

Abstract

Twitter is changing the way investors approach the stock market by facilitating a place for large numbers of people to express their ideas and opinions about certain stocks. Many portfolios are created based on technical analysis, all of which are focused on the past trends and current action of the market. However, this type of analysis leaves out critical information, such as the opinions of the buyers and sellers of the stocks. We used Twitter scraping to build an investment portfolio that took into account whether there was a positive or negative connotation associated with different stocks in the S&P 500 index and assigned weights within the portfolio based on those connotations. After comparing the portfolio to the S&P 500 Index, Nasdaq Index, and Dow Jones Index, it was found that the portfolio built in our analysis was competitive but didn't have enough statistical significance to outperform the market. While the portfolio didn't beat the market, using tweets to build an investment portfolio, the performance may have been more significant. Regardless, it was encouraging to see that a portfolio created from only tweets and what they said was competitive with some of the most popular indexes in the market.

Background Information

There are a variety of ways investors will construct and evaluate investment portfolios based on their inherent risk level and goal return rate. By far one of the most popular investing theories is the Modern Portfolio Theory (MPT), first introduced by Harry Markowitz. It provides insight on how to examine a portfolio of assets within a portfolio and the specific financial metrics to examine it. The theory is based on two drivers, risk and return, which can be managed through portfolio diversification. Many applications of modern portfolio theory assume that investors are risk averse and prefer more return for each unit of risk. In Markowitz work, he developed an efficient frontier that shows the optimal weight to place in each asset based on optimal levels of risk and return (Wade, 2020). Using Modern Portfolio Theory, the Capital Asset Pricing Model was developed by Sharpe, Lintner, and Mossin and has been regarded as one of the most widely used theories for evaluating an asset within a portfolio or a portfolio against the market. CAPM shows the level of undiversifiable risk that an asset contributes to a portfolio, reflected within the individual asset's return rate. CAPM relationships are estimated by regressing multiple years of individual asset returns against the same time series of market returns (Sharpe, Lintner, and Mossin, 1964). The CAPM model provided the framework for evaluating the portfolio performance in this study.

This analysis uses the investing strategy of shorter term trading from month to month while still using both MPT and CAPM as the framework for analyzing the portfolio performance. This short-term trading requires investors to be very hands on, and they will need high amounts of leverage to finance negative swings. A common driver of shorter term trading is based on news or current financial events. A short term trader must stay informed and prepared to react to economic statistical reports, industry insights, current events, and specific company

news. These traders try to capitalize on increased price volatility due to news. This means their overall risk level is high, making their potential for higher or lower returns greater. Learning to evaluate the impact of reports or events is crucial to have a successful investment portfolio (Picardo 2021).

This analysis used Twitter as the source of news that dictates the direction of the portfolio. Twitter has become one of the most widely used social media platforms that gives people the ability to communicate short bits of important information during all times of the day. Investors and consumers alike have been using Twitter for sources of news since its inception. It has sparked a new revolution in high frequency trading where people can gather thousands of articles and information on companies to make investment decisions. According to Towards Data Science, traders will run sentiment analysis on tweets every hour to find how the public is reacting to companies or news that could affect industries. This can then be used to form both short and long positions and gives traders the opportunity to react almost immediately to world events (Mukhtar 2020).

The last year has brought another level of attention to social media and the role that it plays in stock market investments. While Twitter is important, Reddit was the platform to start the new trend. In January of this year, a Reddit page by the name of r/wallstreetbets was ultimately responsible for running the price of GameStop's (GME) stock up dramatically. In early January, GME was trading for slightly more than \$13.00. By the end of the month, the stock hit a high of nearly \$500.00. Having a large audience allowed r/wallstreetbets to accomplish this task through sheer volume. Twitter also played a large role in increasing the value of GME's stock. A good example is when Elon Musk simply tagged r/wallstreetbets in a tweet that said "gamestonk!!" In after hours trading, GME increased in value by 140%.

Examples like this show how vital of a role social media, particularly Twitter, plays in market information and trends (Thorbecke, 2021).

As mentioned above, it is possible for a large group to get behind a movement and influence the stock market on Twitter. However, a more common method, like the tweet Elon Musk posted, is for celebrities to tweet about the market. A part of the market that has seen influence from celebrities on Twitter is cryptocurrency. One cryptocurrency that has received attention recently is dogecoin. Similar to GME, dogecoin has had significant increases in value during 2021. In January, each coin was worth less than a penny. Now, each coin is worth between 60 and 70 cents. Celebrities such as Elon Musk and Mark Cuban are largely responsible for this increase in value. There was more than one instance where dogecoin's price surged after tweets from celebrities, including a jump of 20% in less than a day (Browne, 2021).

