

Modeling Tesla Stock Price Using Tweets

Tilina Alzaben, Jihyo Chung, Marion Haney, Divya Rao

04-21-2024

Executive Summary

Our research investigated the relationship between investor sentiment on Twitter and the financial performance of Tesla, analyzing 37,422 tweets along the company's stock data from September 30, 2021, to September 30, 2022. We applied time series and sentiment analysis, using models like GARCH for volatility and VAR for feature selection. Our findings revealed only a weak statistically significant correlation between the sentiment of Tesla-related tweets and stock returns, particularly with a two-day lag in tweet sentiment showing a minimal predictive impact. This indicates that while there is some relationship between public sentiment and stock performance, its predictive power is limited for practical financial forecasting. Future research will aim to refine these models and include additional economic factors, broader market indicators, and tweet engagement metrics to enhance understanding and predictive accuracy of the impact of social media on stock prices. This study highlights the challenge of using social media sentiment as a reliable predictor for stock market behavior.

1 Introduction

Stock markets are driven by a complex interplay of factors including economic indicators, investor sentiment, geopolitical events, corporate earnings, and monetary policy. Factors such as economic indicators, earnings and monetary policy are often slow moving events, whereas geopolitical events are sudden and unpredictable. Apart from these factors, a key driver of day to day stock prices is investor sentiment.

The purpose of this study is to investigate the impact of investor sentiment on stock prices. By examining patterns and correlations between investor sentiment and stock market action, we hope to gain insights into behavioral aspects of market participants. Also, the analysis can provide further guidance on the other factors that need to be taken into consideration for a broad based quantitative analysis of stock market behavior.

This study focuses on Tesla, an acknowledged pioneer in the electric vehicle (EV) market segment, with a current market capitalization of \$500B. Tesla is particularly interesting due to its meteoric rise as an EV market leader in the short period since its founding in 2003, as well as due to its volatile stock, and due to its CEO, Elon Musk, who is perceived as a controversial figure. We selected this stock due to the availability of a wealth of investor sentiment, both positive and negative, in the form of stock tweets.

To measure investor sentiment, we use textual data gathered from Twitter, a text-based social media with millions of English-speaking users. Tweets mentioning Tesla or the company's stock ticker, TSLA, over one year were collected (09-30-2021 to 09-30-2022). From the tweets, we assign sentiment scores based on the positive and negative language used from the text of the tweets, giving us a measurable proxy for public opinion. For measuring the impact on market action, we use the adjusted closing stock price for TSLA and its returns over same the year. As indicated earlier, Tesla's stock TSLA is a notably volatile stock, jumping between \$209.38 and \$409.97 several times during the year of data.

The time series analysis in this report can be generalized and adapted to any large cap stock with a reasonably active investor base, and it is not specific only to TSLA. The analysis attempts to investigate Tesla's Twitter sentiment and stock returns over the year of data.

1.1 Research Questions

The project aimed to answer two main questions: First, is there a relationship between the sentiment of Tesla-related tweets and the company's stock returns? Second, can the sentiment derived from tweets mentioning Tesla be used to forecast the company's stock returns over the next few days?

1.2 Data

For this analysis, we utilized two related datasets from Kaggle. The first dataset includes 80,793 tweets related to 25 different companies, while the second provided daily closing stock prices for these same companies over a period from September 30, 2021 to September 30, 2022. These companies are the top 25 "most watched" stocks from Yahoo Finance and we filtered our data to only include tweets that mention Tesla or TSLA stock. This left us with 46% of the tweets in data mentioned TSLA (37422 tweets) across the year of data collection.

2 Methods

2.1 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted for deciding on reasonable data transformations and analysis, determining which type of model to use, and choosing the parameters for these models.

2.2 Number of Tesla Tweets Per Day

Our data included tweets from 09-30-2021 to 09-30-2022 (excluding weekends) which mentioned either Tesla's stock ticker or the company name itself. Our data included 37,422 tweets regarding Tesla over the year. Here, we view the number of tweets mentioning Tesla per day plotted over time along with the ACF and PACF plots of the time series.

