COMP4971C -Independent Study (Summer 2018)

Can Donald Trump's Tweets be used for Trading?

Trading with Sentiment Analysis on tweets from @realDonaldTrump

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1. Abstract

Short term prices in markets are heavily influenced by news and social media sentiment. Social media posts from a prominent figure like the President of the United States could possibly influence investor confidence and may be useful as a signal for traders. This project analyses the effectiveness of using President Trump's tweets as a signal for predicting changes in short term stock prices. Trading is simulated for prominent stock markets that are in countries mentioned several times in Trump's tweets. The results of the simulated trading are presented in this report.

2. Overview

We first extract a corpus of Tweets from Trump's twitter account (Section 3). We then identify the tweets relevant to our analysis using a 'bag of words' method for each region in our analysis (Section 4). Afterwards, we run the tweets through different Sentiment analysis services which assign a numerical value to a tweet based on how positive or negative it was perceived to be (Section 5). A trade simulation is then conducted using the tweet sentiment score a signal for buys and shorts (Section 6). Finally, for each stock in our analysis we present a heatmap of results obtained using different parameters and sentiment analysis services for the simulated trading. (Section 6.1-6.8)

3. Extracting the Tweets

Twitter's API returns at most 3200 of a user's most recent tweets. However, for a complete analysis, we wanted to have the full corpus of Trump's tweets since his election as President. To do this, we used a web scraping python script that iterates through the pages of a Twitter account and saves the data for each individual tweet, producing a total of 3877 tweets from November 1st, 2016 up till July 25th, 2018.

For each region included in our analysis, we made a case-insensitive 'bag of words' of terms relating to that region. A tweet found to contain any term in a region's 'bag of words' was then subjected to sentiment analysis, and the result of this sentiment analysis was used to make a trade decision. For instance, a tweet that mentioned any of the terms ‘China’, ‘Chinese’ or ‘President Xi’ would signal our simulation to make a buy order for the Shanghai Composite Index, if the tweet contained strongly positive sentiment. The bag of words used to identify tweets for each region in this analysis is shown in Table 1. At least one of the terms appeared in at least one of the analysed tweets.

Region	Bag of Words used to Identify Relevant Tweets
China	China, Chinese, Beijing, President Xi
Europe	Europe, Euro, European, Germany, German, Merkel, France, Italy
Russia	Russia, Russian, Russians, Vladimir, Putin, Moscow
Korea	Korea, Korean, Koreans, Chairman Kim, Jong Un, Seoul, Pyongyang
Canada	Canada, Canadian, Toronto, Trudeau

Table 1: Bag of Words Used to Identify Tweets Relevant to a Region

4. Analysing Tweet Sentiment

Sentiment analysis is a process that aims to determine the emotional tone of text or voice data. For our sentiment analysis of Trump's tweets, we take the tweet text as input and pass it to an algorithm that outputs a perceived sentiment score between -1 and +1. The more negative the tweet, the closer the value would be to -1, the more positive the tweet the closer the value would be to +1.

Sentiment analysis is an inherently a subjective process: different algorithms may not agree upon the exact sentiment score that should be assigned to a piece of text. We stress that the sentiment score of an algorithm is a perceived value, and whether this score closely matches the sentiment of the text is open to further analysis. In our study we examine the performance of sentiment analysis algorithms from 3 popular services in merely making a judgement that leads to successful trades. The results presented at the end of this report compare the performance of these sentiment analysis algorithms for simulated trading. We have included the free use limits of these services should the reader wish to use them for their own work. The services we used were:

- **Google Cloud Natural Language API** [1]**:** Allows up to 5000 requests/month free
- **Aylien API** [2]**:** Allows up to 2000 requests/month free
- **TextBlob** [3]**:** A free Natural Language Processing library for Python

We scaled the output sentiment values of each service to lie between -1 and 1 using Equation 1, where min_sentiment is the most negative sentiment value the algorithm can output, and max_sentiment is the most positive sentiment value an algorithm can output. How this sentiment value is used for simulated trading is explained in the next section.

scaled_sentiment = 2*(unscaled_sentiment – min_sentiment) / (max_sentiment – min_sentiment)

Equation 1: Scaling Sentiment score to range [-1, +1]

5. Simulating Trades with Tweet Data

Section 5.1 describes the algorithm used for the trade simulation. Section 5.2 shows a table of the different stock markets included in the analysis and the motivations behind including them.

5.1 The Trade Simulation Algorithm

The following pseudocode describes the process of a trade simulation. The input parameters for the simulation are described here:

- **Stock**: the stock to simulate the trade for
- **SentimentAnalysisService**: the sentiment analysis service use to assign the tweet a sentiment score (either Google Cloud, TextBlob or Aylien
- **sentimentToBuy**: the minimum sentiment score (between 0 and 1) for a tweet that signals a buy for the mentioned stock. This dictates at minimum how apparently positive a tweet needs to be to signal a buy. We show the effect of using different values of this in Section 6.
- **sentimentToSell**: the maximum sentiment score (between 0 and -1) that signals a short for the mentioned stock. This dictates at minimum how apparently negative a tweet must be to signal a short. We show the effect of using different values of this in Section 6.
- **daysToHold:** the number of days the stock is held before it is sold (in the case of a buy order) or bought back (in the case of a short order). We show the effect of using different values of this in Section 6.

```
func trade(stock, SentimentAnalysisService, sentimentToBuy,
sentimentToSell, daysToHold):
     totalBuys = 0
     totalShorts = 0
     profitableBuys = 0
     profitableShorts = 0

     for each tweet in trumpTweets.filterBy(stock.region):
          sentiment = SentimentAnalysisService(tweet)

          if sentiment > sentimentToBuy:
               totalBuys += 1
               priceBought = stock.price(tweet.date)
               priceSold = stock.price(tweet.date + daystoHold)
               if priceBought < priceSold:
                   profitableBuys += 1
          elif sentiment < sentimentToSell
               totalShorts += 1
               priceShorted = stock.price(tweet.date)
               priceBoughtBack = stock.price(tweet.date+daystoHold)
               if priceShorted > priceBoughtBack:
                   profitableShorts += 1
     return totalBuys, totalShorts, profitableBuys, profitableShorts
```

Equation 2: Trade Simulation Algorithm

A trade simulation is conducted for a given stock using a given sentiment analysis service. First, we filter the corpus of tweets for tweets relating to the region of the stock market (This process is described in Section 3). Then for each tweet, we check the sentiment score assigned to the tweet by our given sentiment analysis service. If this sentiment score is more positive than the sentimentToBuy parameter, we simulate a buy order. If the price of the stock rises after daysToHold, we consider it a profitable buy. It the sentiment score is more negative than sentimentToShort, we simulate a short order. If the stock price falls after daysToHold, we consider it a profitable short.

5.2 Stock Markets in this Included in this Analysis

We identified some stock markets that Trump could plausibly have influenced, based on the nature of US foreign affairs since his election. We included these markets a section for each of these markets in our analysis.

Stock Market	Motivation for Analysis
SSE (Shanghai Composite Index)	Trump's Trade War with China
HSI (Hang Sang Index)	Trump's Trade War with China
STOXX50 (Europe 50 Index)	Trump's Trade War with Europe
DAX (German 30 Index)	Trump's Trade War with Europe
MICEX10 (Moscow 30 Index)	Trump's alleged collusion with Russia
KS11 (Korea Composite Stock Price Index)	Trump's Deal with North Korea

Table 2: Motivation behind the analysis of stock markets

In addition, we identified some USD currency pairs that Trump could have influenced included them in our analysis.

Currency Pair	Motivations for Analysis
CAD/USD	Trade War with Canada
EUR/USD	Trade War with Europe

Table 3: Motivation behind the analysis of USD Currency Pairs

6. Analysing the Results of Trade Simulations

For each trade simulation, we show a heat map with the sentiment threshold on the y axis and the days the stock is held on the x axis. This information can be used to judge how strong a tweet's sentiment may need to be for it to be useful for trading as well as what the ideal period of time is to hold that stock. Each cell shows both the percentage of profitable trades made with those parameters as well as a fraction (profitable trades) /(total trades). Cells on the positive sentiment axis represent buys and those on the negative sentiment axis represent shorts.

6.1 Results for China, Using the SSE Shanghai Composite Index

6.1.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for China to trade shares of the SSE Shanghai Composite Index. The results for each of the 3 sentiment analysis services is presented on the next pages. Some illustrative tweets and the corresponding sentiment scores given by the 3 different sentiment analysis services are presented here.

"President Xi, thank you for such an incredible welcome ceremony. It was a truly memorable and impressive display!" **(Sentiment: 1.0 Google Cloud, 0.64 TextBlob, 0.99 Aylien)**

"So much Fake News about what is going on in the White House. Very calm and calculated with a big focus on open and fair trade with China…" **(Sentiment: 0.57 Google Cloud, 0.048 TextBlob, 0.64 Aylien)**

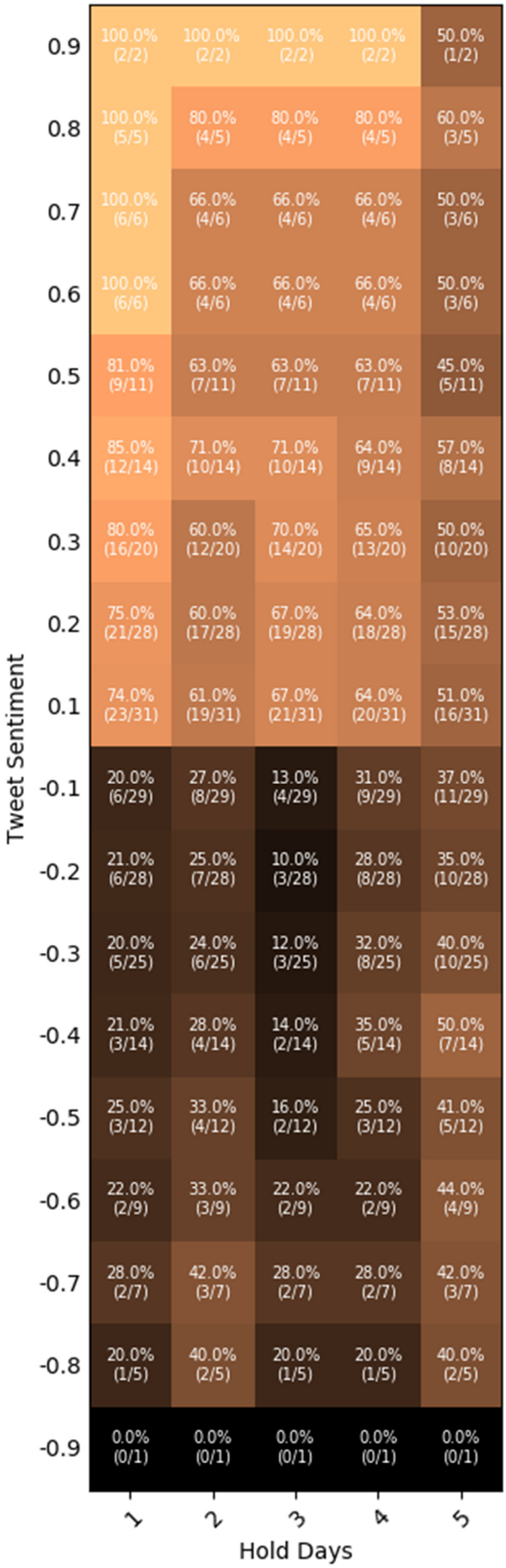


Figure 1: SSE Shanghai Composite Index Heat Map w/ Google Cloud API Sentiment Analysis

