Exploring the Effect of Tweets Sentiments on Companies Stock Prices

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Abstract

The stock market's volatility is caused by an overwhelming amount of variables. In addition to causing volatility in the stock market, I believe that these variables are the components that contribute the most to them make up of consumer confidence as well. I attempt to evaluate consumer confidence to create a better predictor of the stock market than the traditional predictors. To calculate consumer confidence I use sentiment analysis to assess how the public feels about a company on the social media website Twitter.

1 Introduction and Background

As I mentioned in the abstract, many different elements cause fluctuation in a companies stock price. Many have attempted to compile these variables in an attempt to predict the stock market. For the most part, this strategy has seen very little success. I believe developing a metric for consumer confidence will allow me to create a less traditional way to predict stock prices. Also, I believe it makes more sense to predict the stock market based on consumer confidence, rather than a bunch of different performance metrics. If people have more confidence in a company, one would expect to stock price to go up and vice versa.

I was inspired to use Twitter to measure consumer confidence by the thought that a person's opinion usually only changes when they are presented with new information or hear someone else's opinion. In this case, Twitter is the perfect place to assess consumer confidence. It is both an outlet that reports live news and allows people can share their opinions, perhaps more efficiently than any other media outlet. Thus I would call Twitter the most influential media outlet when it comes to consumer confidence. Twitter is also very convenient to use when conducting sentiment analysis due to text being the primary form of communication, compared to Snapchat or Instagram, where most communication is through images or videos. Hence, making it easier for me to create a metric for consumer confidence because I believe the average sentiment score, the measure for how positive/negative a tweet is, given to a company would translate over well enough.

While I would like to assume my thought process is correct and start using average sentiment scores to predict stock prices, I still have to find evidence to show that this would be beneficial. Therefore, what I look to accomplish in this paper is to find evidence that there is a relationship between stock price and sentiment scores, and that the sentiment score affects the stock price, not vice versa.

2 Finding a Relationship Between Stock Price and Sentiment

As I stated earlier, the first step of assessing whether average sentiment scores are a good predictor of the companies stock price is to see if there is any relationship between stock price and sentiment scores. I am not looking for a specific type of relationship yet; all I am looking for is that in a time when a stock is experiencing high volatility, there is also a change in the companies sentiment scores.

I chose to examine this by isolating Kodak's stock price data and sentiment scores. At the end of July 2020, Kodak's stock price became extremely volatile when news broke of a deal reached between Kodak and the government, where it was agreed upon that Kodak would begin producing pharmaceuticals. I found this to be the perfect event to examine due to Kodak not being present in the media prior to the deal. This essentially guarantees any change in the trend of sentiment score is almost certainly due to the news of the deal.

To test to see if there is evidence of a relationship between stock price and sentiment scores, I first had to obtain Twitter data containing tweets about Kodak. I was able to get this data by using a Twitter API that allows me to download tweets using specific search terms. In this case, I used "Kodak" as the search term. I also decided I only wanted original tweets; in turn, I filtered out retweets, quote tweets, etc. I also decided for this step of the project to exclusively use tweets from verified users because I cared more about the quality of tweets than the number of tweets. By doing this I was able to collect tweets that were mainly from news outlets, which contain information. When I don't filter out verified users, I download many more Tweets, but many of them are only contain Kodak's updated stock price. This information isn't useful to me considering I am analyzing the tone of words with sentiment analysis. After this, I graphed the sentiment scores of the tweets I downloaded and looked for fluctuation in sentiment scores.

As shown in figure 1, as I expected, there was a change in Kodak's sentiment scores, however, it was a slightly different result than I expected. I expected the frequency of sentiments of scores to increase when volatility when highest, which they did. I also expected the sentiment scores moved further from zero in the positive direction volatility was at its highest, but instead, they moved further from zero in both directions. After seeing these results, I understood that not everyone could have good things to say about Kodak's deal, therefore causing more negative sentiment scores. Overall, these results were encouraging enough to investigate the relationship between tweets and sentiment scores further.