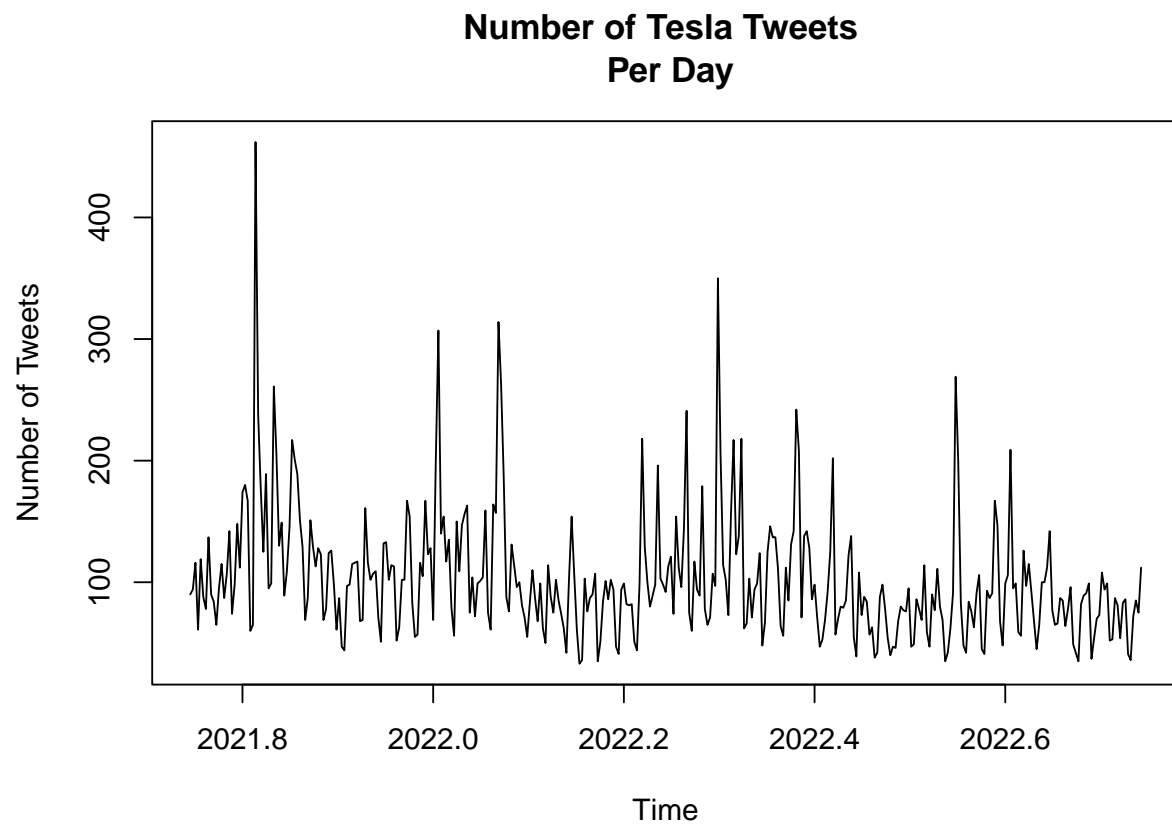


Figure 1: Number of Tesla Tweets Per Day

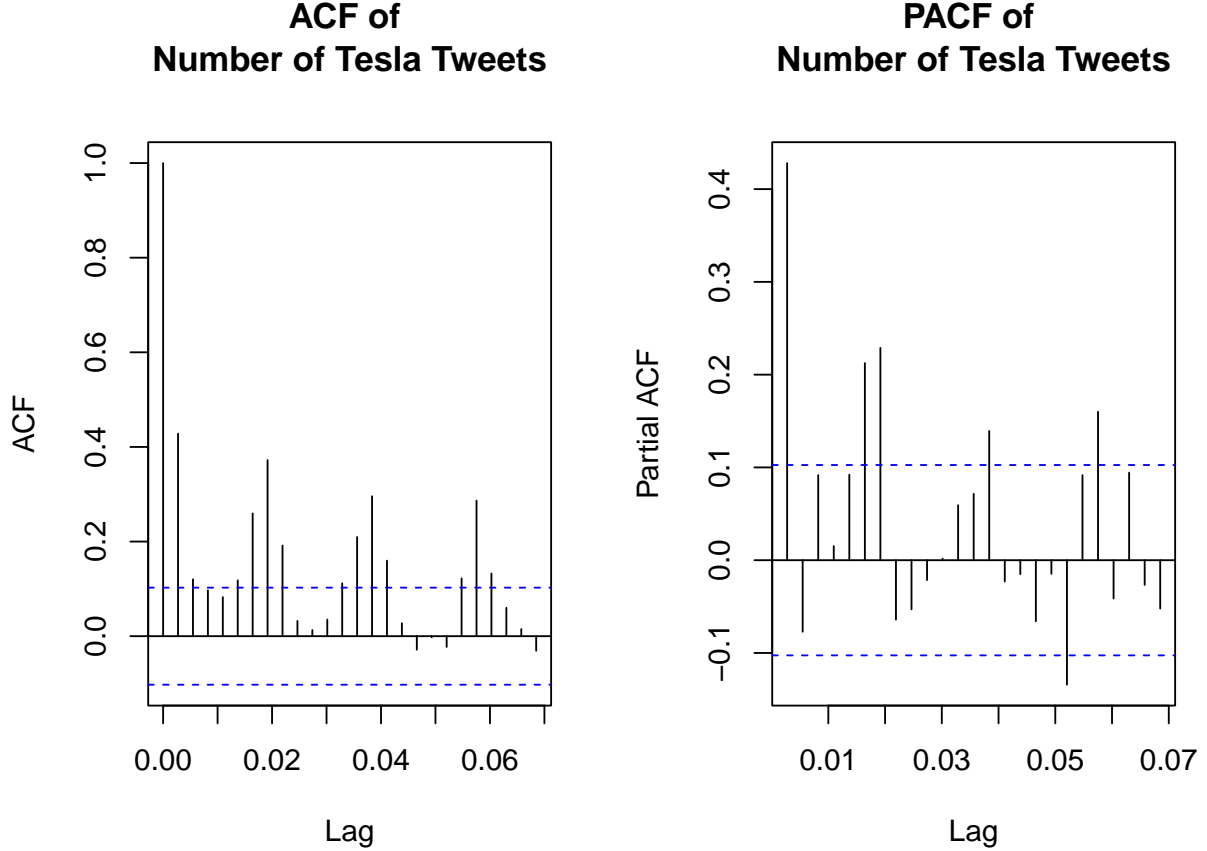


Figure 2: ACF and PACF of residuals for Tesla Tweets

The time series of the number of Tesla tweets per day shows non-stationary characteristics, with noticeable fluctuations and periodic spikes indicating changes in the mean and variance over time. The ACF plot specifically shows possible seasonality with four clusters of ACF spikes over the time period of the data. These spikes in the number of tweets mentioning Tesla appear to occur approximately every three months, possibly related to earnings announcements.

2.3 Daily Sentiment of Tesla Tweets

For our analysis, we calculated a daily score representing the average sentiment (positive or negative) for Tesla tweets posted on the given day. Our approach involved breaking each tweet into a bag of words representation, where each word is given a sentiment score of 1 if it is positive, -1 if it is negative, and 0 otherwise (neutral). These individual word scores were then summed into a sentiment score for each tweet. The sentiment scores per tweet ranged from -9 to 9. Finally, the individual tweet sentiment scores were averaged into a daily tweet sentiment score for the day. The daily sentiment scores ranged from -0.575 to 1.65.

We can view the daily sentiment of tweets over the year of our data along with the ACF and PACF in the charts below.