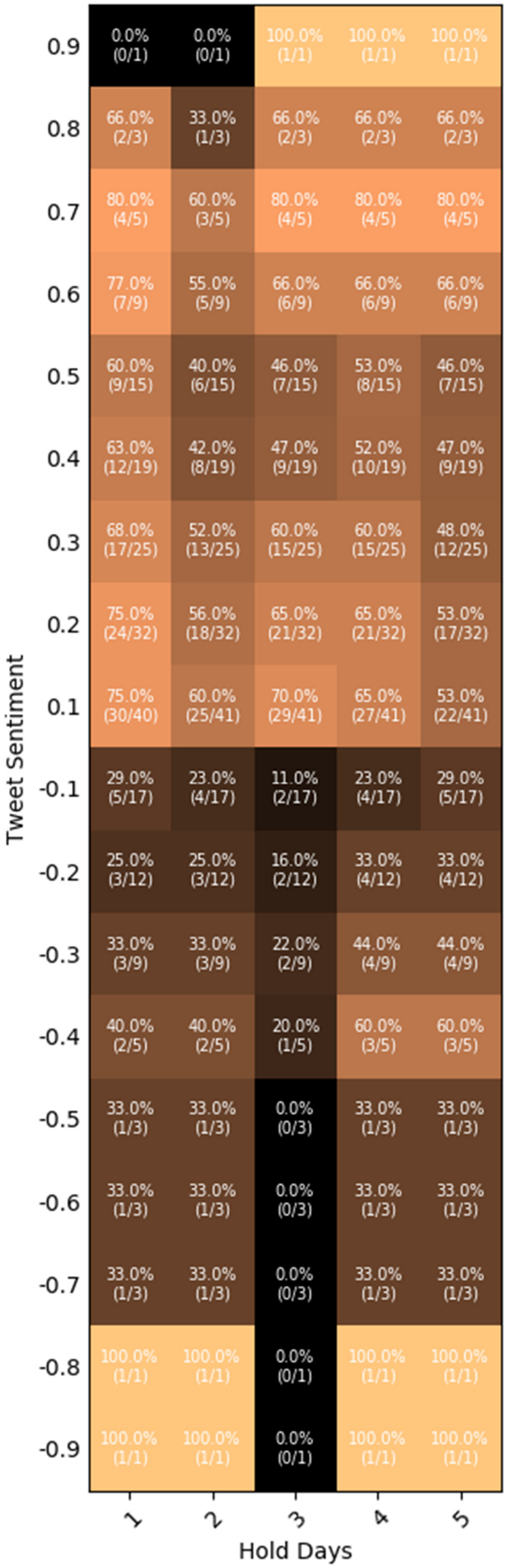


Figure 2: SSE Shanghai Composite Index Heat Map w/ TextBlob API Sentiment Analysis

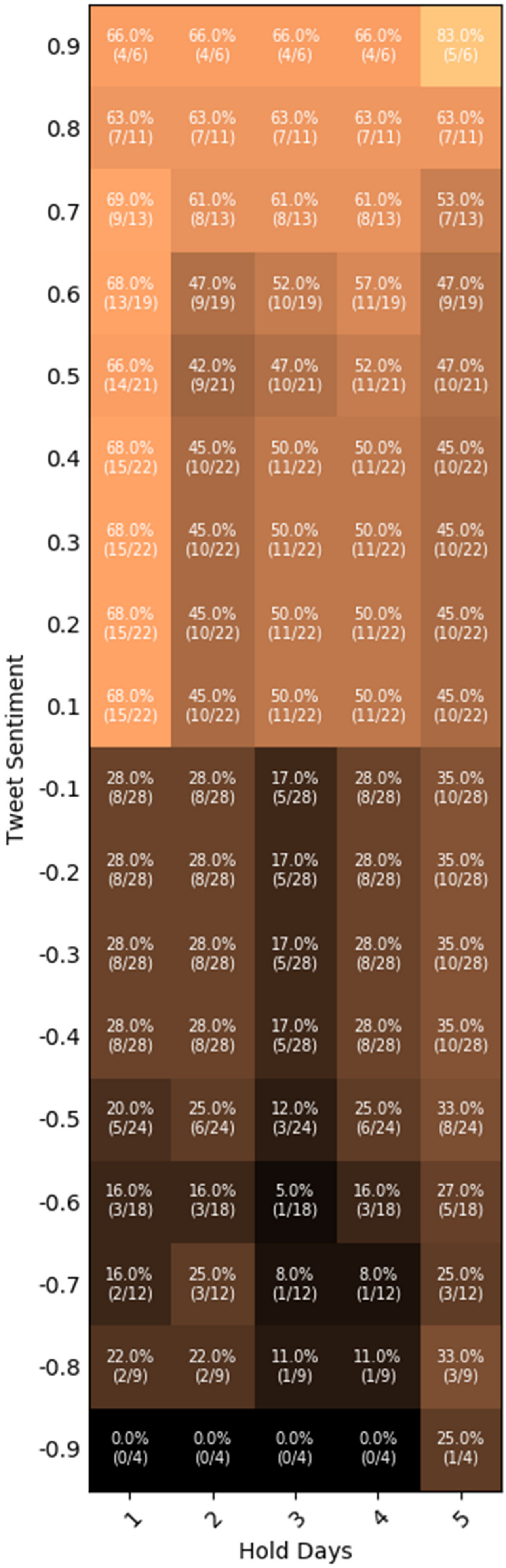


Figure 3: SSE Shanghai Composite Index Heat Map w/ Aylien API Sentiment Analysis

6.1.2 Conclusion

Both the Google Cloud and TextBlob seem to have some success in identifying positive tweets that follow a rise in prices of Chinese stocks. Following tweets that Google Cloud and Text Blob considered to be overwhelmingly positive, prices of the SSE increased for a few days. Following tweets considered to be less positive, the price often fell after one day.

Trading with positive tweets using Google Cloud Sentiment analysis showed the best results. Trading with negative tweets gave poor results for all 3 algorithms. While positive tweets may be useful signal for price rises in the Chinese market, the simulation does not indicate that negative tweets about China are useful signals for the fall of in Chinese stock prices.

The most effective algorithm in the SSE trade simulation is the Google Cloud algorithm, and the minimum positive sentiment for a tweet to be tradeable would be > (0.4-0.5).

6.2 Results for Hong Kong, Using HSI Hang Seng Index

6.2.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for China to trade shares of the HSI Hong Kong Index. The results for each of the 3 sentiment analysis services is presented on the next pages.

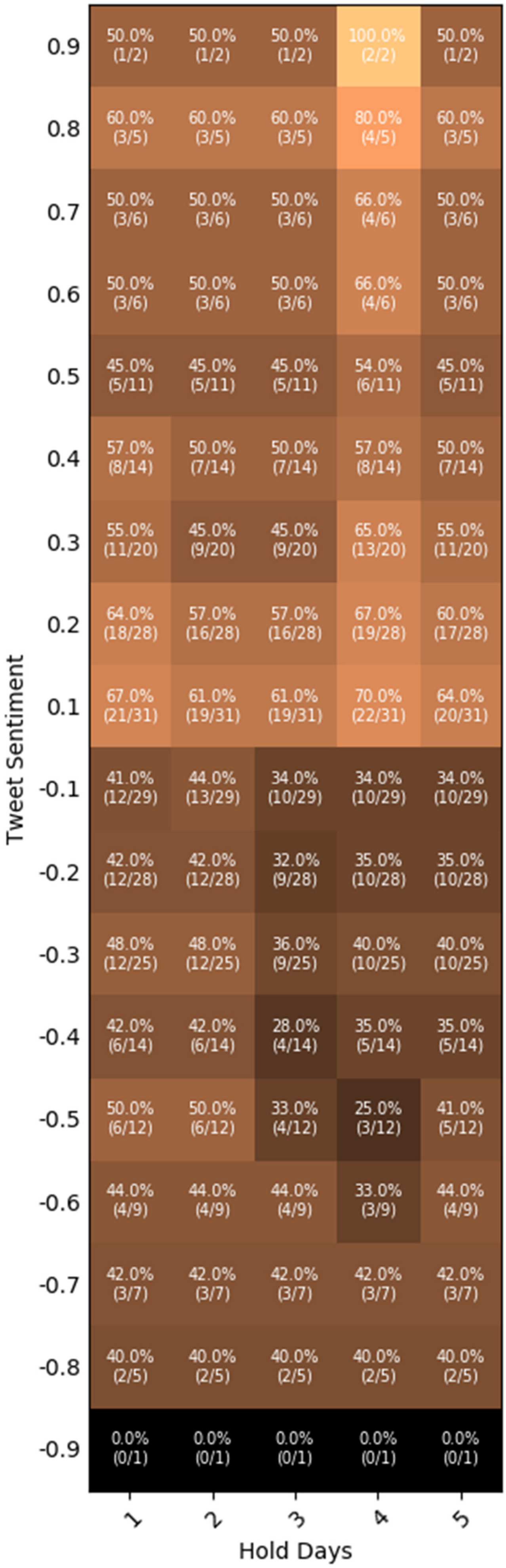


Figure 4: HSI Hang Seng Composite Index Heat Map w/ Google Cloud API Sentiment Analysis