3 Determining if Sentiment Affect Stock Price

Now that I have some sort of evidence of a relationship between tweet sentiments and stock prices, the next step is finding out what affects what. Ideally, the tweet sentiments would affect the stock prices because that would mean people are reacting to the news and buy/sell the stock, causing the price to rise or fall. This would also mean sentiments could give investors a potential warning that a dramatic change is going to occur to a companies stock price. If it is the opposite relationship(Sentiments are affected by changes in stock prices) that would mean the media is reacting to the change in price. While this result would leave tweet sentiments a lot less useful, it doesn't leave them completely useless. It would not allow investors to get ahead of a period of volatility, but it would allow us to learn how people react given the occurrence of a certain event. This information is still useful information when trying to make predictions. For example, if a company is planning a big product launch, and the tweet sentiments are generally positive after this event, one may want to investigate this company further. However, this is not anywhere as useful as sentiments being an indicator of future stock prices.

The first step for this part of the project was to collect market data. By getting a list of 2,705 stock symbols from eoddata.com, I was able to create a program that collects stock prices from Yahoo Finance for all of these stocks in two-minute frequencies. Moving on from gathering market data, I will now have to download tweets for all of the companies whose stock price changed by 4 percent on the given day. This leaves me with 119 companies. Now, unlike the previous step where I had to gather Twitter data, in this step, I care more about the number of tweets over quality. Unlike the situation with Kodak, many of the companies I am examining in this step are not prominent enough to grab the attention of the major media outlets. Therefore, I could afford not to filter out unverified users and have to deal with the loss of quality. I also decided to adjust my search term for this step. People rarely refer to a company by their exact name, making it more difficult to gather tweets about the company. To combat this, I decided to search for tweets using the cashtag notation on Twitter. A cashtag is like a hashtag, but instead of a word or phrase following a hashtag, it is a companies stock symbol following a dollar sign. Searching the cashtag of a company will show all of the tweets that contain that cashtag. It is also useful because the cashtag eliminates the possibility of gathering irrelevant tweets. For example, if I search for tweets with the word "Apple" looking for tweets concerning the company, I would get tweets about the company, but also about the food and pie. The downside to using cashtags is that they are not used very frequently by the major media outlets, which is not ideal, but I had to accept. In the end, I believe taking the number of tweets over the quality of tweets was fair when considering all of the trade-offs.

After finding all the sentiments of the tweets collected for each of the 119 companies, I decided to analyze their sentiments in three different ways. The first strategy I use was to compare the average sentiment scores before and after the price change for all 119 companies. For simplicity, I am defining price change as the point in time where the stock first changed four percent on the day. It just so happened that all of the stocks I am working with opened with a four percent change, so it is a coincidence that I am comparing the average sentiment score before and after the market opened. The second strategy I use is very similar to the first, but I remove the sentiment scores that are equal to zero. I chose to remove the sentiment scores that are equal to zero because that would indicate that something is perfectly neutral. A tweet being perfectly neutral is close to impossible. The zeros that occur are most likely due to my program performing a very basic sentiment analysis and being unable to give precise scores. The last strategy I use is that I find the percent of scores that were not zero before and after the price change. I use this strategy because while it is a less informative measurement, I believe it is a more accurate one. By just looking at whether the scores are nonzero, it removes the error that my basic sentiment analysis program introduces. However, it does change what effect I am looking for. In the other strategies, I am looking to see if sentiment scores are increase/decrease after the price change. For this strategy, I am just looking to see if there are more or fewer scores equal to zero after the price change. I still find this useful because if there are more nonzero scores after the price change, that is evidence that the price change affects the sentiments.

To analyze the results of these three strategies, I used histograms (Figures 2,3 and 4). If the sentiments of tweets do affect the stock prices, I would expect the histogram representing the sentiments before the price change to overlap the histogram representing the sentiments after the price change. Any other result is evidence that the sentiments are affected by the stock prices.