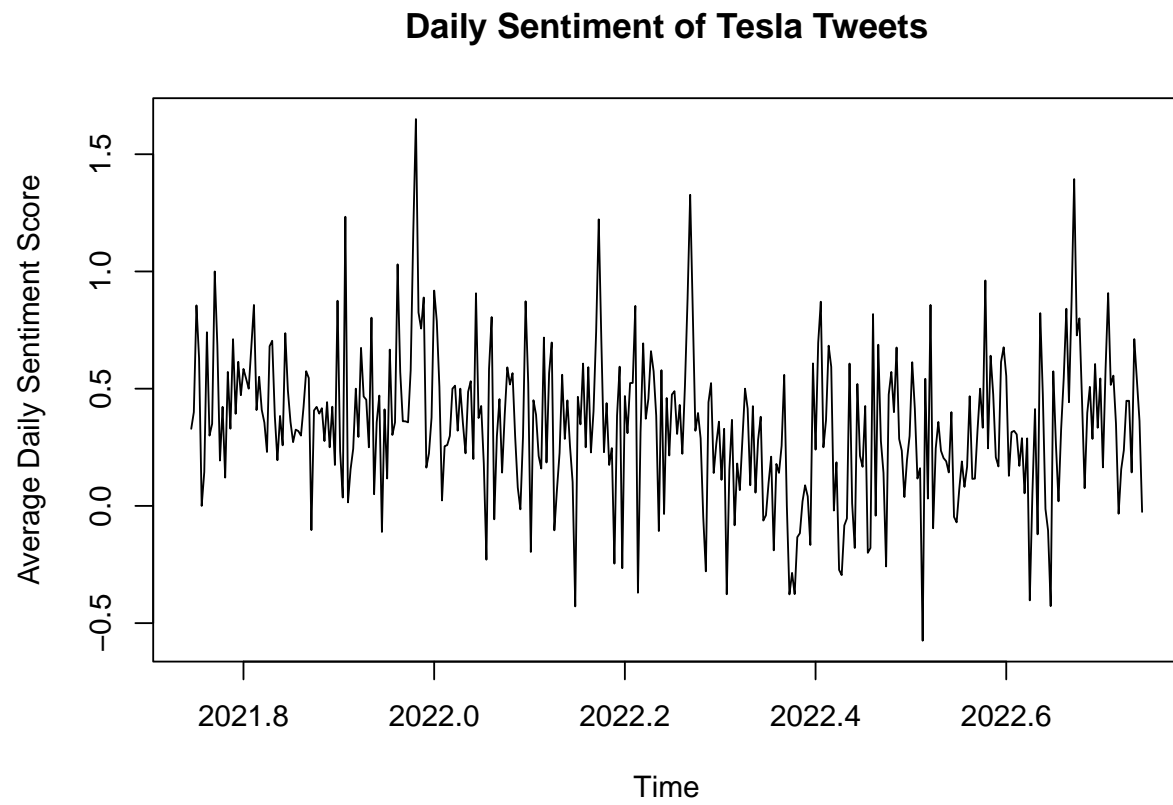


Figure 3: Daily Sentiment of Tesla Tweets

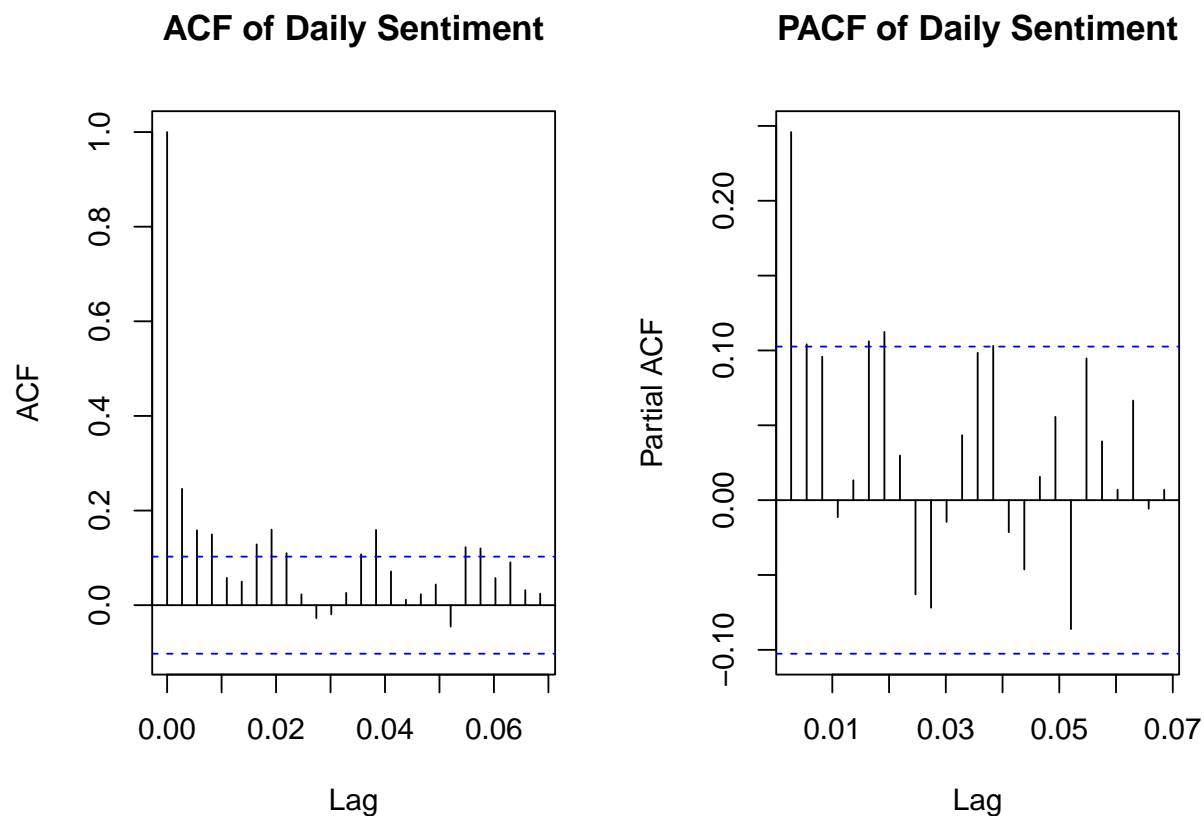


Figure 4: ACF and PACF of Daily Sentiment Scores

Similarly, we observe non-stationary characteristics for the daily sentiment of Tesla tweets. We see four sections of ACF spikes approximately 3 months apart, suggesting seasonality. However, the magnitude of the spikes for daily sentiment of tweets is less severe than the magnitude of the corresponding spikes for the number of tweets per day. This is potentially due to the averaging of each individual tweet's sentiment score to produce a daily metric.

2.4 TSLA Stock Price and Returns

We calculated the returns of the TSLA stock by differencing the adjusted close price of TSLA to 1 degree.