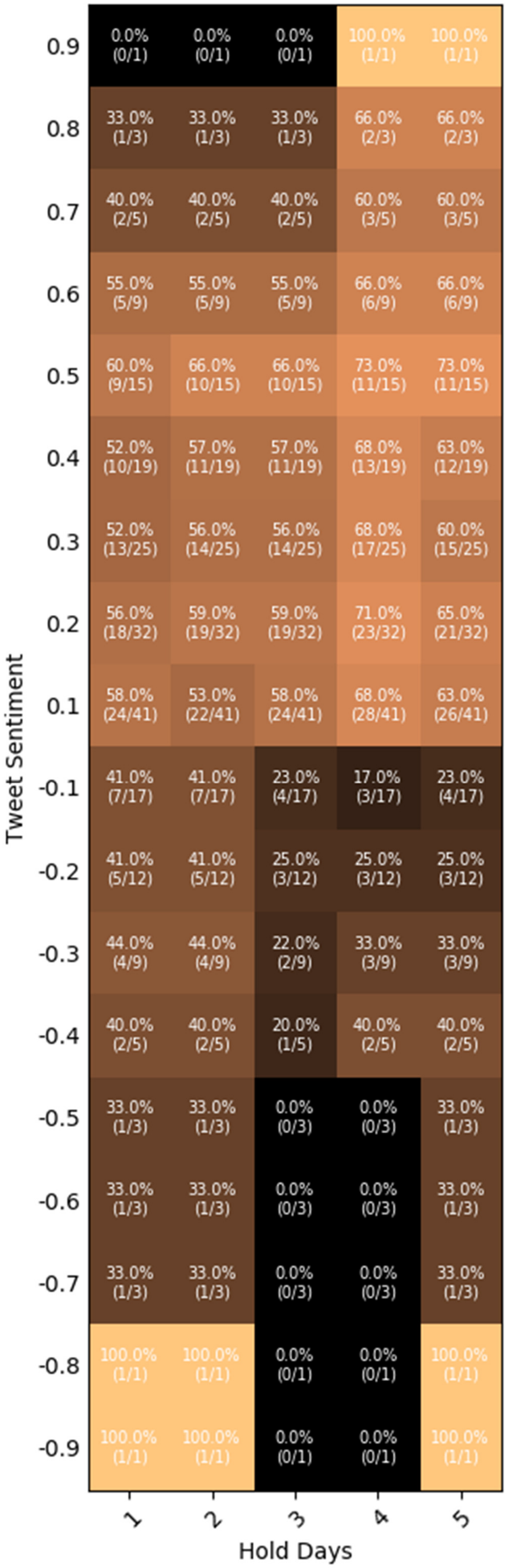


Figure 5: HSI Hang Seng Composite Index Heat Map w/ TextBlob Sentiment Analysis

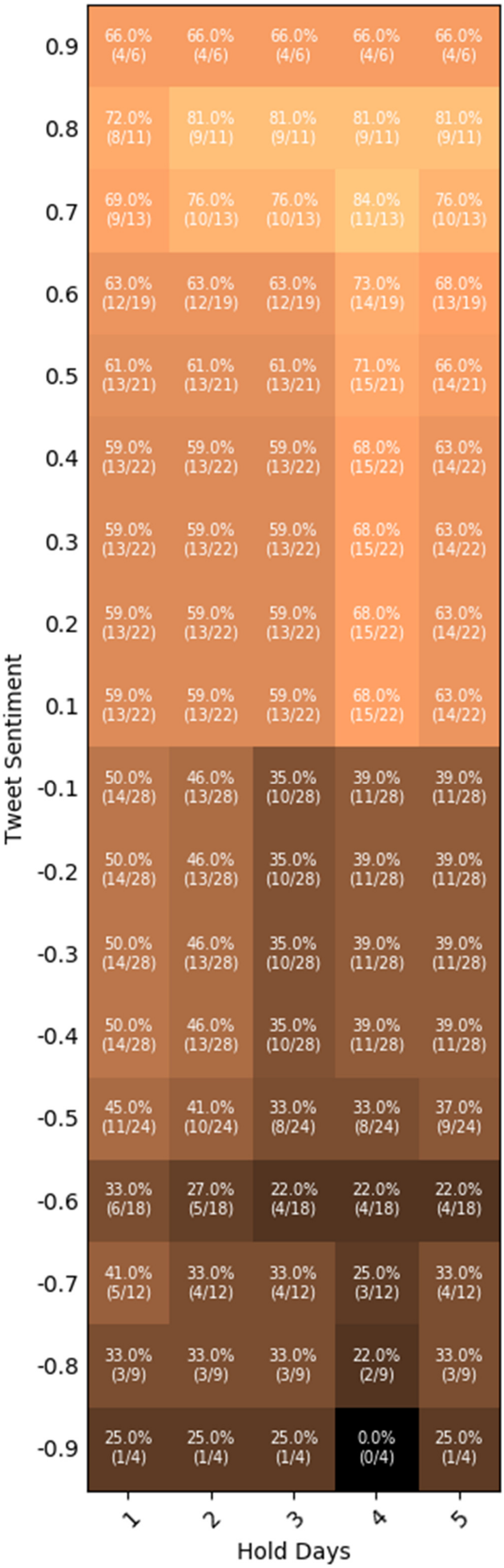


Figure 6: HSI Hang Seng Composite Index Heat Map w/ Aylien API Sentiment Analysis

6.2.2 Conclusion

This simulation tested whether Trump's tweets about China would affect Hong Kong stock prices. While the Aylien algorithm shows the best results for the trade simulation, with a trade success of > 90% for positive tweets, there is good reason to question whether these results were coincidental. The tweets are much more directly linked to China than Hong Kong. If they were useful signals for Hong Kong market prices, the expected result would be the tweets that traded well for China would most likely be the ones that trade well for Hong Kong. Google Cloud and TextBlob, which performed much better than Aylien at identifying tradeable positive China tweets, do not perform very well here leading us to believe the exceeding performance of Aylien in this case may be coincidental.

None of the algorithms performed well when trading with negative tweets suggesting that negative tweets are a poor signal for fall in Hong Kong stock prices.

In any case, the Aylien algorithm performed the best in this case, identifying a very high percentage of tradable tweets for a minimum positive sentiment of >= 0.7.

6.3 Results for Europe, Using STOXX50 Europe 50 Index

6.3.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for Europe to trade shares of the STOXX50 Europe 50 Index. The results for each of the 3 sentiment analysis services is presented on the next pages. Some illustrative tweets and the corresponding sentiment scores given by the 3 different sentiment analysis services are presented here.

“It was a great honor to be with President @EmmanuelMacron of France this afternoon with his delegation. Great bilateral meeting!” **(Sentiment: 0.72 Google Cloud, 0.9 TextBlob, 0.82 Aylien)**

“Just met the new Prime Minister of Italy, @GiuseppeConteIT, a really great guy. He will be honored in Washington, at the @WhiteHouse, shortly. He will do a great job - the people of Italy got it right!” **(Sentiment: 0.79 Google Cloud, 0.42 TextBlob, 0.99 Aylien)**

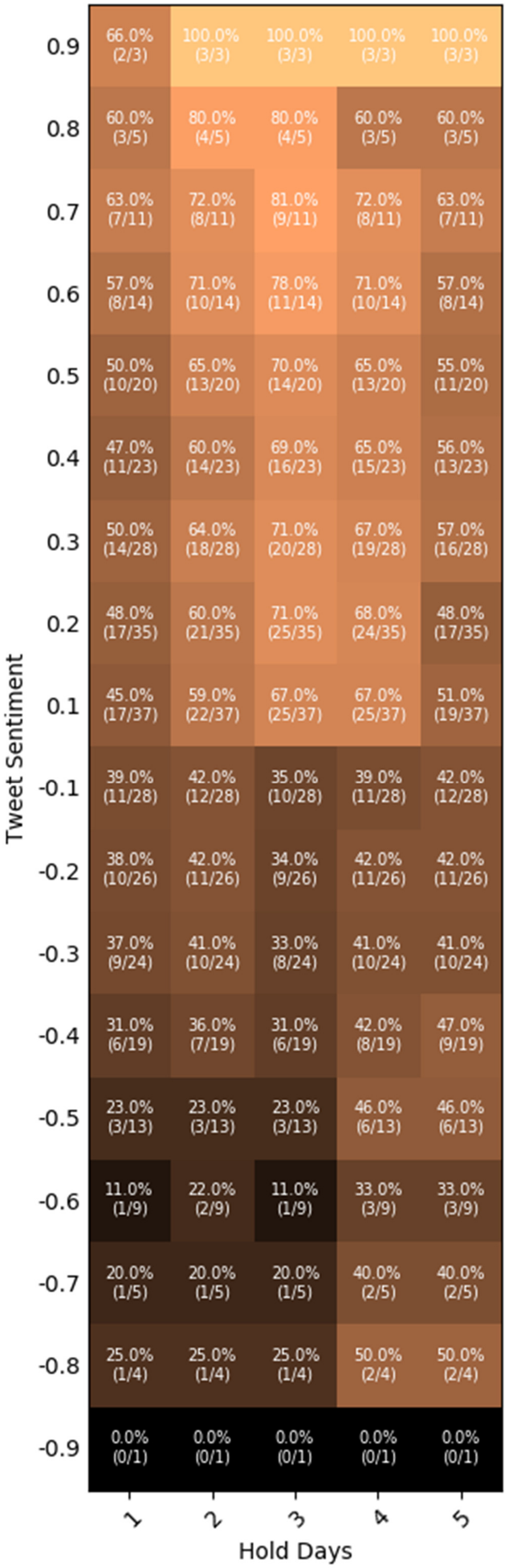


Figure 7: STOXX50 Europe 50 Index Heat Map w/ Google Cloud API Sentiment Analysis