Looking at figures 2 and 3, where I am looking at average sentiment scores, there is no noticeable difference between the before and after histograms. As I mentioned prior, this shows evidence that the sentiments affect the stock price. However, in figure 4 where I am looking at the percentage of nonzero sentiment score, I would say there is a noticeable difference between the two histograms. This suggests that if I were to have the truly accurate sentiment scores, I would most likely find the sentiment scores are affected by the stock prices. Overall, I obtained encouraging results but also signs that I should be cautious with what I take from these results.

4 Discussion

Overall, I find that my results obtained from this research are encouraging, but I refuse to make any claims based on it. Everything I have completed in this project is very preliminary, to get to a point where I will feel confident making a decisive claim about anything, my techniques will have to become much more accurate and precise. I will detail several improvements I can make below.

First of all, when deciding whether there is a relationship between stock prices and tweet sentiments, I would need to have more evidence than one specific case where a relationship is detected. All I proved, in this case, is that there may be a relationship between sentiment and stock price, not that it exists in every case. In addition, I lack the ideal amount of data to access the relationship in my example of Kodak. However, this lack of data is mainly due to a lack of a reliable internet connection and not being able to monitor my tweet collecting programs closely. However, for what it's worth, the results I obtained were decent for a preliminary study.

In the case of assessing if sentiment scores are affected by stock prices or vice versa, there are many flaws. Similar to the step where I was trying to detect a relationship, I did not have enough data for this step either. Ideally, I would like several weeks of data instead of a day's worth, but again, due to the internet connection and computing power I have, this amount of data is difficult to obtain. In addition to collecting more day's worth of data, this research would benefit greatly by expanding the search terms when downloading tweets. However, to do this, one would have to come up with a list of search terms for every one of the 2,705 stock there is data for. Then after one creates this list they would have to find a way to filter out the irrelevant tweets that got wrapped up in the download. The time it would take to complete this upgrade this process is large, but the upgrade is complete, it would improve the quality of this research greatly.

Before I claim anything, I will also have to find a way to make my program that conducts sentiment analysis more accurate and precise. Right now, the program uses a generic library when, for this project, it would be extremely beneficial to have a financial library. A financial library would give a much more accurate score given the context of the text that I am working with. Having these improved sentiment scores would greatly improve my confidence in this research as a whole.

5 Future Research and Conclusion

In contrary to what it may seem like from the discussion section of this paper, I still believe that this research has potential. If figuring out the stock market was easy, everyone would do it. I still think my idea of using average sentiment scores as a metric for consumer confidence would be a great predictor for stock prices; it just needs more work to get to that point. Below I will detail a few suggestions for future research.

My first suggestion I touched on in the previous section and is the need for more accurate sentiment analysis. Before I mentioned the need for a financial library, that is still valid, but there is also the need for the program to understand the English language better. Right now the program just evaluates the tone of each word in the tweet and finds the sum to get a sentiment score. However, it is very possible for the tone of the word to change given the words that come before it. Any sentiment analysis tools available to the public, as of now, does not take this into consideration, and again would be very time consuming to implement.

Another suggestion is collecting tweets and stock prices at the same time, allowing them to interact with each other. What I mean by this is to have the changes in stock prices dictate what company's tweets you download. This would optimize the data collection process, considering the most desirable data is tweets and market data surround a period where there is a change in stock price. I successfully wrote programs to do this, but their usage was hindered due to a lack of computing power and the lack of bandwidth of my WiFi.

In conclusion, I would say that this project was a success. I did not get to the point of creating a metric for consumer confidence, nor did I find any conclusive result. However, what I did show that it is possible, and given more time and some adjustments, conclusive results could be achieved. If results show that the sentiments of tweets related to a certain company affect its stock price, I believe this information would become extremely useful to any investor.