There is a lot of talk about if the influence of Twitter on the stock market is purely speculation or if it has lasting effects. Either way, it is obvious that Twitter and other social media have the power to influence prices. This analysis will display whether or not developing a portfolio based on Twitter data is a viable option. Clearly the market will move based off of a popular tweet from the right person, but the challenge is to successfully trade stocks for an extended period of time.

Data

The two main sources of data in this study are from Twitter and Yahoo Finance. Tweets were pulled from 30 different twitter accounts that have a large following or are otherwise relevant/active within Fintwit (the Twitter's financial market community). The following accounts were used: @WSJbusiness, @YahooFinance, @ftfinancenews, @NYSE, @CNNBusiness, @ReutersBiz, @breakingview, @Forbes, @CNBCFastMoney, @MadMoneyOnCNBC, @SquawkStreet, @MorningstarInc, @markets, @TheStreet, @SeekingAlpha, @Stocktwits, @IBDinvestors, @DanZanger, @traderstewie, @dKellerCMT, @allstarcharts, @KimbleCharting, @hmeisler, @SJosephBurns, @steve_hanke, @MarketWatch, @bespokeinvest, @CNBC, @SquawkCNBC, @barronsonline. Twitter's API allows for a maximum of approximately 3000 tweets to be collected from each account, which were evaluated from 04/01/2020 to 05/01/2021. This time period eccompasses a unique time period in financial history due to the COVID-19 pandemic.

Each tweet was "cleaned" and filtered by restrictions described in the methods section then sentiment analysis was run on the resulting tweets. The portfolio was weighted from results of the sentiment analysis and price data from Yahoo Finance was downloaded for each ticker during this time frame. Price data from the benchmarks used to evaluate the portfolio was also downloaded: S&P500, Nasdaq, and Dow Jones. The adjusted close price was used when calculating the returns to account for any dividend payments.

Methods

During this analysis, 30 different twitter accounts were selected to scrape tweets from. Each of the accounts specialized in picking different stocks to invest in and tweeting investing advice. A maximum of 3,000 tweets were scraped from each account, which were spread out over the course of the last year. All of the tweets were required to have a stock ticker (ex. AAPL) within the tweets. After collecting the tweets, each tweet was paired to the stock ticker that it mentioned.

Along with pairing the tweet to the ticker, a sentiment analysis was performed on each tweet in order to determine a positive or negative connotation. A score was assigned to every tweet based on the sentiment analysis, with tweets saying bad things receiving a score less than zero and tweets saying good things receiving a score greater than zero. The sum of the sentiment scores were then calculated for every stock ticker, per month, for the 12 month period. The tickers were cleaned again to exclude any tickers that couldn't be found on the yfinance library.

After the tweets were analyzed, each stock from the first month with a sentiment score that added up to more than zero was put into the portfolio. This meant that, in general, our portfolio consists only of positive things said about those stockse. Weights were assigned throughout the portfolio based on how large the monthly sum of sentiment was. The higher the score, the better people thought the stock was going to do. So, we wanted to buy more of it. After the stocks and weights were set, the portfolio was purchased on the first day of trading of the following month.

The investments were left untouched for the entire month before the positions were closed out on the last trading day of the month. The process was repeated monthly, using the Twitter data from the previous month to build the portfolio for the next month's investments.

Returns were calculated as the daily adjusted close price change for each stock, and weighted to get the portfolio daily returns. As a measure of risk, the standard deviation was calculated based on the portfolio daily returns. Both the portfolio daily returns and daily risk were annualized considering 251 trading days. A risk-free rate of 3% per year was considered to calculate the Sharpe ratio for the portfolio. The same measures were obtained from the S&P 500, Nasdaq, and Dow Jones indexes. Finally, the performance was compared to the S&P 500, Nasdaq, and Dow Jones.

Results

Overall, the dominating stock in the portfolio was Tesla, JP Morgan, Amazon, and Google falling closely behind. The portfolio moved in a similar direction to all three benchmarks considered which was to be expected as the stocks utilized in the portfolio are also within the indexes considered (see figure 1 below).

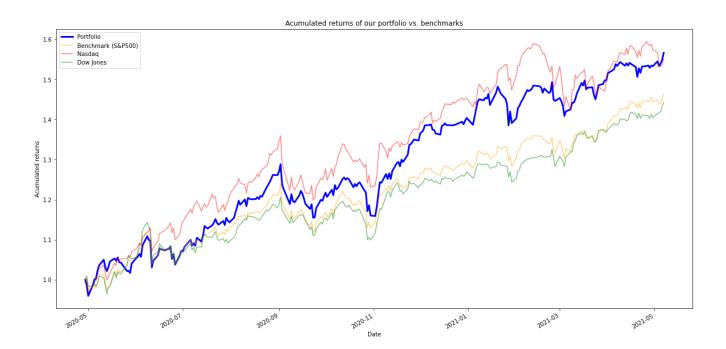


Figure 1. Accumulated returns of our portfolio vs. benchmarks

When annualizing the performance of the portfolio and benchmarks considered, the portfolio outperformed the benchmarks. This in turn mapped to a high Sharpe ratio which measures the excess return achieved per unit of total risk. See Figure 2 for more details.