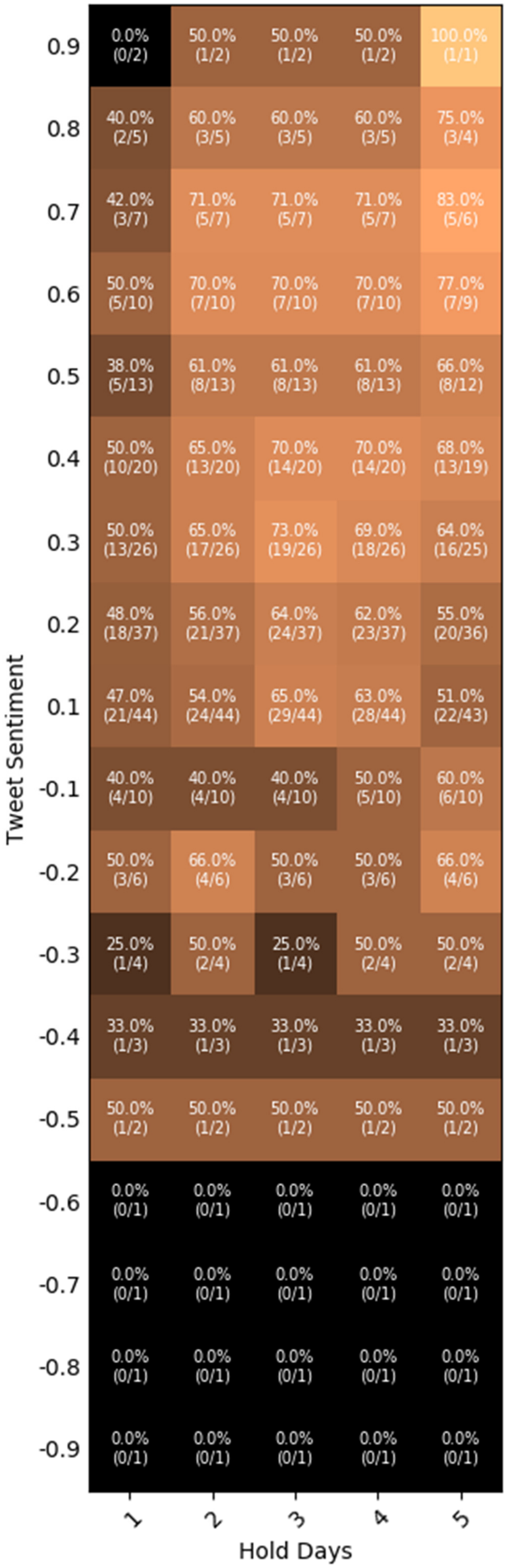


Figure 8: STOXX50 Europe 50 Index Heat Map w/ TextBlob Sentiment Analysis

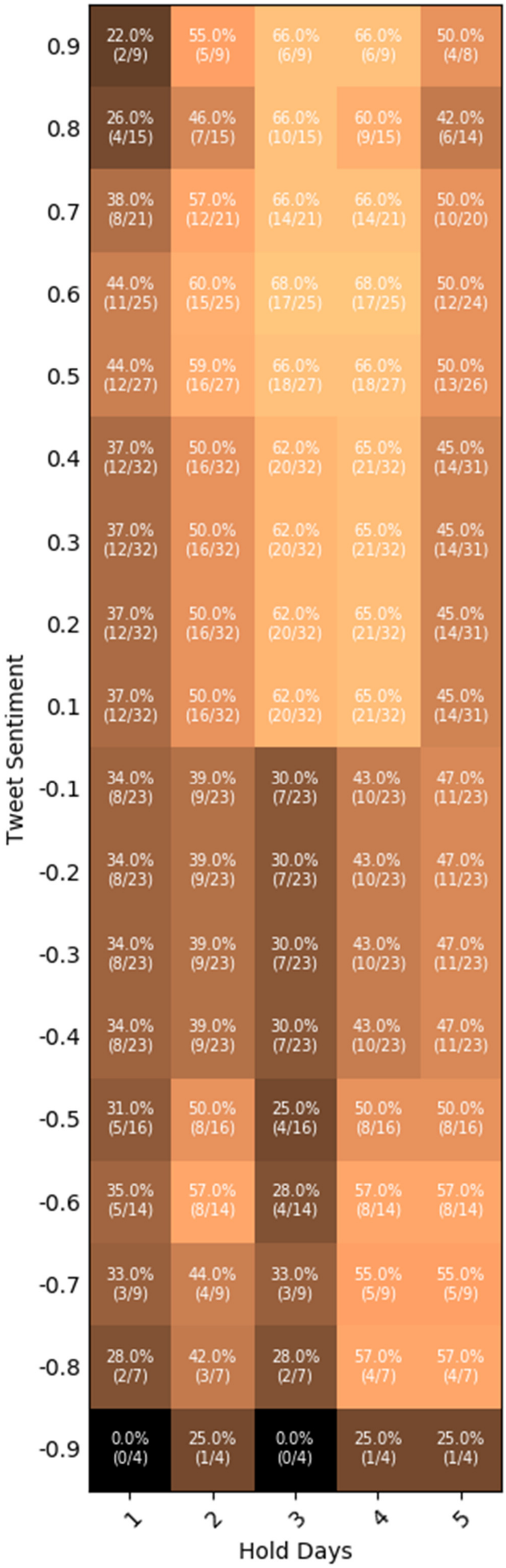


Figure 9: STOXX50 Europe 50 Index Heat Map w/ Aylien API Sentiment Analysis

6.3.2 Conclusion

Both Google Cloud and Text Blob identified a high percentage of tweets that followed a rise in European stock prices. The buy orders made using tweets considered very positive by TextBlob and Google Cloud were profitable when selling the stock over a range of days after the tweet

None of the algorithms performed well for trading with negative tweets suggesting that such tweets do not signal a fall in European stock prices.

The Google Cloud algorithm performed the best for simulated trading, for a sentiment score of > 0.7 though the TextBlob algorithm performed very similarly with for a sentiment score of >0.7.

6.4 Results for Germany, Using DAX German 30 Index

6.4.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for Europe to trade shares of the DAX German 30 Index. The results for each of the 3 sentiment analysis services is presented on the next pages.

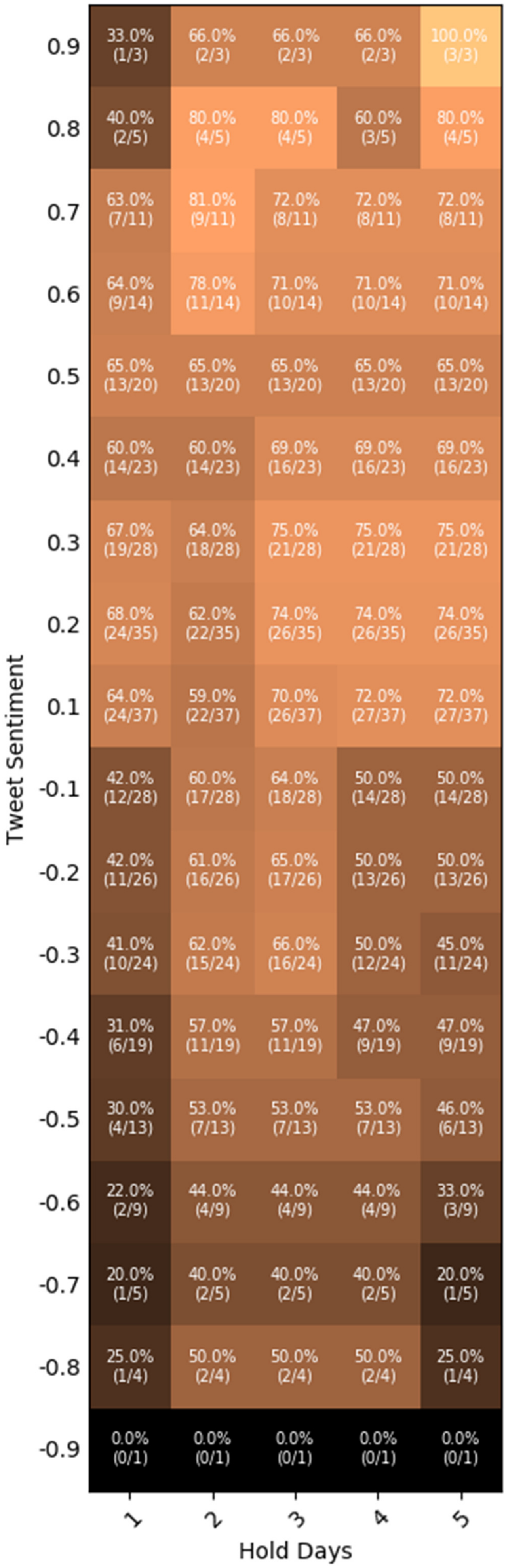


Figure 10: DAX German 30 Index Heat Map w/ Google Cloud API Sentiment Analysis

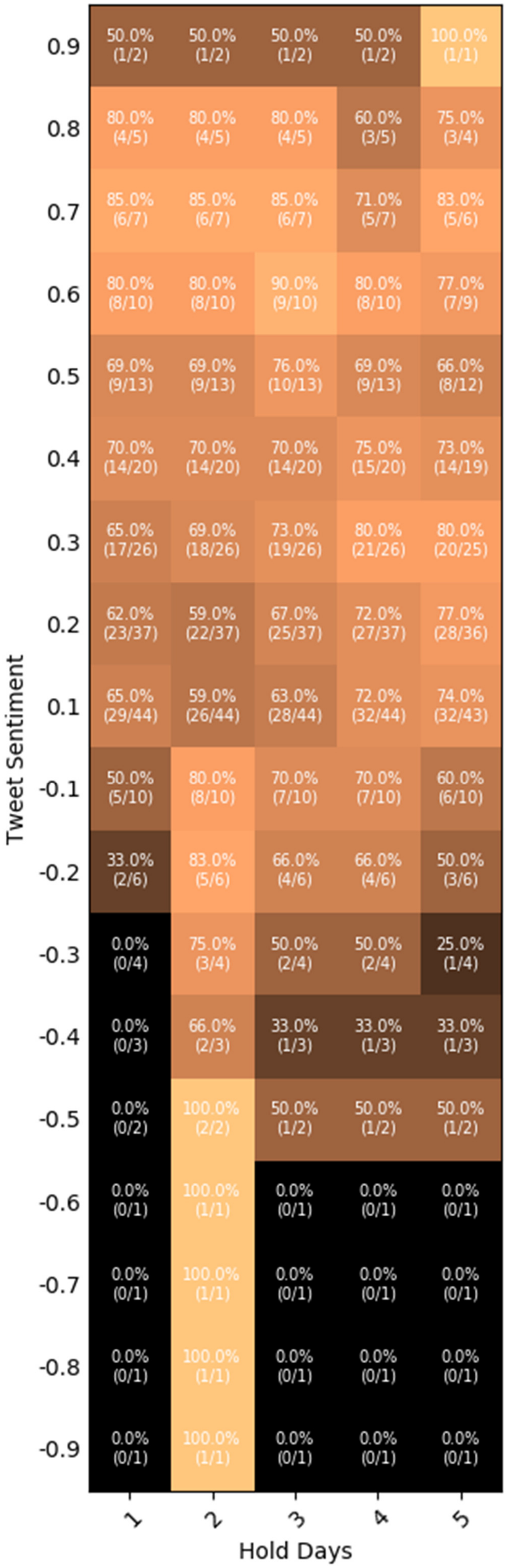


Figure 11: DAX German 30 Index Heat Map w/ TextBlob Sentiment Analysis

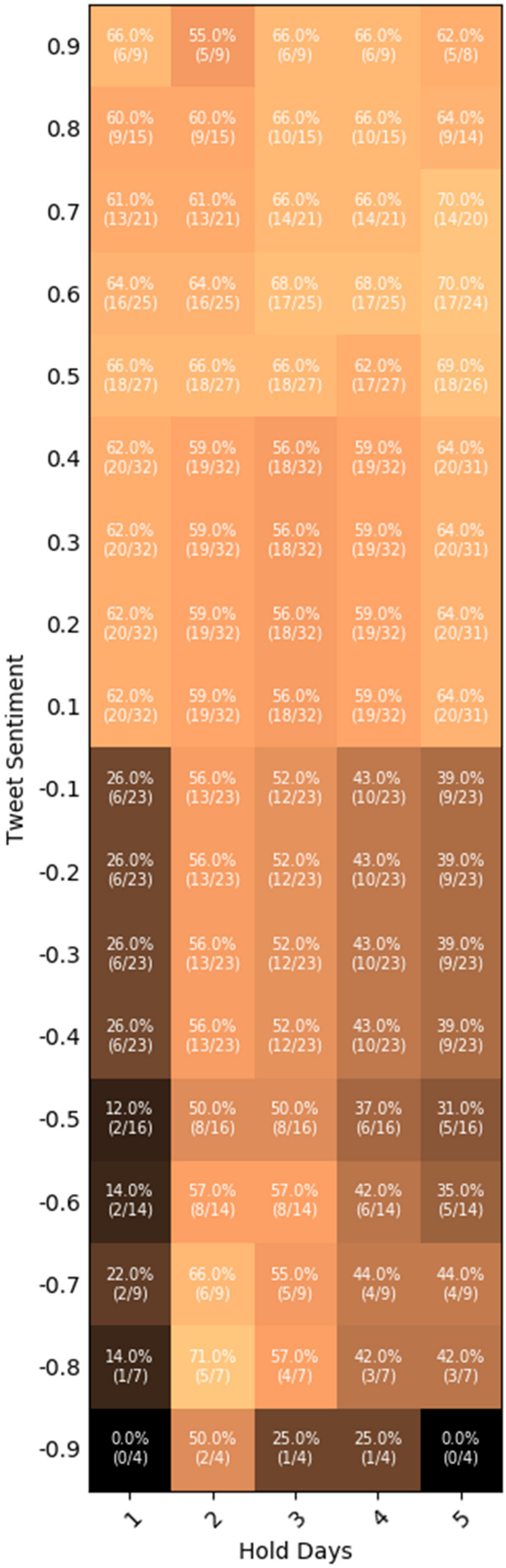


Figure 12: DAX German 30 Index Heat Map w/ Aylien Sentiment Analysis

6.4.2 Conclusion

The simulation for trading the DAX German 30 index was done using the same tweets in the analysis from the analysis of the Europe 50 index. Similar to the results in the analysis of the Europe 50 Index, positive tweets produced profitable simulation results while negative tweets do not produce profitable simulation results. The strong performance of Google Cloud and Text Blob here indicate that the same tweets worked well as signals for a rise in European market prices also signaled a rise in German market prices.