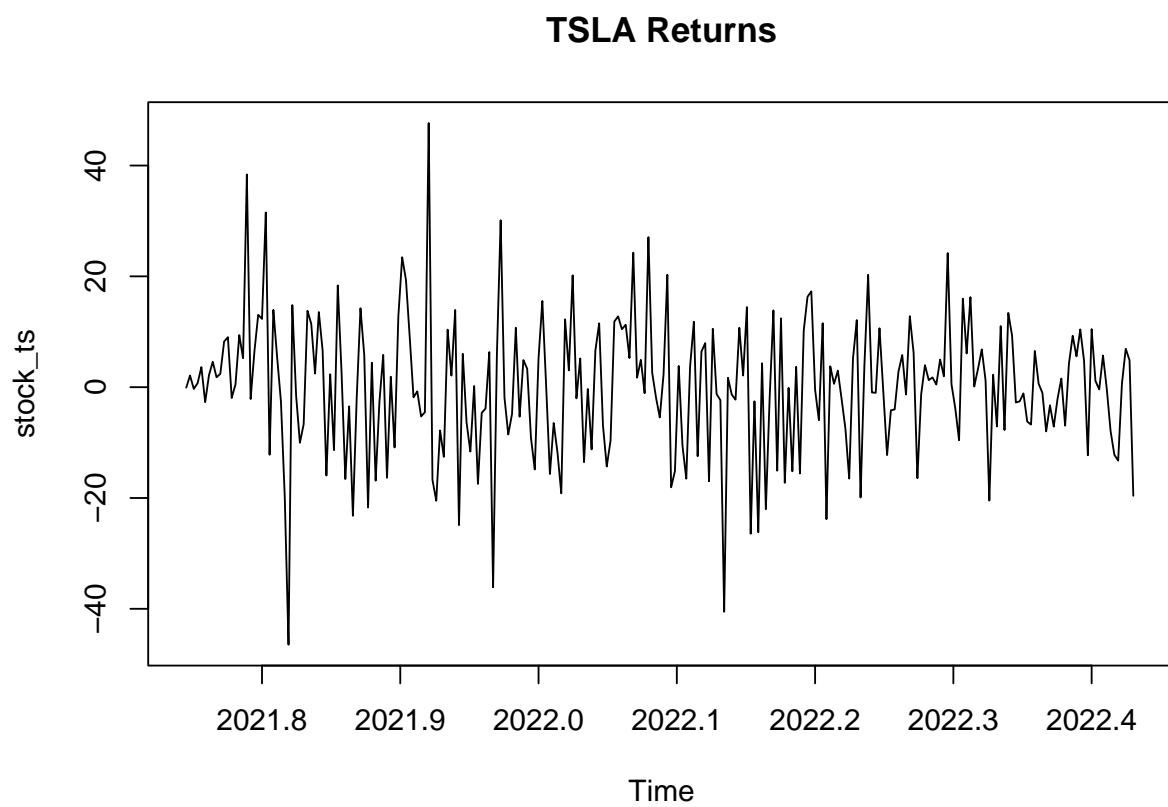


Figure 5: Tesla returns over time

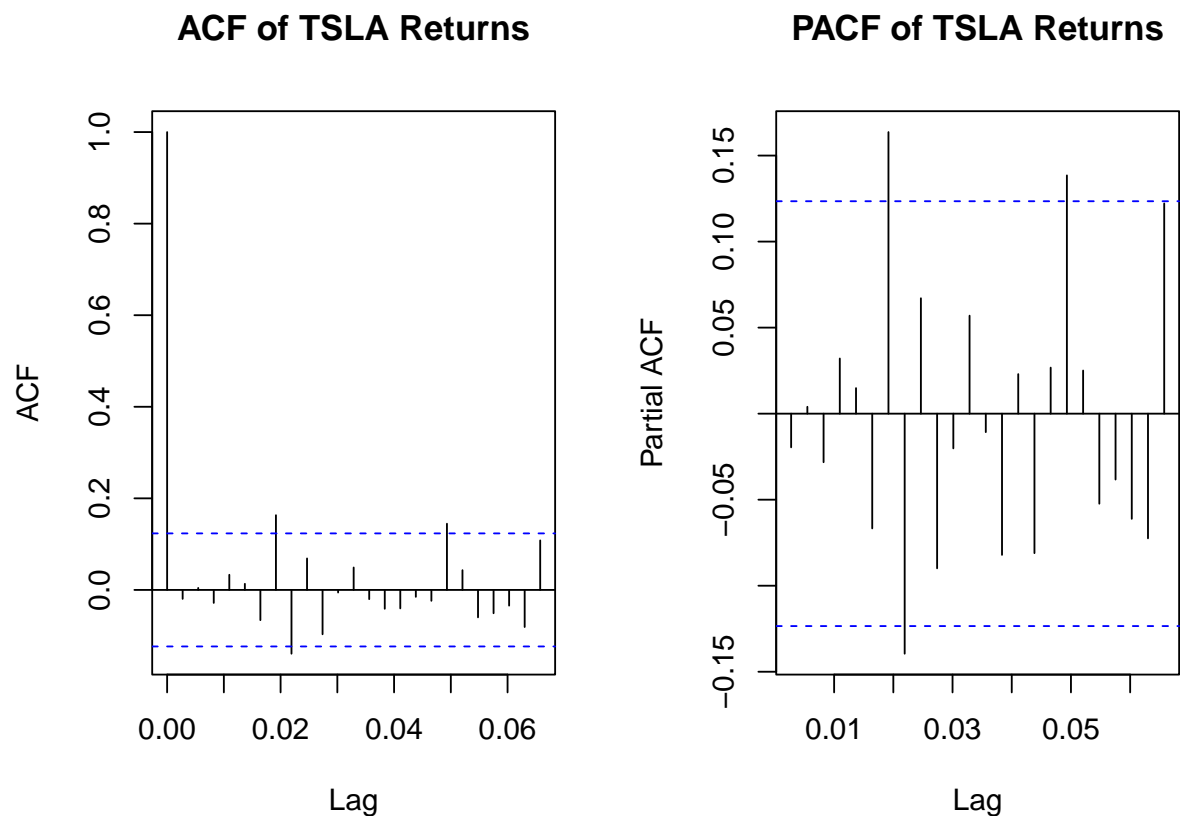


Figure 6: ACF and PACF plots of Tesla Returns

For TSLA returns, we see slight non-stationary characteristics. The ACF and PACF plots exhibit spikes outside the white noise error bounds at around lag 0.02 and 0.05. The time series plot of TSLA returns also exhibits some evidence of heteroskedasticity, with a truncated shape of the time series. The earlier returns exhibit a wider variance than the later returns.

We investigate the square logged returns to better understand its stationary or non-stationary characteristics as well as heteroskedasticity in order to help us determine whether we can use GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models which are often suitable for financial time series analysis.