Annualized Risk-Return of portfolio and benchmarks

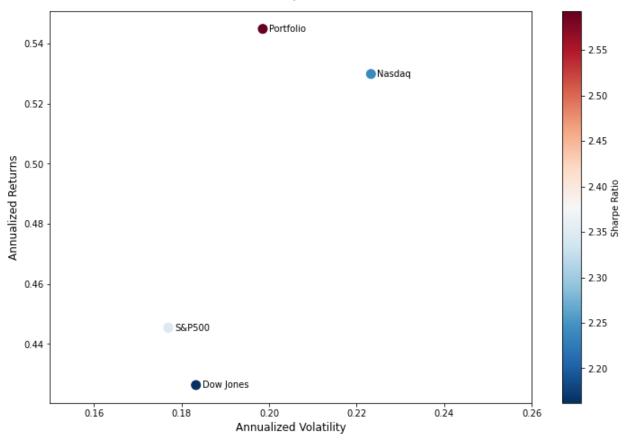


Figure 2. Annualized risk, returns and sharpe ratios for portfolio and benchmarks

At first glance, it looks like the portfolio outperformed the benchmarks but to truly evaluate the performance of it, the CAPM expected return was calculated using the S&P 500 as the benchmark for the market performance. Jenson's alpha was then utilized to measure how the portfolio performed relative to the predicted CAPM value. After running the regression results, it was found that the portfolio formed generated .0003% daily excess returns over the market which was not statistically significant. These results concluded that the portfolio formed based on the twitter data did not beat the market if CAPM is used to evaluate the performance. See Figure 3.

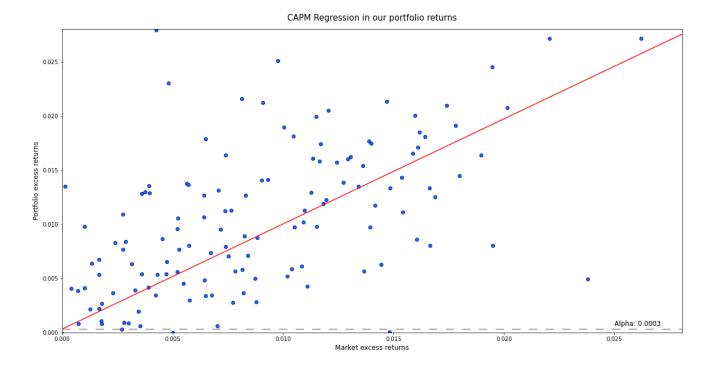


Figure 3. CAPM Regression of portfolio returns

There are a few limitations within this analysis. First being that due to the limitations of the Twitter API, we only considered a selection of accounts which could skew the results.

Accounts were also chosen somewhat arbitrarily as we only considered tickers in the form of \$TICKER while a lot of accounts would just spell out the name of the company. Tweets were only considered if they mentioned one ticker while some tweets would mention multiple tickers. We also assume no transaction costs or taxes and that we would be able to buy and sell the stocks at the opening and closing prices which may not be realistic. The study also only considers a 1 year investment horizon due to the API restrictions and would likely provide a better insight if a longer term was considered. Other factors that could skew the results could come from analyzing the sentiment scores. For example, if a tweet read "TSLA stocks are exploding" then Twitter

may assign it a negative sentiment score. Other tweet limitations could come from the use of emojis after mentions which would eliminate the ticker from the data set.

Conclusion

This analysis has attempted to use Twitter data to follow current events and create a portfolio based on good sentiment scores of S&P 500 ticker symbols mentioned from the accounts of reliable financial news sources. The goal was to provide insight on how Twitter data could be a useful investment tool to either follow or outperform the market. Specifically, we relied on sentiment analysis to determine whether a stock had a negative or positive connotation associated with it during changing news events. This could be quite beneficial for investors seeking to simultaneously evaluate portfolio changes with incoming news. The results suggest that the portfolio formed from the twitter data, moved in relation to the benchmarks considered and did outperform the market if only the Sharpe ratio is considered. However when evaluating the performance under the CAPM model, the excess returns generated over the market were not statistically significant. A longer investment horizon or a more complete data set of tweets could provide for more conclusive results.

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