It is possible that the Google Cloud and Aylien sentiment analysis algorithms produced several successful trades in the European simulation by chance and given the strong link between German markets and European markets at large, repeated this coincidental success. However, the overall upward trend of trade success as we move up the heat map with the repeated success of the same sentiment analysis applied to the same tweets indicates that positive Trump tweets about Europe could signal rises in European market prices.

The best performing algorithms for this simulation are Google Cloud and Text Blob, though the difference in performance is marginal. The best results were produced when trading with tweets that TextBlob and Google Cloud gave a sentiment score of >0.7.

6.5 Results for Russia, Using MICEX10 Moscow Exchange 10

6.5.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for Russia to trade shares of the MICEX10 Moscow Exchange 10. The results for each of the 3 sentiment analysis services is presented on the next pages. Some illustrative tweets and the corresponding sentiment scores given by the 3 different sentiment analysis services are presented here.

“Some people HATE the fact that I got along well with President Putin of Russia. They would rather go to war than see this. It’s called Trump Derangement Syndrome!”. **(Sentiment –0.16 Google Cloud, -1.0 TextBlob, -0.89 Aylien)**

“The ‘Intelligence’ briefing on so-called ‘Russian hacking’ was delayed until Friday, perhaps more time needed to build a case. Very strange!”. **(Sentiment Analysis: -0.2 Google Cloud, 0.14 TextBlob, -0.86 Aylien)**

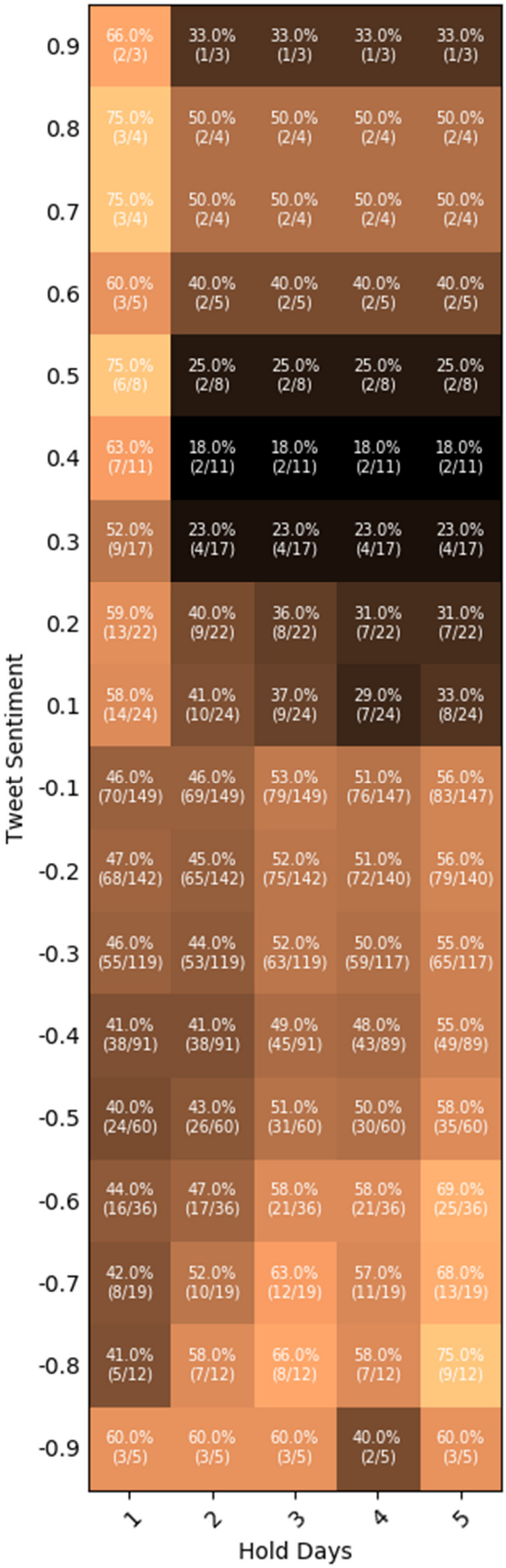


Figure 13: MICEX10 Moscow 10 Index Heat Map w/ Google Cloud Sentiment Analysis

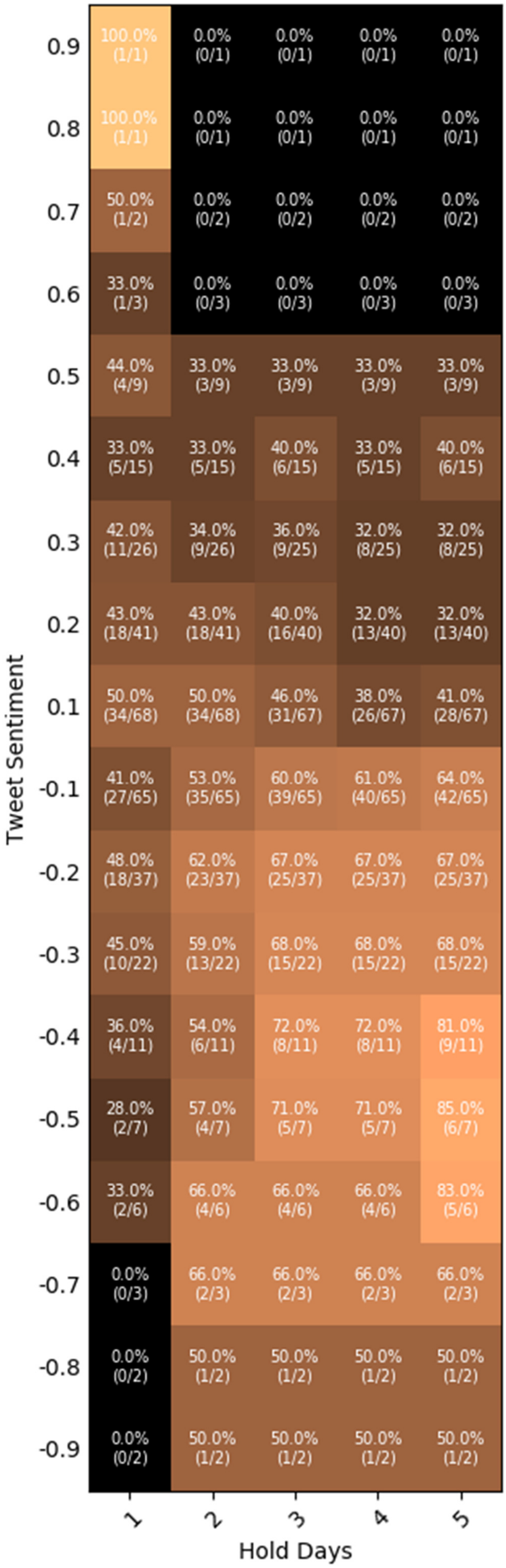


Figure 14: MICEX10 Moscow 10 Index Heat Map w/ TextBlob Sentiment Analysis

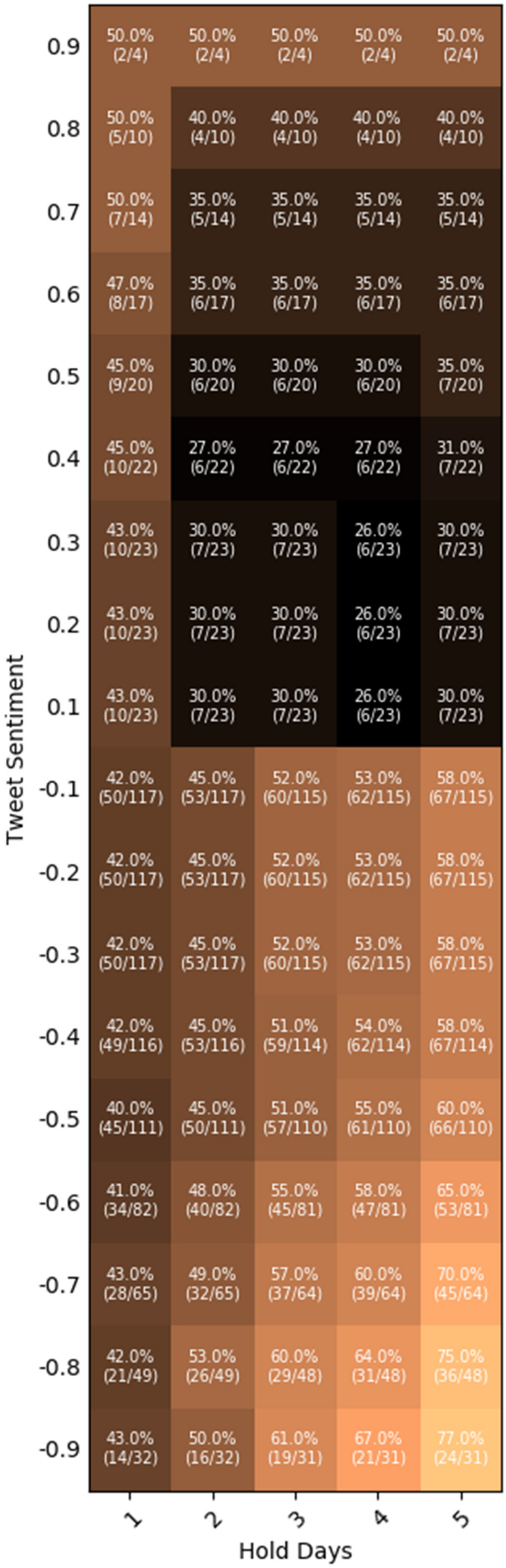


Figure 15: MICEX10 Moscow 10 Index Heat Map w/ Aylien Sentiment Analysis

6.5.2 Conclusion

All 3 algorithms produce a modest percentage profitable trade only when trading using tweets that a sentiment analysis algorithm classifies as negative. The most profitable simulation was made suing the Text Blob algorithm though Aylien did identify a large number of negative tweets that followed a fall in the price in Russian markets.

An interesting point to note is that the tweets identified as negative for Russia tend to defend Russia and express negative sentiment towards Trump's critics. It is difficult to see how such statements would link to Russian stock market prices. Perhaps Trump tends to defend Russia at key moments in the Russian collusion investigation and maybe that investigation itself a signal for falling stock prices. The content of the tweets themselves and the time delay for the predicted price change suggest a weak link between Trump's tweets and Russian market prices.

