2017.04.002

Lee, P. M., & James, E.H. (2007). She'-e-os: Gender effects and investor reactions to the announcements of top executive appointments, *Strat. Manage. J.* 28 (3) 227–241. https://doi.org/10.1002/smj.575

Mohammad, S. (2010). NRC Word-E*motion Association Lexicon.* http://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

Wei, P., & Wang, N. (2016). Wikipedia and Stock Return: Wikipedia Usage Pattern Helps to Predict the Individual Stock Movement. In Proceedings of the 25th International Conference Companion on the World Wide Web. *International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva,* CHE, 591–594. https://doi.org/10.1145/2872518.2890089