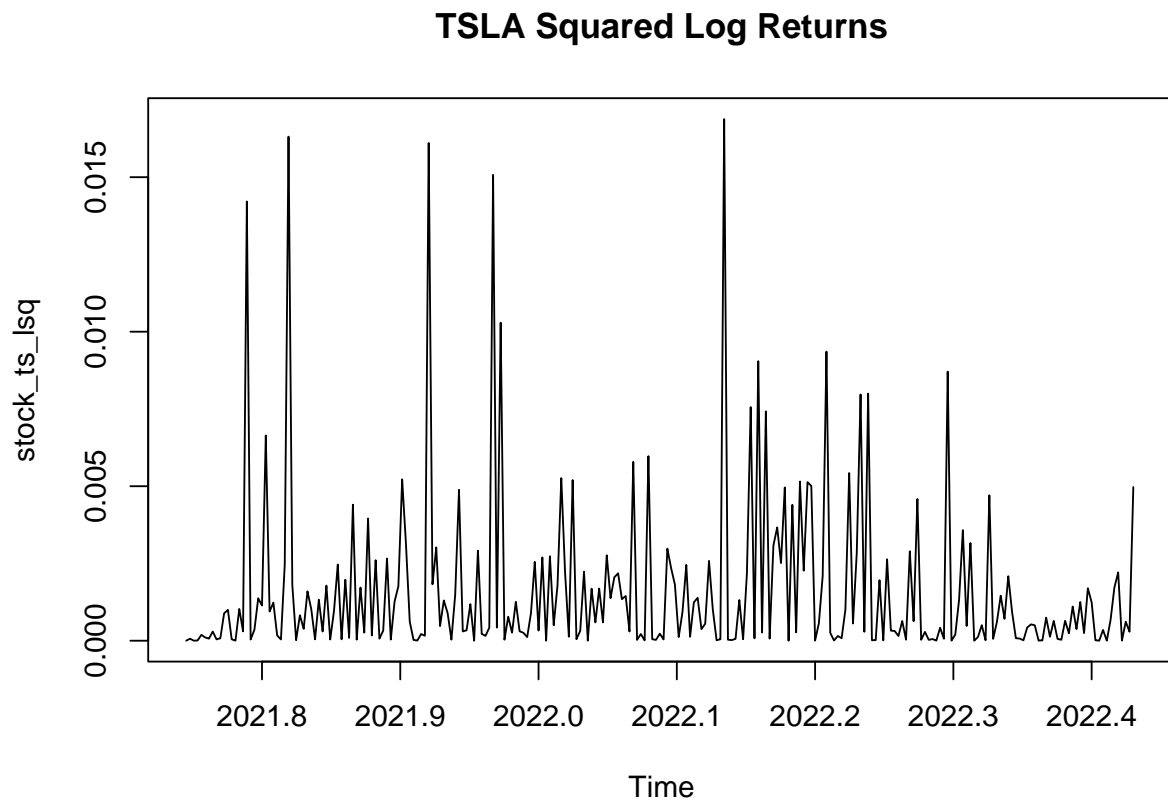


Figure 7: Squared log returns of Tesla stocks over time

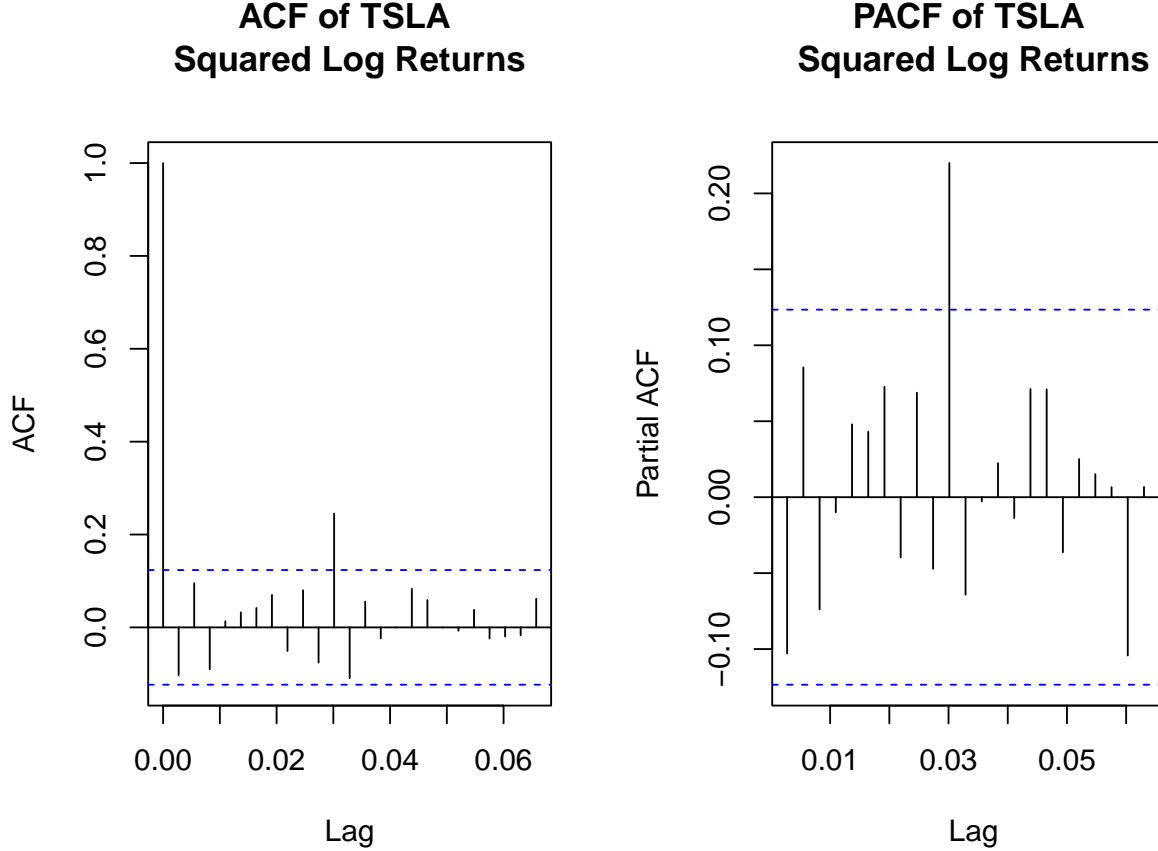


Figure 8: ACF and PACF plots of squared log returns of Tesla stocks

The square of logged TSLA returns exhibits only one ACF and PACF spike at around lag 0.03 and the plot of the square of logged TSLA returns no longer has a truncated shape.

2.5 GARCH Model

Based on the non-constant variance and non-stationarity seen from the EDA for daily sentiment, we decided to use a GARCH model. A GARCH model uses values of the past observations and variances to model the variance at time t . GARCH is used commonly with financial data because of the high volatility. Since we calculated the order of the model from running `auto.arima()`, we decided to fit a GARCH(1, 1) model to returns, which is calculated as the difference of the log of the adjusted closing price.

2.5.1 Automatic ARIMA

The `auto.arima()` function was applied on the squared logged returns, which is the difference of the log of the adjusted closing price squared. This helped identify if there was autoregression or moving average patterns in the volatility of the returns and helps determine the order of the GARCH model.

The best ARIMA model returned by the function was ARIMA(1,0,1) with a non-zero mean. The output of the function can be found in the Appendix.

2.6 VAR

We used a VAR (Vector Autoregression) model to perform feature selection for linear modeling. We also used the VARselect() function to identify the optimal lag using AIC in modeling returns as well as daily sentiment using the lagged values of daily sentiment and lagged values of returns. Finally, we use these two variables at specific lags in two linear models: one linear model to predict TSLA stock returns and one to predict the average daily sentiment of Tesla tweets. The function output is included in the Appendix.

3 Results

The summary of our GARCH(1,1) model is below.

```
##
## Title:
##   GARCH Modelling
##
## Call:
##   garchFit(formula = ~garch(1, 1), data = stock_ts, trace = FALSE)
##
## Mean and Variance Equation:
##   data ~ garch(1, 1)
## <environment: 0x1265efea8>
##   [data = stock_ts]
##
## Conditional Distribution:
##   norm
##
## Coefficient(s):
##           mu           omega          alpha1          beta1
## 0.00034657 0.00007856 0.01438639 0.93899717
##
## Std. Errors:
##   based on Hessian
##
## Error Analysis:
##           Estimate Std. Error t value Pr(>|t|)
## mu      3.466e-04  2.557e-03   0.136   0.892
## omega   7.856e-05  8.856e-05   0.887   0.375
## alpha1  1.439e-02  1.997e-02   0.720   0.471
## beta1   9.390e-01  5.494e-02  17.090 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
##  448.0723    normalized:  1.785149
##
## Description:
##   Sun Apr 21 23:49:59 2024 by user:
##
##
## Standardised Residuals Tests:
##                                     Statistic    p-Value
```

```

## Jarque-Bera Test    R    Chi^2  11.8733436 0.002640804
## Shapiro-Wilk Test   R    W       0.9837818 0.005887743
## Ljung-Box Test      R    Q(10)  17.7126029 0.060009507
## Ljung-Box Test      R    Q(15)  19.0600447 0.211025838
## Ljung-Box Test      R    Q(20)  27.7444493 0.115588155
## Ljung-Box Test      R^2  Q(10)  11.4358694 0.324582474
## Ljung-Box Test      R^2  Q(15)  30.6866295 0.009672734
## Ljung-Box Test      R^2  Q(20)  33.2456537 0.031704058
## LM Arch Test        R    TR^2   21.5516296 0.042863209
##
## Information Criterion Statistics:
##      AIC      BIC      SIC      HQIC
## -3.538425 -3.482243 -3.538922 -3.515816