6.6 Results for Korea, Using KS11 Korean 11 Composite Stock Index

6.6.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for Russia to trade shares of the KS11 Korean 11 Composite Index. The results for each of the 3 sentiment analysis services is presented on the next pages. Some illustrative tweets and the corresponding sentiment scores given by the 3 different sentiment analysis services are presented here.

“A very nice note from Chairman Kim of North Korea. Great progress being made!”. **(Sentiment: 0.5 Google Cloud, 0.89 TextBlob, 0.97 Aylien)**

“A Rocket has not been launched by North Korea in 9 months. Likewise, no Nuclear Tests. Japan is happy, all of Asia is happy. But the Fake News is saying, without ever asking me (always anonymous sources), that I am angry because it is not going fast enough. Wrong, very happy!” **(Sentiment: 0.11 Google Cloud, 0.17 TextBlob, -0.5 Aylien)**

“The denuclearization deal with North Korea is being praised and celebrated all over Asia. They are so happy! Over here, in our country, some people would rather see this historic deal fail than give Trump a win, even if it does save potentially millions; millions of lives!” **(Sentiment: 0.45 Google Cloud, 0.28 TextBlob, 0.99 Aylien)**

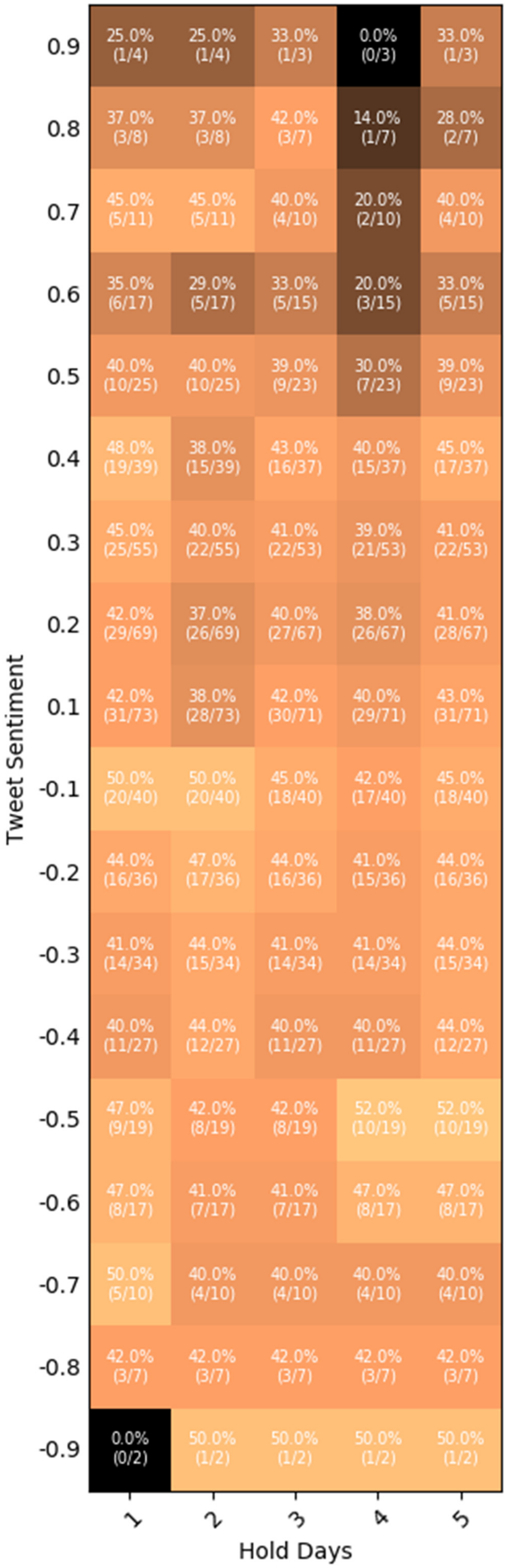


Figure 16: Korean 11 Composite Index Heat Map w/ Google Cloud Sentiment Analysis

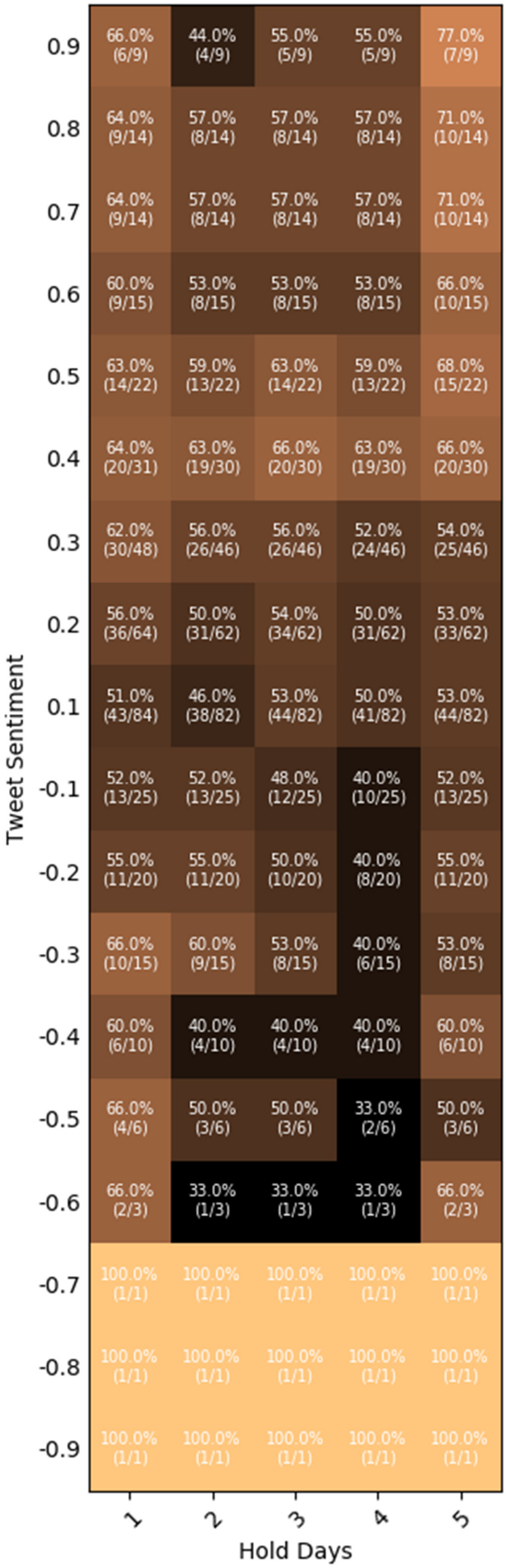


Figure 17: Korean 11 Composite Index Heat Map w/ TextBlob Sentiment Analysis

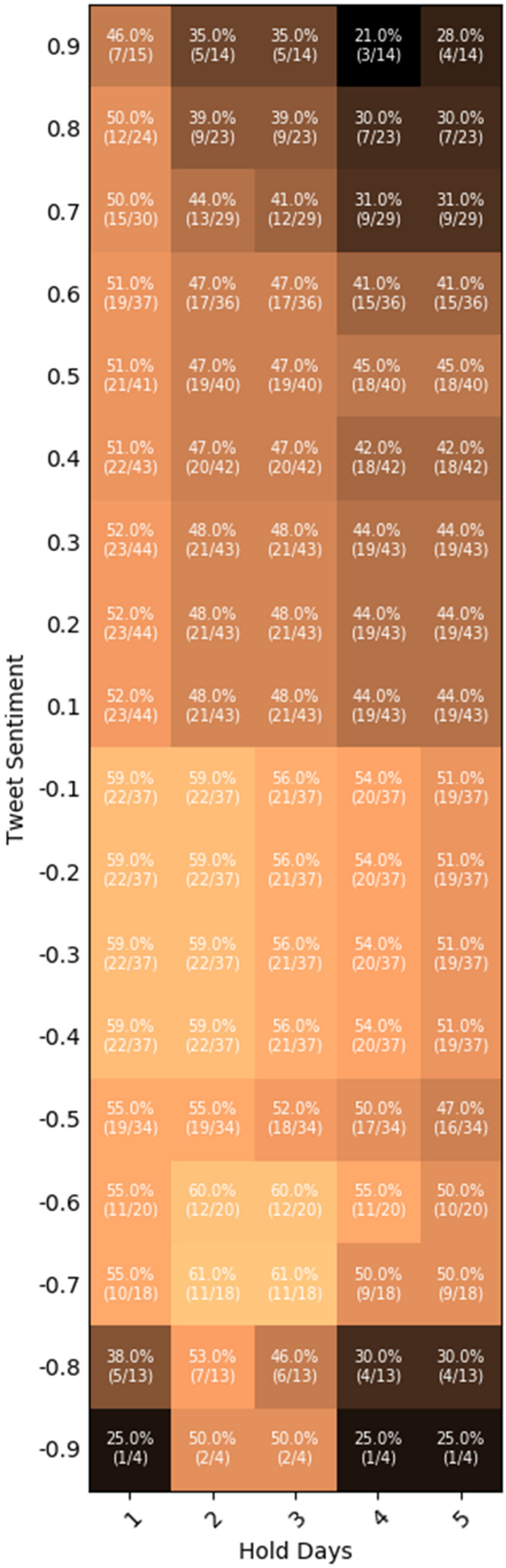


Figure 18: Korean 11 Composite Index Heat Map w/ Aylien Sentiment Analysis

6.6.2 Conclusion

None of the 3 algorithms produce profitable results for trading with sentiment analysis tweets about Korea. The cause of this could be that the effect on the stock market of a negative tweet relating to Korea isn’t necessarily negative: for instance, a positive tweet about North Korea could have a negative impact on the South Korean market.

6.7 Result for CAD/USD, Canadian Dollar - US Dollar Currency Trading

6.7.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for Canada to trade the Canadian Dollar US Dollar currency pair. The results for each of the 3 sentiment analysis services is presented on the next pages. Some illustrative tweets and the corresponding sentiment scores given by the 3 different sentiment analysis services are presented here.