6 Graphs

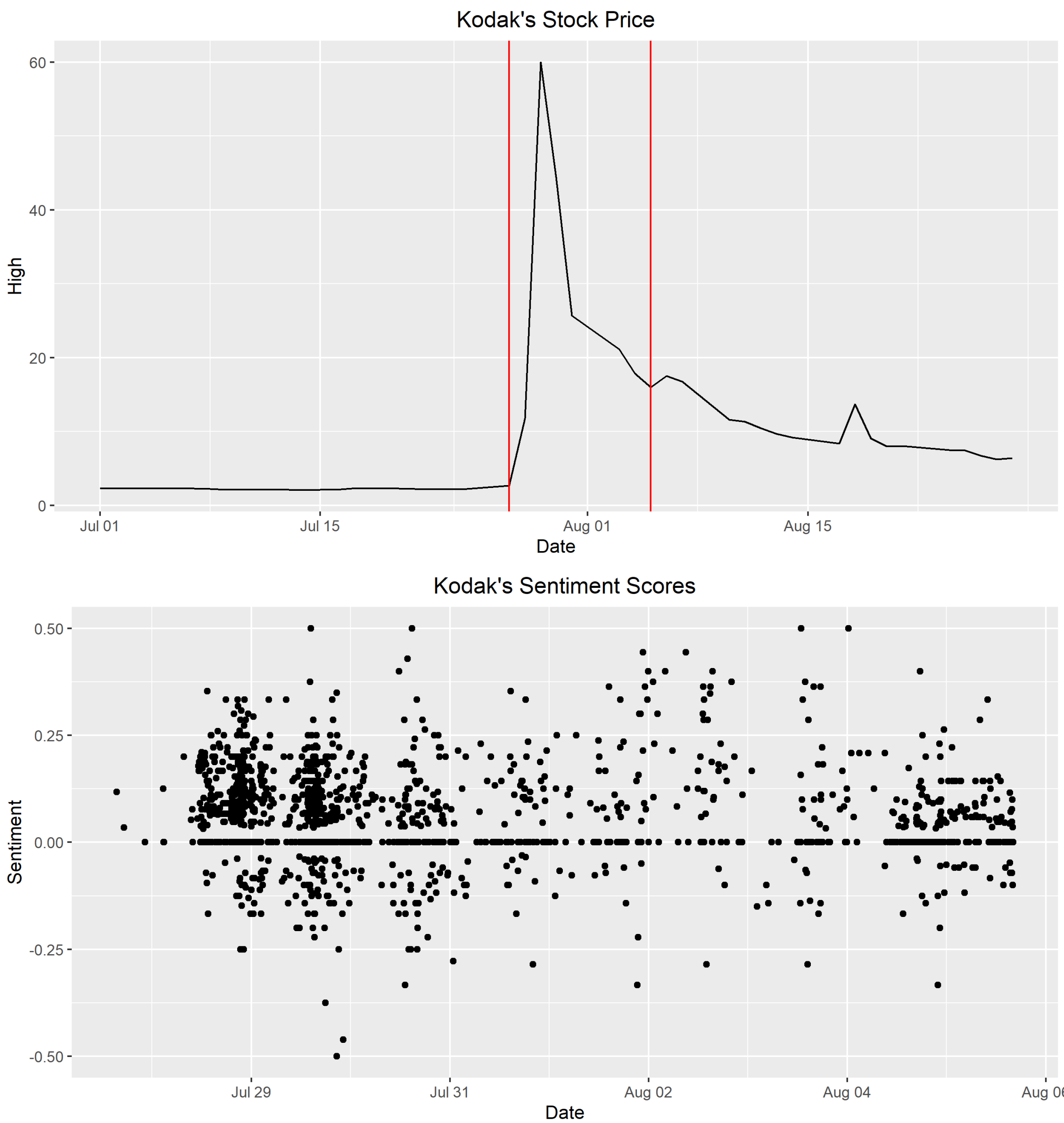
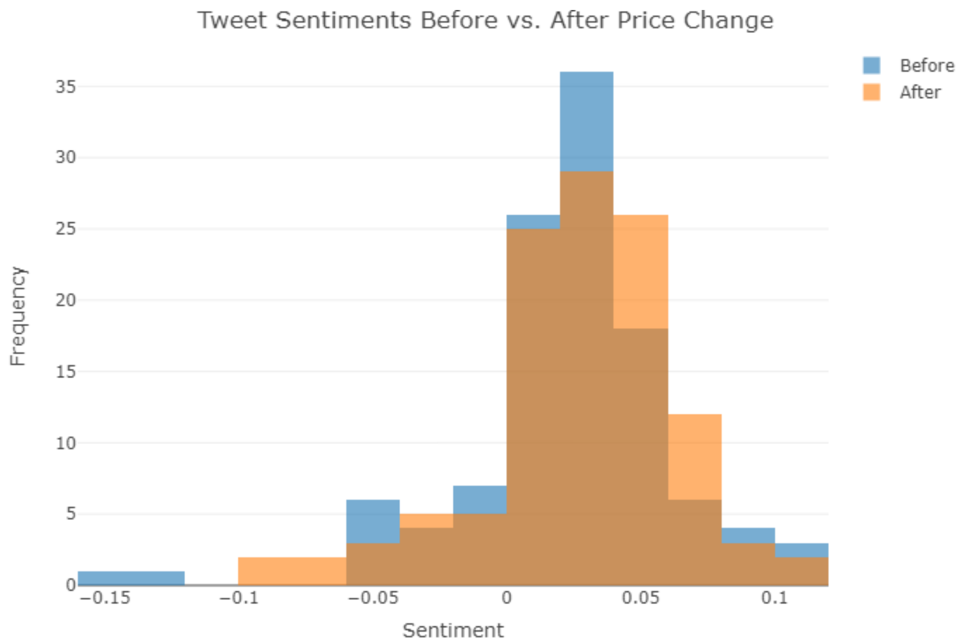
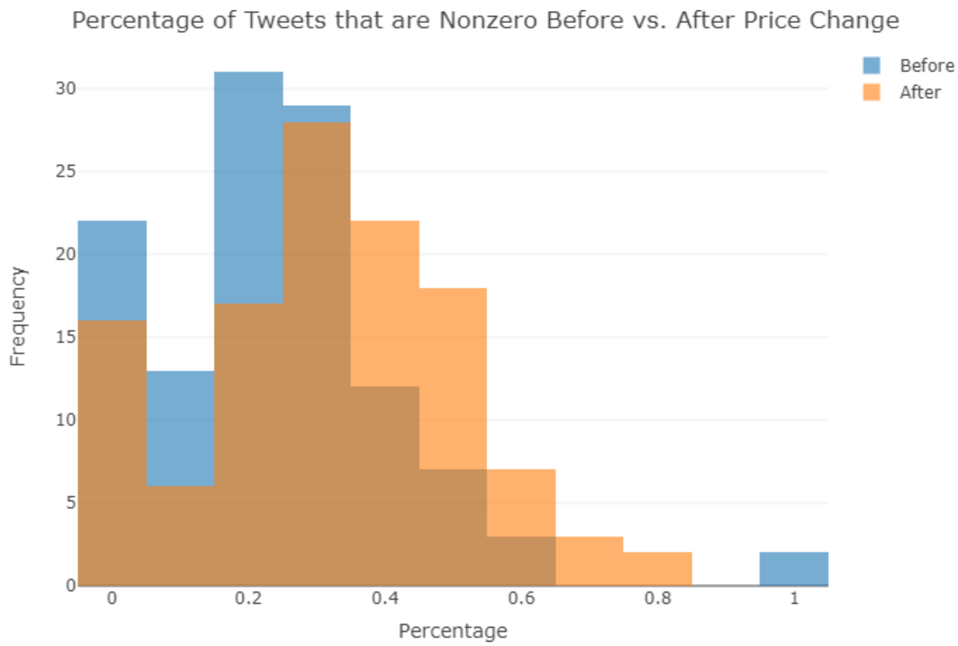


Figure 1: The Red lines Represent the time period of the Kodak Sentiment Scores Graph {figure 1}



{figure 2}

{figure 3}



{figure 4}

7 Sources of Data

https://finance.yahoo.com/

https://eoddata.com/

https://twitter.com/