```

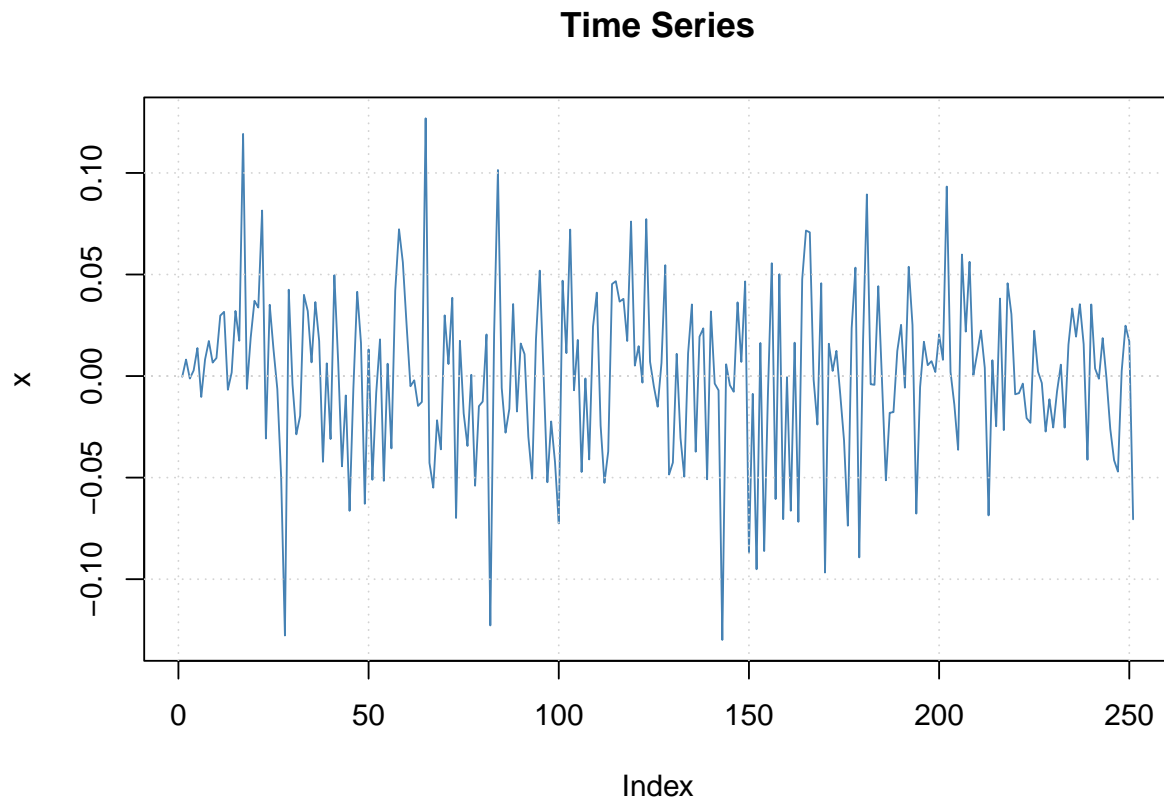


Figure 9: Fitted GARCH model on the time series data

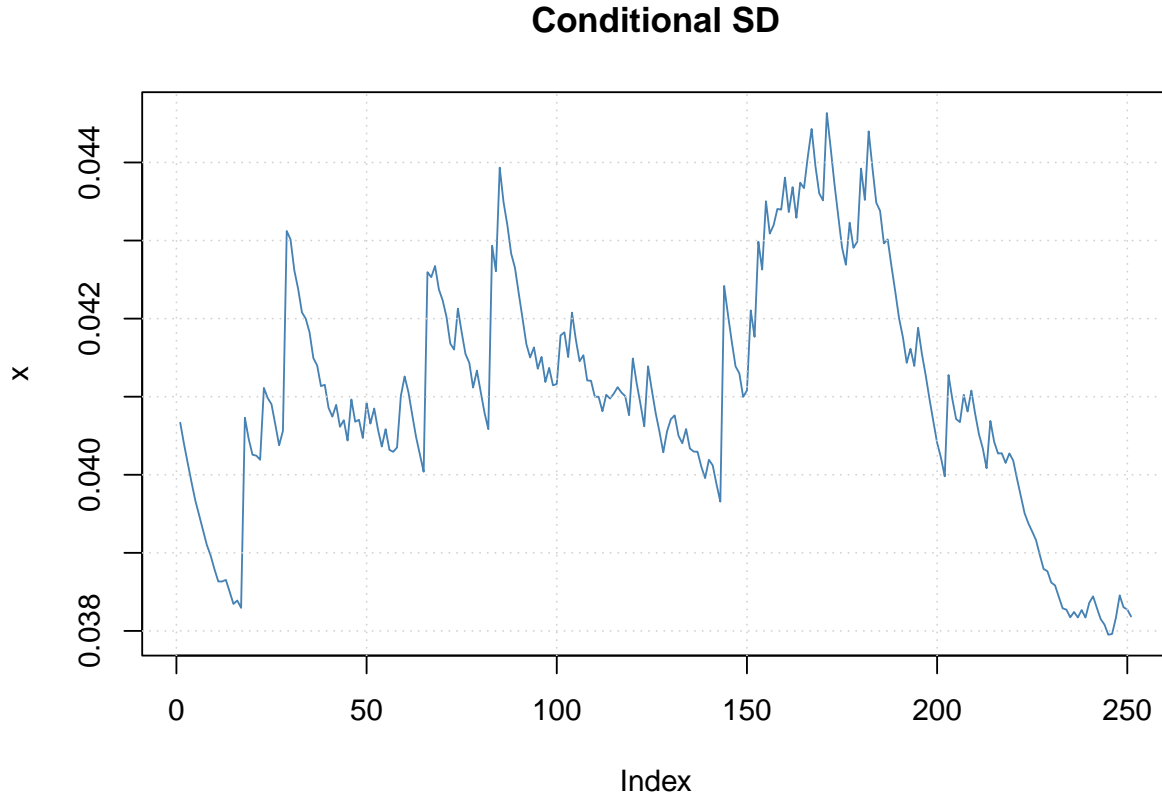


Figure 10: Conditional Standard Deviation of the fitted GARCH model

Based on the GARCH(1,1) fit, we see that only the GARCH coefficient of 0.939 is significant at $\alpha = 0.05$ level ($p \approx 0$). This model suggests that the volatility of the Tesla's stock returns is best predicted by the lagged conditional variance since other coefficients are not statistically significant. If we take a look at the conditional volatility plot, we indeed see that the conditional volatility is in different clusters of high and low volatility, meaning that it exhibits volatility clustering.