"PM Justin Trudeau of Canada acted so meek and mild during our @G7 meetings only to give a news conference after I left saying that, US Tariffs were kind of insulting and he will not be pushed around. Very dishonest and weak. Our Tariffs are in response to his of 270% on dairy!". **(Sentiment Analysis: -0.67 Google Cloud, -0.13 TextBlob, 0.0 Aylien)**

"Why isn't the European Union and Canada informing the public that for years they have used massive Trade Tariffs and non-monetary Trade Barriers against the U.S. Totally unfair to our farmers, workers & companies. Take down your tariffs & barriers or we will more than match you!". **(Sentiment Analysis: -0.49 Google Cloud, -0.005 TextBlob, 0.5 Aylien)**

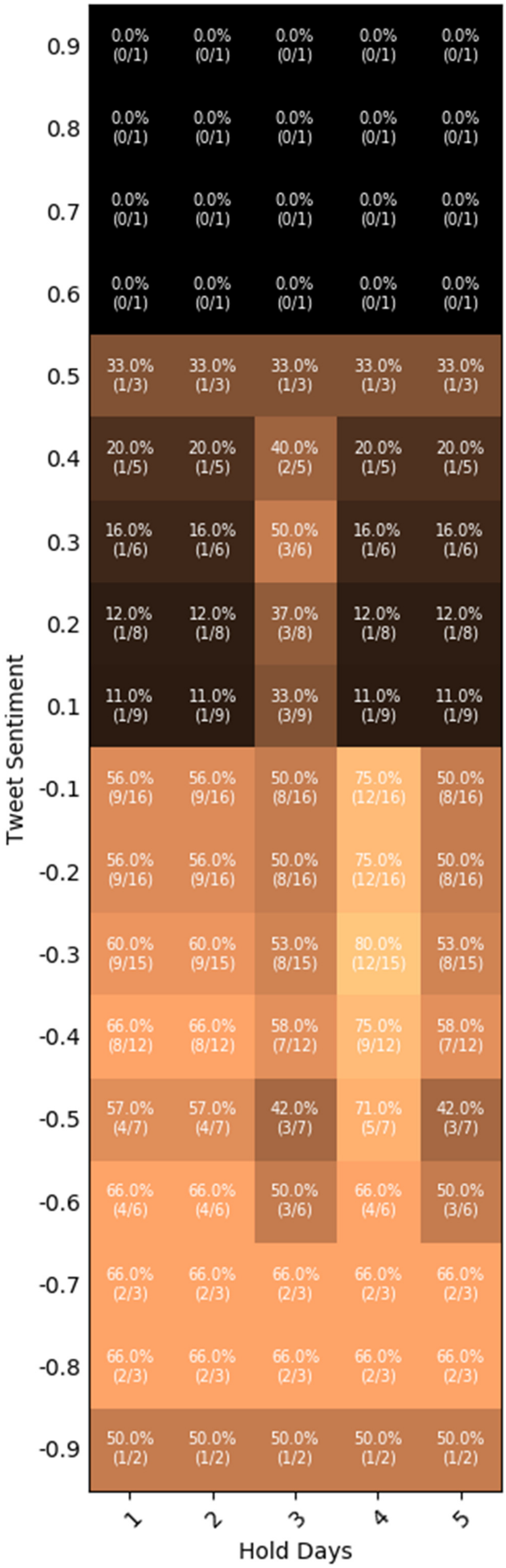
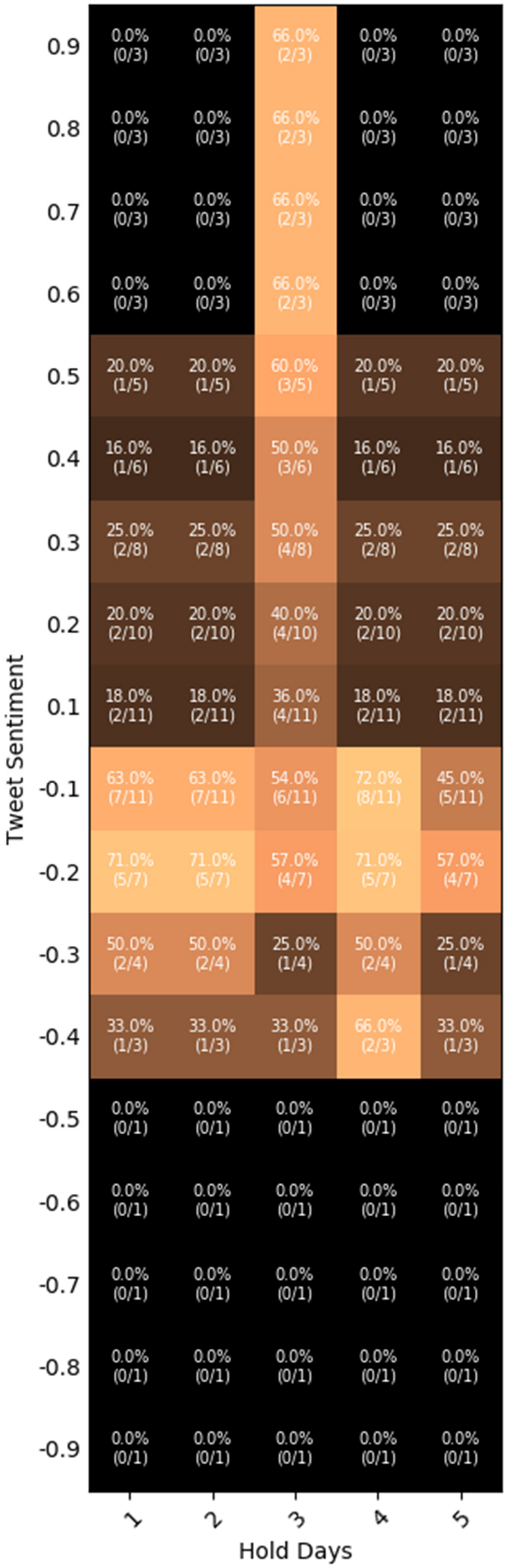


Figure 19: Canadian Dollar – US Dollar Currency Trading Heat Map w/ Google Cloud API Sentiment Analysis



Tweet Sentiment	1	2	3	4	5
0.9	0.0% (0/3)	0.0% (0/3)	66.0% (2/3)	0.0% (0/3)	0.0% (0/3)
0.8	0.0% (0/3)	0.0% (0/3)	66.0% (2/3)	0.0% (0/3)	0.0% (0/3)
0.7	0.0% (0/3)	0.0% (0/3)	66.0% (2/3)	0.0% (0/3)	0.0% (0/3)
0.6	0.0% (0/3)	0.0% (0/3)	66.0% (2/3)	0.0% (0/3)	0.0% (0/3)
0.5	20.0% (1/5)	20.0% (1/5)	60.0% (3/5)	20.0% (1/5)	20.0% (1/5)
0.4	16.0% (1/6)	16.0% (1/6)	50.0% (3/6)	16.0% (1/6)	16.0% (1/6)
0.3	25.0% (2/8)	25.0% (2/8)	50.0% (4/8)	25.0% (2/8)	25.0% (2/8)
0.2	20.0% (2/10)	20.0% (2/10)	40.0% (4/10)	20.0% (2/10)	20.0% (2/10)
0.1	18.0% (2/11)	18.0% (2/11)	36.0% (4/11)	18.0% (2/11)	18.0% (2/11)
-0.1	63.0% (7/11)	63.0% (7/11)	54.0% (6/11)	72.0% (8/11)	45.0% (5/11)
-0.2	71.0% (5/7)	71.0% (5/7)	57.0% (4/7)	71.0% (5/7)	57.0% (4/7)
-0.3	50.0% (2/4)	50.0% (2/4)	25.0% (1/4)	50.0% (2/4)	25.0% (1/4)
-0.4	33.0% (1/3)	33.0% (1/3)	33.0% (1/3)	66.0% (2/3)	33.0% (1/3)
-0.5	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)
-0.6	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)
-0.7	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)
-0.8	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)
-0.9	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)	0.0% (0/1)

Figure 20: Canadian Dollar – US Dollar Currency Trading Heat Map w/ TextBlob Sentiment Analysis

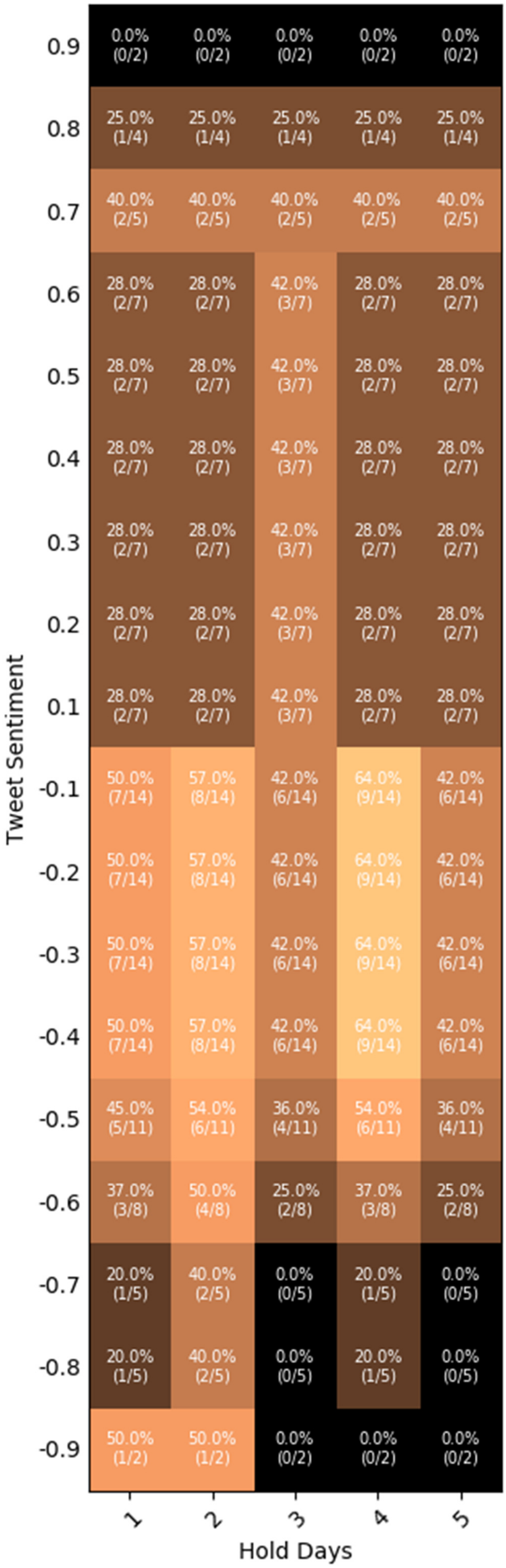


Figure 21: Canadian Dollar – US Dollar Currency Trading Heat Map w/ Aylien API Sentiment Analysis

6.7.2 Conclusion

Sentiment analysis by all 3 algorithms failed to identify many tweets as strongly positive or negative.. Google Cloud does identify > 75% negative of tweets that follow a price dip in CAD/USD but this isn’t well corroborated by the other algorithms and the fact that the price fall is signaled correctly after 4 days does seem odd. While it is possible that there is a link between Trump’s tweets and the CAD/USD price, particularly in the ability of negative tweets to cause a fall in the price of CAD/USD, without more data, it’s hard to tell.

6.8 Result for EUR/USD, Euro - US Dollar Currency Exchange

6.8.1 Introduction

This section shows the results of the trade simulation when using tweets identified by the bag words for Europe to trade the Euro -US Dollar currency pair. The results for each of the 3 sentiment analysis services is presented on the next pages. Some illustrative tweets and the corresponding sentiment scores given by the 3 different sentiment analysis services are presented here.

“The European Union makes it impossible for our farmers and workers and companies to do business in Europe (U.S. has a $151 Billion trade deficit), and then they want us to happily defend them through NATO, and nicely pay for it. Just doesn’t work!” **(Sentiment: -0.83 Google Cloud, 0.22 TextBlob, -0.47 Aylien)**

“Billions of additional dollars are being spent by NATO countries since my visit last year, at my request, but it isn’t nearly enough. U.S. spends too much. Europe’s borders are BAD! Pipeline dollars to Russia are not acceptable!” **(Sentiment: -0.86 Google Cloud, -0.18 TextBlob, -0.76 Aylien)**

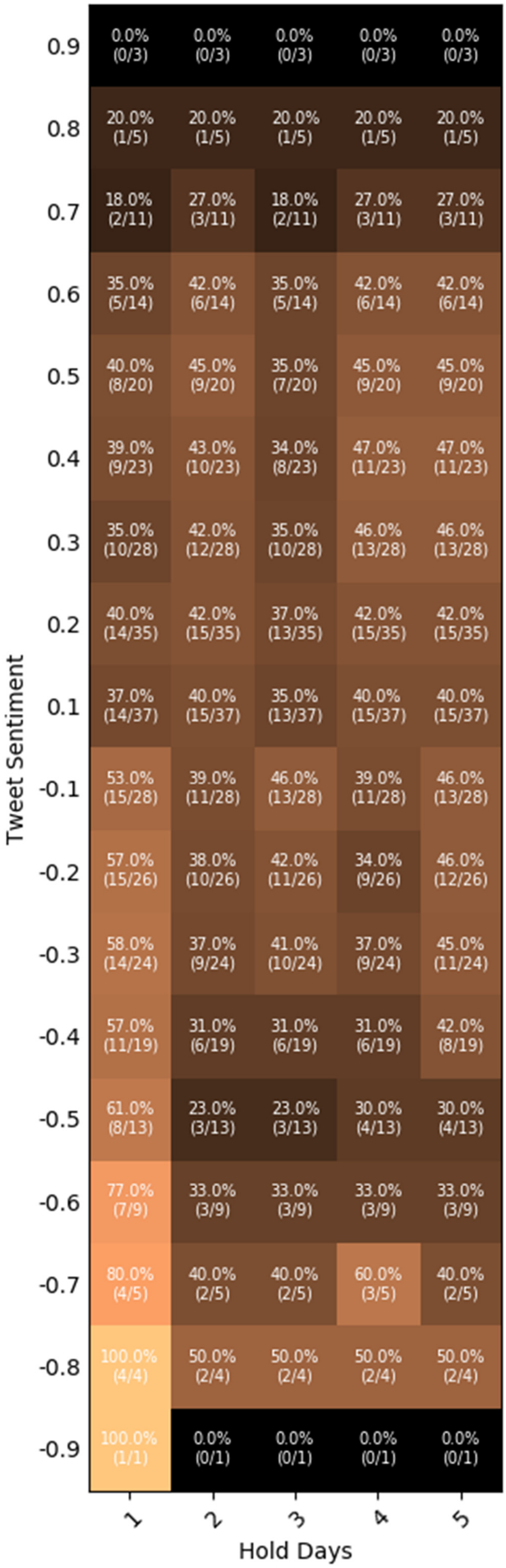


Figure 22: Euro – US Dollar Currency Trading Heat Map w/ Google Cloud API Sentiment Analysis

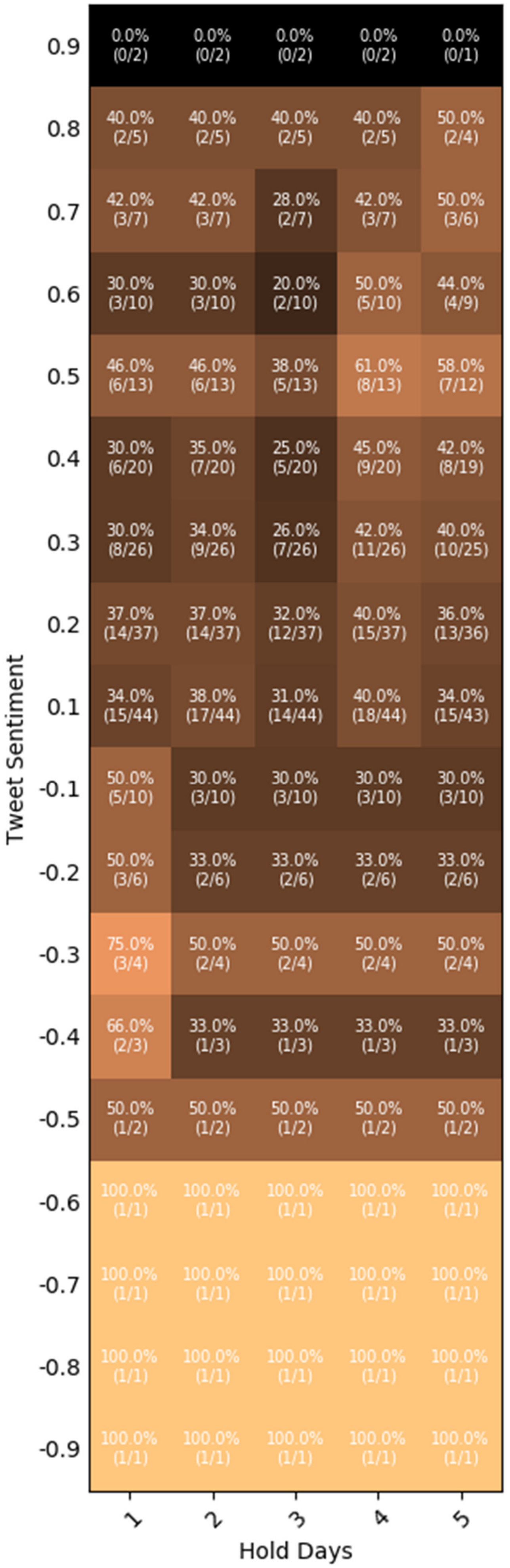


Figure 23: Euro – US Dollar Currency Trading Heat Map w/ TextBlob Sentiment Analysis

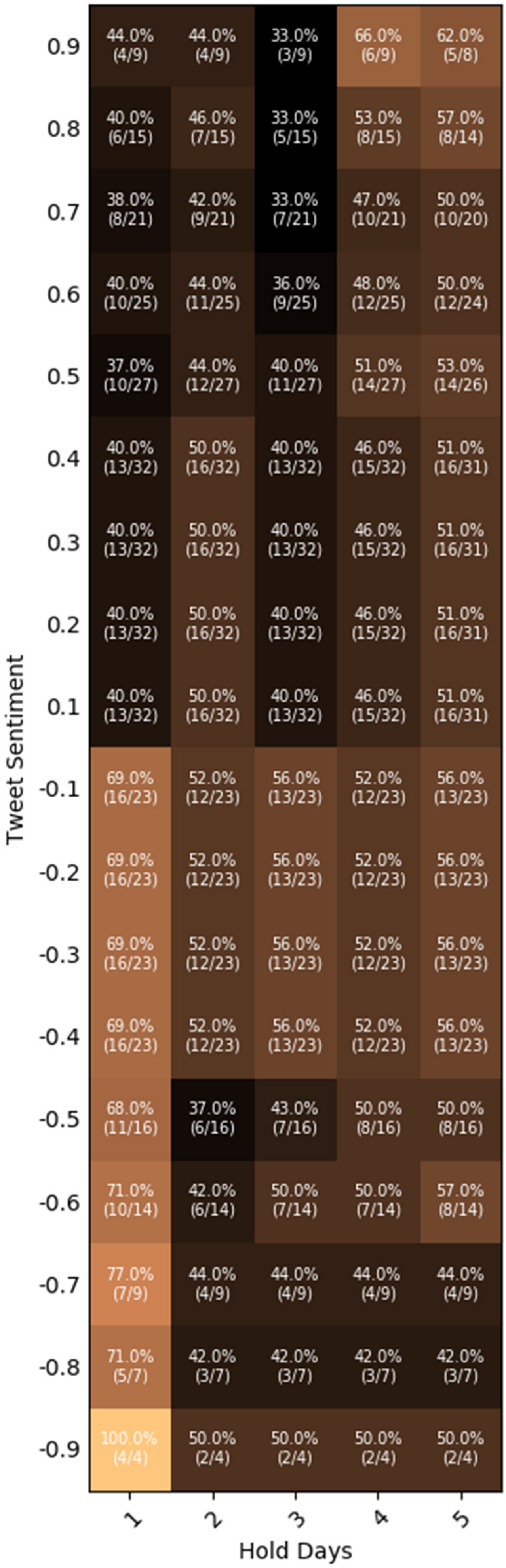


Figure 24: Euro – US Dollar Currency Trading Heat Map w/ Aylien API Sentiment Analysis

6.8.2 Conclusion

Unlike European Composite indices, simulated with the Euro USD currency pair produced more profitable results with tweets analyzed to have negative sentiment rather than positive sentiment. Selling the Euro for the US Dollar was most profitable in simulations that sold in 1 day.

Tweets identified by Aylien as having negative sentiment resulted in profitable trades ~70% of the time regardless of the minimum sentiment score threshold used. In the simulation that used Google Cloud for sentiment analysis, a more negative sentiment threshold for selling the Euro generally resulted in a higher percentage of profitable trades. TextBlob, which produced profitable simulations for European composite indices, failed to identify many negative tweets here so we cannot compare its performance here.

7. Conclusion

This study tested whether the sentiment analysis of Trump's tweets can be used as a signal for the trend of market prices in different parts of the world. The results overall do not suggest a strong link between market prices and the tone of Trump's tweets as determined by sentiment analysis. However, some useful findings are noted here for future study.

Simulations provided better results for regions for which a high percentage of tweets talked about sanctions and the economy. This was the case for Europe and China. The days for which shares needed to be held in the case of profitable trades was in the range of 1-2. These gives some more credence to our results for these regions as social sentiment tends to be a very short-term influence on market prices.

The trade simulations for 2 European composite indices performed modestly well using Trump's tweets that sentiment analysis identified as positive. Euro – US Dollar currency pair trading showed better results using tweets marked as negative by sentiment analysis. Though the sample size of tweets that produced profitable trades was small, further analysis of the link between Trump's tweets and European markets could be useful given this performance.

Profitable trade results for Russia and Hong Kong are less concrete. In the case of Hong Kong, firstly the region itself is not mentioned in the tweet. Unlike Europe and Germany's economies, Hong Kong's economy may not be so strongly linked with China's economy. For Russia, tweets rarely talk about trade or anything related to Russia's economy specially so there isn't a strong reason to believe that they have any relationship with Russian market prices. For both Hong Kong and Russia trade simulations, the days for which stocks needed to be held to make significant profitable trades was 4. This suggests that the trades made a profit more likely due to coincidence rather than as a direct result of the predictions made by the sentiment analysis of Trump's tweets

Tweets containing complicated relationships to the entities mentioned do not produce very accurate sentiment scores with the basic entity unaware sentiment analysis in our study. This was shown in the simulations for the South Korean markets. As tweets usually mention North Korea, a model that can extract the implicit sentiment with South Korea in a tweet would be needed to test the link between Trump's tweets and South Korean markets.

Finally, a simulation can fail to produce useful results if not sentiment analysis does not identify any tone in many tweets relating to a region. This produces insufficient trades to test the link between Trump's tweets and prices in that market. This was the case in our trade simulation of the CAD/USD currency pair, where too few such trades were made to suggest the existence or non-existence of a link with Trump's tweets.

References

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