Going further into modeling the Tesla's stock price, we used the lag 1 and lag 2 terms of the returns, and also the lag 1 and lag 2 of the daily sentiment scores of the tweets. Our model is:

$$\text{Return} = \beta_0 + \beta_1 \text{Return}_1 + \beta_2 \text{Return}_2 + \beta_3 \text{sentiment} + \beta_4 \text{sentiment}_1 + \beta_5 \text{sentiment}_2$$

The linear model output is below.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.001044	0.004789	-0.2179	0.8277
Returns_l1	-0.0182	0.06541	-0.2783	0.781
Returns_l2	0.02776	0.06567	0.4228	0.6728
daily_sentiment	-0.002767	0.01051	-0.2634	0.7925
daily_sentiment_l1	-0.01416	0.01044	-1.356	0.1763
daily_sentiment_l2	0.02117	0.01028	2.06	0.04045

Table 2: Fitting linear model: Returns \sim Returns_l1 + Returns_l2 + daily_sentiment + daily_sentiment_l1 + daily_sentiment_l2

Observations	Residual Std. Error	R^2	Adjusted R^2
249	0.04085	0.02186	0.001734

Based on the output, we see that only the L2 term for daily sentiment score is significant with estimate of 0.02($p=0.0405$). The adjusted R^2 value is 0.001734, which means that we can only explain the 0.1734% of the variability in the response value. We conclude that the daily sentiment is not very useful for predicting the returns.

For predicting the daily sentiment score based on its previous lagged terms and the returns, the model is:

$$\text{sentiment} = \beta_0 + \beta_1 \text{sentiment}_1 + \beta_2 \text{sentiment}_2 + \beta_3 \text{Return} + \beta_4 \text{Return}_1 + \beta_5 \text{Return}_2$$

The second linear model output is below:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.1871	0.02666	7.019	2.223e-11
Returns	-0.1031	0.3916	-0.2634	0.7925
Returns_l1	1.311	0.3905	3.358	0.0009101
Returns_l2	0.7894	0.3979	1.984	0.04837
daily_sentiment_l1	0.1618	0.06313	2.564	0.01096
daily_sentiment_l2	0.1585	0.06247	2.537	0.01182

Table 4: Fitting linear model: daily_sentiment \sim Returns + Returns_l1 + Returns_l2 + daily_sentiment_l1 + daily_sentiment_l2

Observations	Residual Std. Error	R^2	Adjusted R^2
249	0.2494	0.12	0.1019

The lagged 1 and 2 terms of both returns and daily sentiment score are significant, which intuitively makes sense. However, predicting the daily sentiment is not as useful as predicting the daily stock return.

4 Discussion

Our goal for this project was to predict Tesla's stock price based on the sentiment of the tweets. For the first linear model, we are predicting returns based on past returns, current daily sentiment, past daily sentiment. We see only one statistically significant coefficient, which means none of the other features have a statistically significant coefficient other than L2 daily sentiment. However, L2 daily sentiment has a small magnitude of 0.02, reflecting a weak correlation between returns and L2 daily sentiment. In the second linear model, we are predicting daily sentiment using returns, past returns, past daily sentiment. Almost all of the features are statistically significant value other than current returns. The adjusted R^2 of 10% suggests that these features account for 10% of the variability of daily sentiment. Past returns and past daily sentiment Granger causes current daily sentiment, i.e. past returns and past daily sentiment can be used to predict the daily sentiment for the current day. However, our original hypothesis was that we would be able to predict returns and stock price using past returns and daily sentiment, which has not proved possible with the current model.

The findings from our model indicate a limited capacity for using tweet sentiment and frequency to predict Tesla's stock price. The significant but minimal correlation found in L2 daily sentiment suggests that while some predictive power exists, it is not strong enough to influence financial decisions effectively. The ability to predict daily sentiment from past stock prices and sentiment highlights potential areas for deeper exploration into the dynamics between social media and financial markets.

4.1 Conclusion

TSLA Stock returns cannot be predicted based on the current or lagged 1 values of daily sentiment or lagged 1 or 2 values for returns. The coefficient for lagged 2 daily sentiment is statistically significant but too small to be useful. Daily sentiment cannot be predicted based on current stock returns but can be explained by the lagged 1 or 2 values of the stock price or daily sentiment.

4.2 Future Work

As we move forward, our project will concentrate on enhancing the predictive models and broadening the analytical scope to better understand the relationship between investor sentiment and stock market behavior. Future efforts will include incorporating broader market performance indicators to understand Tesla's stock movements within the larger financial ecosystem. We can also add factors such as economic indicators, geopolitical events, corporate earnings and monetary policy. Additionally, we plan to incorporate tweet engagement metrics such as likes, retweets, and views, which may offer deeper insights into how social media dynamics can influence stock price movements. Through these improvements, we aim to build stronger predictive tools for financial market analysis, refining our approach to use the predictive power of social media sentiment more effectively.

Appendix

4.3 Automatic ARIMA output

The output from `auto.arima()` is below.

```
## Series: stock$Returns~2
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##          ar1      ma1      mean
##        -0.6196  0.5105  0.0017
## s.e.    0.1958  0.2102  0.0002
##
## sigma^2 = 7.706e-06:  log likelihood = 1122.91
## AIC=-2237.83   AICc=-2237.66   BIC=-2223.72
##
## Training set error measures:
##              ME          RMSE          MAE          MPE          MAPE          MASE
## Training set -4.434692e-07 0.002759389 0.001733483 -17226.44 17257.83 0.7116065
##              ACF1
## Training set 0.01881578
```

4.4 VAR function output

The output from `VARselect()` is below.

- **names:** *Returns* and *daily_sentiment*
- **varresult:**
 - **Returns:**

	Estimate	Std. Error	t value	Pr(> t)
Returns.l1	-0.02184	0.06382	-0.3422	0.7325
daily_sentiment.l1	-0.01461	0.01028	-1.421	0.1565
Returns.l2	0.02559	0.06502	0.3935	0.6943
daily_sentiment.l2	0.02074	0.01013	2.048	0.04161
const	-0.001562	0.004358	-0.3584	0.7204

Table 6: Fitting linear model: $y \sim -1 + .$

Observations	Residual Std. Error	R^2	Adjusted R^2
249	0.04078	0.02158	0.005541

- **daily_sentiment:**

	Estimate	Std. Error	t value	Pr(> t)
Returns.l1	1.314	0.3897	3.371	0.0008695

	Estimate	Std. Error	t value	Pr(> t)
daily_sentiment.l1	0.1634	0.06275	2.603	0.009799
Returns.l2	0.7868	0.397	1.982	0.04862
daily_sentiment.l2	0.1563	0.06183	2.529	0.01208
const	0.1873	0.02661	7.04	1.942e-11

Table 8: Fitting linear model: $y \sim -1 + .$

Observations	Residual Std. Error	R^2	Adjusted R^2
249	0.249	0.1198	0.1054

- covres:

	Returns	daily_sentiment
Returns	0.001663	-0.0001715
daily_sentiment	-0.0001715	0.06198

- corres:

	Returns	daily_sentiment
Returns	1	-0.01689
daily_sentiment	-0.01689	1

- logLik: 441.4
- obs: 249
- roots: 0.5583, 0.3913, 0.2375 and 0.2375
- type: const
- call: VAR(y = df, p = optimal.lags)

```
#####
# STYLE EDITS: IGNORE THIS
#####

# normally you'll want to include this with the libraries at the beginning of your document
knitr::opts_chunk$set(
  message = FALSE, # include this if you don't want markdown to knit messages
  warning = FALSE, # include this if you don't want markdown to knit warnings
  echo = FALSE, # set echo = FALSE to hide code from output
  fig.height = 5,
  fig.width = 7
)
suppressMessages(library(tidyverse))
suppressMessages(library(lubridate))
suppressMessages(library(tidytext))
suppressMessages(library(textdata))
suppressMessages(library(dplyr))
```

```

suppressMessages(library(quantmod))
suppressMessages(library(fGarch))
suppressMessages(library(pander))
# Gather stock tweets data
tweets <- read.csv("../data/stock_tweets.csv")
# Retaining the year, month, day
tweets$day <- as.Date(tweets$Date,"%Y-%m-%d %H:%M:%S")
# Filter to just Tesla tweets
tesla <- filter(tweets,
  tweets$Company.Name == "Tesla, Inc." | tweets$Stock.Name == "TSLA")
num_tweets_tesla <- data.frame(table(tesla$day))
names(num_tweets_tesla) <- c("day", "num_tweets")
# Time series for number of Tesla tweets per day
tesla_ts <- ts(num_tweets_tesla$num_tweets,
  start = c(2021, 273),
  frequency = 365)
plot(tesla_ts, main = "Number of Tesla Tweets \n Per Day",
  ylab = "Number of Tweets")
par(mfrow=c(1,2))
acf(tesla_ts, main = "ACF of \nNumber of Tesla Tweets")
pacf(tesla_ts, main = "PACF of \nNumber of Tesla Tweets")
df <- read.csv("../data/stock_tweets.csv")

df <- df %>%
  filter(Stock.Name == 'TSLA') %>%
  mutate(Tweet.ID = row_number()) %>%
  dplyr::select(Tweet.ID, Date, Tweet)

df$Date <- ymd(substr(df$Date, 1, 10))
tweets <- data.frame(df)

# Sentiment analysis
map_bing_sentiment <- function(sentiment) {
  ifelse(sentiment %in% c("positive"), 1, ifelse(sentiment %in% c("negative"), -1, 0))
}

map_nrc_sentiment <- function(sentiment) {
  nrc_positive_sentiments <- c("positive", "anticipation", "surprise", "trust", "joy")
  nrc_negative_sentiments <- c("negative", "anger", "disgust", "fear", "sadness")
  ifelse(sentiment %in% nrc_positive_sentiments, 1,
    ifelse(sentiment %in% nrc_negative_sentiments, -1, 0))
}

tweet_tokens <- tweets %>%
  unnest_tokens(word, Tweet)

sentiments <- get_sentiments("bing") %>% mutate(sentiment_score = map_bing_sentiment(sentiment))

tweets_sentiment <- tweet_tokens %>%
  inner_join(sentiments, by = "word", relationship = "many-to-many") %>%
  distinct(Tweet.ID, Date, word, .keep_all = TRUE)

tweets_sentiment_summary <- tweets_sentiment %>%

```

```

group_by(Tweet.ID, Date) %>%
  summarise(sentiment_score = sum(sentiment_score, na.rm = TRUE), .groups = "drop")

daily_sentiment <- tweets_sentiment_summary %>%
  group_by(Date) %>%
  summarise(daily_sentiment = mean(sentiment_score))
sentiment_ts <- ts(daily_sentiment$daily_sentiment,
  start = c(2021, 273),
  frequency = 365)
plot(sentiment_ts, main = "Daily Sentiment of Tesla Tweets",
  ylab = "Average Daily Sentiment Score")
par(mfrow=c(1,2))
acf(sentiment_ts, main = "ACF of Daily Sentiment")
pacf(sentiment_ts, main = "PACF of Daily Sentiment")
df <- read.csv("../data/stock_yfinance_data.csv")

df <- df %>%
  filter(Stock.Name == 'TSLA') %>%
  dplyr::select(Date, Adj.Close)
df$Date <- as.Date(df$Date)
df$Returns <- c(diff(df$Adj.Close), NA)
stock_ts <- ts(df$Returns,
  start = c(2021, 273),
  frequency = 365)
df$Returns <- c(diff(log(df$Adj.Close)), NA)
stock_ts_lsqr <- ts(df$Returns^2,
  start = c(2021, 273),
  frequency = 365)
stock <- data.frame(df)
stock <- stock %>% na.omit()
# EDA TSLA returns
plot(stock_ts, main="TSLA Returns")
par(mfrow=c(1,2))
acf(stock_ts, main="ACF of TSLA Returns", na.action = na.pass)
pacf(stock_ts, main="PACF of TSLA Returns", na.action = na.pass)
plot(stock_ts_lsqr, main="TSLA Squared Log Returns")
par(mfrow=c(1,2))
acf(stock_ts_lsqr, main="ACF of TSLA \nSquared Log Returns", na.action = na.pass)
pacf(stock_ts_lsqr, main="PACF of TSLA \nSquared Log Returns", na.action = na.pass)
stock_ts <- ts(stock$Returns,
  start=c(2021,9),
  frequency=365)
garch_model <- garchFit(~ garch(1,1), data=stock_ts, trace=FALSE)
summary(garch_model)

par(mfrow=c(1,1))
plot(garch_model, which = 1)
plot(garch_model, which = 2)
combined_data <- left_join(stock, daily_sentiment, by = "Date")
#cor(combined_data$daily_sentiment, combined_data$Returns, use = "complete.obs")
model <- lm>Returns ~ daily_sentiment, data = combined_data)
#pander(summary(model))
suppressMessages(library(dplyr))

```

```

combined_data <- combined_data %>%
  arrange(Date) %>%
  mutate(
    Returns_l1 = lag>Returns, 1),
    Returns_l2 = lag>Returns, 2),
    daily_sentiment_l1 = lag(daily_sentiment, 1),
    daily_sentiment_l2 = lag(daily_sentiment, 2)
  )

model <- lm>Returns ~ Returns_l1 + Returns_l2 + daily_sentiment +
  daily_sentiment_l1 + daily_sentiment_l2, data = combined_data)

pander(summary(model))
model <- lm(daily_sentiment ~ Returns + Returns_l1 +
  Returns_l2 + daily_sentiment_l1 +
  daily_sentiment_l2, data = combined_data)

pander(summary(model))
suppressWarnings(library(forecast))

arma_rt_squared <- auto.arima(stock$Returns^2, max.p = 5, max.q = 5, max.order = 10,
  stationary = T, seasonal = F, trace = F,
  stepwise = F, approximation = F)

summary(arma_rt_squared)
suppressMessages(library(vars))
df <- combined_data[, c("Returns", "daily_sentiment")]
# VARselect
lag.select <- VARselect(df,
  lag.max = 30,
  type = "both")
optimal.lags <- lag.select$selection['AIC(n)']

# Fit the VAR model
var.model <- VAR(df, p = optimal.lags)

pander(summary(var.model))

```